UNIVERSITY OF SOUTHAMPTON

Faculty of Engineering and Physical Sciences
Transportation Research Group

Integrating Connected Vehicles into Urban Traffic Management Systems

by

Craig Benjamin Rafter

ORCID ID 0000-0003-3411-114X

Thesis for the degree of Doctor of Philosophy

Under the supervision of:
Prof. T. J. Cherrett
Dr. B. Anvari
Dr. S. Box
Dr. B. Waterson

November 2020

UNIVERSITY OF SOUTHAMPTON

ABSTRACT

FACULTY OF ENGINEERING AND PHYSICAL SCIENCES
TRANSPORTATION RESEARCH GROUP

Doctor of Philosophy

INTEGRATING CONNECTED VEHICLES INTO URBAN TRAFFIC MANAGEMENT SYSTEMS

by Craig Benjamin Rafter

Connected intelligent transport systems contain a wealth of data accessible to traffic signal controllers. However, algorithms that use data from a connected environment do not fully exploit the potential of this new data source. Instead, traffic signal controllers rely on speed and position data to supplement data from infrastructure. This research aims to understand which data that are available from connected vehicles are useful for integrating with existing traffic signal control systems in urban environments. Vehicle positions and speeds fit well into our current understanding of traffic theory, but more abstract data such as passenger counts and stop frequencies may offer new ways to optimise traffic signal controllers to reduce traffic delays.

The contributions of this research include 1) A traffic signal control algorithm which combines position information from connected vehicles with data from existing inductive loops and signal timing plans to perform decentralised traffic signal control to reduce delays at existing urban intersections. The algorithm adapts to scenarios with low numbers of connected vehicles and degraded infrastructure, an area where existing traffic signal control strategies are limited. 2) A framework for testing connected traffic signal controllers based on a large urban corridor in the city of Birmingham, UK. The testing framework overcomes the limitations of existing research by implementing a large-scale, realistic simulation case study, which accounts for mixed-mode traffic, multiple levels of traffic demand, degraded loop detector coverage, non-ideal wireless communications, and a full 24-hour simulation period. 3) A greedy stage sequence optimisation algorithm that abstracts for arbitrary connected vehicle data. 4) A method for introducing implicit stage coordination to greedy stage optimisation paradigms. 5) Insights that show coordination is redundant when signal controllers have accurate data and can react fast enough to traffic changes.

This research shows how data connected vehicles can be exploited to improve urban traffic signal control, and how using connected vehicle data differs from traditional sources. The outcomes of this research have a significant impact on the implementation of connected intelligent transportation systems and policy for the transportation industry.

Contents

List of Figures

List of Tables

List of Algorithms

Nomenclature

Chapter 3: Augmenting Traffic Signal Control Systems for Urban Corridors with Connected Vehicles

Symbol	**Description**	**Unit**
$t_{\text{clear,queue}}$	Time needed to clear a queue	s
l_{queue}	Length of a queue	m
$l_{\text{queue,max}}$	Maximum length of a queue in a lane	m
$t_{\text{green,max}}$	The maximum stage green time	s
$t_{\text{clear,CV}}$	Time to clear a CV through the intersection	s
$d(\mathbf{x}_1, \mathbf{x}_2)$	The Euclidean distance between a pair of 2-D Cartesian coordinates	m
$\mathbf{x}_v$	2-D Cartesian coordinates for the position of a vehicle	(x (m), y (m))
$\mathbf{x}_i$	2-D Cartesian coordinates for the position of an intersection	(x (m), y (m))
v_{vehicle}	The speed of the vehicle	m/s

Chapter 4: Greedy Stage Optimisation Using Connected Vehicle Data

Symbol	**Description**	**Unit**
M	The number of rows (data points) in the utility matrix	–
N	The number of columns (stages) in the utility matrix	–
U_{ij}	The greedy algorithm utility matrix of size $M \times N$	–
$\widehat{U}_{\text{ij}}$	The normalised utility matrix	–
ω_i	Weighting column vector	–
S_{j}	The utility aggregate row vector	–
S^*_{j}	The coordinated utility aggregate row vector	–
α	The coordination scaling factor	–
c_{j}	The stage coordination row vector	–
x_{i}	The stage index at decision point i	–
T_{j}	The stage time for stage j	s
T_{elapsed}	The time elapsed since the beginning of the current stage	s

Acronyms

ACC	Adaptive Cruise Control
AI	Artificial Intelligence
ANPR	Automatic Number Plate Recognition
API	Application Programming Interface
APM	Action Point Model
AV	Autonomous Vehicle
CACC	Cooperative Adaptive Cruise Control
CAM	Cooperative Awareness Message
CAV	Connected and Autonomous Vehiclex
CDOTS	Connected Data Optimised Traffic Signals
CFP	Cyclic Flow Profile
CSV	Comma Separated Value (file)
CTT	Cumulative Travel Time
CV	Connected Vehicles
CVP	Connected Vehicle Penetration
DARPA	Defence Advanced Projects Agency
DENM	Decentralised Environmental Notification Message
DGPS	Differential Global Positioning System
DSRC	Dedicated Short Range Communication
ETSI	European Telecommunication Standards Institute
EU	European Union
FCC	Federal Communications Commission
FHWA	Federal Highways Administration
FIFO	First-In First-Out
FSM	Four-Step Model
GPS	Global Positioning System
HBEFA	Handbook Emission Factors for Road Transport
HEOMM	Highways England Operational Metrics Manual
HGV	Heavy Goods Vehicle
HPC	High Performance Computer
ICU	Intersection Capacity Utilisation
ID	Identity

IDM	Intelligent Driver Model
IEEE	Institute of Electrical and Electronics Engineers
IMA	Intersection Management Agent
IMU	Inertial Management Unit
ITS	Intelligent Transportation Systems
LED	Light Emitting Diode
LGV	Light Goods Vehicle
LIDAR	Light Detection and Ranging
LOS	Line-of-Sight
LTE	Long Term Evolution
MATS	Multi-mode Adaptive Traffic Signals
MC	Motorcycle
MHVDM	Multiple Ahead and Velocity Difference Model
MILP	Mixed-Integer Linear Program
MOVA	Microprocessor Optimised Vehicle Actuation
NHTSA	The National Highway Traffic Safety Administration
NLOS	Non-Line Of Sight
NMEA	National Marine Electronics Association
OAF	Oldest Arrival First
OD	Origin-Destination
OFDM	Orthogonal Frequency Division Multiplexing
OPAC	Optimisation Policies for Adaptive Control
OSI	Open Systems Interconnection
OSM	Open Street Maps
OVM	Optimal Velocity Model
PAMSCOD	The Platoon-based Arterial Multi-modal Signal Control with Online Data algorithm
PHEM	Passenger car and Heavy-duty Emission Model
PI	Performance Indicator
PL	Packet Loss
PMSA	Predictive Microscopic Simulation Algorithm
PRODYN	PROgramme DYNamique
RADAR	Radio Detection and Ranging
RFID	Radio Frequency Identification
RHODES	Real-time Hierarchical Optimised Distributed Effective System
RHW	Road Hazard Warning
RMART	R-Markov Average Reward Technique
RSU	Roadside Unit
RTCM	Radio Technical Commission for Maritime Services
SAE	Society for Automotive Engineers
SCATS	Sydney Coordinated Adaptive Traffic Signals
SCOOT	Split Cycle and Offset Optimisation Technique
SDM	Safety Distance Model

SUMO	Simulator of Urban Mobility
SWOT	Strength-Weakness-Opportunity-Threat Analysis
SYNCDOTS	Synchronised Connected Data Optimised Traffic Signals
TRANSYT	Traffic Network Study Tool
UBI	Usage-Based Insurance
UHF	Ultra-High Frequency
UK	United Kingdom (of Great Britain and Northern Ireland)
US	United States (of America)
USA	United States of America
USB	Universal Serial Bus
UTMC	Urban Traffic Management
UTOPIA	Urban Traffic OPtimization by Integrated Automation
UV	Unconnected Vehicle
UWB	Ultra-Wideband
WLAN	Wireless Local Area Network
XML	Extensible Markup Language

Declaration of Authorship

I, Craig Benjamin Rafter, declare that this thesis entitled '*Integrating Connected Vehicles into Urban Traffic Management Systems*' and the work presented in it are my own and has been generated by me as the result of my own original research.

I confirm that:

1. This work was done wholly or mainly while in candidature for a research degree at this University;
2. Where any part of this thesis has previously been submitted for a degree or any other qualification at this University or any other institution, this has been clearly stated;
3. Where I have consulted the published work of others, this is always clearly attributed;
4. Where I have quoted from the work of others, the source is always given. With the exception of such quotations, this thesis is entirely my own work;
5. I have acknowledged all main sources of help;
6. Where the thesis is based on work done by myself jointly with others, I have made clear exactly what was done by others and what I have contributed myself;
7. Parts of this work have been published as: Rafter, C.B. et al. 20XX. See Appendix A for a list of the published articles.

Signed:

Acknowledgements

I like to acknowledge the support from the Engineering and Physical Sciences Research Council (EPSRC) under Centre for Doctoral Training grant EP/L015382/1 in partnership with the Transport Research Laboratory (TRL). I also acknowledge the use of the IRIDIS High-Performance Computing Facility, and associated support services at the University of Southampton, in the completion of this work.

I want to extend my sincerest thanks to my supervisory team. Thanks to Dr Bani Anvari, for supervising me for the most significant portion of my research, and without whose tireless support, encouragement, enthusiasm, and dedication, my research would not have progressed. Thanks to Dr Simon Box, who started me on this academic journey. Thanks to Prof. Tom Cherrett, who saw me through the final stage of my research, and whose feedback on this thesis was immeasurably helpful. Thanks to Dr Ben Waterson for always sharing his knowledge and insights. Finally, thanks to Prof. Nick Hounsell, for his support and guidance. I would also like to extend my gratitude to my colleagues in the Transportation Research Group and CDT in NGCM for their encouragement and support over the course of my PhD.

I also want to extend thanks to the team at TRL, who sponsored and supported this research. In particular, Chris Kettell and Islam Abdelhalim for their valuable feedback over many meetings. I would also like to thank Andy Kirkham, Tom Fanning, Peter Vermaat, Chris Lodge, Jim Binning, and Mark Crabtree for their help with this research. I would also like to thank Prof. Alan Stevens for his mentorship, guidance, and advice throughout this research project.

I want to thank my original mentors for setting me on the path of research. Dr Nikola Godinović for encouraging me to think deeper about problems of science, and Dr Paul Curran for encouraging me to question everything.

Last but not least, I would like to thank my family, my mother Gladys and father Ivan for their love and unwavering support in my pursuit of knowledge, and my brother Andrew for always providing a laugh and distraction during my time off. Thank you to my extended friends and family, who did not always understand what I was doing but encouraged me unreservedly nonetheless. Finally, I would like to thank my partner Emily, there are not enough words to express how much your love and support means to me. Thank you for cheering me on, I could not have done it without you.

Chapter 1

Introduction

The introduction of Connected Vehicles (CV) within Intelligent Transport Systems (ITS) presents unique opportunities and challenges for urban traffic management. Increasing vehicle numbers competing for ever restricted road space present significant challenges when trying to optimise network capacity where there are limited resources to do so. Connected vehicles present new opportunities to gather data about the transport network, which can be used for traffic signal control. Traffic signal control is a known way to reduce delays in transport networks, but they require data to do so.

This thesis will focus on using data from CVs to augment existing traffic signals in urban corridors. Although others have investigated traffic signal control using connected vehicle data, this thesis aims to understand how traffic signal control systems interact with existing traffic infrastructure in urban corridors. This area is not well studied. This thesis also aims to investigate what data from connected vehicles, if any, are beneficial for traffic signal control in urban corridors.

1.1 Challenges in Urban Traffic Management

1.1.1 Economic Costs Associated with Delays

Traffic delay in the transport system is forecasted to incur significant costs to the global economy over the next 15 years (CEBR, 2014). INRIX (2017) estimated that in the UK, Germany, and the USA alone, traffic congestion costs their economies a combined $450 billion in lost time and wasted energy. In the UK, in 2019, drivers lost 115 hours due to congestion on average, costing the economy an estimated £6.9 billion (INRIX, 2020). Traffic delays are a significant problem in developed countries. Traffic management at intersections is one way of managing vehicle flows to reduce traffic delays in urban environments.

1.1.2 Road Traffic Safety

Traffic safety measures aim to reduce accidents and loss of life of road users. Traffic safety measures are features such as traffic signage, cycle lanes, speed enforcement, ramps, traffic islands, and pedestrian crossings that are added to the roadway to make it safer for drivers and pedestrians. Still, in urban areas, there are a host of issues with operating vehicles in densely crowded environments with single-vehicle, vehicle-vehicle, and vehicle-cyclist/pedestrian collisions all being common accident types (Archer and Vogel, 2000). In 2018 there were over 160,000 road accident casualties in the UK (UK Govt. Dept. Transport, 2019*b*), with driver error determined to be a contributory factor in over 80% of cases (UK Govt. Dept. Transport, 2019*c*). A review of road safety at signalised intersections by the Transport Research Laboratory (TRL) (Kennedy and Sexton, 2009) identified that signalisation reduces traffic accidents by up to 40%. They also identified that systems which mitigate red-light running reduce right-angle collisions by up to 30%. Still, there is significant room for improvement in the development of traffic systems that help mitigate the number of annual road traffic accidents at signalised intersections.

1.1.3 User Experience and the Impact on Driver's Behaviour

In the context of transport systems, user experience defines a user's emotional response as they interact with and journey through the transport network. The issues that concern users include being able to travel to their destination quickly, reliably, and comfortably (Wirtz and Jakobs, 2013). In terms of information provision, Wirtz and Jakobs (2013) also reported that users are interested in convenient and reliable access to travel information during the planning stage of their journeys. Understanding drivers' desire to make their journeys efficient is essential when adjusting traffic signal timings. For example, Felicio et al. (2015) showed that in a survey of drivers, over 75% reported that they slow down for amber signals, however, when traffic was directly observed, over 80% of drivers were speeding up or maintaining their speed for an amber signal. Van Der Horst (1988) showed that increasing amber-light duration preceding a red-light to 4 s at 30 mph and 5 s at 50 mph halves instances of red-light running. Both of these studies show how critical driver expectation is to their driving behaviour at intersections, and that drivers will compromise their safety if they think they can 'beat the traffic signals' to save time.

1.1.4 Environmental Concerns Related to Traffic Growth

Vehicle emissions severely impact the environment and increase rates of illness for people regularly exposed to air pollution (Zhang and Batterman, 2013). In the UK, Public Health England (2019) estimated that 28,000 to 36,000 deaths a year are attributable to long-term exposure to air pollution. Furthermore, they also identified that air pollution incurs a societal cost of over £20 billion. De Coensel et al. (2012) showed that the coordination of traffic signals reduces emissions by up to 40%. As traffic signal controllers manage traffic flow, they can adapt their control strategy to attempt to mitigate emissions as well as reduce delays in order to improve air quality.

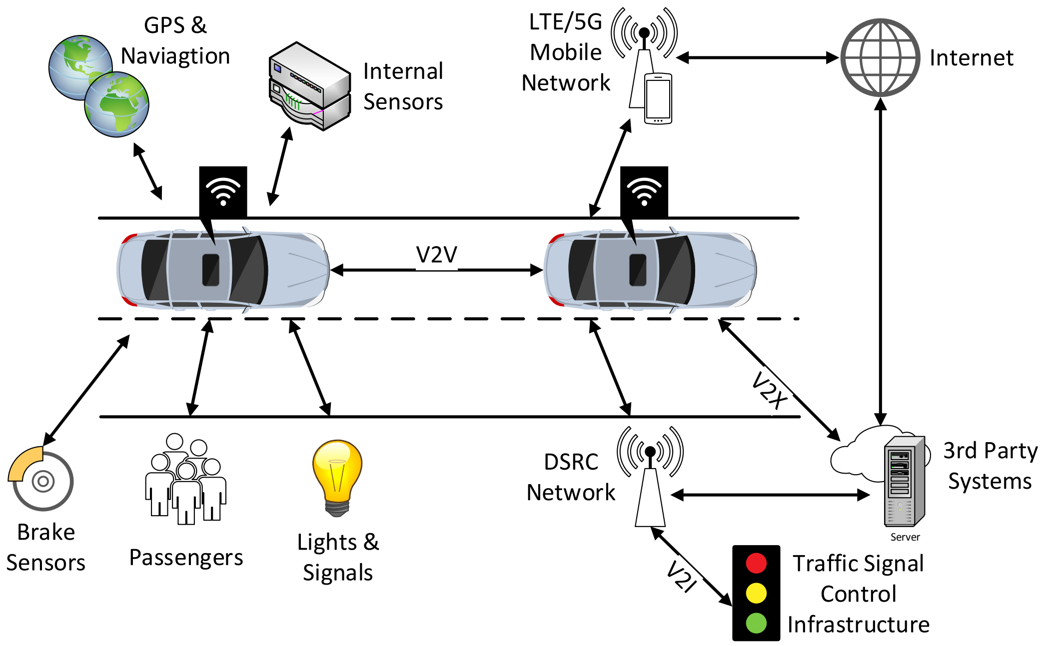
1.2 Addressing Urban Traffic Challenges with Connected ITS

Connected Intelligent Transport Systems (C-ITS) integrate and apply communications, control, and information processing technologies to the transport system to improve traffic safety, minimise environmental impact, and improve the quality and reliability of traffic management systems (ETSI, 2018*a*). Connected Vehicles (CV) use wireless communication technologies to enhance Vehicle-to-Vehicle (V2V), Vehicle-to-Infrastructure (V2I) (e.g. roadside units and cell towers), and Vehicle-to-Anything (V2X) (e.g. cyclists, pedestrians, vehicles, or infrastructure) communication in order to support and improve traffic management, driver and public safety, traveller information, and user experience as well as to reduce fuel consumption and exhaust emissions (Bishop, 2005*a*,*b*; Van Arem et al., 2006). In terms of traffic management capability, data sent from connected vehicles to connected infrastructure allow traffic management systems to know much more about the state of individual vehicles in the network. Current detection systems such as inductive loops and video systems only gather data at specific points. In contrast, connected data can provide a complete view of the demand on the network at a higher resolution. By knowing more about the vehicles in the network, traffic management systems will be able to make better-informed decisions about how best to optimise traffic signals, prioritise certain road users, and reduce emissions.

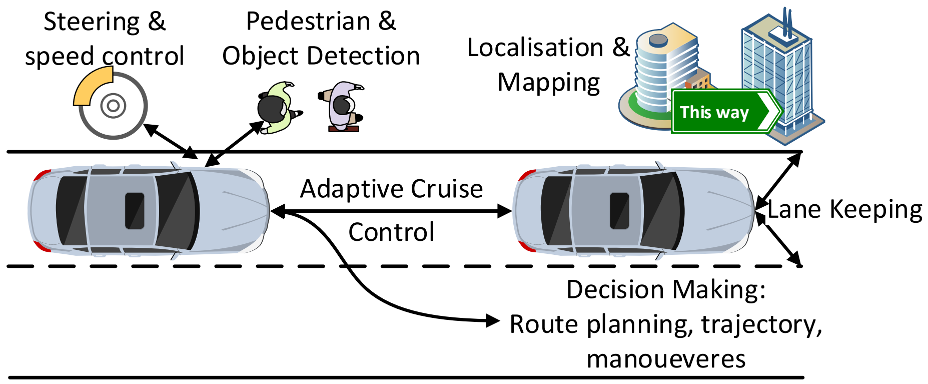
1.2.1 Defining Connectivity and Autonomy

When referring to vehicles in ITS, the words *'connected'* and *'autonomous'* are often seen together. In this thesis, the focus is using data from connected vehicles for urban traffic signal control. In order to define the behaviours of interest to his research, the following distinctions are made:

- *Connected* - Connectivity refers to the dissemination of data between vehicles, infrastructure, and other services within C-ITS. Connectivity is primarily concerned with managing data streams within C-ITS. Vehicles with only connected technologies are referred to as Connected Vehicles (CV).
- *Autonomous* - Vehicle autonomy refers explicitly to the non-human control of a motor vehicle. Autonomous systems are primarily concerned with increasing driver safety. Vehicles with only autonomous capabilities are referred to as Autonomous Vehicles (AV).



(a) CV operations



(b) AV operations

Figure 1.1: Diagrams showing the functionality of CVs compared with AVs. CVs are focused on sharing data, while AVs are focused on driving behaviours.

A vehicle may have both connected or autonomous features exclusively, or in some cases, both. As shown in Figure 1.1(a), a purely *connected vehicle* is primarily controlled by a human driver but may transmit or receive data relating to, for example, car's position, speed, turn signals, and the number of passengers. The data can be used for services such as traffic signal management in the vicinity of the CV to help them through the network. In contrast, purely *autonomous vehicles* (see Figure 1.1(b)) exhibit autonomous driving systems that exert partial to complete control over a vehicle. *Connected and autonomous vehicles* (CAV) have partial/complete automated driving systems, but also send and receive data in the same way as CVs. Throughout this research, the focus is on developing traffic signal control systems that use CV technology. In certain sections of the literature review, CAVs are referred to where technologies impact both CVs and AVs. The focus of this research is on systems of CV and V2I data transfer, where the infrastructure is a traffic signal controller.

For this research, the distinction between CVs and probe-vehicles should also be considered. Probe vehicles, also referred to as 'floating-cars', are closely related to CVs. Probe vehicles are those that record vehicle position, speed, and a timestamp for either offline analysis, or use in live systems through communication with a traffic management centre (Zheng and Van Zuylen, 2013). Unlike CVs, probe vehicles are used for polling the state of the traffic network for traffic management purposes only and are not designed to be ubiquitous or interoperable. CVs are distinct from probe vehicles in that they are designed to be interoperable, and share their data beyond traffic management centres. CVs also present the opportunity to report non-traditional metrics such as passenger counts, and at high market penetrations, represent a more diverse and comprehensive sample than probe vehicles.

The main advantage of CV is that they do not require expensive infrastructure. However, their networking protocols are more complex compared to unconnected vehicles, and they require significant fleet penetration before their applications become effective. Current traffic control schemes for CVs in C-ITS assume ideal communication between vehicles and infrastructure or require the dominant presence of autonomous or connected vehicles in the network (Au et al., 2015; Goodall et al., 2013; HomChaudhuri et al., 2016). As CVs are only set to be introduced from 2020 onwards, it will take time for the vehicle fleet to turnover (Litman, 2019). Figure 1.2 is generated based on the UK Department for Transport's dataset (UK Govt. Dept. Transport, 2019*d*), and it shows the spread of cars on UK roads in 2018 based on their age (the average age of a car is 7.3 years). Additionally, the average age of a car in the US was 11.4 years in 2014 (United States Department of Transportation, 2015). The UK and US are representative of developed vehicle markets, and the average vehicle ages highlight that the transition to CV will not be immediate. Therefore, there is a need for developing signal control strategies for urban areas that can modify existing infrastructure and support the transport network as it becomes increasingly connected.

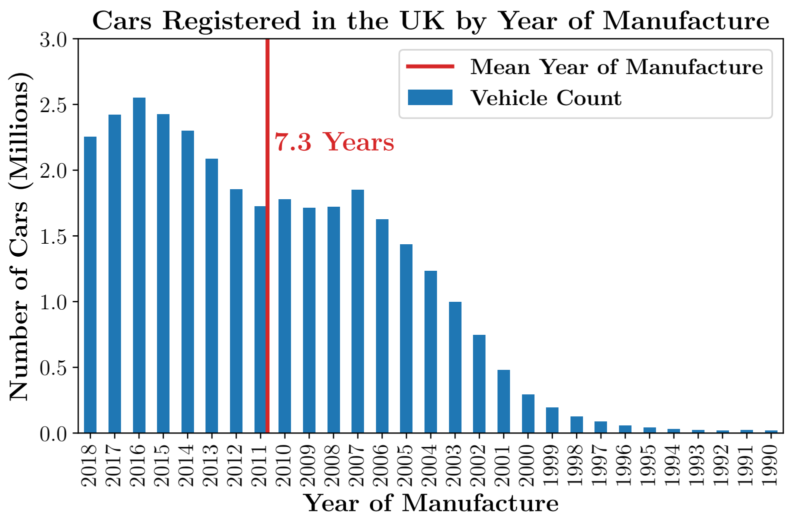


Figure 1.2: Distribution of cars registered in the UK as of 31st December 2018 by year of manufacture. This plot highlights the persistence in the vehicle fleet, and that it will take time for CAVs to filter into the fleet. Based on (UK Govt. Dept. Transport, 2019*d*)

1.2.2 Current applications of ITS

CVs are a proposed way of improving traffic management in urban areas. There are also complementary ways in which roadside and vehicular technologies have been modernised to incorporate computer-controlled or data-driven systems in order to manage traffic, improve driver safety, and enhance user experience.

1.2.2.1 Reducing Traffic Delay

In urban areas, traffic responsive intersection control uses collected sensor data to modify stage times based on intersection demand, and coordinate the stages between adjacent junctions to improve traffic flow and reduce delays. CV systems are inherently well suited to mitigate delay (Au et al., 2015; Van Arem et al., 2006), by allowing different vehicle and infrastructure agents in the network to assist each other through V2V and V2I communication cooperatively. For instance, a vehicle can communicate with an oncoming vehicle on the opposite lane in C-ITS and therefore can receive information about congestion, weather, or the road surface conditions ahead of it.

1.2.2.2 Improving Safety

On highways, E-tolling is employed in many places to toll road users. Rather than creating a bottleneck with a toll-booth, Automatic Number Plate Recognition (ANPR) or Radio Frequency Identification (RFID) tags are used to apply tolls. The detectors for ANPR and RFID usually sit above the road, so users do not need to decelerate, and they have the convenience of paying their toll automatically. Variable speed limits and emergency notification systems increase traffic flow and safety by tactically controlling vehicle flow along certain highway sections, and informing users of hazard through the use of computer-controlled road signage.

The National Highway Traffic Safety Administration (NHTSA) studied the benefits of V2V and V2I connectivity by investigating crash types (such as right-angle collisions, head-on collisions). It identified that 80% of non-impaired crash types could be avoided by V2V DSRC (Dedicated Short Range Communication) connectivity (Najm et al., 2010). DSRC connectivity allows high-speed periodic data transmission (10x/second) among mobile vehicles equipped with a DSRC transmitter and receiver. Sophisticated algorithms in the vehicles understand the relative distance between the vehicles and, for instance, give a warning to the driver if there is an imminent crash situation.

There are several scenarios where vehicle collisions can be mitigated through forward-collision warning systems. For example, vehicles with deployed air-bags, or undergoing sudden deceleration or stopping manoeuvres, can transmit warning messages to other vehicles in their vicinity. Warning messages can be disseminated further than a vehicle's transmission range by using other connected vehicles and roadside infrastructure as relays.

Vehicles running red stoplights at intersections frequently cause side-impact collisions. If both vehicles in this scenario are connected, the system can forewarn other drivers of a collision, and prevent a new accident. Similarly, at blind crossings, connected vehicles can recognise each other and inform the driver when it is safe to proceed (Au et al., 2015).

1.2.2.3 User Experience

Adaptive Cruise Control (ACC) and Cooperative ACC (CACC) are systems placed in modern vehicles that assist drivers in keeping constant headways between vehicles on highways which have been shown to improve traffic flow stability (Dunbar and Caveney, 2012; Mamouei et al., 2018; Milanes et al., 2014; Swaroop and Hedrick, 1996). The studies on the impact of V2V communication systems on drivers' car-following behaviour shows that CACC harmonises the behaviour of drivers, reduces vehicle's speed and the range of acceleration and deceleration differences among them, and reduces fuel consumption and exhaust emissions, contributing to improved user experience (Shladover et al., 2015; Van Arem et al., 2006). Other technologies that are being incorporated into vehicles to improve user experience include for instance: (1) automatic lane changing, which couples with (C)ACC to allow vehicles to change lanes if necessary; (2) self-parking, which allows users to benefit from the convenience of leaving their vehicle to park itself or assist the driver in parking.

Inter-vehicle communication systems play an essential role in traffic management, improving public safety, and enhancing user experience as they enable mobile vehicles to communicate required data and travellers information.

1.2.2.4 Ethics of Connected Vehicle Systems

Transport connects people to places, and transport changes can disadvantage vulnerable groups such as the elderly, disabled, and low-income communities if not planned correctly (Public Health England, 2019). Vulnerable user groups are known to avoid or be reluctant to adopt technologies viewed as 'unknown' or 'complicated' (Sochor and Nikitas, 2016). Therefore, it is essential to make sure that new technologies and CV data used for traffic signal control is beneficial for all road users.

C-ITS rely on users sharing their data. It is essential to understand if users would consent to share their data with an urban traffic management service. In an implementation of an ITS, users must be aware of the type of data they agree to share, with whom they agree to share it with, and how their data are being kept secure from unauthorised access. The main ethical issue here is privacy. If the data requested by traffic management services are personal, it no longer constitutes a system providing a service and is instead a system for surveillance (Van Zoonen, 2016).

1.2.2.5 Environmental Impact Reduction

Particulate emissions from vehicles have severe effects on public health and exacerbate respiratory and cardiovascular conditions (Krzyzanowski et al., 2005). Hybrid and electric vehicles have been introduced to reduce the amount of pollutants vehicles emit by supplementing or replacing traditional combustion engines with a battery-powered drive train (Hawkins et al., 2012). Congestion charging is another approach that is used to reduce emissions by charging drivers to enter certain areas with the intent that it will reduce the number of vehicles in the area (Santos and Shaffer, 2004).

Although efforts such as congestion charging discourage vehicle usage, there will inevitably be vehicles that remain. To reduce the emissions for the remaining combustion vehicles, eco-driving is a driving style that encourages drivers to adopt smoother driving patterns to reduce their emissions and fuel consumption (Barkenbus, 2010). Traffic signal control algorithms such as the IntelliGreen algorithm (Datesh et al., 2011) and the research of Yang et al. (2019), send speed advisory information to drivers of CVs to help them use the appropriate speed to minimise their environmental impact and smooth traffic flow.

1.3 Unaddressed Challenges

The NHTSA has produced a series of reports (United States Department of Transportation, 2016) identifying the current state of the transport network design tools, and identified their expectations in terms how the technologies being developed will be adopted, the impact they will have, and the infrastructure they will require. Notably, they identify the weaknesses in the current analysis tools, techniques, and data. Current design methods and simulation techniques do not account for changes to C-ITS infrastructure, there are no systems for optimising C-ITS traffic networks or supporting network design decisions, and there are currently no means to assess the actual benefits of implementing C-ITS quantitatively. Therefore, for traffic signal control, this means that it is not understood how using CV data to manage traffic signals will impact the transportation network in its present state. It is also not known which data from CVs, if any, are beneficial for traffic signal control. These weaknesses restrict the integration of CVs into the transport network, which means the transport network is not prepared to exploit the introduction of CVs efficiently.

In urban corridors that are already close to capacity, changes that reduce link capacity can detrimentally affect traffic delay, road safety, and user experience. Simulation is one way in which new systems can be tested to see if they are beneficial enough to deploy in live traffic systems. This research develops traffic systems and models that are suited to analysing the impact that C-ITS will have on the transport network and aims to highlight the gaps and areas where further work is needed to simulate C-ITS comprehensively. Moreover, this research addressed how to use the data available from vehicles in a C-ITS for traffic signal control and recommend how best to integrate connected traffic signal strategies into the transport network.

1.4 Research Aim and Objectives

It has been highlighted in Figure 1.2 that the transition to CVs will not be immediate. Furthermore, there are challenges in delay, safety, and user experience that need to be addressed. C-ITSs are a promising way to address these challenges, as they offer richer data than current technologies. Currently, the tools for modelling C-ITS are limited, and there is little knowledge of how to fully exploit the richer datasets they produce to reduce delays, stops, and emissions, in the transport network.

1.4.1 Aim

This research will investigate methods for integrating data from connected vehicles into existing traffic signal control infrastructure on urban corridors. The integration will take the form of traffic signal control algorithms whose performance will be assessed against existing signal control systems.

1.4.2 Objectives

To determine which data are generated by CVs and evaluate their usefulness for urban traffic signal control through simulation.
The objective is to determine which data are most useful for a V2I based traffic signal control strategy. For example, high-resolution GPS data may be irrelevant if it does not provide performance benefits over inductive loops. Information that is not already commonly attainable such as a vehicle's turn signals, passenger count, size, emissions profile, and stopping frequency, may afford improved control options.

To quantify how the presence of CVs in the vehicle fleet impacts on the efficiency of the transport network for increasing CV penetration from 0% to 100%.
Urban corridors incorporating connected and unconnected vehicles, and the developed intersection control strategies that utilise V2I data need to be evaluated. The evaluation of urban corridors scenarios involving connected systems allows the impacts of CVs on the transport network to be assessed through comparison of the connected system and existing unconnected systems. The control strategies' robustness to communication delays and measurement errors also need to be considered to more closely approximate their real-world performance.

To formulate urban traffic signal control strategies based on state-of-practice and state-of-the-art knowledge that are beneficial for both connected and unconnected vehicles.
In developing control strategies for signalised intersections using V2I data, there is not only a challenge in improving traffic flow and reducing delays but also in determining which types of control strategy are beneficial at low connected vehicle penetrations. Considering both connected and unconnected vehicles is vital so that the new technology does not create a bias between the two user groups.

To inform policymakers and transport planners on how to design better, safer urban corridors that are towards the integration of CVs using a state-of-the-art literature review combined with the findings of this research.
Part of this research comprises recommendations to policymakers and transport planners. The recommendations are based on the acknowledged gaps in the literature, and the results from the evaluation of the developed intersection control strategies in connected urban corridor environments. The recommendations inform policymakers and transport planners on the best course of action to integrate connected vehicles into the transportation network.

1.5 Contributions to the Field

With respect to the research aims and objectives, the contributions of the thesis to the state-of-the-art knowledge in the field of traffic signal control using CV data are as follows:

1. An assessment of the current quality of simulations involving traffic signal control in the presence of CVs, and the development of a testing framework for traffic signal control in the presence of CVs. It has been acknowledged that the analysis tools for analysing traffic models using CV data are limited. This research synthesises the current resources used in the literature for modelling traffic signal control in the presence of CVs, identifies weaknesses in current approaches, and proposes a testing framework that addresses the identified weaknesses.

2. Development of an algorithm that optimises traffic signal timings at intersections by combining existing infrastructure with data from CVs. It will take time for vehicle fleets to transition to being fully connected, and for technology to be adapted to utilise data from connected vehicles. This research proposes a traffic signal control algorithm that combines data from two offline infrastructure resources with data from CVs and can switch the context of its control based on the data available. This research offers control options that are effective for both CVs and unconnected vehicles. The proposed algorithm is beneficial for upgrading existing systems to use data from CVs, saving effort and installation costs for traffic signal operators.

3. Development of an algorithm that can combine multiple data from CVs to optimise stage sequencing and achieve coordination. CVs present a wealth of data that was previously unavailable for traffic signal control, often at higher resolutions than roadside infrastructure. This research presents a heuristic that, for the first time, combine multiple disparate data into a single algorithm which can be used to optimise stage sequences and coordinate traffic signals implicitly. Previously traffic signal coordination required explicit coordination. This research demonstrates that through the use of data from CVs coordination can be achieved implicitly.

4. A demonstration on a real-world case study that when control actions are performed sufficiently fast enough, signal coordination is redundant.

1.6 Thesis Structure

This section provides a descriptive summary of each of the nine chapters in this thesis and their contributions. A diagram summarising the topics covered in each chapter of the thesis is provided in Figure 1.3.

Chapter 1: Introduction
Chapter 1 presents the motivation for this research, outlines the research aims and objectives, and the structure of this thesis.

Chapter 2: Literature Review
Chapter 2 reviews communication systems and standards, and roadside and vehicular ITS enabling technologies. The chapter also reviews the state-of-the-art in intersection control strategies. The discussion of the reviews indicates where the present challenges in modelling C-ITSs are, and discusses future trends in connected vehicle technologies.

Chapter 3: Augmenting Traffic Signal Control Systems with Connected Vehicles
Chapter 3 presents a novel traffic signal control algorithm called Multi-mode Adaptive Traffic Signals (MATS) which combines position information from connected vehicles with data obtained from existing inductive loops and signal timing plans in an urban corridor to perform decentralised traffic signal control at urban intersections. The MATS algorithm is capable of adapting to scenarios with low numbers of connected vehicles, an area where existing traffic signal control strategies for connected environments are limited.

Chapter 4: Greedy Stage Optimisation Using Connected Vehicle Data

Chapter 4 proposes a greedy stage sequence optimisation algorithm that abstracts for arbitrary connected vehicle data. In Chapter 4, signal timings were optimised using position speed and heading data from CVs, in Chapter 4 the algorithm is extended to consider arbitrary data from connected vehicles to optimise the traffic signal stage order. The optimal dataset and parameters for the greedy algorithm are determined, and it is integrated into the existing Multi-mode Adaptive Traffic Signals (MATS) algorithm from Section 3 to form the Connected Data Optimised Traffic Signals (CDOTS) algorithm.

A method for implicitly coordinating stages at signalised intersections using CV data that integrates with the Greedy stage optimisation algorithm is also proposed. Coordinating stages in traffic signal control strategies that change rapidly is challenging. Here a term for the CDOTS algorithm is proposed to promote stage coordination implicitly. The advantages of an implicit approach to signal coordination are two-fold. Firstly, in highly adaptive systems which are responding in real-time (on the scale of seconds) to their inputs, explicitly coordinating the stage times is challenging as it may be desirable to end the stage at any time. Conversely, rolling-horizon/predictive signal coordination paradigms manage stage times co-dependently, so the independent termination of a stage would not be optimal. Secondly, the weighting of the stages allows for a coordinating stage to be promoted without explicitly forcing the signal controller into a coordinated state which may not be advantageous. The previous chapters showed how to optimise stage order and green times. Here it is investigated whether signal coordination is still beneficial in connected environments.

Chapter 5: Research Methodology

Chapter 5 discusses the methods that can be used to evaluate the impact of CVs in the transportation network. Section 5.1 summarises the selected workflow for this research. Section 5.2 decides the methods that are used to perform the research. Section 5.3 discusses the tools that are used to perform the evaluation. Section 5.4 selects the models that are used in the evaluation. Section 5.5 develops a realistic case study and testing framework for evaluating the developed research. Section 5.7 discusses how the performance of the research is assessed. Finally, Sections 5.6.6–5.6.8 define tests for assessing the fairness of the developed algorithms, their performance against an actuated traffic signal controller, and their computational efficiency.

Chapter 6: Results and Discussion

Chapter 6 discusses the results from testing the algorithms developed in this reasearch on the case study corridor, and the supporting tests defined in Chapter 5. Section 6.1, the results of testing the MATS algorithm against TRANSYT on the case study are presented and discussed. Section 6.2 shows results from determining the data to provide the CDOTS algorithm. Section 6.3 shows how the coordination factor for the CDOTS algorithm was determined and it is investigated whether signal coordination is still beneficial in connected environments. In Section 6.4, the results of testing the CDOTS algorithm against TRANSYT and the MATS algorithm on the case study are presented and discussed. Section 6.5 compares the performance experienced by connected and unconnected vehicles under the CDOTS and MATS algorithms. Section 6.6 compares CDOTS and MATS against MOVA. Section 6.7 compares the computational efficiency of the MATS and CDOTS algorithms with that of the TRANSYT algorithm.

Chapter 7: Impacts and Implementation Issues

Chapter 7 provides a discussion of the ramifications of this research based on the experiments and tests performed, and their impacts on transport planning and policymaking. First, a review of user perceptions on sharing data with urban traffic management systems is presented. Second, the implementation recommendations for transport planners are made based on the findings of this research are given. Finally, policy implications of this research for local and national governments are described with respect to the findings of this research.

Chapter 8: Contributions, Conclusions, and Future Research

Chapter 8 summarises the findings of this research, how the research done fulfils the objectives of the research, and discusses the opportunities for future work.

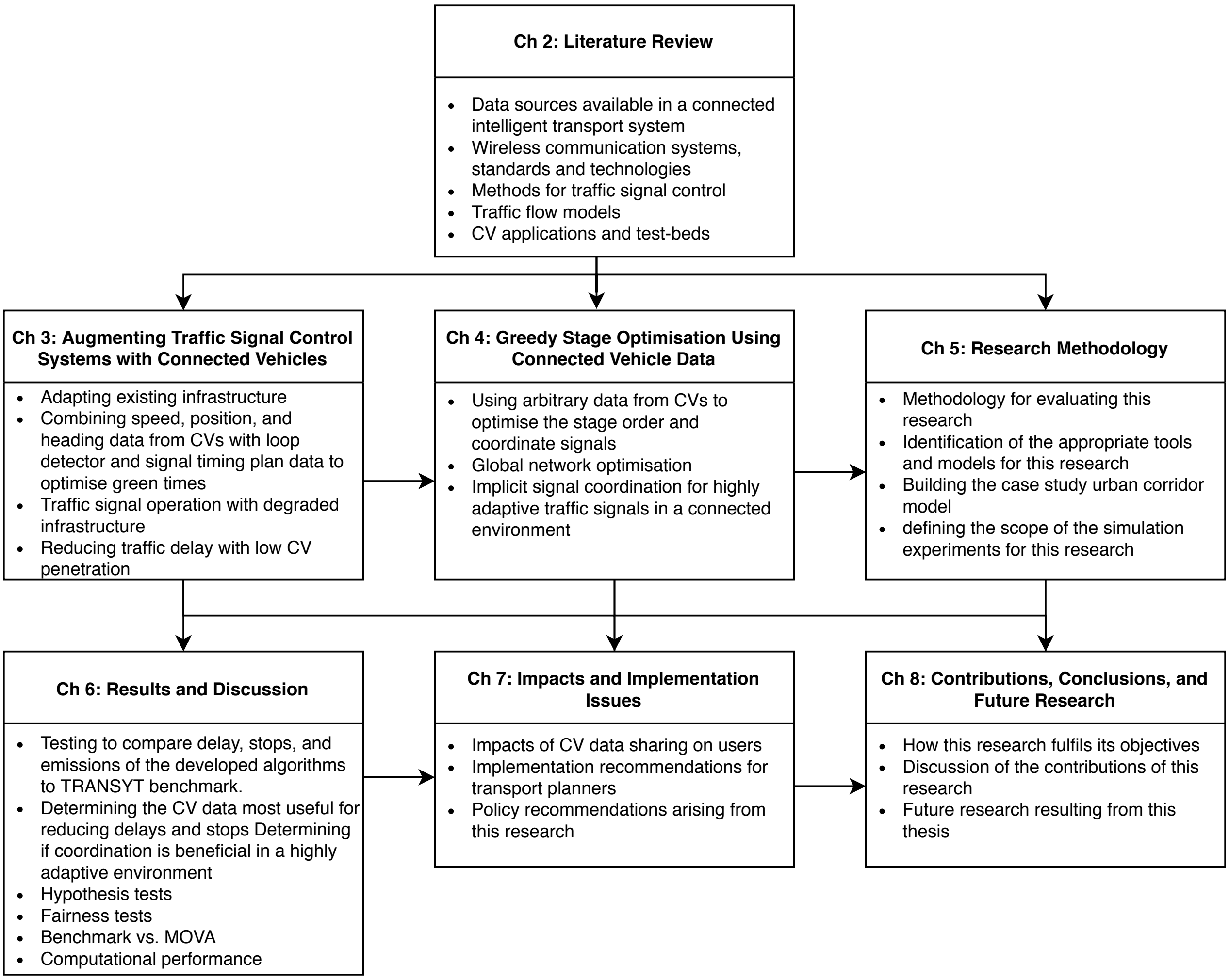


Figure 1.3: The topics underpinning each chapter in this research.

Chapter 2

Literature Review

The introduction of Connected Vehicles (CV) within Intelligent Transport Systems (ITS) presents unique opportunities and challenges in urban traffic management. Connected ITSs (C-ITS) are the integrated application of communications, control and information processing technologies to the transport system. The data that technological resources provide to the transport system can be leveraged strategically to reduce traffic delay, increase road safety, and improve road user experience. In order to best determine which control strategies make effective use of the C-ITS dataset, it is necessary to model C-ITSs for the evaluation of different traffic models and intersection management strategies.

As determined in Chapter 1, the focus of this thesis is to develop traffic signal control algorithms that augment existing infrastructure in urban corridors with CV data. In order to establish the current state-of-the-art of the technologies underpinning the aim of this thesis, this chapter reviews vehicular communications technologies and standards, current research in traffic signal control, and trends in CV applications and testing. By reviewing the models and systems pertinent to CVs and C-ITS, this review aims to determine if the transport network is prepared to integrate CVs. The contributions of this chapter are as follows:

- Reviews of vehicular communications enabling technologies, the data sourced from vehicular and roadside communication systems, how the data are transmitted, and the traffic control models that make use of the technologies and data.
- A discussion of the developments, and shortcomings, in urban ITS, concerning communications systems, traffic signal control, and applied traffic models.
- A review of other applications and trials related to CVs that may be beneficial to this thesis.

This chapter is organised as follows: Section 2.1 provides an overview of the technologies being incorporated in C-ITS roadside infrastructure systems and vehicles. The technologies that comprise a C-ITS determine the scope of its performance and define the communicable data stream available for use in urban corridor control strategies. Section 2.2 discusses the communication systems that facilitate message passing between vehicles and infrastructure. Robust communication systems are critical in a connected environment to ensure vehicles have access to external data reliably in real-time. Section 2.3 summarises the message standards developed to facilitate interoperable message passing between C-ITS agents. In an environment where many C-ITS agents must communicate, it is important to standardise how vehicles and infrastructure communicate so that communication is possible independently of the equipment manufacturer or device age. Section 2.4 reviews both the prevailing and state-of-the-art intersection control strategies. It is important to discuss the current state-of-the-art in intersection control in order to understand how urban corridors behave and are optimised in order to progress to strategies that incorporate increasing levels of connectivity. Section 2.5 reviews other technologies to which CV data is being applied, and real-world trials and testbeds that are aiming to assess the practical implementation of CVs. Finally, the critical gaps in the literature and areas for future work are discussed along with the chapter conclusions in Section 2.6. A visual summary of the technical sections in this chapter is provided in Figure 2.1.

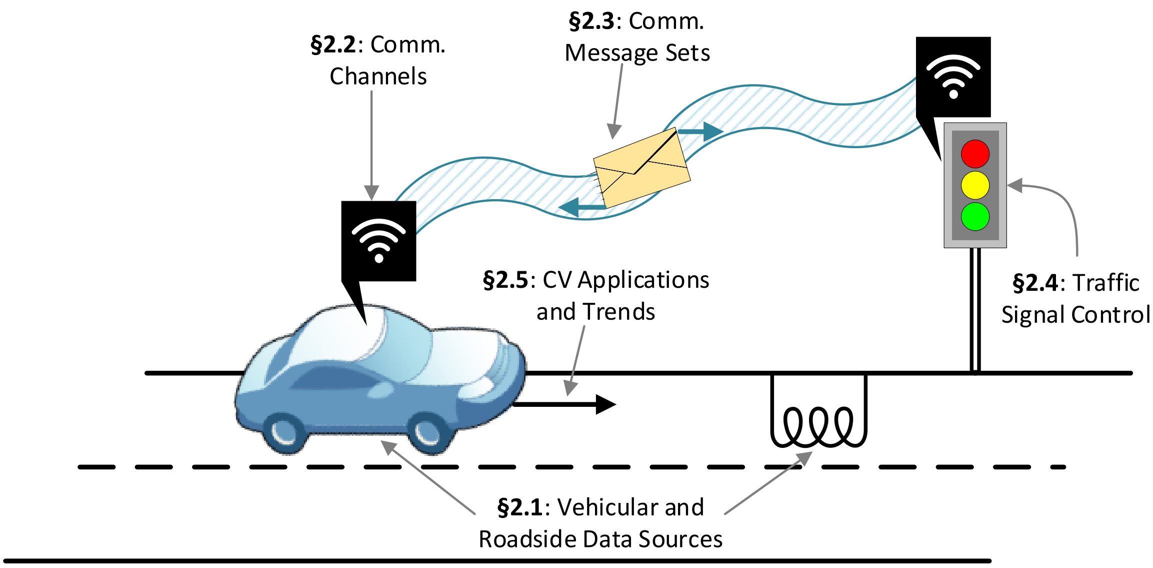


Figure 2.1: A visual summary of the technical sections in the literature review. **Section 2.1** reviews what data is available in the transport network. **Section 2.2** reviews how data can be sent wirelessly between actors in the network. **Section 2.2** reviews the rules and formats for sending data. **Section 2.4** reviews how traffic signal control is performed. **Section 2.5** reviews other current trends and applications for CV technology.

2.1 Key Data Sources for Vehicular Communication Systems

There are several ways data can be gathered from the transport network. Traditionally, technologies such as inductive loops are integrated into infrastructure and vehicular systems to improve drivers' experience and reduce delays (Vincent and Peirce, 1988). In transportation networks, data gathering technologies can be classified as being either a vehicular or a roadside (infrastructure-based) data source. In this section, the technologies used for both vehicular and roadside data sourcing in C-ITS applications are described, then are summarised in Tables 2.1 and 2.2.

2.1.1 Vehicular Data Sources

2.1.1.1 Global Positioning System

The Global Positioning System (GPS) is a network of satellites operated by the US Department of Defence. The satellites operate at two carrier frequencies L1 (1227.6 MHz) and L2 (1572.42 MHz), in the Ultra-High Frequency (UHF) band (300 MHz - 3 GHz) (Hofmann-Wellenhof et al., 2012). The UHF band is used to penetrate the ionosphere and light cover (such as foliage) facilitating line-of-sight operation. 2-Dimension operation (longitude and latitude) requires line-of-of sight at least three satellites, and a minimum of 4 satellites for 3-Dimension operation (longitude, latitude, and elevation) (Grewal et al., 2001). Civilian applications (i.e. automotive GPS) are restricted to the L1 band.

GPS receivers gather position and time information from orbiting satellites and use the difference in time between its internal clock and the received times determine the device's location through trilateration. GPS resolution is typically around 5m or less depending on the number of overhead satellites used, and what correction techniques are implemented in the receiver (Grewal et al., 2001). However, tall urban structures can increase GPS error due to non-line-of-sight (NLOS) and multi-path propagation (Hsu, 2018; Sun et al., 2020). A map-matched position can be used to provide a more accurate position than raw GPS coordinates if spatial road network data is available to the receiver (Quddus et al., 2007). Refresh rates of 1 Hz is typical of commercial GPS receivers, although 5 Hz and 10 Hz receivers are available for applications such as vehicle control, where more frequent updates are required (Bae et al., 2001).

In automotive applications, such as the vehicles used in the Defence Advanced Projects Research Agency (DARPA) Grand Challenges, 10 Hz GPS receivers with sub-meter accuracy were used in the Stanley (Thrun et al., 2006), Junior (Montemerlo et al., 2008), and Boss (Urmson et al., 2008) vehicles. In smartphones, the GPS sampling frequency is 1-3 Hz (Tao et al., 2012), but supporting technologies such as the Wi-Fi positioning system (WPS) and Global System for Mobile Communications Positioning System (GSMPS) can be used to improve the accuracy of the position measurements (Oshin et al., 2012).

2.1.1.2 Radar and LIDAR

Radar (originally RADAR - RAdio Detection And Ranging) and LIght Detection And Ranging (LIDAR) are systems for detecting nearby objects using electromagnetic radiation. For radar, radio waves are emitted, whereas laser light is emitted from LIDAR sensors. Both systems operate on the same principle, electromagnetic radiation is emitted from an antenna, then, if the radiation reaches an object, some of it will be reflected onto the antenna, and the objects' range and position relative to the receiver can be determined (Skolnik, 1990). Automotive radars can have ranges up to 250 m, and are accurate to the order of centimetres and are only limited by line-of-sight (Dickmann et al., 2016; Skolnik, 1990). LIDAR has trouble detecting objects at short distances but can achieve resolution less than 1° (Khader and Cherian, 2018). The systems scan their environment and use the gathered data to create a set of points corresponding to positions of nearby objects called a 'point cloud'.

In automotive systems, radar has been used for object detection in the 60-250 m range (Urmson et al., 2008), and LIDAR systems have been used for object detection up to 80 m from the vehicle (Urmson et al., 2008). Radar and LIDAR are often used together for vehicle localisation, hazard/environmental warnings, and object perception. Vehicle localisation is the process of determining where the vehicle is relative to its surroundings. Localisation is often part of a Simultaneous Localisation and Mapping (SLAM) process, where a vehicle constructs a map of its (potentially unknown) environment and its position in it (Chen et al., 2007; Hata and Wolf, 2016). Hazard/environmental warnings can be given if shapes in the point cloud are too close, or will interact with the vehicle without intervention (Mukhtar et al., 2015). Examples of hazards may include other vehicles or terrain issues such as pot-holes. Closely related to hazard warnings, object perception is used to detect specific elements in the point cloud such as other vehicles, bicycles, pedestrians, and bollards (Mukhtar et al., 2015).

2.1.1.3 Video Systems

In automotive systems, video cameras record streams of high-resolution digital images of the vehicle surroundings. The images are 2-dimensional representations of the 3-dimensional environment. Numerically, the video is a set of matrices whose elements correspond to the light-levels of in the images and can be analysed by computer vision software (Bradski, 2000), to extract roadway information. Common applications of this technology include localisation and object perception (Bertozzi et al., 2000). Localisation is often achieved through sensor fusion (combining multiple sensors) with radar and LIDAR systems (Deelertpaiboon and Parnichkun, 2008). Object perception applications include: pedestrian detection and lane-keeping (Eskandarian, 2012), hazard warning (Posner et al., 2008), and traffic light detection (Fairfield and Urmson, 2011).

2.1.1.4 Dead-reckoning

Dead-reckoning is the process of combining wheel odometers and accelerometers to enhance the accuracy of position estimation by updating a previous position estimate using offline measurements (Miah et al., 2020).

Wheel odometry is the process of estimating the position of a vehicle from the movement of its wheels (rotation and angle). Monitoring wheel motion is essential in helping orient the vehicle and correcting its position (Thrun et al., 2006). Estimation of a vehicles location, orientation, and trajectory, often referred to as the pose of the vehicle, is achievable through wheel odometry (Nourani-Vatani et al., 2009; Urmson et al., 2008). The pose of other vehicles can be achieved through video analysis (Nistér et al., 2006; Nourani-Vatani et al., 2009). Slippage in the vehicle wheels can also be detected through video analysis and wheel encoding (Howard, 2008; Urmson et al., 2008).

Accelerometers measure the force exerted on a vehicle in the x, y, and z axes. Monitoring the acceleration of a vehicle allows improved determination of its speed and heading when coupled with wheel odometry to correct vehicle navigation during GPS outages (Chen et al., 1994; Dissanayake et al., 2001; Thrun et al., 2006; Urmson et al., 2009).

2.1.1.5 Internal Vehicle Sensors

Modern vehicles are equipped with many electronic sensors designed to convey information to both the driver and other road users. The Society of Automotive Engineers (SAE) has identified several data points available from the sensors in modern vehicles that could reasonably be shared if the vehicle was connected (SAE, 2016):

Type: The manufacturer could pre-program information about if the vehicle is a truck, car, motorbike, or another vehicle type.

Occupancy: Seat-belt sensors can detect passengers not using a seat-belt, so could reasonably count the number of passengers if a sensor was equipped in every seat.

Turn signals: Drivers can indicate their intention to turn to other drivers. The turning information could be shared with a traffic management service, for example.

Speed: The vehicles exact speed can be determined from its speedometer.

State: General information about if the vehicle is stopped/moving, whether its handbrake is on/off, and what gear it is in for example.

Route: Vehicular navigation systems could share the vehicles' intended route through the network.

Emissions class: Information about the emissions class of the vehicle, its engine type, and fuel type.

Temperature: Thermometers outside the vehicle and in its cabin can tell the ambient (outdoor) temperature, and internal temperature.

2.1.2 Roadside Data Sources

2.1.2.1 Inductive Loops

In traffic detection, inductive loops are used to detect the presence of vehicles and monitor traffic flow. Inductive loop detectors are composed of a coil of wire embedded in the road and attached to a sensor. As vehicles contain metal, a vehicle passing over the inductive loop will change the impedance of the coil, and therefore the current flow in the wire (Lenz's Law (Schmitt, 2002)), which can be detected by the sensor and its presence registered.

Inductive loops can be placed at stop lines to check for waiting vehicles Beak et al. (2017). In traffic signal control, individual vehicles can be counted and aggregated over time to determine the flow of vehicles. The vehicle flows can be used by actuated and adaptive traffic signal controllers such as MOVA (Vincent and Peirce, 1988), and SCOOT (Robertson, 1986) so that traffic signal timings can be adjusted based on the current traffic demand.

2.1.2.2 Video Systems

Similarly to in-vehicle video systems, video cameras can be used at the roadside to monitor vehicle flows and for Automatic Number Plate Recognition (ANPR). To monitor vehicle flows, machine vision software is used to count vehicles and aggregated them into flows. ANPR also uses machine vision, but to capture the number plates of passing vehicles (Chang et al., 2004). ANPR systems can be used to count vehicles, but also to track vehicles between two points and to work out their average speed and automatically enforce speed limits.

2.1.2.3 Infrared Cameras

Similar to the previously described video systems, infrared cameras record video of the roadway. Infrared cameras differ from video cameras in that they record the infra-red light spectrum (700 nm - 1 mm) rather than the visible light spectrum (400-700 nm) (Haynes, 2014). Infrared images and videos are useful as they capture information about the thermal emissions of objects.

In traffic infrastructure, infrared cameras have been used to detect vehicles(Iwasaki et al., 2013) and pedestrians (Morgan et al., 2015). In the UK, the PUFFIN pedestrian crossing system (Davies, 1992) uses infrared cameras to detect pedestrians that want to cross, and extend the crossing time for pedestrians still crossing.

2.1.2.4 Intersection Management Systems

Traffic signal management systems contain useful information regarding the signal phases (which lights are green/red), and times, the layout/geometry of the intersection, and the traffic levels at the intersection gathered from other roadside infrastructure (SAE, 2016).

2.1.3 Discussion and Critical Gaps

Table 2.1: Summary of the vehicular data produced within a C-ITS with references supporting each datum.

Enabling Technology	Dataset Contribution
GPS	• Vehicle position, velocity, and heading (Bae et al., 2001; Grewal et al., 2001; Hofmann-Wellenhof et al., 2012)
Radar/LIDAR	• Hazard/Environmental warnings (Mukhtar et al., 2015; Skolnik, 1962, 1970; Wandinger, 2005) • Localisation data (Hata and Wolf, 2016; Maddern et al., 2015; Schuster et al., 2016; Ward and Folkesson, 2016) • Nearby vehicle/obstacle detection/perception (Cho et al., 2014; Schneider, 2005)
Video System	• Hazard/Environmental warnings (Dahlkamp et al., 2006; Darms et al., 2009; Kulchandani and Dangarwala, 2015) • Localisation data (Bertozzi et al., 2000; Chen et al., 2007; Churchill and Newman, 2012*a*,*b*; Fairfield and Urmson, 2011; Garcia-Garrido et al., 2006; Linegar et al., 2015; Pascoe et al., 2015; Posner et al., 2008; Upcroft et al., 2014)
Dead-reckoning	• Wheel position and vehicle pose (Nistér et al., 2006; Nourani-Vatani et al., 2009) • Wheel slip correction (Howard, 2008; Nistér et al., 2006) • Vehicle acceleration and heading (orientation) (Chen et al., 1994; Dissanayake et al., 2001; Thrun et al., 2006; Urmson et al., 2009) • Sensor-fusion to enhance position accuracy (Miah et al., 2020)
Internal Sensors	• Vehicle: type, occupancy, turn signals, speed, state, route, emissions class, ambient (outdoor) or in-vehicle temperatures (SAE, 2016)

GPS: Global Positioning System
LIDAR: Light detection and ranging
Radar: Radio detection and ranging

Table 2.1 details technologies that commonly feature in CAVs (Thrun et al., 2006; Urmson et al., 2009). For each technology, the data they have been shown to contribute to the C-ITS dataset is described, and references to the key literature describing the data contribution. The data vehicles contribute to the C-ITS dataset provides multiple data points that scale relative to the number of CVs present and have high rates of change depending on vehicle movements and the state of the road environment. The potential size of the dataset offers opportunities for more dynamic and adaptive control of the transport system.

Table 2.2: Summary of the roadside data produced within a C-ITS with references supporting each datum.

Enabling Technology	Data Stream Contribution
Inductive Loops	• Vehicle flow (Cheung et al., 2004) • Road occupancy (Yang et al., 2014) • Vehicle classification (Cheung et al., 2004; Gajda et al., 2001)
Infrared Camera	• Pedestrian/Car waiting information (Davies, 1992; Iwasaki et al., 2013; Morgan et al., 2015; Walker et al., 2005)
Video System	• Pedestrian/Car waiting information (Dollar et al., 2012; Piniarski et al., 2015) • Vehicle classification (Xiaoxu Ma and Grimson, 2005)
ANPR	• Vehicle flow/travel time (Kanayama et al., 1991; Liu et al., 2011) • Vehicle tracking (Chang et al., 2004; Du et al., 2013)
Intersection Management System	• Signal phase and timing, intersection layout, traffic levels (SAE, 2016)

ANPR: Automatic Number Plate Recognition

Similarly, Table 2.2 lists the roadside technologies that contribute to the C-ITS dataset and references the key literature where the application of the technology is demonstrated. Roadside vehicular technologies do not contribute data on the same scale as vehicular technologies but do provide useful information about waiting vehicles, vehicle flows, and vehicle types. Most of the data from roadside infrastructure can be determined from vehicular technologies if the data are communicated, but will remain useful for supporting legacy vehicles in the transition towards a CV dominant fleet.

Comparing Tables 2.1 and 2.2 shows that having access to data directly produced by vehicles introduces a significant amount of data that is not available from roadside data sources alone. The extended dataset offers higher resolution data about each vehicle, thus more options for traffic management optimisation.

In this section, both vehicular and roadside technologies that enable data collection within a C-ITS were reviewed. Loop detectors are the most commonly used sensor type in urban transport networks, but the ability to obtain data from in-vehicle sensors may change this. Improvements to sensor hardware and algorithms will allow better utilise the data these technologies can provide. There will also be a need to develop robust hardware that delivers data quickly to withstand the constant use it will receive during driving and deliver data to safety-critical applications on time.

2.2 Communication Systems for Transmitting V2X Data

In Section 2.1 the sources of data in a C-ITS were identified. The key feature of a C-ITS is that the vehicles and infrastructure can communicate this data with one another. Therefore, the communication system underpinning the C-ITS is of key importance. Communication systems for C-ITS can be categorised into two types: Dedicated Short Range Communication Systems, and cellular systems. First, the current DSRC and cellular communication systems will be described. Second, Table 2.3 compares the specification of key vehicular communication systems, and Tables 2.5 and 2.4 offer key findings regarding communication systems and their applications in C-ITS.

2.2.1 DSRC Systems

DSRC systems, are those that provide dedicated access to a communication channel for specific applications (e.g. C-ITS services) that cover a smaller area than cellular technologies.

2.2.1.1 Bluetooth

Bluetooth was originally developed in 1998 to enable short-range, radio frequency communications between portable electronic devices like laptops and cell phones (Haartsen et al., 1998). In transport, Bluetooth has been used for tracking vehicles (Lees-Miller et al., 2013), and estimating travel times on motorways (Bhaskar et al., 2015; Martchouk et al., 2011). Flow estimation is possible, but if there is high uncertainty in the number of equipped vehicles, the estimates can be unreliable (Barcelo et al., 2010).

2.2.1.2 IEEE 802.11p

The IEEE 802.11 standard defines the technical specifications for wireless local area networks (WLAN), and details any enhancements or extensions to the functionality of the physical layer and medium access control functions of WLAN technologies (IEEE, 2012). An amendment to the 802.11 standard is 802.11p (IEEE, 2010), DSRC (FCC, 2003*a*) within the context of a wireless access vehicular network (WAVE)(IEEE, 2014). The DSRC defines a 75 MHz section of the frequency spectrum from 5.850-5.925 GHz referred to as the 5.9 GHz band for intelligent transport applications.

802.11p uses orthogonal frequency division multiplexing (OFDM) (see (Li and Stüber, 2006) for details) as a subset of the 802.11a OFDM implementation. The 802.11a WLAN scheme defines its OFDM protocol for three-channel widths 20, 10, and 5 MHz. In 802.11p, DSRC commonly utilises the 10 MHz channel (Kenney, 2011). 802.11a achieves bit rates from 6-54 Mbps. However, 802.11p uses forward error correction, which coupled with the lower

10 MHz channel width effectively halves the effective bit rates to 3-27 Mbps, while increasing the chance of successful decoding, which is imperative for ITS applications.

The range of 802.11p transmitters depends on local standards governing radiated emissions. However, for FCC compliant (FCC, 1998, 2003*b*, 2006) devices in the US, or devices compliant under 2006/771/EC in Europe (European Commission, 2006), ranges of 1000 m at the recommended power outputs (approximately 25 dBm) are feasible.

2.2.1.3 ZigBee

The ZigBee communications standard was proposed to address the need for low-power, low-latency communications between sensor devices to maximise their battery life (Kinney, 2003). ZigBee has been studied for mobility applications, but it was found that device mobility damages the network established between devices, and incurs high levels of packet loss (Chen et al., 2010). ZigBee has been shown that it can support communications at road junctions if there is a coordinating ZigBee node at the junction. However, the high-speed movement of vehicles will cause data loss (Gheorghiu and Iordache, 2017).

2.2.1.4 WiMAX - Worldwide Interoperability for Microwave Access

IEEE 802.16 (IEEE, 2018), describes the Worldwide Interoperability for Microwave Access (WiMAX) system which provides high-speed, wide-area, wireless communications. WiMAX is intended to provide a wireless product to compete with wired broadband wireless access. WiMAX operates in two bands, 2–11 GHz where Line-Of-Sight (LOS) operations are impaired, and 10–66 GHz where LOS operation is possible and practical (Kamali, 2018).

WiMAX has been studied for vehicular communications. Msadaa et al. (2010) observed that WiMAX is competitive with IEEE 802.11p in terms of performance as it offers high data rates, low delays, and coverage over a wide area, but that IEEE 802.11p is superior at low vehicle loads. The main limitation with WiMAX technology is that it is not widely adopted and lags its main competitor, LTE, significantly in terms of deployment (Kang and Downing, 2015).

2.2.1.5 UWB - Ultra-Wideband

UWB differs from the previous technologies in that rather than transmitting data with high power a narrow frequency band, UWB transmits data in a comparatively short, low-power, wide frequency burst. UWB systems operate in the 30 MHz–10.6 GHz range of frequencies and a system is UWB if it transmits in a band greater than 500 MHz or a band greater than 20% of it is allocated bandwidth (ETSI, 2019*b*).

In vehicular applications, UWB is being researched as a method of decreasing localisation error by compensating for GPS measurements (Zhang et al., 2019). UWB has the benefit of being robust to NLOS and multi-path effects, which is desirable in urban environments (Gerrits et al., 2005). However, UWB systems are limited in that they require comparatively large antennae, their low power output may reduce their range and penetration depth (Uvarov et al., 2019), their application to C-ITS is not widely studied beyond localisation enhancement at this time, and the requirement of a wide bandwidth can be costly (Sarjoghian et al., 2016).

2.2.2 Cellular Communication Systems

In contrast to DSRC systems, cellular communication systems are large area networks designed to support mobile telephone services. The current and next-generation cellular telephone systems that can support V2X applications are Long Term Evolution (LTE) and 5G, respectively.

LTE (3GPP, 2016) is a high-speed radio-based communications standard for mobile telephony applications standardised by the 3rd generation partnership project (3GPP), and the successor to the previous 3G network (3GPP, 1997). LTE is designed to offer a minimum data rate of 100 Mbps with scope for data rates up to 1 Gbps, as well as offering reduced latency and increased quality of service to users for whom mobile broadband is increasingly important (Oshin and Atayero, 2015). LTE has been tested for vehicular communications and proven to be beneficial at distributing decentralised messages over a wide area. However, LTE is limited in its ability to transmit periodic messages as it suffers from poor uplink and latency during congested periods (Araniti et al., 2013).

The 5G standard has been in development since its proposal in 2013 (The 5G Public Private Partnership, 2014) and is already undergoing an initial roll-out (McGarry, 2019). The 5G standard has been developed to provide an order of magnitude improvement over the specifications of its predecessor LTE (5G-PPP, 2015). 5G differs from LTE in that it has been developed with C-ITS as an expected use case and is designed to handle the additional burden a C-ITS would put on the network (ETSI, 2018*b*). 5G also considers the technical challenge of data transmission to CVs travelling at high speed. 5G can theoretically support vehicles travelling at up to 130 km/h without degradation of service. The system is also specified to be able to locate a CV to within 0.1 m accuracy and support up to 200 CVs (ETSI, 2018*b*).

2.2.3 Comparison of Communication Systems for C-ITS

Table 2.3 discusses the performance of the physical communication systems under the following headings:

Frequency band: The frequency band defines the portion of the frequency spectrum in which the communication system operates. Higher frequency signals do not penetrate solid objects as well as low-frequency signals for similar antennas using the same power output. Higher frequency systems may offer higher data rates depending on how the system is specified. The range issue can be partially overcome using beamforming technology such as in IEEE 802.11ac (IEEE, 2013). As transport systems generally cover large areas, highly directional antennae may not be suitable. Additionally, it can be seen in Table 2.3 that the lower frequency bands, in particular, 2.4 GHz, is covered by five of the six systems. The 2.4 GHz band is a highly shared section of the frequency spectrum. It is so popular because it operates in one of the unlicensed Industrial Scientific and Medical (ISM) band of frequencies. The popularity and ease of access to the 2.4 GHz frequency band mean it can be particularly crowded. So in device dense areas, the signal environment has the potential to be noisy, affecting the signal range and transmission success.

Max. data rate: The maximum data rate defines the upper limit on how fast data can be sent, essentially capping the system throughput. Data rates are typically measured in *bits per second (bps)* (one bit represents one binary number).

Channel width: Channel width defines the size of the portion of the frequency band allocated to a single device, the wider the channel width, the higher the data rate per device.

Outdoor range: As the communications systems are being compared for C-ITS applications, it is important to determine what their effective range is in outdoor environments.

C-ITS dedicated: A system is 'C-ITS dedicated' if it has been designed specifically with C-ITS applications as a use case.

Mobility support: A communication system supports mobility if it has been designed to support devices that are in motion. In Table 2.3, a communication system is only designated to support mobility if the mobility specification covers vehicle mobility, not only pedestrian mobility.

Tables 2.4 and 2.5 reference key findings relevant to the application of the selected communication systems to C-ITS. Table 2.5 focuses on Dedicated Short Range Communication (DSRC) technologies, while Table 2.4 covers cellular technologies. DSRC systems use specific hardware access points to facilitate communication in a local area. In contrast, cellular technologies use large base stations to cover large areas. The literature shows that the most suitable communication systems for C-ITS are IEEE 802.11p DSRC and 5G cellular. ZigBee is not suitable for high mobility situations and has a comparatively low data rate. Bluetooth suffers from limited range which is not practical for large intersections or wide area networks. UWB technology may be useful for V-ITS applications as it is robust to NLOS and multi-path noise which is desirable in urban environments. However, UWB is not widely studied for vehicular applications beyond improving vehicle localisation accuracy. While UWB may complement a more developed communication system, more work needs to be done to assess its applicability to broader C-ITS applications. LTE and WiMAX are similar in range, data rate, and mobility support, but the uptake of LTE is an order of magnitude greater than that of WiMAX (Kang and Downing, 2015), and LTE is actively developed towards supporting C-ITS applications (Seo et al., 2016) making it the better choice. 5G still has only recently exited its standardisation and testing phase but is being developed to be an order of magnitude better than its predecessor LTE (ETSI, 2019*a*). Furthermore, V2X applications are standardised as a core application of the 5G service (ETSI, 2018*b*).

IEEE 802.11p is currently the most suitable standard for C-ITS communication systems, at it is specifically designed to support V2X (vehicle-to-vehicle (V2V) and vehicle-to-infrastructure (V2I)), including the periodic messages outlined in the communication standards discussed in Section 2.3. However, developments in LTE and the coming 5G network standard (Agiwal et al., 2016; Palattella et al., 2016) do not rule the systems out. Moreover, for reliable quality-of-service, a hybrid network that combines cellular and DSRC systems may be beneficial (Dreyer et al., 2016).

Table 2.3: Summary of key vehicular communications systems.

Communication Standard	**Frequency Band (GHz)**	**Max. Data Rate (Mbps)**	**Channel Bandwidth (MHz)**	**Outdoor Range (km)**	**C-ITS Dedicated**	**Mobility Support**
Bluetooth (Bluetooth Special Interest Group, 2016)	2.4	1-3	1	0.8	No	–
IEEE 802.11p (IEEE, 2010, 2012)	5.9	27	5/10/20	1	Yes	Yes
LTE (3GPP, 2016)	0.7–2.6	1000	1–20	100	No	Yes
5G (3GPP, 2019*a*)	0.4–100	10000	100-1000	–	Yes	Yes
ZigBee (ZigBee Alliance, 2012)	2.4	0.25	2	0.1	No	No
WiMAX (IEEE, 2018)	2–66	100	1.25-20	50	No	Yes
UWB (ETSI, 2019*b*)	0.03–10.6	100-1000	>500	–	No	Yes

LTE: Long Term Evolution
Mobility support determined in terms of vehicular, not pedestrian velocities

Table 2.4: Literature summary for vehicular applications of the cellular communications systems.

Communication Standard	Key Findings and Literature
LTE	• LTE is achieves higher data rates than 802.11p for vehicular networking(Hameed Mir and Filali, 2014; Vinel, 2012) • LTE in not suited for sending periodic messages (Hameed Mir and Filali, 2014; Vinel, 2012) • LTE is not dedicated so its performance in a shared network must be determined (Hameed Mir and Filali, 2014; Vinel, 2012) • LTE is evolving to support V2X (Seo et al., 2016) • High mobility and dense urban networks are challenges in LTE based V2X applications (Seo et al., 2016) • LTE is a cost effective enabler of V2X services (Seo et al., 2016) • LTE experiences less packet loss and delay than IEEE 802.11p for short message lengths, but higher delay for larger packets (Cecchini et al., 2017) • LTE is shown to be more reliable than IEEE 802.11p for long distance (>300 m) communications (Bazzi et al., 2017)
5G	• 5G supports connected device density of 10^6 per kilometre (ETSI, 2019*a*), with 200 CVs (ETSI, 2018*b*) • 5G supports vehicle mobility up to $130\ \mathrm{km/h}$ (ETSI, 2018*b*) • 5G will support data rates up to 100 Mbps per user (3GPP, 2019*a*,*b*) • 5G's maximum end-to-end latency of $25\ \mathrm{ms}$ for cooperative V2X applications (ETSI, 2018*b*) • 5G is specified to support: Vehicle platooning, (semi-)automated driving, extended sensing, and remote driving (3GPP, 2019*a*,*b*; ETSI, 2018*b*)

LTE: Long Term Evolution, 4G cellular
V2X: implying a vehicle-to-vehicle (V2V) or vehicle-to-infrastructure (V2I) application

Table 2.5: Literature summary for vehicular applications of the DSRC systems.

Communication Standard	Key Findings and Literature
Bluetooth	• Bluetooth and inductive loops can be used to determine vehicle travel times and trajectories (Bhaskar et al., 2015) • A Bluetooth C-ITS is cost-effective to implement (Martchouk et al., 2011) • Vehicles can be tracked using Bluetooth (Lees-Miller et al., 2013) (this also applies to vehicular networks in general (Mejri et al., 2014)) • Short-range communications can be offloaded to a Bluetooth network to reduce the load on networks handling longer range communications (Iordache et al., 2017) • Bluetooth channels receive different levels of interference depending on the Wi-Fi channel used (Gheorghiu et al., 2017)
IEEE 802.11p	• IEEE 802.11p achieves reliable V2V performance in urban environments (Lv et al., 2016) • Characterisation of IEEE 802.11p V2V packet loss for line-of-sight/non-line-of-sight conditions (Lv et al., 2016) • Obstacles such as buildings, trucks, and roundabouts greatly affect IEEE 802.11p performance in urban areas (Gozalvez et al., 2012) • Significant changes in terrain elevation affect IEEE 802.11p connectivity (Gozalvez et al., 2012) • High traffic density increases the packet delivery ratio variability on IEEE 802.11p links (Gozalvez et al., 2012) • V2V CAM transmission is negatively impacted at high traffic density (Shagdar et al., 2017) • Proposes a reduction in domestic Wi-Fi transmit power to allow more reliable IEEE 802.11p communication (Khan and Harri, 2017) • LTE is shown to be less reliable than IEEE 802.11p for short distance (<300 m) communications (Bazzi et al., 2017)
ZigBee	• Demonstrates that the performance of ZigBee enabled mobile agents travelling at velocities of 1-5 m/s and finds that ZigBee performance suffers from increasing mobility (Chen et al., 2010) • Compares performance and various numbers of nodes and routing strategies (Chen et al., 2010) • Zigbee may be suitable for localised communication at intersections but requires a mesh of transceivers (Gheorghiu and Iordache, 2017)
WiMAX	• WiMAX offers greater flexibility, speeds, and capacity than 3G and Wi-Fi systems (Andrews et al., 2007) • WiMAX is competitive with IEEE 802.11p for V2X applications but not for small numbers of CVs (Msadaa et al., 2010) • Describes the complete technical workings of WiMAX (Andrews et al., 2007) • Demonstrates that WiMAX is suitable for vehicular applications (Dhilip Kumar et al., 2016) • Shows that WiMAX can be combined with IEEE 802.11p to improve performance for V2X applications (Dhilip Kumar et al., 2016)
UWB	• UWB antennae can be used to increase GPS localisation accuracy (Gao et al., 2014; Zhang et al., 2019)

DSRC: Dedicated Short Range Communication
V2X: implying a vehicle-to-vehicle (V2V) or vehicle-to-infrastructure (V2I) application
WirelessMAN: Wireless Metropolitan Area Network

2.3 Message Sets and Standards for V2X Communication

In Section 2.1 it is shown that a significant amount of data are available through C-ITS enabling technologies, and in Section 2.2 methods for transmitting the data were identified. In this section, the rules and format for transmitting data on wireless channels known as message sets are described. It is critically important to determine which data are the most useful to transmit in a C-ITS for a given application, as not all data in the C-ITS data stream will be relevant to every operator in a C-ITS. Message sets ensure that the messages transmitted in a C-ITS are:

1. Short enough to contain only necessary data for a specific application.
2. Can be transmitted efficiently and compliantly on the specified wireless channel.
3. Are compatible between agents in the network to minimise channel use.

Message sets are essential to ensure standard operation of data-driven systems such as adaptive traffic signals. For example, the SCOOT traffic signal control algorithm (Robertson, 1986) defines the M02, M10, and M11 messages (Moore et al., 2005), as well as the U06 messages (Waterson et al., 2005) to standardise and compartmentalise the information gathered by the controllers.

The two authorities that have defined message set definitions for C-ITS applications are the European Telecommunications Standards Institute (ETSI) (ETSI, 2009, 2010*a*), and the Society of Automotive Engineers (SAE). ETSI defines two message types for C-ITS applications, namely the Cooperative Awareness Message (CAM) (ETSI, 2011), and the Decentralised Environmental Notification Message (DENM)(ETSI, 2010*b*). SAE also define message set dictionary SAE J2735 (Kenney, 2011; SAE, 2016), which describes several message types for DSRC applications. Table 2.6 displays the names and descriptions of the messages in the SAE J2735 standard. Although there are multiple message types, here signal phase and timing, and map messages are discussed in more detail as they are the most different to ETSI CAM and DENM messages.

Table 2.6: Summary of the SAE J2735 Message Types (Kenney, 2011; SAE, 2016).

Message Type	Purpose
Message Frame	Generic message, flexible content
Basic Safety Message	Vehicle state information necessary to support V2V safety applications
Common Safety Request	Request state information from another vehicle
Emergency Vehicle Alert Message	Alerts driver of active emergency vehicle in the vicinity
Intersection Collision Avoidance	Provides vehicle location information relative to a specific intersection
Map Data	Sent by RSU to convey the geographic description of an intersection
NMEA Corrections	NMEA style 183 GPS corrections
Personal Safety Message	Broadcast safety data regarding vulnerable road users
Probe Data Management	Sent by RSU to manage data collection of vehicle probe data
Probe Vehicle Data	Vehicles status report for its current road section; aggregated to derive the road condition
Roadside Alert	Sent by the RSU to alert passing vehicles to hazardous conditions
RTCM Corrections	RTCM style GPS corrections
Signal Phase and Timing Message	Sent by an RSU at a signalised intersection to convey signal phase and timing information
Signal Request Message	Vehicles can use this to request priority signals or a signal pre-emption
Signal Status Message	Sent by the RSU to convey the status of signal requests
Traveller Information Message	Sent by the RSU to convey advisory information
Test Message	Used to support new message development for regional use

NMEA: National Marine Electronics Association
RSU: Roadside Unit
RTCM: Radio Technical Commission for Maritime Services
V2V: Vehicle-to-vehicle

2.3.1 Cooperative Awareness Message

CAMs (ETSI, 2014*a*) provide periodic status and position information to other agents within a C-ITS. The ETSI CAM specifies C-ITS agents engaging in V2X communications must be able to transmit and receive CAMs. CAMs are transmitted periodically at a minimum frequency of $1\ \mathrm{Hz}$ and a maximum frequency of $10\ \mathrm{Hz}$. CAMs are generated if any of the following conditions are met:

- A change in vehicle heading greater than $4°$ occurs.
- The vehicle's position changes by more than $4\ \mathrm{m}$.
- The vehicle is travelling at a velocity greater than $0.5\ \mathrm{m/s}$.

The system checks the above conditions every $100\ \mathrm{ms}$. CAM transmission is regulated by a Decentralised Congestion Control (DCC) (ETSI, 2012) system, which varies the transmissions rate between the minimum and maximum CAM generation intervals $T_{\mathrm{GenCamMin}} = 1/10\ \mathrm{Hz} = 0.1\ \mathrm{s}$ and $T_{\mathrm{GenCamMax}} = 1/1\ \mathrm{Hz} = 1\ \mathrm{s}$ respectively, at a period $T_{\mathrm{GenCamDCC}}$. CAMs will be transmitted if $\Delta t \geq T_{\mathrm{GenCamDCC}}$, where Δt is the time since the last CAM transmission.

CAMs provide information to C-ITS agents, granting them an awareness of the positions and status of the other agents in the network. For instance, a traffic signal controller could use the speed and position data in place of data from inductive loops detectors to perform traffic signal control based on information from individual vehicles rather than aggregated information. Figure 2.2(a) depicts an example of a standard-compliant CAM and the data such as longitude, latitude (degrees), and heading contained within. The status of the C-ITS can be determined from information about its mobility, privacy, and physical relevancy (i.e. its state of presence on the road).

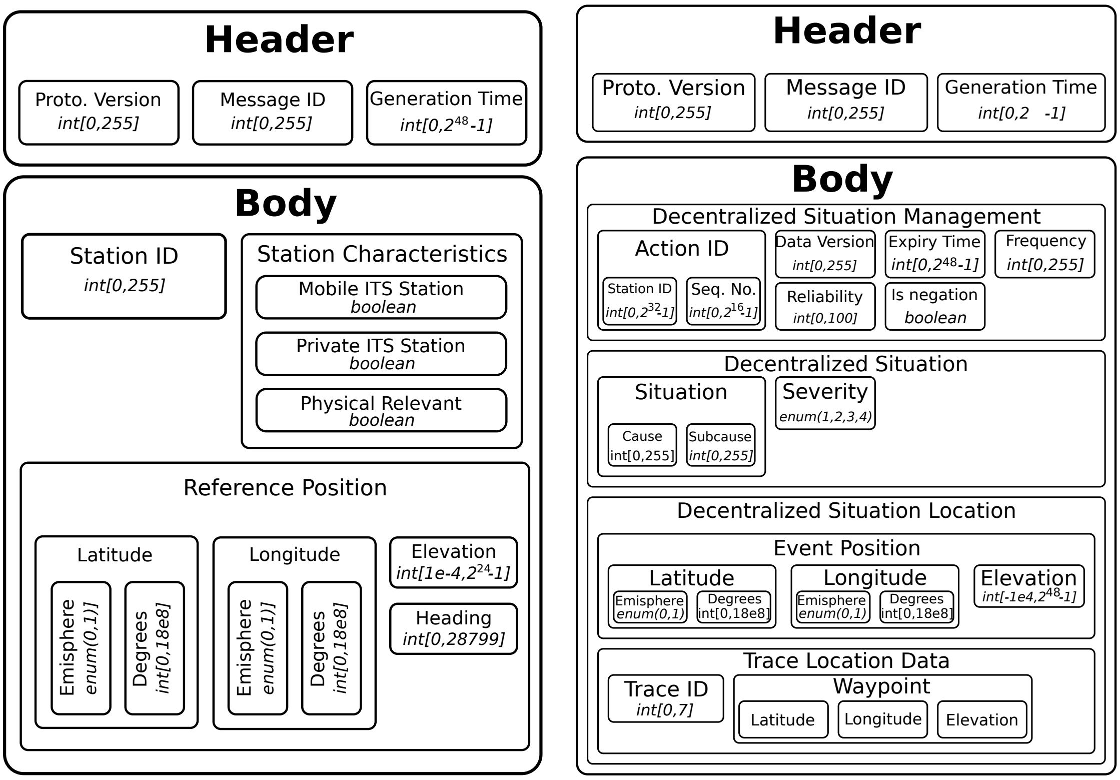
CAMs also support definitions for data including, temperature, accident cause codes, measurement confidence, curve of motion (indicating turns), indicator status, dangerous goods indication, vehicle dimension, vehicle acceleration profile, vehicle distance to the stop line, exterior light status, vehicle occupancy, emergency response type and whether the siren is in use for emergency vehicles, road segment ID, speed, and traffic light priority.

2.3.2 Decentralised Environmental Notification Message

DENMs (ETSI, 2014*b*) are an asynchronous counterpart to CAMs that specifically inform of Road Hazard Warnings (RHWs). DENMs are broadcast urgently upon the identification of a RHW by and C-ITS agent and are transmitted continuously while the RHW remains. RHWs cover incidents including emergency braking, stationary vehicles, traffic jams, roadworks, collision risks, hazardous locations, heavy precipitation/wind, and low road adhesion/visibility.

Figure 2.2(b) is an example of a DENM complaint message. It can be seen that the DENM contains information about the RHW, its cause, severity, and location. A DENM may also indicate a region of effect for the RHW so that other vehicles drive cautiously in the affected area, and may also transmit any information that defined for CAMs.

DENMs allow C-ITS agents to build more detailed Local Dynamic Maps (LDMs) by supplementing geographic, terrain, and localisation data they collect. The additional contextual information provided by DENMs allows vehicles to assess their environment better, allowing them to drive by interpreting the state of the road based on the context of their situation similarly to how humans drive.



(a) CAM (b) DENM

Figure 2.2: An example of CAM and DENM compliant message structures reproduced from Santa et al. (2013).

2.3.3 Signal Phase and Timing, and Map Messages

Signal Phase and Timing (SPaT) and Map are related messages definitions from the SAE J2735 message set (SAE, 2016). SPaT messages contain information about the traffic signal states on each of the lanes approaching an intersection. The information in a SPaT message describes which signals are active/inactive in each lane, and information about the green time and waiting for information for each signal. In order to reduce the amount of data transmitted, SPaT messages group lanes with similar traffic state together. For example, lanes are grouped by traffic signal colour and the time until the signal colour changes (persistence). SPaT messages have been applied to help improve driver response times at signalised intersections (Islam et al., 2016) and facilitate vehicles to control their approach to intersections to conserve energy (HomChaudhuri et al., 2016).

Map messages describe the exact layout and geometry of and intersection, making them a natural counterpart to SPaT messages. Map data can be used by CV navigation systems to determine the location of an intersection's lanes, how they connect and inform the vehicle's route planner how to traverse the intersection.

2.3.4 Critical Gaps and Areas for Future Work

In this section, the message set standards that support interoperable V2X communication were reviewed. The message sets discussed were found to comprehensively cover the range of messages C-ITS agents need to be able to transmit to each other. The only data not covered by the ETSI CAM and DENM, and SAE J2735 message sets is the specification of localisation data, i.e. data regarding another vehicles interpretation of a particular road environment. Localisation data may be necessary to vehicles employing strategies where data from previous vehicle's trips may be used to remove the need to interpret the journey through a new road section by using prior trip data from other vehicles that have already travelled on that same road section. The proprietary SAE J2735 message standard is dominant in the USA, whereas the open-source ETSI CAM and DENM standards are popular in Europe. There are many similarities between the SAE and ETSI standards, and there are ongoing efforts to harmonise them (EU-US ITS Task Force Standards Harmonization Working Group, 2012).

As there are no widely implemented C-ITSs, there is a need for test systems to be created so that large scale trials of the top contending communication systems can be performed. Comparisons can then be made so that commitments can be made for country-wide system deployments. Without decisions on which communication systems are to be implemented, the transport network cannot prepare itself in advance of the arrival of CVs.

2.4 Traffic Signal Control Strategies for Urban Environments

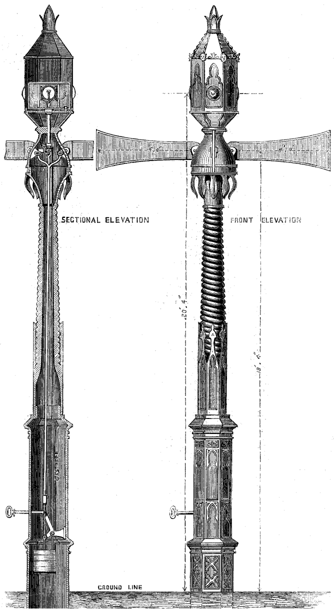
2.4.1 The History of Traffic Signal Control

The first traffic signals, such as the one shown in Figure 2.3(a), were inspired by railway semaphore signals and combined mechanical arms with a gas-powered lamp that could alternate between red and green, to regulate vehicle and horse traffic (The Engineer, 1868). Although the imposing, 24ft tall pillar was lauded at the time, it still required manual operation by a police officer.

In 1908 traffic began increasing rapidly due to the introduction of the Ford Model T, one of the first mass-produced and relatively cheap motorcars (History.com, 2009). With motoring becoming more affordable and reliable, increasing numbers of commuters took to the roads, causing increasingly severe traffic jams (McShane, 1999). In response to the increasing traffic demand, semaphore based traffic signals were used, but, in contrast with their predecessors, coloured signals were used for the first time (Sessions, 1971).

The first electric traffic signals were developed by Lester Wire, in the USA, in 1912, and used red and green signals to control traffic flow (McShane, 1999). Three signal traffic lights that resemble their current form were introduced in the USA in 1920 by police officer William Potts (Mueller, 1970). The primary function of early traffic lights was to allow the police officers on traffic duty to be reassigned elsewhere. In the 1920s, 5500 New York traffic officers were reassigned to other duties, saving the city $12,500,000 (McShane, 1999), and supporting the cause for traffic signal automation elsewhere. The third signal also improved on the two signal design by using the third signal to be used to create clearance time between signals, reducing collisions. By the 1930's the first international standardisation of traffic signal operations, the "Convention on the Unification of Road Signals" was agreed upon in Switzerland (Fédérale, 1931).

The rapid development of computer systems in the 1960s began the era of modern traffic signal control. For the first time, computer systems were able to rapidly optimise traffic signals based on collected data to create fixed time plans (Robertson, 1969). Computers also allowed the integration of data from roadside infrastructure to allow traffic signal control to be adapted to prevailing traffic conditions (Miller, 1963). The next advancement in traffic signal control was using computers to coordinate groups of traffic signals to increase performance over signals that were controlled independently of one another (Hunt et al., 1981).



(a)

(b)

Figure 2.3: A comparison of (a) the first semaphore based traffic signals introduced on Bridge Street, Westminster, UK (The Engineer, 1868), with (b) a modern three-signal LED traffic light.

2.4.2 Modern Traffic Signal Control

An abundance of signal control strategies have been developed with the intent of improving traffic flow and reducing delays at signalised intersections. This section builds upon the reviews of traffic control strategies by (Shepherd, 1992), Papageorgiou et al. (2003), (Stevanovic, 2010), Goodall et al. (2013), and Hamilton (2015), and discusses a selection of control strategies commonly used in urban environments under the three key classes of intersection controller. Namely isolated, coordinated fixed-time, and coordinated traffic-responsive control. Each controller class is then subdivided into novel approaches to achieving the corresponding class of control.

Before the discussion, the common terminology for describing traffic signal control strategies is introduced. The following terms relate to the properties of a signalised intersections:

- An intersection comprises several approaches, each of which contains one or more lanes.
- Each lane has an associated queue and vehicle flow.
- Measurement of the vehicle flow typically occurs locally via inductive loops or video systems if the process is automated.
- A phase is an indication of movement priority on a particular lane (e.g. green to go, or red to stop).
- A stage defines a set of non-conflicting phases.
- The cycle-time defines the time it takes to complete all of the intersections' stages.

Since the early research into computerised traffic signal control by Miller (1963) and Allsop (1971), control strategies have come to be characterised in the following ways.

- If the strategy controls a *single intersection*, it is referred to as *decentralised* or *isolated*.
- If the strategy controls *multiple intersections*, it is referred to as *centralised*.
- The strategy is *fixed-time* if it creates timing plans from historical data.
- The strategy is *actuated* if it uses external data from roadside infrastructure to extend its signal timings in real-time.
- The strategy is *adaptive* if it uses external data to adjust its behaviour in real-time based on current traffic conditions to *coordinate* traffic signals, i.e. if it attempts to synchronise green light timings between intersections.

Finally, the following terminology is used when discussing traffic signal control operations:

Blocking-back: Given a set of adjacent intersections, if the vehicles from the upstream intersection cannot move due to a queue in the lane shared with the downstream intersection, the movement is said to be blocked-back.

Cycle length: A cycle is one full operation of all the stage for an intersection. Its length is the time it takes for all the stages to occur.

Double cycle: A double cycle is when stages appear more than once per standard cycle time. Usually done to increase response time at intersections with low traffic demand.

Gap: The space between two vehicles.

Gap out: The termination of a stage when the gap has become too large and thus inefficient.

Heuristic/Optimisation: Optimisation is the process of finding the best possible result of a function for a given set of parameters (often a minimisation or maximisation process). A heuristic is a strategy for finding sufficient, but not necessarily optimal, improvement in a system.

Offset: An adjustment made to the beginning of a stage to help it coordinate with other stages.

Phase: A single signal at an intersection.

Progression: given a set of coordinated intersections, the fewer times a vehicle has to stop relative to the number of intersections it encounters, the better the progression.

Rolling horizon: The process of optimising over a specific interval into the future to reduce computational complexity.

Saturation: An intersection is saturated if vehicles are arriving at the maximum rate a continuous stream of vehicles could be expected to arrive under normal driving conditions. An intersection is *oversaturated* if vehicles arrive at a rate such that it cannot clear all waiting vehicles arriving at the intersection for a specific stage. An intersection is *undersaturated* if it can clear all the vehicles that want to access it on a particular stage.

Stage: A collection of phases that allow specific lanes of traffic access to an intersection.

Split: The proportion of green time allocated to a stage within a fixed cycle length.

In this section, the current state-of-practice fixed-time, actuated, and adaptive traffic signal control algorithms will be discussed, followed by a summary discussion.

2.4.2.1 Fixed-time Plans

Fixed-time traffic control systems are those that operate fixed signal times and do not change based on external factors. Fixed-time signal plans often calibrated based on historical data to optimise signal timing plans. Fixed-time plans are suitable in areas where traffic remains similar to the calibration state. As fixed-time plans do not adapt to live traffic conditions, they do not perform well when traffic demand deviates from its expected levels. As traffic demand changes over time, the performance of fixed-time plans degrade by up to 3% per year and need to be recalibrated to remain effective (Bell and Bretherton, 1986).

TRANSYT - TRAffic Network StudY Tool

A notable example of a fixed-time signal timing system is TRANSYT (Robertson, 1969). TRANSYT (Robertson, 1969) is a macroscopic offline computer program for analysing signals for isolated and coordinated intersections and is one of the most widely deployed fixed-time optimisation packages still in modern usage. TRANSYT uses historic flow measurements to generate optimum signal timing plans for both isolated and networked intersections. The timing plans can be calibrated to differ for specific days and times of day to capture time-varying demand characteristics. TRANSYT calculates the optimal signal timings for a given road network model by minimising a performance function consisting of the delay, the number of stops and economic factors (Binning et al., 2013).

The TRANSYT algorithm has two main elements: 1) a traffic model from which the performance index for a given set of signals are calculated, and 2) A hill-climbing optimisation algorithm makes incremental changes to the signal settings to determine if the new settings improve the performance index. In the traffic model, TRANSYT makes the flowing assumptions (Binning et al., 2013):

1. The traffic flow is cyclic. (Repeats for a given period).
2. Where signals are coordinated, they have a common cycle time or their cycle time is a fraction of the greatest cycle time.
3. The proportion of turning vehicles and their rate of arrival is constant over a given period.

The performance index for TRANSYT is given by:

$$PI = \sum_{i=1}^{N_\mathrm{v}} (W_\mathrm{v} w_\mathrm{i} d_\mathrm{i} + K k_\mathrm{i} s_\mathrm{i}) + \sum_{i=j}^{N_\mathrm{p}} W_\mathrm{p} w_j d_j \tag{2.1}$$

where:

N_v	Number of traffic streams and links
W_v	Cost per vehicle-hour of delay
w_i	Delay weighting on traffic stream/link i
d_i	Delay on traffic stream/link i
K	Cost per vehicle stop
k_i	Stop weighting on traffic stream/link i
s_i	Number of stops on traffic stream/link i
N_p	Number of pedestrian crossing sides
W_p	Cost per average pedestrian-hour of delay
w_j	Delay weighting on pedestrian crossing side j
d_j	Delay on crossing side j

The TRANSYT optimiser seeks to minimise Equation 2.1. If the PI were reduced to zero it would mean every vehicle arriving at the intersection would find a green signal and be able to proceed without delay or stopping.

In the UK, TRANSYT has been shown to reduce delays by up to 40% in Glasgow, Scotland (Wood, 1993). TRANSYT was shown to reduce delay up to 24% over pre-existing signal timing plans in the New England region of the USA (Agbolosu-Amison et al., 2004). Skabardonis (2001) demonstrated that recalibration of traffic signals in the State of California with TRANSYT achieved 7.7% reductions in travel time, 13.8% reductions in delays, and a 12.5% reduction in stops. In Malaysia, Nesheli et al. (2009) showed that TRANSYT could reduce delays by up to 55% at peak hours.

LinSig

LinSig (Simmonite, 1985) is a computer program designed for the assessment and modelling of isolated and networks of signalised intersections. Similarly to TRANSYT, LinSig uses Cyclic Flow Profiles (CFP) to model traffic movements. A CFP is the average traffic flow passed a fixed point during each phase of the signal cycle over a fixed period. From the CFPs, LinSig models the arrival and discharge profiles at the intersections in discrete time slices. Three CFPs are used to model the signal timing (JCT Consultancy, 2018). The arrival profile models the vehicles that will arrive at the intersection. The accept profile contains the vehicles presently queuing and those that arrive during the green phase. Finally, the leave profile describes the vehicles, that will pass the intersection during the green phase.

Unlike TRANSYT which optimises an economic PI, LinSig uses the junction geometry and CFPs to either maximise capacity or minimise average delay (JCT Consultancy, 2018). LinSig is a less comprehensive model than TRANSYT, considering only platoon dispersion. In contrast, TRANSYT considers platoon dispersion, congested platoon dispersion, cell transmission, and localised traffic flares (ODHIAMBO, 2019).

In the UK, LinSig has been shown to reduce delays by up to 9% at signalised roundabouts (Simmonite, 2008). A case study in Slough, UK showed the delay at an intersection could be reduced by up to 22% during the AM peak.

MAXBAND

MAXBAND (Little et al., 1981) is a traffic signal timing algorithm for maximising bandwidth at intersections. Unique features of the MAXBAND algorithm are that: it automatically selects optimal cycle times from within a given range, it can suggest optimal speed limits within a given tolerance, lead or lag patterns for left-turn phases can be optimised, time can be allocated for the queue that accumulates during red signals, and is optimised for triangular loop networks. MAXBAND calculates cycle times, offsets, speed limits, and left-turn phase orders to maximise bandwidth. The system used a series of matrices, which describe the optimisation problem as a mixed-integer linear program (MILP), the solver then solves the system of equations to minimise Webster's equations.

MAXBAND was originally developed for the Federal Highways Administration (FHWA) in the US (Little et al., 1981). Although it was not used commercially, its formulation of the traffic signal control problem as a MILP was a significant contribution and inspired many subsequent works (Arsava et al., 2016; Cabezas et al., 2019; Chaudhary and Messer, 1993; Zhang et al., 2015).

PASSER

PASSER (Chaudhary and Messer, 1993) is an extension of MAXBAND, with the objective of overcoming MAXBAND's limitations. Namely, the simplistic model, computational impracticality, and lack of traffic measure reporting (delays and stops). PASSER was developed in response to the practice of using MAXBAND to determine the initial conditions to be passed to a TRANSYT optimisation process. Unlike MAXBAND and TRANSYT, PASSER employs a three-step optimisation process. Firstly, link synchronisation is determined; next, the network level synchronisation is determined. Lastly, the best link and network synchronisation results to optimise the signal timing constraints.

Yang compared PASSER, with TRANSYT and Synchro for road networks in Kansas, USA and found that PASSER calculated the best plans in a comparison of delay, stops, fuel consumption and emissions. In a comparison against the HCM and Synchro (Benekohal et al., 2002), PASSER was found to be a capable optimisation procedure but frequently flagged reasonable cycles times as being erroneous, and could not perform delay calculations for right-turn movements.

Synchro

Synchro (Trafficware, 2019) is a proprietary offline macroscopic analysis and traffic signal optimisation package. Synchro supports signalised and unsignalised intersections, and roundabouts. Synchro's signal optimisation routine is based on the specifications in the Highway Capacity Manual (HCM) (Elefteriadou, 2016), supports weighting specific phases, and can optimise phase splits, cycle lengths, offsets. The objective of Synchro's optimisation process is to minimise delay at each intersection. To optimise cycle lengths, Synchro optimises the performance index:

$$PI = \frac{D + 10S}{3600} \tag{2.2}$$

where D is the delay in seconds, and S is the number of stops (Udomsilp et al., 2017). In Bangkok, Thailand, Synchro was shown to reduce rush-hour delays compared with the existing signal timing plans (Udomsilp et al., 2017). In a comparison against the HCM and PASSER (Benekohal et al., 2002), Synchro was found to be the most accessible software package, but discrepancies in its delay results compared to the control results. The discrepancy is possibly attributable to Synchro's comparatively weak optimisation procedure and performance indicator and was deemed to need further validation.

2.4.2.2 Actuated Traffic Signal Control

The survey work needed to gather updated information to recalibrate fixed-time plans is costly and time-consuming. With ever-growing numbers of signalised intersections and traffic congestion, recalibration is not always feasible. To address this, actuated signal control systems use data from roadside infrastructure such as inductive loops or video cameras to extend the green time of a signal stage between a minimum and maximum value in response to the prevailing traffic conditions. Inductive loops are the most commonly used vehicle detector in the UK (Gardner et al., 2009). Although their installation requires a higher initial cost, they mitigate the need for recalibration fixed-time plans suffer from, which saves person-hours and reduces vehicle delays over time.

System D

System D (of Transport, 1984) is an early vehicle actuation scheme that was developed in the 1960s to replace pneumatic detectors with inductive loop detectors and is one of the most commonly used vehicle actuation systems in the UK (UK Govt. Dept. Transport, 2006). The System D loop configuration consists of three detectors named the X, Y, and Z detectors, sited at 39m, 25m, and 12m from the stop line respectively. System D operates on the detection of vehicle presence and gaps in traffic. System D extends the green time of a signal between a minimum and maximum green time in fixed time increments. The minimum green time is determined by the time it takes to clear vehicles between the stop line and Z detector (Yulianto, 2018).

A criticism of System D is that it behaves well in under-saturated conditions, but is a poor solution when intersections become over-saturated. The deterioration in over-saturation conditions occurs as if the system cannot clear the queue. The green time in each phase becomes the maximum green time, in which case the control becomes a fixed-time plan with sub-optimal timings (Yulianto, 2018).

MOVA - Microprocessor Optimised Vehicle Actuation

MOVA (Vincent and Peirce, 1988) is a sophisticated vehicle actuation controller that user per lane detectors to optimise delay, stops, and intersection capacity. In the UK, MOVA is installed at half the intersections it is compatible with, with an additional 200-300 new installations each year (TRL Software, 2019).

In MOVA installations, similarly to System D, loop detectors are positioned upstream of the junction. In contrast to System D, loop detectors for MOVA are positioned upstream of stop lines based on the cruise speed of approaching vehicles. The cruise speed is the 15th percentile speed of vehicles approaching the intersection after the initial queue has begun discharging. The inductive loop detectors are placed 3.5 s (X-detector) and 8 s (IN-detector) upstream of the intersection at the cruise speed in each lane, although these locations can vary slightly without performance changing noticeably (Crabtree, 2017). MOVA first calculates an initial green time to clear all the observed vehicles queuing between the stop line and the X-detector. The MOVA detector will then search for the end-of-saturated flow if vehicles are queuing beyond the X-detector, by monitoring traffic until gaps greater than a threshold size appear. After the saturation flow has ended, MOVA decides which of its two modes of operation it should use. MOVA does not adhere to a strict cycle time due to its flexible optimisation process. However, upper bounds are usually imposed to prevent significant waiting times.

MOVA manages oversaturated and undersaturated road conditions with separate approaches. When the junction is undersaturated (end-of-saturation detected after the initial green) MOVA attempts to minimise delay and stops for the entire intersection. MOVA minimises delay and stops by polling the detectors in each active lane and calculates which vehicles benefit from extending the green time. Simultaneously, MOVA monitors the queues and estimated arrival rates in the inactive lanes and calculates the detriment of extending the green time to them. When the net benefit of extending the green time is outweighed by the accruing delay of vehicles in other lanes the stage is changed. During oversaturation, MOVA maximises the capacity for the congested approaches (Crabtree, 2017). Oversaturation is detected if the queue on a lane has not discharged fully. If one or more lanes are deemed to be saturated, the entire link is treated as oversaturated. Under oversaturated conditions, intersection capacity is maximised by keeping the stage green as long as the oversaturation is still detected up to a maximum green time limit. Changing the signals less frequently limits the time lost due to changing signals.

In the UK, Wood et al. (2007) studied a MOVA installation at motorway M42 Junction6 and found that MOVA reduced traffic delays by up to 10% over previous measurements. Hertfordshire County Council (2011) identified that MOVA typically reduces delay at isolated intersections by 13% on average over other actuated systems. They also identified that MOVA reduces accidents by up to 30% and outperforms SCOOT at isolated intersections. In terms of installation costs, MOVA was estimated to recover its installation cost in 7-21 weeks depending on the size of the installation and the amount of traffic whose delay could be reduced.

ACS-Lite - Adaptive Control System Lite

ACS-Lite is an adaptive control system developed by the FHWA to be an economical adaptive signal control solution (Luyanda et al., 2003). The main objectives of ACS-Lite are to operate closed-loop systems with state-of-practice techniques, use inductive loops to provide appropriately adaptive signal timings, maintain plan quality over long timescales, and to provide superior performance to fixed-time plans (Luyanda et al., 2003). ACS-Lite adapts signal phases, splits, and offsets incrementally with respect to the current baseline plan and the current traffic conditions. ACS-Lite assumes its baseline plan provides a good set of initial conditions, then optimises the plan to reduce delay and minimise the impact that modifying the signal plan would have on the local traffic. Additionally, ACS-Lite uses a forecasting module to incorporate historical trends and emerging trends in the traffic flow characteristics into its optimisation process. A unique feature of ACS-Lite is that it times the deployment of its new timing plans to minimise the impact the transition will have on traffic flow.

ACS-Lite is sensitive to the availability and frequency of detector data (Luyanda et al., 2003). Furthermore, ACS-Lite only works for linear arterials. A study of ACS-Lite in New York, USA found that while ACS-Lite is effective a reducing delay in congested corridors, it causes extra delays at boundaries where it interacts with intersections with other traffic signal control systems (Sun et al., 2018). Shelby et al. (2008) conducted a study comparing the performance of ACS-Lite across four sites in the USA. The findings showed that ACS Lite reduced vehicle delay, arterial travel time, vehicle stops, and fuel consumption, and the estimated the economic benefits of improved traffic flow surpassed the system deployment costs within a year.

Transit Priority

Transit Priority is a system whereby certain vehicle types, chiefly buses, are given priority over others in order to promote public transport in dense urban areas (Wu and Hounsell, 1998). In bus priority systems, a pre-signal used to allow buses to move before other vehicle traffic to assist them in maintaining their schedule (Wu and Hounsell, 1998). A variety of detectors, including inductive loops, video cameras, and GPS measurements can be used to detect buses near signalised intersections (Hounsell and Shrestha, 2012).

Although priority systems disadvantage other certain road users, this is often a deliberate action in a wider strategy to increase the use of public transport and reduces traffic and emissions in congested urban areas such as London, UK (Hounsell and Shrestha, 2012; Wu and Hounsell, 1998).

PTV Epics

PTV Epics is a proprietary adaptive traffic signal control algorithm developed by PTV Group (Weichenmeier et al., 2015). PTV Epic's optimisation policy is to minimise total delay. The algorithm achieves this by modelling stage sequences over a 100 s time horizon and selecting the configuration that provides the lowest delay. The internal traffic model uses loop detector data and a queue length estimation algorithm to determine the queue lengths at the intersection (Chandan et al., 2017).

In a trial in four Polish cities with 180 equipped intersections, PTV Epics reduced travel times for drivers compared with the previously installed system by up to 35% in some areas. However, they increased travel times by up to 25% in others (Weichenmeier et al., 2015).

2.4.2.3 Adaptive Traffic Signal Control

Although vehicle actuation is a marked improvement over fixed-time systems, they do not exploit the information available from neighbouring intersections as they are isolated. Adaptive signal controllers use data from infrastructure in real-time to optimise an objective function to reduce traffic delays and congestion. Adaptive strategies will either work at isolated (decentralised) intersections or will attempt to coordinate groups of signal controllers to increase traffic throughput. Coordinating signals between adjacent intersections can be beneficial as it facilitates the creation of 'green-waves', which allow vehicles to pass through subsequent intersections uninterrupted. Establishing coordination is usually beneficial when two or more intersections that handle high volumes of traffic are close to one another (Koonce et al., 2008). Coordination has been shown to decrease delays and stops by up to 40% compared with fixed-time plans (Robertson and Bretherton, 1991).

Like vehicle actuation, adaptive traffic signal control strategies rely on roadside infrastructure to operate. If the strategy is coordinated, then it will use information from detectors to predict the operation of the intersection over a specified time horizon. Although adaptive strategies have been shown to reduce delays significantly, their performance is contingent on roadside detectors, so hardware failures can severely hinder their operation. In the case of the SCOOT controller, the benefits of the adaptive control would be lost for detector failures rates above 15% (Robertson, 1986). In this section, the most widely used adaptive traffic signal controllers are reviewed below in chronological order.

SCOOT – Split Cycle Offset Optimisation Technique
SCOOT (Hunt et al., 1981) is the most commonly used traffic control system in the world and is installed at more than 250 towns and cities internationally (TRL, n.d.). SCOOT is a coordinated system and uses upstream inductive loops to monitor flows at the approaches to the junctions under its control. The key principles of SCOOT (Robertson, 1986) are to:

1. Measure flow profiles in real-time
2. Update an online model of queues continuously
3. Incrementally optimises signal settings.

SCOOT is often referred to as an online version of TRANSYT due to the similarities in their optimisation process. SCOOT updates a traffic model with readings from loops detectors then optimises the signals for the next cycle to reduce delays and stops. The changes are incremental to minimise the disturbance the changes create (Stevanovic et al., 2009). SCOOT optimises three components of the signal timing separately: splits, cycle lengths, and offsets.

The goal of the split optimiser is to equalise the saturation at an intersection. The split optimiser runs 5 s before the end of each stage and considers if a reduction or increase of the stage time by 4 s would be beneficial, or if it should stay the same. The stage time reallocations are constrained by maximum and minimum stage times. SCOOT does not support vehicle actuation, but phases can be skipped if no demand is present (Stevanovic et al., 2009). If a stage is skipped locally, this information is fed back to the master controller so it can adjust the network level strategy accordingly.

The offset optimiser runs once per cycle to keep the cycles of the coordinating intersections aligned. As with the phase optimiser, the stage offsets can be adjusted by ± 4 s or kept the same. The optimiser chooses the offsets that will minimise delays and stops across the intersections.

The cycle length optimiser considers the saturation levels at each intersection and optimises the cycle lengths to ensure progression between them. If the minimum practical cycle time is increased if the intersection is above 90% saturated and decreased if it below the same threshold. Sometimes higher cycle lengths are chosen to allow for double cycling (stages more than once per cycle) at lightly loaded intersections.

SCOOT has been deployed successfully internationally. In the UK, SCOOT has been shown to reduce traffic delays by 12% on average, but up to 33% compared with TRANSYT, and 26% on average but up to 48% compared with an isolated vehicle actuation scheme (Bretherton, 1990). In Toronto, Canada, SCOOT controls over 300 intersections and reduces traffic delays by up to 40% (Bissessar et al., 2015; Greenough and Kelman, 1997).

OPAC – Optimisation Policies for Adaptive Control

OPAC (Gartner, 1990) is a real-time decentralised signal timing strategy with the aims of being:

1. Better than offline methods.
2. Better at managing demand variability by not being constrained to the notions of splits, offsets, and cycle times.
3. Truly demand responsive. Not relying on historical or predicted values.
4. Not being restricted to control periods of set lengths.

In OPAC, signal timings are only constrained by minimum and maximum stage lengths, and otherwise optimise vehicle delays and stops. Although the algorithm originally required knowledge of vehicles over the entire length of the stage, this was difficult to achieve in practice, so it moved towards a rolling-horizon approach which simplifies the optimisation. OPAC optimises stages in intervals of 50-100 s. During each interval, there is between 1 and 3 stage changes. The stages are modelled using 15 s of upstream data and 45 s of predicted data and resampled every 5 s. The total delay, total stops, or both are minimised for all possible stage sequences and the sequences which yield the minimum result selected.

OPAC has been deployed at several cities in the USA but has not achieved widespread adoption due to the algorithm complexity and the cost of its associated infrastructure (Stevanovic, 2010).

PRODYN – PROgramme DYNamique

PRODYN (Henry et al., 1984) is a bi-level hierarchical algorithm that uses forward dynamic programming to optimise signal timings and coordinate signals. PRODYN decomposes the larger coordination problem into several smaller optimisation problems which can be solved and recombined interactively to solve the global problem. PRODYN decides whether to change stage every 5 s, using data from inductive loops placed 50 m and at the link entrance of each lane. The optimisation policy minimises total delay. PRODYN monitors the stage time and last time since each intersection switched; the saturation flows, jams and queues for each lane; and the number of vehicles travelling at free-flow speed on each link. Similarly to OPAC, PRODYN uses a rolling horizon optimisation technique, to minimise total delay over the whole horizon and implement the optimal strategy for the next 5 s.

PRODYN was trialled in Toulouse, France as part of the ZELT project and was shown to reduce delays by 10% on average over fixed-time (Henry and Farges, 1990).

SCATS – Sydney Coordinated Adaptive Traffic System
SCATS is a hierarchical adaptive traffic signal coordination system developed in Australia during the 1980's (Lowrie, 1990). SCATS is not an optimisation procedure. Instead, it acts as a heuristic feedback system that adjusts signal timings using flow information from previous cycles. SCATS' bi-level heuristic feedback process uses an "upper level" to select the pre-defined timing plan which most closely matches the current traffic conditions. Then, the "lower level" optimises the splits and cycle-times.

First, SCATS performs a cycle length adjustment for each system of 1 or more intersections. SCATS will 'marry' subsystems that exhibit good progression. The 'marriage' is contingent on the differences between intersection cycle lengths not exceeding a certain threshold. Under low traffic demand, the highest cycle time estimation for the intersections in the subsystem is used. In high demand scenarios, the linear relationships between cycle length and the degree of saturation are used. The cycle length adjustments are scaled based on the last three cycle lengths to avoid large variations (Stevanovic et al., 2009). After all cycle lengths are calculated, the intersections that are permitted to marry are compared, and for those who meet the criteria for marriage, the largest cycle time among the intersections is chosen.

To adjust the splits, SCATS selects the pre-defined split plan that minimises saturation at the intersections. SCATS then increments the template split plan by up to $\pm 4\%$ of the cycle length each cycle

Finally, SCATS updates its offsets by calculating link plans which pair offsets with cycle lengths. The link plan offsets are adjusted based on a linear relationship with the cycle lengths to improve progression.

In trials, SCATS was shown to reduce delays and stops better than SCOOT in Utah, USA (Stevanovic et al., 2009). In Australia, SCATS was shown to reduce stops by up to 9% in central areas, and up to 30% on arterials (Wood, 1993).

UTOPIA – Urban Traffic OPtimization by Integrated Automation
UTOPIA (Mauro and Di Taranto, 1990) is a traffic signal control and transit priority system developed for wide area networks. UTOPIA applies systems control theory to the traffic signal control problem by topologically decomposing the control problem into a decentralised, hierarchical problem; defining functions for the decomposed problems and their interactions; defining methods for solving the problems.

At the local level, UTOPIA creates 'zones' of one or more intersections. Each local control zone is comprised of an 'observer' and a 'controller'. The observer uses data from inductive loops and traffic signal states to microsimulation groups of vehicles in 3 s steps to derive a state vector describing the arrival times of the vehicles at the intersection. The state vector allows the observer to estimate queue lengths, travel times, turn ratios, and saturation flows. The controller then uses information from the observer to optimise signals over a 120 s time horizon every 3 s. The local optimisation process seeks to minimise the time loss, queues, and the number of stops experienced by each vehicle.

At the area level, there are also an ‘observer’ and ‘controller’. The observer gathers traffic count data from the extent of the network and supplements it with estimated traffic statistics to predict the routes’ traffic will take and the demand levels on those routes. The major routes are modelled macroscopically into storage units, and each unit’s associated traffic is updated every 3 minutes. The controller module optimises average speed and saturation for each storage unit over a 30-60 minute time horizon to minimise travel time throughout the area.

UTOPIA was initially deployed in Italy but has also been implemented in The Netherlands, USA, Norway, Finland, and Denmark (KonSULT, 2009). UTOPIA was shown to increase traffic flow speeds by up to 16% on average, and up to 35% at peak times compared with fixed-time plans (Wood, 1993).

MOTION – Method for the Optimisation of Traffic signals In Online controlled Networks

MOTION (Bielefeldt, 1994) was developed to respond to constantly increasing traffic demands in Germany. MOTION was developed with the ability to integrate with existing infrastructure which may not be ideally placed, or are limited in number. MOTION is unique in that controllers are responsible for their local timings, and the network adaptive logic provided updated reference frameworks for the local controllers to follow every 5-15 minutes. MOTION has four levels of operation (Hounsell and McDonald, 2001):

Data acquisition: The central module gathers data from detection equipment in the network. The data is then used for incident detection and origin-destination (OD) determination.

Traffic modelling and analysis: The traffic model is used to determine the current traffic status. OD counts and turning movement from the previous step are used to calculate the green time splits, and cycle times for the controlled intersections.

Control variable optimisation: During this process, MOTION optimised the stages, stage sequences, transitions, intergreen times, and minimum green times. First, minimum signal plans are calculated and then recalculated every second to adjust the plan according to the demand on the intersections. The top-level controller determines a common cycle time from the revised plans and minimises delays and stops in the network using a platoon dispersion model.

Signal decisions: If the revised signal plans offer a significant improvement on the current plans, the plans are updated across the local controllers. Otherwise, they remain the same.

MOTION is deployed in many cities across Germany, where it has improved travel times by up to 14% (Busch and Kruse, 2001).

BALANCE

BALANCE (Friedrich and Keller, 1994) is another German traffic signal control system. BALANCE is a lightweight control strategy that allows for minimal usage of detectors and can work with existing detection systems. The goals of BALANCE are to be (Friedrich, 2003):

Modular: The system can operate even in the absence of a central controller.
Robust: System faults can be detected, analysed, and compensated for.
Evolutionary: The control systems can adjust itself independently of its original configuration.
Interoperable: Data from different hardware and systems can be synthesised and managed.
Integrated: A common approach can be achieved the distributed hierarchical system architecture.

At a local level, BALANCE operates the MicroBALANCE strategy. MicroBALANCE reacts every second to model random variations in the system, such as calls for public transport priority. To achieve this objective, microsimulation and a rolling horizon forecast are used to estimate vehicle arrivals. At the global level, BALANCE operates MacroBALANCE. MacroBALANCE is a heuristic optimiser for splits, offsets, and cycle times. MacroBALANCE decomposes the network level problem into linear sub-problems which it optimises every 5-15 minutes.

Trials of BALANCE in Munich, Germany; Glasgow, UK; and London, UK show that delay could be reduced by up to 14% over the pre-existing control strategies in those cities (Friedrich, 2003).

ALLONS-D – Adaptive Limited Lookahead Optimisation of Network Signals - Decentralised

ALLONS-D (Porche and Lafortune, 1997) is a decentralised controller that aims to minimise delay on all approaches to the intersection. For each intersection, queue length and vehicle arrival information are gathered from as far upstream as the immediately adjacent intersections (others further upstream are ignored). The optimiser takes a snapshot of the network state and optimises signal timings every 5-15 s. The optimiser decides whether a stage should be green for each second of its optimisation horizon. A decision tree is created and traversed for each stage choice until the optimum stage choice is found. Coordination in ALLONS-D is implicit as it takes data from as far upstream as the adjacent intersection, and the use of a rolling horizon. The implicit features do not guarantee optimal network-level performance, so a weighting scheme to prioritise stages that pair favourably between intersections was introduced to promote coordination in grouped intersections.

TUC – Traffic-responsive Urban Control

TUC (Diakaki, 1999) models traffic control as a physical process. Each junction and its approaches are represented as a graph of related nodes and links with monitored inflow and outflow. From the network graph, a state vector of the vehicle numbers within the links can be determined, and their evolution expressed as a linear-quadratic equation. Oversaturation is mitigated by minimising the relative link occupancies to prevent queue spillback. The system of equations describing the graph acts as a multivariable regulator which responds indirectly to disturbance. The regulator has the advantage of not needing to predict future traffic conditions.

TUC has been deployed in Chania, Greece; Glasgow, UK; Southampton, UK; and Munich, Germany where it reduced travel times up to 34% and outperformed incumbent SCOOT, and TASS controllers, and performed comparably to BALANCE (Diakaki et al., 2002; Kosmatopoulos et al., 2006).

RHODES – Real-time Hierarchical Optimised Distributed Effective System

RHODES (Mirchandani and Head, 2001) is a traffic signal control systems designed to respond well to the naturally stochastic nature of vehicle traffic. To achieve this objective, RHODES:

1. Aggregates traffic at different levels (individual vehicles, platoon, and macroscopic flows) once per minute.
2. Identifies the response of each traffic level to signal control.
3. Allows the traffic to move such that their objectives are fulfilled (minimising queue length, delay, or the number of stops).

RHODES is unique in that it optimises specific stage durations rather than splits, cycle lengths, and offsets like the other controllers. As with ALLONS-D, coordination is implicit as RHODES does not have a fixed cycle time. Data are gathered from stop bar and upstream loop detectors to minimise the delay of vehicles passing through the intersection. An internal prediction model estimates vehicle flows to adjacent intersections and sends it to those intersections resulting in implicit coordination.

RHODES has been deployed at four sites in the USA, where it has achieved delay reductions of up to 19% in its target networks (Zhao and Tian, 2012).

InSync

InSync (Rhythm Engineering, 2019) is a video-based traffic signal controller developed by Rhythm Engineering in the USA. InSync uses shielded video cameras in combination with machine vision and AI to coordinate signals in real-time by monitoring platoon progress. Platoons are moved through the network using what are what Rhythm Engineering refers to as 'time tunnels', whereby an intersection facilitate a platoon by being green during its expected arrival window. When not tunnelling vehicle platoons, InSync counts traffic at arterial approaches to the intersection and schedules green time for them. In the event of fog or camera failure preventing data being gathered, four weeks worth of historic green split data aggregated for the time-of-day and day-of-week is aggregated for the controller to use as a backup.

In Florida, USA, InSync was shown to reduce both delays and numbers of stops by up to 32% compared with time-of-day fixed-time plans(Stevanovic et al., 2017).

2.4.3 Future methods in Urban Traffic Signal Control

In the previous section, it was shown that current methods for traffic signal control rely on roadside infrastructure for vehicle detection. C-ITSs offers an exciting opportunity to glean more information from vehicles and infrastructure. C-ITSs use wireless communications to allow vehicles and infrastructure to share information, for example, speeds, positions, and other data points from vehicles could be made available in real-time to a traffic signal controller.

Gradinescu et al. (2007) were among the first to formulate a signal control strategy that utilises data from CVs. However, current developments in the area of CVs and C-ITS technologies offer continued opportunities to improve on the prevalent control strategies discussed, and even develop new strategies that harness the C-ITS data described in Section 2.1. In this section, proposed traffic signal control algorithms that use CV data are reviewed based on the methods they use to achieve traffic signal control. The discussion builds upon the work (Feng, 2015) and (Peng et al., 2017). The simulation features that were used in the evaluation of each algorithm are given in Table 2.7.

2.4.3.1 Traffic Signal Control Reformulation for Numerical Optimisation

CV data potentially allows a traffic signal controller to know the precise state of the traffic in its vicinity. This concept has led to many works where the problem of traffic signal control has been reformulated to fit numerical optimisation techniques developed in other fields.

Algorithms for Isolated Intersections

Gradinescu et al. (2007) were the first to propose a traffic signal control strategy that used data from connected vehicles. The strategy gathers vehicle, speeds, positions, and headings once per cycle to calculate a new cycle length for the prevailing traffic demand. Once the cycle length has been determined, the green splits are calculated to minimise delay and balance the saturation across the lanes. The study simulated traffic flows on a single intersection comparing the proposed method against fixed-time control. However, the conditions were highly-idealised in that no pedestrians, other signals, or communication errors were considered.

Lee et al. (2013) presented an actuated algorithm based on cumulative-travel-time (CTT) data from CVs. Vehicles accumulate travel time on their approach to an intersection, the intersection controller then aggregates the CTT for each stage and determines the stage with the maximum CTT. The CTT estimates are updated in intervals of 5 s, and as long as the CTT for the active stage is greater than the CTT for the other stages, the stage stays active if it drops below the CTT for another stage, the stage changes to serve the new stage with the highest CTT. In networks that do not have 100% CV penetration, the algorithm supplements the CTT aggregation with a Kalman filter estimation process. The algorithm is limited as it does not consider the effect of multiple intersections, and the quality of the estimation needs to be improved to better compensate for unconnected vehicles in the network.

Chang and Park (2013) proposed an algorithm that uses position data from CV to estimate the queue length in each approach to the intersection. The algorithm optimises the cycle length, and green splits to clear the queues while minimising delays, stops, and overall throughput. The testing procedure in this study is unique in that it is the only paper on a traffic signal control strategy for CVs to consider the effects of a pedestrian cycle on the performance of the intersection. However, the study is limited in that the base comparison case is a randomised control algorithm rather than a calibrated system.

Cai et al. (2013) presents an approach for approximating travel times which can be used in an adaptive dynamic programming context to reduce delays and stops at an intersection. The adaptive dynamic programming procedure approximates the solution to a set of equations. It has the benefit of being able to adapt its performance to compensate for traffic flow variations iteratively. The tests of the algorithm show that it can reduce delays and stops at a signalised intersection. However, although the authors acknowledge that non-ideal data can negatively impact results, they chose to use ideal data.

Tiaprasert et al. (2015) use a novel discrete wavelet transform to enhance the estimation of queues lengths at intersections using data from connected vehicles. The major limitation of the method is that it requires CV penetration to be known, which can be challenging to obtain in practice. The wavelet transform is shown to provide accurate queue length estimates under both pre-timed and actuated control.

Feng et al. (2015) proposed a bi-level dynamic programming approach. At the upper level, the optimal stage length and plan are calculated. At the lower level, the phases are optimised to reduce either delay or the number of stops. CV data is used to estimate speeds, and queue lengths to feed into the optimisation process. In simulations with ideal data, the algorithm outperforms a vehicle actuated strategy above 50% CV penetration.

Algorithms for Coordinated/Multiple Intersections

Ezawa and Mukai (2010) presented an algorithm that is novel in that vehicle routes are used to calculate expected traffic congestion. The roads and intersection system are represented as a series of nodes and links, the position and route information is then applied to the links to work out the demand each vehicle has on the links for its route. Cycle lengths between 90 s and 180 s are calculated based on previously measured cycle lengths for each intersection. The green splits are allocated for between 30% and 70% of the cycle time for the intersection. Offsets are used to synchronise coordinating pairs of inflow and outflow links. The algorithm was simulated based on real traffic demands from the Chiyoda-ku, Japan, and reduced average waiting times when compared to a fixed-time strategy.

Waterson and Box (2012) investigated a bid-based signal control and coordination algorithm and quantifies the impact of position noise on the performance of the algorithm. At the intersection level, bids composed of the vehicle distance to the intersection and their speed are calculated. The bids are calculated every 10 s, and the stage with the highest bid is selected. At a zone level, coordination is achieved implicitly by matching bids across complementary stages and selecting the stage combinations with the highest bids. The paper shows that delays can be reduced by up to 25% without coordination, and by up to 40% with coordination, compared with MOVA.

Xiang and Chen (2016) present an algorithm that uses CV data to optimise signal timings and to feedback routing information to drivers. The vehicle position and heading data are used as inputs for a co-learning optimisation algorithm which calculates the demand for each link in the network and can offer re-routing suggestions to vehicles. The estimation models are implemented as agent-based processes which monitor their decisions and learn to reinforce behaviours that improve system performance. The algorithm is tested using microsimulation, and reduced average delays and stops by up to 38% and 19% respectively compared with a fixed-time plan, and 26% and 11% respectively compared with an actuated plan.

Islam and Hajbabaie (2017) propose an algorithm that achieves distributed coordinated control for networks with 100% CV penetration. The algorithm optimises signal timings for single intersections to maximise throughput while penalising queues. Coordination is achieved by sharing local control decisions and traffic flow levels with nearby intersections. The shared data are used to coordinate local decisions in response to traffic at neighbouring intersections. The distributed approach is computationally efficient as the coordination effort is not focused on a centralised coordination layer. In simulations on 2 model networks, the proposed algorithm increased throughput by up 5%, and decreased travel times by up to 48% compared with a coordinated adaptive controller.

Beak et al. (2017) propose a bi-level algorithm that coordinates and optimised green times. At the local level, the algorithm optimises green times subject to coordination constraints. At the global level, the algorithm uses data gathered at the local level to calculate the offsets for the coordinated corridor which are then updated across the local controllers. The optimisation process occurs every 2 s or at the end of a stage, and the coordination restraints are recalculated every time the optimisation problem is solved. The algorithm seeks to reduce the total delay and number of stops. The simulation used a model of 5 intersections in San Mateo, California, and the algorithm was shown to reduce delays by up to 19% and the number of stops by up to 16% compared with a coordinated actuated strategy.

Shaghaghi et al. (2017) present a method of determining traffic flow density from multiple communication message types. Analysing multiple message types improved traffic density estimation accuracy compared with only considering one message type. The traffic density estimates were then inputted into the standard Signal Timing Manual (STM) (Koonce et al., 2008) guidelines and Webster's equations (Webster, 1958) to determine the signal timings for the intersections. The algorithm was tested against single message source approaches and found to reduce the average delay per vehicle up to 14% and CO_2 emissions up 13%.

Aziz et al. (2018) present a traffic signal controller which uses a reward-based method for reinforcement learning. First, the state of the system is defined using the normalised queue lengths for each lane at the intersections. The system then takes action based on the current state of the system. The action is to use an ϵ-greedy algorithm which weights the probabilities of each stage being selected based on a Boltzmann distribution and selects the stage from it. Typically, a greedy algorithm will select the maximum value, in contrast, the advantage of adding randomness through the ϵ-greedy selection is that it allows other approaches to be taken occasionally and reinforced if they are beneficial. The reward function considers queue length, average delay, and the normalised queue index. When compared with a fixed-time control system, the algorithm reduced average queue lengths by up to 45% and average delay by up to 29%.

Han et al. (2019) propose a three-module system for traffic signal optimisation. The first module uses vehicle speeds and positions to estimate their arrival time at the intersection and the queue length in each lane. The second module calculates the stopped delay for each vehicle every second. Finally, the traffic signal control module calculates the stage length that minimises the delay for each stage. The arrival time and stopped delay data are then used to assign the stage sequence that minimised stopped delays. The algorithm was shown to reduce average delay in the network by up to 69% compared with a fixed-time Synchro strategy.

Review

Reformulating traffic signal control for numerical optimisation is an interesting area as it allows the problem of traffic signal control to be investigated using novel inputs such as CV data (Chang and Park, 2013; Gradinescu et al., 2007; Islam and Hajbabaie, 2017; Lee et al., 2013). Furthermore, traffic signal control problems can be solved using methods from other disciplines such as Wavelets (Tiaprasert et al., 2015), dynamic programming (Beak et al., 2017; Feng et al., 2015), Topology (Ezawa and Mukai, 2010), Auctions (Waterson and Box, 2012), and machine learning (Aziz et al., 2018). The literature reviewed shows that there are many ways of formulating the problem of traffic signal control in order to reduce traffic delays. The drawback to these methods is that like the OPAC algorithm (Gartner, 1990), their complexity overshadows their beneficial performance compared with other traffic signal control algorithms, which can prevent them from being adopted by the transport industry (Stevanovic, 2010).

2.4.3.2 Rolling Horizon Optimisation

Rolling horizon optimisation of traffic signals is one of the most common approaches of achieving traffic signal coordination, as evidence by the techniques' use as the basis of the controllers OPAC (Gartner, 1990), PRODYN (Henry et al., 1984), BALANCE (Friedrich and Keller, 1994), and ALLONS-D (Porche and Lafortune, 1997) reviewed in Section 2.4.2.3.

Priemer and Friedrich (2009) developed an approach for using CV data for decentralised traffic signal control of multiple intersections. The algorithm is stage based but does not use cycle times or offsets. The signals are optimised in 5 s intervals based on a rolling horizon optimisation over 20 forecasted seconds. The algorithm uses queue length estimation to compensate for sparse data at low CV penetration rates. The algorithm also uses stop-line loop detector data at low CV penetrations to serve unconnected vehicles. The optimisation process seeks to minimise the total delay for each intersection over the 20 s time horizon. The algorithm forces a stage change if the waiting time in any lane becomes more than 70 s. The algorithm is novel in that it provides transit priority for special vehicles. The algorithm is shown to reduce delays by up to 24% when compared with TRANSYT at 100% penetration. The limiting factor in the algorithm is that it is unstable below 12% CV penetration.

Goodall et al. (2013) presented the Predictive Microscopic Simulation Algorithm (PMSA). PMSA continuously adjusts traffic signals over a 15 s rolling horizon to reduce traffic delay. To determine the next phase, the speed, position, and heading of every vehicle in a 300 m radius of the intersection are taken. The data are used to simulate all possible stages after the vehicles in the current stage are allowed to clear for 15 s, and the stage which best minimises delay is selected. The stage length is calculated by simulating the time it would take to clear the vehicles in the next stage over the 15 s time horizon. If all the vehicles would clear the intersection, the stage simulations are repeated for that time point, if not, phase re-evaluation is triggered when the vehicles in the active stage reach 95% of their desired speed. If blocking-back is detected, priority is given to the phase that would clear it. In the Virginia case study, PMSA showed that delays could be reduced by up to 27% and stops reduced by up to 28% compared with Synchro. The limiting factor of PMSA is that it does not function well below 25% CV penetration or in oversaturated traffic conditions.

Ilgin Guler et al. (2014) proposed an algorithm to enumerate and optimise discharge sequences to reduce delay. Each sequence of vehicle departures was evaluated, and the sequence which minimised the objective function was selected. The algorithm was tested at CV penetrations from 0-100% on an intersection with two one-way streets at two demand levels, and with ideal communications. The algorithm reduced the delay by up to 60% compared with a FIFO algorithm. Liang et al. (2019) extended this work by incorporating coordination and speed guidance into the algorithm. A rolling horizon optimisation is used to monitor platoons in a zone of interest, and identify the one with the least delay. The platoon departures are then converted into SPaT plans which are used to optimise the green times. Finally, the SPaT plans are used to offer speed advisories to the connected vehicles such that their stops are minimised. By simulating the algorithm at multiple CV penetrations, it was found that the number of stops and average delay could be decreased with increasing CV penetration.

Review
Rolling horizon approaches take a more direct approach to optimising traffic signal control than the numerical optimisation methods discussed previously. Rather than optimising traffic signal parameters through completely numerical means, they use simulation to evolve a representation of traffic in the network to a point in the future. Rolling horizon approaches simplify coordinating signals, as the effects of multiple signal timings can be compared over the simulation horizons. However, rolling horizon methods are limited in that control is periodic. As traffic flow is a stochastic process, the real state of the network can deviate from the simulated horizon resulting in imprecise estimations of signal timing parameters.

2.4.3.3 Rule-Based Control

As CVs potentially allow the state of traffic in the network to be more precisely known than with inductive loops, rule-based control algorithms have emerged, and take a more naive approach to traffic signal control than rolling-horizon or numerical optimisation approaches. Rule-based algorithms make decisions on what actions to take based on the matching of the state of traffic to rules defining the behaviour that is desirable under those conditions.

Algorithms for Isolated Intersections
Chou et al. (2012) presented an algorithm that was novel in that passenger counts and vehicle emissions were considered in the signal timing process. Green times are extended using vehicle arrival times to determine if more time is needed to allow the vehicle to pass the intersection. If the vehicle needs extra time, the passenger count and emissions data are used to quantify the benefit of allowing the vehicle to pass the intersection. If the benefit of letting the approaching vehicle through the intersection outweighs the benefit of changing the stage

to allow waiting vehicles to use the intersection, the stage is extended. The algorithm was tested with and without passenger information for a single intersection, and it was found that using passenger data was beneficial for emissions and delay reduction.

Algorithms for Coordinated/Multiple Intersections

Hu et al. (2015) proposed an algorithm that considered bus priority in connected environments. The objective is to minimise the delay per-person for groups of passengers through giving buses priority in the signal coordination calculation process. The objective is achieved by reallocating green time from other stages to allow the bus to pass the intersection. The algorithm was shown to reduce delays for both buses and cars, but the benefits for cars were small.

Beak et al. (2018) present a peer-to-peer (P2P) for improving transit priority requests at signalised intersections. A backhaul network is used to monitor priority vehicles (e.g. buses) throughout the network. If a vehicle exits an intersection linked to an upstream intersection, its estimated arrival time is sent to the upstream intersection controller over the backhaul network rather than waiting for it to be within DSRC range. The advanced notice of the priority vehicle allows the intersection controller more time to schedule its priority green time. The algorithm was simulated at two sites based on Anthem, Arizona, and Salt Lake City, Utah, both in the USA. Compared with the actuated and coordinated strategies in the test-bed networks, the P2P algorithm reduced the delay by up to 94% on certain intersections (46% on average).

Tonguz and Zhang (2019) present an algorithm for leveraging DSRC for traffic signal control at low CV penetrations. If no CVs are present, fixed time signals are used. If CVs are present pre-timed signals are used if CVs are detected on the active stage. If there are no CVs in the active stage, but there are CVs in an inactive stage, the algorithm will change to the inactive stage immediately if the minimum green time for the current stage has been exceeded. The simulation results showed that average waiting times could be reduced by up to 36% compared with a regular fixed-time plan.

Review

Rule-based methods are based in Transit Priority methods (Wu and Hounsell, 1998). They simplify traffic control by modifying signals in response to specific events such as passenger priority Chou et al. (2012), bus-priority Beak et al. (2018); Hu et al. (2015); Priemer and Friedrich (2009), and checking for CV presence Tonguz and Zhang (2019). Rule-based methods are simple and understandable for transport planners and are useful for enforcing abstract conditions such as bus priority. In comparison with controllers that run optimisation processes, the performance benefits they achieve are more modest.

2.4.3.4 Platooning and Scheduling

As CV data allows the position of vehicles to determined, it also allows nearby vehicles to be grouped or clustered together into platoons. Monitoring vehicle platoons allows for new strategies that consider how to schedule vehicles collectively rather than as individual entities optimally. Considering traffic signal control as a scheduling problem also allows for different scheduling optimisation approaches from other disciplines to be considered.

Algorithms for Isolated Intersections

Ahmane et al. (2013) present an algorithm where vehicles are grouped into 'teams' to negotiate right-of-way at an intersection. Approaches to the intersection are used as storage zones. The objective is to move vehicles with both First-In-First-Out (FIFO) priority and in their teams, through the conflict zone, which is the centre of the intersection. Petri nets are used to provide a structural model of the system, which allows vehicles to be scheduled with a security time distance between them to prevent collisions.

Pandit et al. (2013) use a multi-disciplinary approach in that they treat platoons of vehicles as jobs in a processor job scheduling algorithm. The oldest job first algorithms are reformulated as the oldest arrival first algorithm (OAF). Speed and position data from CVs are used to organise vehicles into platoons of one or more vehicles. Each platoon is one job. If the traffic movements of two jobs conflict, they cannot be scheduled simultaneously. The time at the intersection is divided into slots, and assuming each platoon is the same size the non-conflicting jobs are scheduled into slots by oldest job first. Mathematically, OAF will result in delays less than or equal to twice the delay of an optimal system.

Kari et al. (2014) proposed an agent-based approach to traffic signal control. A Vehicle Agent (VA) relays information to an Intersection Management Agent (IMA) which optimises traffic signals based on the information it receives. The IMA uses a novel finite state machine to adapt the stage sequence flexibly. The IMA seeks to minimise queue lengths by serving as many vehicles as possible during its green period.

Au et al. (2015) propose an autonomous intersection management system without traffic signals using slot reservation. Vehicles announce their presence to an intersection manager. The intersection management system then reserves time at the intersection for each vehicle and responds to the vehicle with instructions about what speed they should travel to cross the intersection without collisions. The system is highly effective at reducing delays with 100% CAV penetration, but these benefits decay rapidly if any unconnected vehicles are present.

Bani Younes and Boukerche (2016) present a method for scheduling and timing stages at both isolated intersections and arterials. For isolated traffic lights, the algorithm defines a ready-area around the intersection in which all vehicles present are ready to cross the intersection. A green stage can be scheduled for vehicles already in the ready-area Any vehicles that arrive in the ready-area subsequently are also allowed to pass through the intersection. Vehicles self-organise into platoons which the intersection manager allocates stage time to reduce delays. In the arterial case, platoon information from the ready-areas of each intersection is shared between intersection managers and factored into the stage. The priority and green time calculations to maximise progression. The algorithms were shown to reduce delays and stops when compared with a random traffic signal control algorithm.

Cheng et al. (2017) proposed a neuro-fuzzy system for grouping and scheduling vehicles. In the proposed algorithm, vehicles need to be uniquely identifiable, and their positions tracked. The fuzzy-grouping algorithm works by incrementally arranging vehicles into groups as they arrive at the intersection. Access to the intersection will always be granted to the leading group in a lane, but may not be granted to following groups at the same time. A feedforward loop reinforces decisions that improve the performance of the controller. The algorithm was shown to reduce waiting times by up to 40% compared to an adaptive traffic signal controller.

Algorithms for Coordinated/Multiple Intersections

Datesh et al. (2011) present the IntelliGreen algorithm. The IntelliGreen algorithm is unique in that it uses k-means clustering to group vehicles based on the time it will take them to reach the intersection. The clusters are labelled red or green, and the green time for the intersection is set to allow the green cluster to pass the intersection. The algorithm was simulated on a model of an arterial corridor in Chantilly, Virginia and reduced delay by up to 12.5% compared with an adaptive Synchro plan (Husch and Albeck, 2003).

He et al. (2012) present the Platoon-based Arterial Multi-modal Signal Control with Online Data (PAMSCOD) algorithm. PAMSCOD concurrently optimises traffic signals for different modes of traffic. Buses and cars are incorporated into a decision framework where the vehicles can make green light requests including their travel mode, position, speed, and requested traffic signal phase (known from digital map information about the intersection.) The controller categorises and clusters the green time requests into platoon groups ordered by priority and requested stage. The aggregated requests are then used to generate optimised signal plans to serve the platoons such that delay is minimised. In simulation tests, PAMSCOD reduces car delay by up to 37% and bus delay up to 30% for high volume traffic compared with a Synchro plan.

Maslekar et al. (2013) presented Car-car communication based Adaptive Traffic Signal systems (CATS). The CATS algorithm uses CV data to cluster the vehicles approaching the intersection into groups. The density of the clusters is then calculated and used to optimise the cycle and stage times to minimise time loss. The CATS algorithm performed better than a fixed-time algorithm in simulated tests.

Yang et al. (2016) develop an algorithm with a similar objective to Au et al. (2015). The algorithm uses trajectory suggestions for autonomous driving systems to make vehicle platoons arrive at the intersection at the right time to encounter a green signal. A heuristic is developed to modify the behaviour of the algorithm to estimate the technology level of the vehicles present by calculating the ratios of unconnected vehicles (using inductive loops), CVs, and

CAVs in the network. The algorithm was shown to reduce delay and stops slightly compared to an actuated control algorithm.

Liu et al. (2017) propose using reinforcement learning and clustering to organise vehicle movements at signalised intersections. Cluster and signal timing information are shared between neighbouring intersections and signals are coordinated to reduce the average waiting time of vehicles. The algorithm was shown to reduce queue lengths and waiting times compared with a fixed-time approach.

Nam Bui and Jung (2018) take a game-theoretic approach to traffic signal control with CV data. The intersections are modelled as agents which can communicate with each other to coordinate to improve traffic flow. Each stage at each intersection is treated as a player in the game. The players form coalitions to cooperatively maximise movement between them, as time elapses and traffic conditions change the coalitions are revised to be the most advantageous for the evolving traffic scenario. The results of the simulation showed that the cooperative game-theoretic approach is better at reducing vehicle waiting times compared to a non-cooperative approach.

Review

Platoon based approaches are a popular method of achieving traffic signal control. Like numerical optimisation methods, the use of CV data not only makes platooning possible but also allows clustering and scheduling algorithms that are well developed in other disciplines to be used for traffic signal control (Pandit et al., 2013). While platooning algorithms are innovative, they present several challenges. The first is forming optimal clusters of vehicles in an environment where the object (vehicles) that are being clustered exist in a dynamic environment and have stochastic behaviour (Cheng et al., 2017; Datesh et al., 2011; He et al., 2012; Liu et al., 2017; Maslekar et al., 2013). The second issue is in how to schedule these dynamic clusters once they have been identified (Ahmane et al., 2013; Au et al., 2015; Bani Younes and Boukerche, 2016; Kari et al., 2014; Nam Bui and Jung, 2018). Finally, platooning algorithms require robust communication systems between vehicles and infrastructure, and vehicles often need to regulate their approach on arrival and through the intersection to meet their scheduled access to the intersection (Au et al., 2015; Nam Bui and Jung, 2018; Yang et al., 2016). These factors indicate that platoon based algorithm are more suited to traffic systems with high penetration of CVs, and at least partial autonomy in order to achieve the precise movements required to execute the scheduled intersection access.

2.4.3.5 Trajectory Management

Trajectory management systems use accurate information about a CVs position and speed to regulate their approach to the intersection, not just their movement through the intersection.

Algorithms for Isolated Intersections

Nafi and Khan (2012) presented an algorithm that dynamically adapts the cycle length in response to data received from individual vehicles. The intersection relays its signal timing plan to the vehicles every 5 s so that they know whether to proceed through the intersection or to slow down. By calming the traffic this way, the algorithm reduces waiting times for vehicles.

Xu et al. (2019) propose a bi-level optimisation algorithm for optimising both traffic signals and vehicle trajectories. At the intersection level, the speed and positions of arriving vehicles are known, and the intersection reschedules their arrivals to reduce their overall travel time. At the vehicle level, vehicles receive speed advisory information from the intersection dictating what engine power or brake force they should use to reach the intersection at their scheduled speed and arrival time. The results show that by optimising the vehicle speed profiles based on the intersection signal timings, intersection operations became more efficient and improved vehicle fuel economy.

Algorithms for Coordinated/Multiple Intersections

Tajalli and Hajbabaie (2018) build on the work of Islam and Hajbabaie (2017) to add dynamic speed harmonisation to traffic controller with distributed optimisation and coordination. For traffic control, the objective is to maximise the cumulative throughput of all intersections and minimise the speed difference between neighbouring cells. For the coordination, signal timing parameters are shared between intersections so that the difference in occupancy and outflow at subsequent cells can be minimised. Speed harmonisation is used to restrict vehicle speed as necessary to meet the optimisation objectives. The algorithm is tested using a microsimulation model based in Illinois, USA. The results show that the algorithm can reduce travel time by up to 15% compared to the algorithm without speed harmonisation.

Yang et al. (2019) present another approach to traffic signal control with speed harmonisation. One of the objectives of the algorithm is to prevent vehicles being caught in the dilemma zone. The dilemma zone is the region around the intersection where if the light changes from green to red, drivers become unsure about whether to stop or proceed through the intersection. Another module predicts queue lengths at the intersection in real-time. By using the queuing information and dilemma zone data, speed advisories are offered to vehicles so that they will minimise their stopped delay. Simulations showed that the algorithm reduced the number of vehicles in the dilemma zone by up to 23%, the average number of stops by up to 36%, and average delay by 17% compared with a fixed-time control algorithm.

Review
Trajectory management traffic signal controllers are related to platooning based algorithms in that traffic control involves managing both vehicles and signals. The main objective of trajectory management controllers is to harmonise vehicle speeds on approach to the intersection. Speed harmonisation reduces delays as vehicles stay in motion longer (Nafi and Khan, 2012; Tajalli and Hajbabaie, 2018; Yang et al., 2019), and reduces fuel consumption as vehicle have shorter dwell times (Xu et al., 2019). The literature shows that while trajectory management is beneficial for fuel economy and safety, they do not reduce delays and throughput as well as the other signal control approaches. The speed restrictions necessary for trajectory management strategies may also be difficult to enforce without the intervention of autonomous systems as human drivers may elect to disregard the speed advisories.

2.4.3.6 Evaluation and Testing of Future Traffic Signal Control Algorithms

The traffic signal control strategies reviewed are those for which the emphasis is on the exploiting CV, not AV, technologies. It can be seen that communication is a key feature of all of the strategies and that shared information facilitates the development of strategies that do not rely solely on loop data and exploit computational methods not traditionally associated with traffic signal control.

As the technology needed for traffic signal control using CV data is not widely available, simulation is widely used to evaluate their performance. In order to determine the level of testing required to evaluate the traffic signal control algorithms, Table 2.7 takes the literature reviewed in this section and for each study compares how the algorithm's performance was assessed under the following headings:

Controller: Literature reference to the traffic signal controller.

CV Data Used: What data from CVs was used in the proposed algorithm.

Number of Signalised Intersections (NSI): The number of intersections equipped with traffic signals modelled in the study.

Demand Levels: The levels of traffic demand for which the proposed algorithm was tested.

CV Penetrations: The levels of CV penetration for which the proposed algorithm was tested.

AVs: ✔/✖ (Yes/No) indication of whether AV driving technologies were used in the study.

Ped.: ✔/✖ (Yes/No) indication of whether pedestrians or a pedestrian stage were modelled in the study simulations.

Error Types: From the literature studied, three main sources of error can affect CV data quality. 1) Measurement error in the positioning system. 2) Delay in the wireless communication channel. 3) Packet loss in the wireless communication channel.

Modes: The types of vehicle modelled in the study.

Table 2.7: Comparison of C-ITS traffic signal control testing strategy features (1 of 3).

Controller	CV Data Used	NSI	Demand Levels	CV Penetrations	AVs	Ped.	Error Types	Modes
Gradinescu et al. (2007)	Speed, position, heading	1, 1	Real peak hour	100%	✖	✖	Ideal, PL	Car
Priemer and Friedrich (2009)	Speed, position	9	Real peak hour	10%, 12%, 14%, 17%, 20%, 25%, 33%, 50%, 100%	✖	✖	Ideal	Car
Ezawa and Mukai (2010)	Position, route	62	720, 900, 1200, 1800, veh/hour per input link	100%	✖	✖	Ideal	Car
Datesh et al. (2011)	Speed, position, signals	4	30 mins. of 85%, 100%, 125%, 150% typical traffic	25%, 100%	✖	✖	Ideal	Car
Chou et al. (2012)	Speed, position, heading, passengers, emissions	1	Static 50-500 veh/hour	100%	✖	✖	Ideal	Car, Bus, Truck
He et al. (2012)	Position	2, 8	30%, 60%, 80%, 90%, 100%, 110% and 120% saturation flow	20-100%	✖	✖	Ideal	Car, Bus
Nafi and Khan (2012)	Speed, position	1	Static	100%	✖	✖	PL	Car
Waterson and Box (2012)	Speed, position	1, 2	Static	5%, 10%, 20%, 40%, 60%, 80%, 100%	✔	✖	Position	Car
Lee et al. (2013)	Position, CTT	1	40 steps from 30% to 110% ICU	0%, 30%, 50%, 70%, 90%, 100%	✖	✖	Delay	Car
Chang and Park (2013)	Position	1	Static	100%	✖	✔	Ideal	Car, Bus
Goodall et al. (2013)	Speed, position	4	0.45, 0.6, 0.75, 0.9 ICU	10%, 25%, 50%, 100%	✖	✖	Position	Car
Ahmane et al. (2013)	Speed, position	1	Static	100%	✖	✖	Ideal	Car
Cai et al. (2013)	Speed, position	1	Static: Moderate, high	100%	✖	✖	Ideal	Car
Maslekar et al. (2013)	Position, heading	7	Static	100%	✖	✖	Delay	Car
Pandit et al. (2013)	Speed, position	1	Multi-stage Poisson distribution	30%, 50%, 70%, 90%, 100%	✖	✖	PL, Delay	Car

CTT: Cumulative travel time. **ICU**: Intersection Capacity Utilisation. **NSI**: Number of Signalised Intersections. **Ped.**: Pedestrians. **PL**: Packet loss.

Table 2.7: Comparison of C-ITS traffic signal control testing strategy features (2 of 3).

Controller	CV Data Used	NSI	Demand Levels	CV Penetrations	AVs	Ped.	Error Types	Modes
Kari et al. (2014)	Arrival time	1	4 static 1 hour demands	100%	✖	✖	Ideal	Car
Au et al. (2015)	Speed, position, size, route, acceleration	1	Static	0-100%	✔	✖	Ideal	Car
Tiaprasert et al. (2015)	Speed, position	1	2 static demands	10%, 30%, 50%, 80%	✖	✖	Ideal	Car
Feng et al. (2015)	Speed, position, heading, state, size	1	2 static demands	25%, 50%, 75%, 100%	✖	✖	Ideal	Car
Hu et al. (2015)	Speed, position, passengers, delay	2	Real flow	100%	✖	✖	Ideal	Car, bus
Yang et al. (2016)	Speed, position	1	Steps from 1000-2000 veh/hour	20-100%	✔	✖	Position	Car
Xiang and Chen (2016)	Speed, position, passengers, route	22	Real data	100%	✖	✖	Ideal	Car
Bani Younes and Boukerche (2016)	Speed, position, heading	1	Static loads from 200-1000 vehicles	100%	✖	✖	Delay, PL	Car
Islam and Hajbabaie (2017)	Position	2, 9	4 static demands	100%	✖	✖	Ideal	Car
Beak et al. (2017)	Speed, position, heading	5	Static	25-100%	✖	✖	Ideal	Car
Shaghaghi et al. (2017)	Speed, position, heading, type	36	100-1400 vehicles/hour/lane	100%	✖	✖	Delay, PL	Car, Truck
Cheng et al. (2017)	Position, route	1	50-190% ICU	100%	✔	✖	Delay, PL	Car
Liu et al. (2017)	Speed, position, type, timestamp	3	36-180 veh/hour	100%	✖	✖	Delay	Car

ICU: Intersection Capacity Utilisation. **NSI**: Number of Signalised Intersections. **Ped.**: Pedestrians. **PL**: Packet loss.

Table 2.7: Comparison of C-ITS traffic signal control testing strategy features (3 of 3).

Controller	CV Data Used	NSI	Demand Levels	CV Penetrations	AVs	Ped.	Error Types	Modes
Aziz et al. (2018)	Position	18	Static: Low, Medium, High	100%	✖	✖	Ideal	Car
Nam Bui and Jung (2018)	Position	3	10-60% ICU	100%	✖	✖	Ideal	Car
Beak et al. (2018)	Position	6	Static	100%	✖	✖	Ideal	Car
Tajalli and Hajbabaie (2018)	Position	8, 20, 40	4 static demands	100%	✖	✖	Ideal	Car
Xu et al. (2019)	Speed, position	1	Static	100%	✔	✖	Ideal	Car
Tonguz and Zhang (2019)	Position	1, 10, 24	Static, Real	0-100%, 20% steps	✖	✖	Ideal	Car
Han et al. (2019)	Speed, position, length	1, 6	Static	25-100%, 25% steps	✖	✖	Ideal	Car
Yang et al. (2019)	Speed, position	5	Real	0-100%, 5% steps	✖	✖	Ideal	Car
Liang et al. (2019)	Speed, position	1	Balanced and unbalanced static	0-100%	✔	✖	Position	Car

ICU: Intersection Capacity Utilisation. **NSI**: Number of Signalised Intersections. **Ped.**: Pedestrians. **PL**: Packet loss.

2.4.4 Critical Gaps and Areas for Future Work

2.4.4.1 Current methods in Urban Traffic Signal Control

The prevalent control strategies for urban traffic control were discussed. The review of the state-of-practice traffic signal controllers highlights that current strategies are reliant on inductive loops and offline data to optimise signal timings. This approach is limited as real-time data can only be gathered from sites where loops are installed, so there are large sections of road for which there is no information. Furthermore, many of the algorithms use rolling horizon predictions to optimise their traffic signal timing parameters. Given the stochastic nature of traffic, predictions, even over a short period, introduce the possibility for error and uncertainty. Furthermore, many algorithms operate a centralised controller which may limit their performance if there are large numbers of controllers in a coordination group. Table 2.8 highlights the advantages and disadvantages of the three control types. There is a clear trade-off, where algorithms get more costly and complex to implement but achieve better results as their complexity increases.

Table 2.8: Comparison of the advantages and disadvantages of the three signal control types adapted from Hamilton (2015).

	Advantages	Disadvantages
Fixed-time	• Simple to implement, and install • They do not need centrally controlled equipment • Coordination is earlier to achieve	• Historical data needs to be collected to calibrate them • The signal plans need to be updated to stay effective • Cannot respond to incidents or spurious demand
Actuated	• Can adjust to traffic fluctuations • Cheaper than fully adaptive systems • Can be beneficial for oversaturated intersections	• They require costly live data infrastructure installation and maintenance • Detector failures reduce their performance • Automated processes may not always behave desirably
Adaptive	• Little data needed in advance • Plans can be adjusted in real-time • Traffic fluctuations can be handled effectively • Incidents and traffic information can be obtained	• Detector failures reduce their performance • They require costly live data infrastructure installation and maintenance • A centralised controller is often required

2.4.4.2 Future methods in Urban Traffic Signal Control

The current developments in control strategies for C-ITS were reviewed, and their testing strategies summarised in Table 2.7. The fundamental issue with the prevalent control strategies is that many of them were developed over ten years ago. The vehicle fleet is set to enter a period of significant change due to the emergence of connected and autonomous vehicles. The prevalent traffic signal control strategies were developed without the data a connected environment can provide in mind, meaning there are opportunities to better prepare for CVs by developing new state-of-the-art, traffic-responsive, traffic signal control strategies.

The review of state-of-practice traffic signal controllers shows that the prevalent strategies do not harness C-ITS data at all, and it remains to be investigated whether this information is beneficial for traffic control. Furthermore, it can be seen from the C-ITS based strategies reviewed, and Table 2.7, that they typically rely on idealised communications and high penetrations of CAVs, and only consider a limited number of modes in their modelled vehicle fleets. Their reliance on communication systems leaves them ill-prepared to deal with fleets with mixtures of connected and unconnected vehicles. Moreover, the robustness of C-ITS traffic signal control algorithms to communication errors is critically understudied. Table 2.7 also shows that although many of the proposed algorithms, only one study include their effects when simulating their algorithm. From the discussion, the proposed methods for traffic signal control in a C-ITS appear to be focused on applying CV data to traffic signal control problems using complex theoretical models without considering the practicality of their deployment, i.e. considering realistic multi-modal vehicle fleets, pedestrians, and non-ideal conditions in their communications together as demonstrated in Table 2.7. If a traffic signal algorithm is not tested in simulation under these basic non-ideal conditions they could reasonably be expected to encounter in a deployment scenario, then they would pose a higher risk to drivers due to potentially unknown behaviours. As traffic signal controllers are a safety-critical system, they are not practical for deployment if their robustness to non-ideal conditions has not been tested beforehand.

Another common limitation among the algorithms reviewed in Table 2.7 is that although they identify that CV data are beneficial for traffic signal control, their scope is limited by only considering traditionally useful metrics for traffic signal control such as position, speed, queue lengths, and flows. In Section 2.1, it was shown that CVs have the potential to offer much richer data than are currently used. However, data which was previously unavailable from infrastructure remains unexploited. For instance, a CV can reasonably obtain and share information about how many passengers it is carrying, how many times it stopped this journey, its emissions class, *etc*. The challenge here is to determine which data are useful for traffic signal control.

2.5 CV Applications, Trends, and Projects

In this chapter's previous sections, the technologies required to implement traffic signal control systems that use CV data were reviewed. However, CV data is not limited to use for traffic signal control. In this section, other technologies that benefit from the use of CV data are discussed.

2.5.1 Cooperative Adaptive Cruise Control - CACC

Adaptive Cruise Control (ACC) and Cooperative ACC (CACC) are systems placed in modern vehicles that assist drivers in keeping constant headways between vehicles on highways which have been shown to improve traffic flow stability (Dunbar and Caveney, 2012; Mamouei et al., 2018; Milanes et al., 2014; Swaroop and Hedrick, 1996). The studies on the impact of V2V communication systems on drivers' car-following behaviour shows that CACC harmonises the behaviour of drivers, reduces vehicle's speed and the range of acceleration and deceleration differences among them, and reduces fuel consumption and exhaust emissions, contributing to improved user experience (Shladover et al., 2015; Van Arem et al., 2006). CACC not only benefits longitudinal driving, but the ability to communicate with surrounding vehicles is also beneficial for increasing safety, stability, and efficiency during lane-changing (Nie et al., 2016).

2.5.2 Green Light Optimised Speed Advisory - GLOSA

GLOSA is the application of I2V connectivity to relay accurate information of the current state of a traffic signal controller to drivers (Stevanovic et al., 2013). The most basic application of GLOSA is to advise drivers waiting at a red light of when the light will become green (Kim and Kim, 2020). The benefits of this form of GLOSA are to reduce start-up loss by ensuring drivers are prepared to drive when the lights turn green, thus reducing delay and increasing throughput within each green cycle.

The main application of GLOSA is to provide speed advisories to drivers approaching an intersection. In this scenario, drivers receive guidance on the speed they should arrive at a GLOSA enabled intersection in order to reduce their wait at the intersection, and assist them in capturing green-waves so that they can more frequently avoid having to stop at intersections (Stevanovic et al., 2013). GLOSA, in this form, has the added benefits of harmonising traffic flow and reducing vehicle emissions (Katsaros et al., 2011).

2.5.3 Road Hazard Warning Systems

Road hazards are events or circumstances that threaten drivers' safety. Common hazards include severe weather events, disabled or crashed vehicles, and lane-closures (Shladover, 2018). Road Hazard Warning (RHW) systems combine the sensor technologies discussed in Section 2.1 with V2X communications to warn drivers of hazards on their route.

Outay et al. (2017) show that combining RHW systems with GLOSA can reduce collision risk by up to 30%. In a study by Jeong et al. (2014), combining RHW of static hazards combined with detection of moving hazards (vehicles driving dangerously), reduced rear-end conflicts by 84% but with a CV penetration rate of 100%. A meta-analysis of CV applications by Siegel et al. (2018) showed that although RHW systems that leverage CV data are beneficial for driver safety, they typically require CV penetrations of at least 60% to have any significant effect.

2.5.4 Vehicle Platooning

Vehicle platooning involves grouping vehicles dynamically into short headway chains in order to increase fuel efficiency through 'drafting' (Kato et al., 2002). Vehicle platoons have the benefit of reducing stop-and-go traffic, improving high-speed merging, and enhancing obstacle avoidance. Platoons also maximise roadway utilisation, thus easing congestion and improving traffic flow (Kato et al., 2002).

The original focus of platooning systems was to increase the efficiency of heavy-goods transport. However, the technology has spread to mixed-vehicle fleets and is being tested in several high way trials, the most notable of which are SARTE and PATH (Bergenhem et al., 2012). The aerodynamics of the vehicles determines the ability of a vehicle platoon to save fuel in the platoon, the number of vehicles in the platoon, the following headway, and environmental conditions are also contributory factors Siegel et al. (2018). Studies suggest that fuel savings of between 3%-15% can be made by exploiting vehicle platoons (Alam et al., 2010; Bonnet and Fritz, 2000; Turri et al., 2017).

2.5.5 Cooperative driving without traffic signals

By combining V2X communications with autonomous driving or GLOSA, a new paradigm has emerged where intersections can be managed without physical signals (Dresner and Stone, 2008). If vehicles know each other's position and trajectory, they can coordinate either with a central server (Au et al., 2011) or amongst themselves in an agent-based paradigm (Hausknecht et al., 2011). The idea is that a vehicle reserves access to the intersection and proceeds through the junction at a determined time, following a set trajectory.

The advantage of cooperative intersection management without traffic signals is that it removes the need for physical traffic signal control infrastructure. However, the challenges in deploying such a technology are that all the vehicles need to have compatible software for negotiating intersection access. Furthermore, with autonomous intersection management, it remains unclear how human drivers interact successfully with such a system, both from the perspective of drivers and pedestrians. In Au et al. (2015), the authors found that having even a single-vehicle without autonomous trajectory management can cause the system performance to degenerate rapidly to fixed-time access, indicating such systems will not be feasible without a significant penetration of CVs and AVs.

2.5.6 CV System Trials

In order to assess the future impact of CV systems on transportation networks, several real trials have been created. This section outlines the trial CV testbeds that have been created to assess their performance.

2.5.6.1 Next Generation Simulation (NGSIM) programme

NGSIM is a US project commissioned by the FHWA to create a dataset that captures empirical microscopic traffic data for use in simulations (FHWA, 2019). NGSIM is a US-centric dataset focused on capturing data and algorithms that are representative of US highway traffic. NGSIM documents and validates datasets that describe multi-modal travel on highways, and the interactions between drivers and traffic control systems, congestion, and environmental features. A critical evaluation of the NGSIM dataset suggested that while the scale of the data is impressive, it lacks accuracy and is not always representative of the roadways monitored (Coifman and Li, 2017).

2.5.6.2 US Department of Transport Projects

The US Department of Transport (DoT) has commissioned several projects to test CV applications.

The purpose of the Safety Pilot Programme developed by the US DoT is to create a testbed for assessing CV safety applications in real-world scenarios (US DoT, 2015). The programme conducted several studies of V2X applications including RHW systems, public transit information systems, and pedestrian awareness systems. The system trials are primarily focused on using V2X technologies in a way that is immediately useful for increasing driver and pedestrian safety, and includes tests sites in, Michigan, New York, Florida, and Wyoming.

Stemming from the Safety pilot programme, the University of Michigan Transportation Research Institute (UMTRI) created a connected vehicle test environment in Ann Arbour, Michigan, USA (UMTRI, 2020). The project was established to assess the potential safety benefits that could be realised by connected technologies, including CVs. So far, the project has equipped over 2000 vehicles to make them connected. A recent project report suggested that the project was being to collected and preliminary analysis was underway (Descant, 2020).

The CV Deployment Programme is towards promoting early CV tech deployment in the US. CV pilot sites have been established in New York, Florida, and Wyoming (US DoT, 2020*b*). The objective of the pilots is to measure the impact of CVs on safety, mobility, and the environment. The project is currently in its evaluation stage and has identified secure credential management best practices (US DoT, 2020*a*), and is trialling numerous safety based technologies across its pilot sites (US DoT, 2020*a*).

2.5.6.3 GAIA Open Dataset

The GAIA open dataset is an initiative by Chinese ride-sharing operator DiDi Chuxing to encourage innovation between the company and academics on data that captures real-world transportation information (DiDi Chuxing, 2020). The dataset covers the city of Chengdu in China. It includes vehicle trajectory data of vehicles in the DiDi fleet, dash camera footage, point-of-interest data, and travel-time index data.

2.5.6.4 Intercor

Intercor (Intercor, 2020) is a series of connected corridor trials in Europe, notably, the A2/M2 connected corridor in the UK is part of this initiative (Highways England, 2018). The purpose of the project is to create a series of interoperable connected highways across Europe. The project aims to create test GLOSA, RHW systems, in-vehicle signage (presenting road signs in vehicles), and gathering probe vehicle data, on international highways.

2.5.6.5 IntelliLight

Wei et al. (2018) proposed IntelliLight, a reinforcement learning approach for intelligent traffic signal control. The algorithm was tested on a simulated traffic network based on the city of Jinan, China, by using vehicle trajectory data gathered from over 1700 video surveillance cameras. The case study recreated traffic flows from vehicle trajectories from 31 days worth of video data in 2016.

2.5.6.6 Mcity

Mcity (Uhlemann, 2015) is a 32-acre site created by the University of Michigan for testing CV and AV technologies in a controlled environment. The Mcity project collaborates with UMTRI as they are based in the same city. However, MCity has primarily been focused on safety testing of AV technologies (Peng, 2019).

2.5.6.7 Chinese Testing Grounds

In China, technology company Baidu completed construction of the Apollo Park testing grounds for running trials of its 200 CAVs (South China Morning Post, 2020). China has also granted regulatory approval for CV testing in six major cities (Zou et al., 2019).

2.5.6.8 ACTIVE-AURORA

ACTIVE-AURORA (Stantec, n.d.) is a Canadian testbed for CAV technology based in the cities of Alberta and Vancouver. The test bed covers urban corridors and urban and rural highway. The project aims to provide testbed infrastructure for assessing CV training, demonstrations, pilot projects and research. The project consists of three CVs and 70 DSRC roadside units and is currently progressing with testing (Michelson et al., 2016).

2.5.6.9 Smart Mobility Living Lab

The Smart Mobility Living Lab (SMLL) (Smart Mobility Living Lab, 2020) is a UK project based in London. The purpose of the SMLL is to evaluate the performance, safety, and benefit of CAVs and related technology. In partnership with the Transportation Research Laboratory (TRL), the SMLL aims at providing research and development support to triallists using the SMLL. The SMLL is due to launch at the end of 2020.

2.5.6.10 Other UK Testbeds

Millbrook (Millbrook, 2020) and RACE (RACE, 2020) provide private testbeds for CAV trials in the UK. Both support DSRC and cellular communications testing for CAV applications. The UK Central CAV Testbed, is a proposed testbed in Coventry and Birmingham in the UK (Horiba Mira, 2020).

2.5.7 Discussion

CVs present numerous opportunities for improving driver safety and user experience. There are also many ongoing and proposed testbeds for assessing the impact of CV technologies. The testbeds are mainly focused on determining the safety of CV systems in highway settings. There is an evident gap in the coverage of CV testbeds for assessing urban environments and traffic signal control systems. Except for the GAIA project, there is limited availability of public data being shared by these projects with which to inform other research.

2.6 Conclusions

In this chapter, the limiting factors and critical gaps in the research are discussed in the context of the technologies that support C-ITS and determine the preparedness of the transport network for CVs and C-ITS is determined. Figure 2.4 shows the percentage of road users travelling via autonomous vehicles over time as forecasted by Litman (2019), and the coverage of the current literature identifying where the critical gaps are.With the assumption that CV deployment is closely related to AV deployment, Figure 2.4 highlights how the current literature is far better developed for the fringe cases where there is either 0% or 100% autonomous vehicle uptake. The majority of the literature to date covers the case where all road users operate manually driven vehicles. The literature for CV developments largely covers the case where CV penetration is 100%. This bias indicates a significant lack of preparation for integrating CVs into the transport network and their interactions with human drivers. The coverage of the fringe cases is partly historic. However, it can also be attributed to more complex dynamics in mixed vehicle traffic (Ngoduy, 2012, 2014) making the cases where there are different vehicle types more difficult to study. Further work must be done to understand the behaviour of the transport network at the intermediate steps towards the complete adoption of CV technologies.

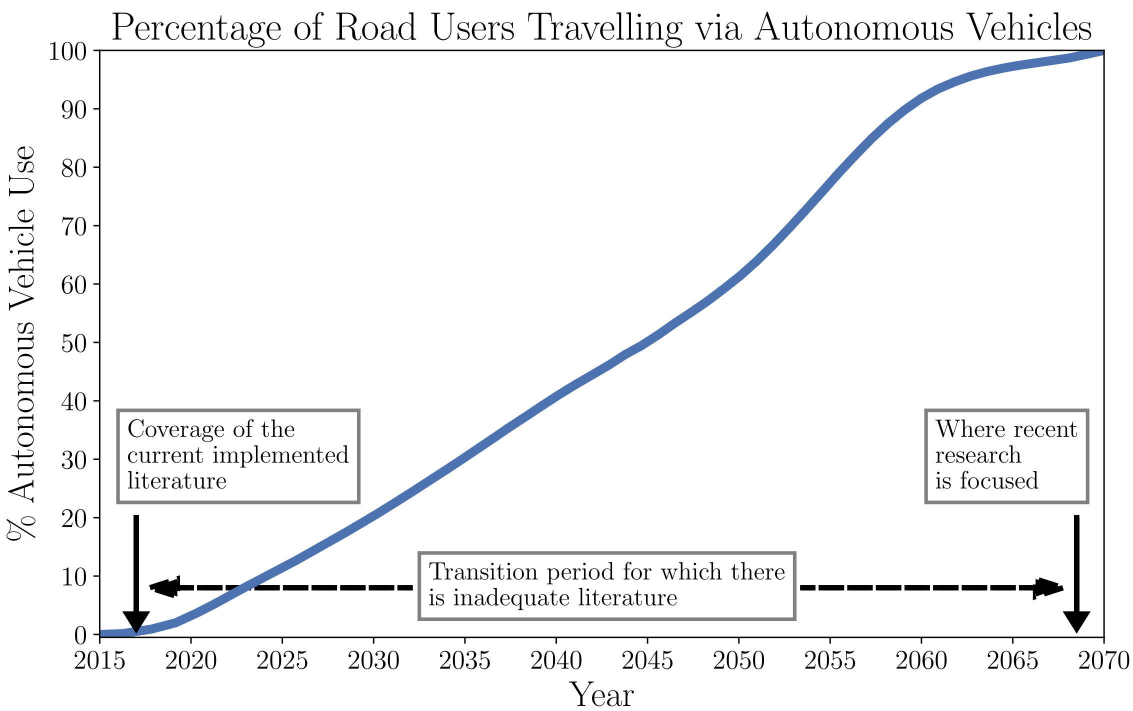


Figure 2.4: Percentage of road users travelling via autonomous vehicles over time as forecasted by Litman (2019). The arrows show the current times where research is being focused, and the timeline for which there is inadequate research.

In this chapter, the set of subject areas that are pertinent to the microsimulation of autonomous and connected vehicle environments have been reviewed. Of specific interest were the communication systems and standards governing the connection between connected vehicles and intelligent infrastructure within a C-ITS. The technologies that collect data facilitate functionality to enhance safety, reduce driver delay and the associated costs, and improve user's experience within a C-ITS were also reviewed.

The prevalent methods for controlling signalised intersections were investigated and found to be lacking the capability to benefit from using the data that connected vehicles and infrastructure can contribute to a C-ITS. Furthermore, more recent control schemes offer solutions for vehicle fleets with high penetrations of CVs or only utilise a limited subset of the available C-ITS data. Similarly, while reviewing traffic flow models, it can be noted that as driving becomes increasingly automated, the nature of traffic flow may be determined from the algorithms governing vehicles' autonomous driving behaviour.

The discussion of the reviewed literature highlights that transport modelling practice is not prepared for the integration of CVs, as it is not understood how they interact with human drivers, or what systems to use. As the number of CVs increases, it is necessary to adapt to the fleet as it changes in order to exploit emerging C-ITSs. Creating models and systems for urban corridors with mixed fleet penetrations of CVs allows for work to be done to forecast the effects of CVs on the transport network, and pre-empt the infrastructure needs required to accommodate their introduction successfully. It is also important to consider how the transport network will adapt to achieve these goals as the vehicle fleet changes, while not reducing urban corridor capacity, and increasing the safety and comfort of road users.

2.7 Summary of Chapter Findings

Section 2.1: Key Data Sources for Vehicular Communication Systems

1. There are a wide variety of sensor technologies that are integrated into vehicular systems.
2. The sensors produce data that that currently cannot be obtained by current roadside infrastructure.

Section 2.2: Communication Systems for Transmitting V2X Data

3. IEEE 802.11p DSRC and 5G were identified as being more suitable for facilitating V2X communications in a C-ITS.
4. The IEEE 802.11p DSRC is the most suitable communication standard currently as 5G is not widely deployed yet.
5. There is no *de facto* communication system for C-ITS. It remains to be seen which systems and standards will be deployed.

Section 2.3: Message Sets and Standards for V2X Communication

6. The proprietary SAE J2735 message standard is dominant in the USA, whereas the open-source ETSI CAM and DENM standards are popular in Europe.
7. Either standard is flexible enough to share any data produced by a CV except for localisation data.
8. There is no *de facto* message standard for C-ITS. It remains to be seen which systems and standards will be deployed.

Section 2.4: Traffic Signal Control Strategies for Urban Environments

9. Existing methods for traffic signal control were not designed to incorporate data from CVs.
10. The proposed traffic signal controls algorithms that use CV data only exploit a small amount of the data available to them.
11. The proposed methods for traffic signal control in a C-ITS appear to be focused on applying CV data to traffic signal control problems using complex theoretical models without considering the practicality of their deployment.
12. The testing done on connected traffic signal controllers is highly limited. The networks are typically small, with predominantly only a single intersection being studied for artificial traffic flows over short periods.
13. The effects of CV penetration and communication channel errors are critically under-studied.
14. There is a need to understand better which data available in a C-ITS are useful for traffic signal control.

Section 2.5: 2.5

15. CVs have many applications beyond traffic signal control that are towards improving the transport network, increasing driver safety and satisfaction, and reducing emissions.
16. There are many proposed test-beds for CV applications. However, these testbeds are still primarily focused on highway traffic rather than urban traffic, and are still ongoing trials with limited external access to data and results.

Chapter 3

Augmenting Traffic Signal Control Systems for Urban Road Corridors with Connected Vehicles

The literature review demonstrated that the effectiveness of urban traffic management systems at reducing delay is improved by using data shared by CVs. CVs have the advantage over inductive loops in that they do not require intrusive roadworks to be undertaken to install infrastructure, such as inductive loops, to use their data. However, their networking protocols are more complicated compared to unconnected vehicles, and they require fleets to contain significant proportions of CVs before their applications become effective. The previous literature does not adequately address the issue of traffic signal delay at low CV penetrations. The current literature also does not correctly address the issue of non-ideal communication channel conditions and testing traffic signal control algorithms at increasing penetrations of CVs, and in realistic scenarios. There is also an absence of literature for traffic signal control in urban corridors with degraded infrastructure, and how CV data can be used to compensate for failing infrastructure elements.

This chapter proposes a novel traffic signal control algorithm called Multi-mode Adaptive Traffic Signals (MATS) which combines position information from CVs with information collected through existing inductive loops and fixed-time plans to perform decentralised intersection control in urban areas to reduce overall traffic delay. The MATS algorithm builds upon the principles for managing oversaturated and undersaturated flows from the state-of-the-art vehicle actuated control algorithm – MOVA (Vincent and Peirce, 1988) and extends those principles with blocking back detection and queue length estimation using CV data. Similar to MOVA, the MATS algorithm reduces delays in undersaturated conditions and increases capacity in saturated conditions. Also, the MATS algorithm uses speed, position, and heading data from CVs in combination with fixed-time plans and data from inductive loop sensors to actuate signal timings, to detect blocking back, and to estimate queue lengths.

The MATS algorithm bridges the gap between existing and future technologies for traffic management by offering multiple modes of operation based on what sources of data are available. At its lowest level of operation, it operates a fixed-time plan in the absence of data from CVs or roadside infrastructure. As data from loop detectors and CVs becomes available, the MATS algorithm adapts its mode of operation to actuate signal timings using the gathered data. Furthermore, it can respond to traffic demand in real-time and preserves driver privacy as it does not require individual drivers to be tracked. Also, it builds on established traffic management techniques and uses optimisation/heuristic procedures that are clearly defined, making the algorithm intuitive for transport planners to deploy. CV data can be manipulated to realise these established traffic management techniques as the data is the same as they currently use, only at a finer resolution. This results in algorithms of similar complexity to their original counterparts. The more significant challenge for transport planners will be to deploy new traffic signal control hardware that supports CV applications.

To increase capacity and reduce delays in urban corridors, the MATS algorithm maintains a cyclic stage pattern and reduces the load on the downstream intersection rather than modifying its stage to serve stages with high demand (i.e. in back-pressure routing). By synthesising fixed-time plans, loop detector data, and CV data into a single algorithm, delays and stops are minimised for road users.

The contributions of this chapter are as follows:

1. A new traffic signal control algorithm, Multimode-Adaptive Traffic Signals (MATS), is proposed.
2. The MATS algorithm is novel in that it combines information from existing fixed-time plans and loop detectors, rather than requiring an ideal system.
3. Position, speed, and heading data from CVs are combined with the legacy data sources to perform decentralised control on signalised intersections.

The MATS algorithm is novel in that it does not require entirely new infrastructure, high penetrations of CVs, or ideal data. Rather, the algorithm can be deployed alongside or over legacy systems to augment them with data from CVs, even under non-ideal communication channel conditions, an area where existing literature is limited.

Section 3.1 describes the proposed MATS algorithm, and the chapter conclusions are drawn in Section 3.2.

3.1 The Multi-mode Adaptive Traffic Signal Control Algorithm

3.1.1 Traffic Signal Control Objectives

The MATS algorithm proposed here has the following objectives:

To perform equal to or better than state-of-practice traffic signal control algorithms
The algorithm should perform as well as systems currently in deployment. Performance should be assessed against the PIs for traffic signal control algorithms identified in Chapter 5, namely delay, stops, and emissions. Theses PIs should be assessed for different levels of CV penetration, under non-ideal communication conditions, and increasing levels of traffic demand. Comparing the developed algorithms against state-of-practice algorithms is necessary, as CV data must be demonstrably beneficial to traffic management systems if connected systems are to adopted and deployed in the transport network.

To use control logic, and optimisation/heuristic procedures that are practical in deployment scenarios
In Chapter 2.4, it was discussed how algorithms which are costly and complex to implement are often unsuccessful at gaining popularity when deployed. The MATS algorithm addresses this flaw by adopting the principles used by state-of-practice traffic signals and enhances them using data from CVs.

To provide traffic control to connected vehicles in real-time
By responding to the current traffic situation, rather than relying on prior information, the MATS algorithm delivers traffic signal control that is flexible to the current traffic demand without the computational effort of predicting future scenarios as in rolling-horizon techniques which may not be real-time (Islam and Hajbabaie, 2017).

To integrate with existing systems
The MATS algorithm achieves this by allowing existing fixed-time plans, and loop detectors to be used. By combining three data sources, the MATS algorithm can compensate for missing CV data or failing loop detectors. It is also more cost-effective to deploy a system compatible with the existing infrastructure than to have an entirely new system.

To preserve driver privacy by not tracking them through the network
Data privacy is essential in transport applications as it is a service relied upon by many people. A real-time traffic control system should not need to store information about individuals to perform control actions on it.

3.1.2 Urban Traffic Signal Control Definitions for Simulation.

Urban corridors are a collection of traffic lanes which contain 1 or more sub-lanes. Points where lanes intersect are known as junctions and are either signalised or un-signalised. Signalised junctions in urban corridors can operate multiple traffic stages. A stage describes the set of traffic phases that either permit or prohibit travel on each intersecting lane at a junction. Table 3.1 defines the possible phases a traffic light can have and their meanings. In this study, lanes showing priority green are referred to as 'active lanes', the others are considered 'inactive'. Inactive lanes display permissive green on routes that are not in conflict with any priority green streams, and red on streams that conflict with priority stream(s). In this chapter, a heuristic for optimising the green time each stage receives is developed. Later chapters develop methods for optimising the stage sequence and stage coordination.

The MATS algorithm is referred to as multi-modal because its mode of operation differs depending on which data are available. Fundamentally, the MATS algorithm operates a fixed time plan in the absence of data from CVs or roadside infrastructure such as inductive loops. As data from external sources become available, the MATS algorithm adapts its mode of operation to best use the resources it can access. The operation of the MATS algorithm can be understood in two parts: data acquisition and intersection control, which are explained in the following sections.

Table 3.1: Traffic light phase definitions.

Phase	Description
Red	Vehicles must stop
Yellow	Vehicles stop if it is safe to do so
Permissive Green	Vehicles proceed if the road is unoccupied by vehicles in a priority green stream
Priority Green	Vehicles proceed if it is safe to do so

3.1.3 Vehicle Data Acquisition

Vehicle data acquisition determines which data originate from vehicles in the junction's control region, which is the area surrounding the junction in which wireless communications are possible.

Figure 3.1(a) illustrates the control regions of two neighbouring junctions. If another junction exists inside the control region, the boundary is cropped to the conflicting junction's nearest stop line. The boundary reduction covers the largest possible control region while allowing data from vehicles associated with other junctions to be ignored. The junction controller receives data from all vehicles inside its control region, ignoring those that are not.

The junction controller monitors time-dependent data regarding the vehicles' positions, headings, and speeds. The junction controller knows about its own layout/map and can determine the headings that correspond to an approach on each of its lanes, as shown in Figure 3.1(b). Vehicles in range of the junction and travelling with headings matching one of the known approaches (± a tolerance to allow for GPS positioning error) are considered to be approaching the junction.

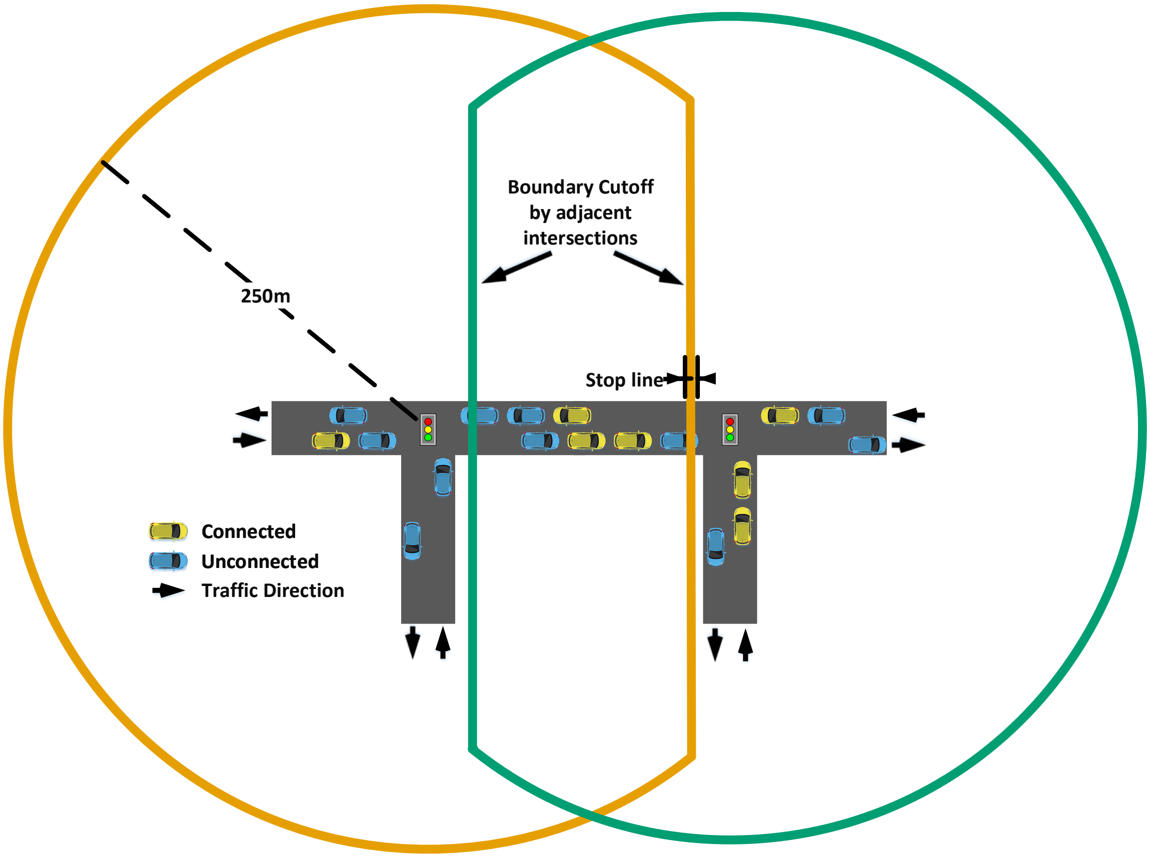
3.1.4 Intersection Control Using Multiple Data Sources

3.1.4.1 Initial Stage Time

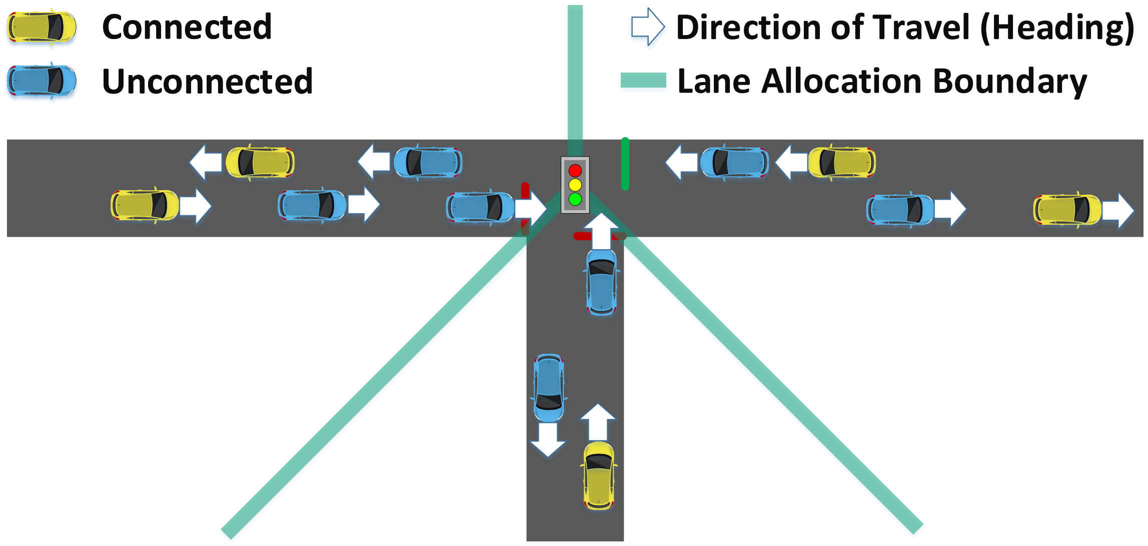
The initial stage time is defined based on the length of the queue in inactive lanes. In Chapter 2.4, it was shown that numerous control strategies use queue length estimates as a parameter, and as a quantity that is desirable to minimise. Figure 3.2 illustrates the queue length estimation process for the MATS algorithm. Queue lengths are determined from the distance of the furthest queuing vehicle from the intersection. A vehicle is considered to be queuing if its speed is less than 0.01 $\mathrm{m/s}$ (inferring that vehicles travelling more slowly are at or approaching the end of the queue). The queue clearance time for a lane is given by:

$$t_{\text{clear,queue}} = \frac{l_{\text{queue}}}{l_{\text{queue,max}}} \times t_{\text{green,max}} \tag{3.1}$$

where $t_{\text{clear,queue}}$ is the queue clearance time, l_{queue} is the queue length, $t_{\text{green,max}}$ is the maximum green time a stage can have, and $l_{\text{queue,max}}$ is the maximum length a queue may have. Setting the queue clearance time in this way means that as the queue length tends towards the maximum range of the communication system, the initial green time tends towards the maximum green time. The queue clearance calculation is unique in that, neglects the start-up loss time that drivers need to react and accelerate. The reason start-up loss is neglected is that the stage time is extended by the presence of the connected vehicle at the tail of the queue if it has not crossed the stop line. This allows the preliminary green time to be automatically corrected if the queue clears slower than expected. In comparison, the MOVA algorithm uses a queue length estimated from vehicle counts over its detectors, so the locations of each inductive loop restrict its estimation.



(a) Junction control region definition



(b) Vehicle to lane allocation

Figure 3.1: Overview of the vehicle data acquisition process for the MATS algorithm. (a) shows the area controlled by each intersection, and how adjacent intersections are considered. (b) shows how captured vehicles are sorted into their lanes based on the junction geometry and the vehicle headings.

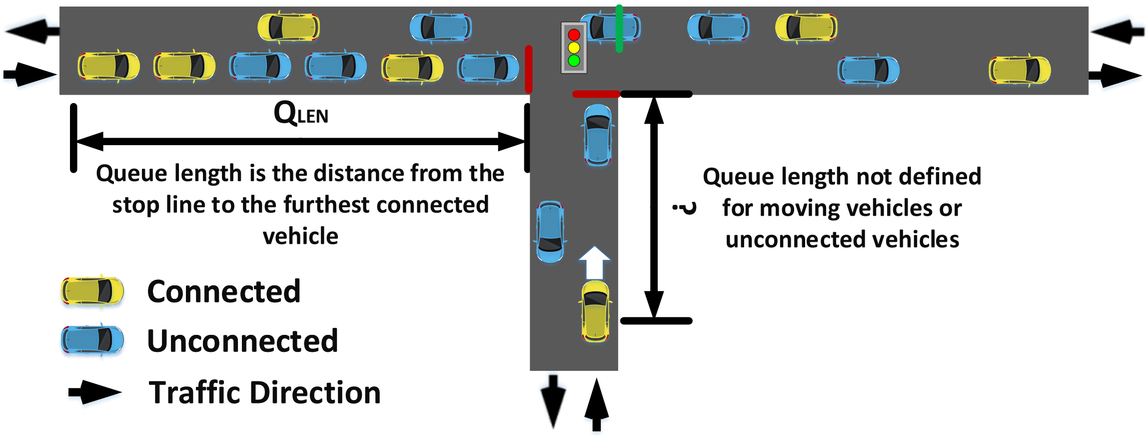


Figure 3.2: Initial stage time allocation in the MATS algorithm. Note how the vehicle on the south approach is still moving so a queue length is not estimated for it.

3.1.4.2 Blocking-back Detection

Blocking-back is an issue that occurs at neighbouring intersections when queues of vehicles at a downstream intersection are long enough to obstruct subsequent vehicles from joining the queue. Blocking-back is problematic, as the corridor may gridlock if traffic cannot proceed in any direction (Wood et al., 1998). Blocking-back is typically alleviated through signal coordination. For example, the SCOOT algorithm measures the proportion of the cycle time where queuing vehicles occupy its detectors. The queuing information is passed to the optimiser, which then minimises the likelihood of the upstream junction creating a blocking queue (Hunt et al., 1981). Even though blocking-back is a well-understood problem (Smith, 2015), recent literature appears to ignore it in favour of presenting a novel method using CV data optimisation. Of the recent literature reviewed in Section 2.4.3, Goodall et al. (2013) and He et al. (2012) were the only studies to consider blocking-back. In Goodall et al. (2013), blocking-back is detected using CV data. If vehicles are blocking a movement, then the movement that clears the blocking vehicles are given higher priority. In PAMSCOD (He et al., 2012), vehicle platoon movements and queue lengths are used to prevent the creation of queue spillback that would cause the intersection to be blocked-back (referred to as 'de facto red' by He et al.).

Here the control is decentralised, so a method of locally detecting blocking-back is developed. As shown in the scenario in Figure 3.3, blocking-back is detected by the MATS algorithm using CV position and speed data to determine if the vehicles are stationary during a stage that should permit the vehicles to travel. If blocking-back is detected, the MATS algorithm ends the current stage to allow vehicles in other lanes to traverse the junction on unobstructed routes. Although stage cancelling reduces service to the vehicles in the cancelled stage, it gives vehicles in other stages the opportunity to use the intersection to increase throughput and gives the downstream intersection time to clear the blocking traffic. Compared with back-pressure routing approaches (Wongpiromsarn et al., 2012), the MATS algorithm maintains a cyclic stage pattern and reduces the load on the downstream intersection rather than modifying its stage to serve stages with 'high-pressure'.

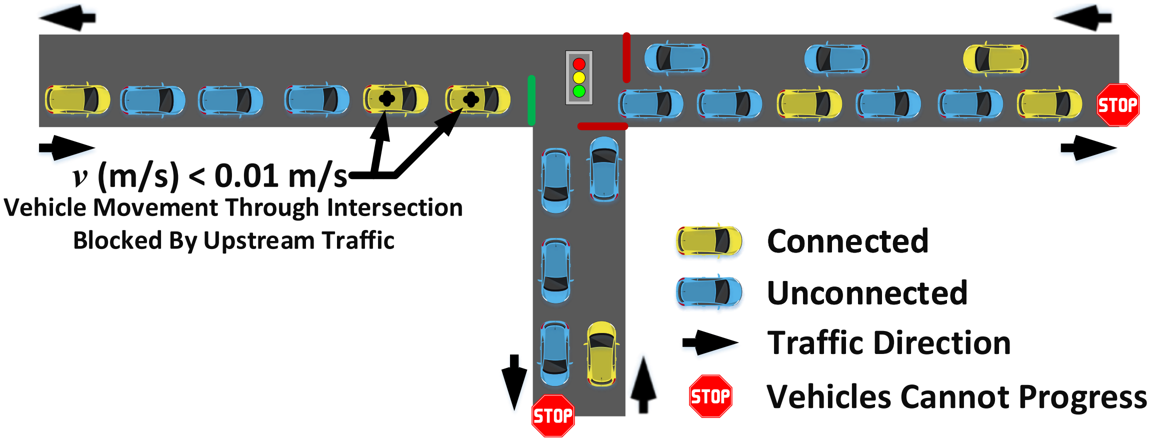


Figure 3.3: Blocking back management in the MATS algorithm. The stage transitions as the vehicles have a green light but cannot move.

3.1.4.3 Inductive Loop Data Integration

The green time extensions are applied when vehicles are detected in real-time on the existing inductive loops in the urban corridor. The MATS algorithm extends the stage by one extension interval if a vehicle is detected in the previous extension interval. The actuation scheme is defined based on the actuated timing parameter recommendations of the Federal Highways Administration Signal Timing Manual (STM) (Koonce et al., 2008).

3.1.4.4 CV Data Integration

Figure 3.4 shows how dynamic real-time information from CVs are used to derive a stage extension time. If a CV is detected close to the intersection in an active lane, the time it takes for that vehicle to reach the intersections is estimated from the driver's current speed and position. This time is added to the stage duration if it satisfies the acceptable travel time requirements set by Highways England (2019). The acceptable travel time factor is 1.67 times the free flow journey time. This factor times the average time headway between vehicles gives the time threshold for green extensions. The time for a CV to clear the intersection is defined as:

$$t_{\text{clear,CV}} = \frac{d(\mathbf{x}_v, \mathbf{x}_i)}{v_{\text{vehicle}}} \tag{3.2}$$

where $t_{\text{clear,CV}}$ is the time it takes a CV to clear the intersection. $d(\mathbf{x}_v, \mathbf{x}_i)$ is the Euclidean distance between the 2-D Cartesian coordinates for the positions of the vehicle $(\mathbf{x}_v)$ and the intersection $(\mathbf{x}_i)$ in meters. v_{vehicle} is the speed of the vehicle. This approach achieves control that is functionally similar to MOVA in that if continuous vehicle flow is present (oversaturation), the algorithm allows vehicles to proceed until the maximum green time is reached or the queue is dispersed, which maximises capacity. If the vehicle flow is undersaturated, the MATS algorithm allows vehicles to pass as long as unacceptable gaps (Highways England, 2019) do not appear in the flow.

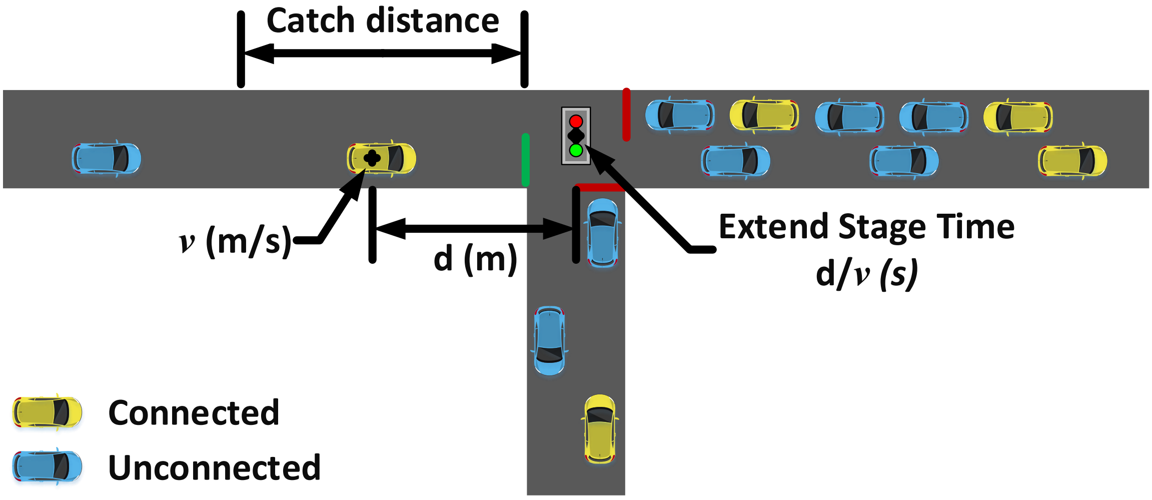


Figure 3.4: Stage extension process for the MATS algorithm.

3.1.4.5 Algorithm Overview

Figure 3.5 shows the flowchart for the MATS algorithm and highlights how the components of the algorithm integrate, and how the MATS algorithm switches its mode of operation based on which data sources it has available to it. The algorithm first sets the stage, and if the elapsed time is less than the minimum green time, the stage stays the same. The stage will change if the elapsed time exceeds the calculated or maximum green time, or if blacking back is detected. The elapsed time is between the minimum green time and the stage end time, and adjustments are made to the stage end time based on which data sources are available to the algorithm. A background process monitors queue lengths in inactive lanes to determine an initial end time for the other stages. In order to reduce the computational load, the algorithm only makes control decisions if the remaining green time is less than a check threshold, which here is 5 s. CV data is only used if the CV penetration is high enough that using the data provides performance superior to fixed-time control. Here, the threshold for CV data usage is found empirically through simulation. The pseudocode for the MATS algorithm is available, and presented as Algorithm 2 in Appendix E.

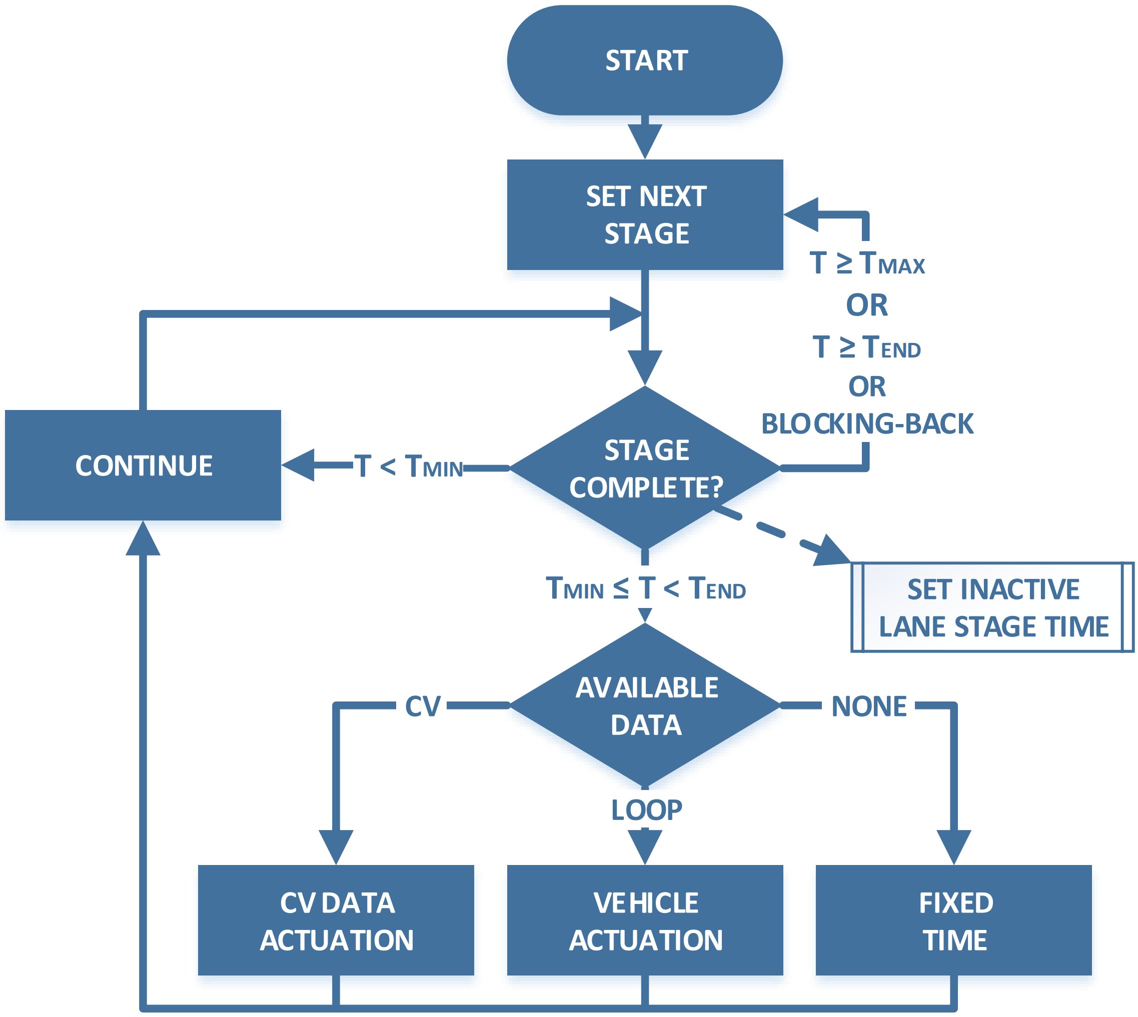


Figure 3.5: Flowchart for the MATS algorithm.

3.2 Conclusions and Future Work

In this chapter, the MATS traffic signal control algorithm that augments existing traffic signal control systems with CV data was introduced.

The MATS algorithm is unique in addressing the issue of achieving real-time, unconstrained, isolated signal control in urban corridors with existing infrastructure by combining CV data with existing fixed-time plan data and inductive loops. MATS achieves this through the development of novel and intuitive heuristics for optimising stage times using data from multiple data sources based on the principles used in state-of-practice algorithms such as MOVA. Based on the literature for traffic signal control algorithms considering CVs in Chapter 2, MATS is also novel among CV traffic signal control algorithms in its ability to detect and respond to blocking-back as it occurs, rather than through prediction as with PAMSCOD (He et al., 2012).

In future work, MATS could consider additional scenarios, including lane closures due to broken/crashed vehicles, response to emergency service vehicles, and adding more sophisticated algorithms such as SCATS (Lowrie, 1990) and SCOOT (Hunt et al., 1981) as benchmarks for the augmented control system. Additionally, a stability and sensitivity analysis of the algorithm mathematically would further prove the effectiveness of the algorithm in support of results from simulations.

3.3 Summary of Chapter Findings

1. The MATS algorithm:

    a) achieves real-time, unconstrained, isolated signal control in urban corridors with existing infrastructure.

    b) develops intuitive heuristics for optimising stage times using data from multiple data sources based on the principles used in state-of-practice algorithms such as MOVA.

    c) does not require any data that would track or uniquely identify road users.

    d) can detect blocking-back at an isolated intersection using CV data.

Chapter 4

A Greedy Algorithm with Implicit Stage Coordination for Optimising Traffic Signal Stage Sequences Using Multiple Data Sources from Connected Vehicles

In the previous chapter, the MATS algorithm was developed, which provided a heuristic for optimising stage times but suffered from issues when high traffic demands and pedestrians are present. The MATS algorithm does well at optimising stage times. However, its stage sequence is cyclic, i.e. its stages appear in the same order every cycle, which reduces the flexibility of the algorithm. Furthermore, it is known that coordinating groups of nearby intersections can improve traffic flow in high demand areas (Koonce et al., 2008). To address the limitations of a fixed stage sequence and isolated a method for optimising the stage sequences with implicit stage coordination is developed in this chapter.

In Chapter 2 future traffic signal control algorithms that use data from a connected environment were reviewed. The common limitation among these studies is that although they identify that CV data are beneficial for traffic signal control, their scope is limited by only considering traditionally useful metrics for traffic signal control such as position, speed, queue lengths, and flows. CVs have the potential to offer much richer data than are currently used. However, data which were previously unavailable from infrastructure remains unexploited. For instance, a CV can reasonably obtain and share information about how many passengers it is carrying, how many times it stopped this journey, its emissions class, *etc*. Faced with this limitation, the challenges to overcome in this study are twofold. Firstly, it is not always straightforward to incorporate data with different units into a single algorithm. Secondly, when presented with a multitude of possible data points, it is not immediately apparent if those data are useful for traffic signal control. To address the limitation, this chapter proposes a greedy stage sequence optimisation algorithm that abstracts for multiple CV data sources.

To address the gaps in the MATS algorithm and the literature, this chapter proposes a greedy stage sequence optimisation algorithm. The optimal dataset and parameters for the greedy algorithm are determined, and the greedy algorithm is integrated into an existing traffic signal control algorithm. The algorithm is tested through microsimulation in SUMO on a real-world case study based in the city of Birmingham, UK, for various traffic demands, CV penetrations, and communication channel conditions. This chapter extends current research by considering data that can be obtained from CVs that are not typically used for traffic signal control. The contributions of this chapter are as follows:

1. A method of assigning utility to traffic stages from disparate CV data points is developed.
2. A greedy stage sequence optimisation algorithm that abstracts for multiple CV data sources is devised and tested.
3. A mechanism for implicitly coordinating traffic signals under the greedy stage sequence optimisation paradigm.

This chapter is organised as follows. First, background information on stage sequence optimisation in traffic signal control is presented in Section 4.1. Section 4.2 reviews the literature on traffic signal coordination methods as it relates to algorithm development. Section 4.3 defines the full optimisation problem that is considered while developing the algorithm. In Section 4.5, the greedy algorithm for stage sequence optimisation is formulated. Finally, Section 4.6 presents the conclusions of this chapter.

4.1 Stage Sequence Optimisation

4.1.1 State-of-practice

In Chapter 2 current traffic signal control strategies are shown to be limited to low-resolution vehicle data, and adjust predefined cycles, splits and offset configurations to manage constantly fluctuating traffic demands. In the UK traffic signal typically follow a fixed stage sequence which infrequently changes with the time of day (Webster, 2011). The Traffic Advisory Leaflet 1/06 recommends that stages follow a cyclic order, and should only omit/skip stages when there is no demand for them (UK Govt. Dept. Transport, 2006). In practice. in the UK, adaptive systems like SCOOT skip stages if there is no demand for them to reduce delay (Laboratory, 1996). It is argued that skipping or reordering stage sequences is unsafe as road users may be used to a specific sequence and make unsafe actions if the stage sequence unexpectedly changed. A study by Bretherton (2003) on stage skipping suggested that there is no evidence to suggest that stage skipping affects accident rates and that the only negative to stage skipping is that it may increase waiting times above the recommended 120 s maximum cycle time (UK Govt. Dept. Transport, 2006).

The Transport Research Laboratory trialled stage skipping as an improvement to bus priority systems (Bretherton, 2003). No increase in accident rates was observed, but there were many constraints on the system, including that stages serving the main road were never skipped, and pedestrian stages were never skipped if there was only one pedestrian stage in the cycle (Hamilton, 2015).

Several European countries, including The Netherlands, use a phase-based approach which results in acyclic stages (Furth and Muller, 1999). The Netherlands uses a FIFO approach which works well under light demand but becomes locked into a static stage sequence under high demands, which may not be optimal (Furth and Muller, 1999).

Although the official UK guidance discourages acyclic stage sequences, citing safety issues, the evidence from trials in both the UK and abroad disprove this assertion. The literature suggests that acyclic stage sequences are a useful tool for optimising traffic signal operations. It will be investigated here if the effects of an acyclic stage sequence provide sufficient benefit to the proposed signal control system to merit recommending that the policy of discouraging acyclic stage sequences be reevaluated.

4.1.2 Future Methods

In research on traffic signal controllers that use CV data, there have been several approaches to stage sequence optimisation. Namely, rolling-horizon optimisation, platoon scheduling, genetic algorithms, greedy algorithms, machine learning.

Rolling-horizon approaches such as Priemer and Friedrich (2009) and Goodall et al. (2013) optimise traffic stages by simulating all stage combinations over a 15 s interval and selecting the one that best satisfies the algorithm objectives such as reducing delay. Rolling-horizon approaches can predict the optimal stage sequence and timing parameters but are limited in that they can be computationally intensive, and the prediction accuracy differs if the traffic conditions do not match the predicted conditions.

Platoon scheduling algorithms such as Pandit et al. (2013), Liu et al. (2017), and Liang et al. (2019) organise vehicle into platoons or clusters which are then scheduled access to the intersection on a first-come-first-served based. Platoon based approaches are useful in that vehicles with small headways can be given access to the intersection in efficient batches. They are limited in that grouping vehicles is challenging given the dynamic nature of traffic, and it can be challenging to decide where platoon boundaries are in dense traffic.

Genetic algorithms are an intelligent optimisation procedure that samples the parameter space of an optimisation process and searches for the optimal solution over multiple iterations. Successful iterations are combined to create new iterations that may have perturbations to find the optimal solution without having to search the entire parameter space. Genetic algorithms are a heuristic optimisation approach that are applied to a variety of optimisation problems (Koza, 1997; Yao et al., 2019). Lertworawanich et al. (2011) used a genetic algorithm approach to optimise traffic signal to reduce intersection spillback, balance queues, and increase throughput. Genetic algorithms are useful for optimising complex problems with multiple objectives that would be too computationally intensive to solve by computing the entire parameter space. They can be challenging to use, as they have many parameters that require tuning, they can be dependent on their initial conditions, require time to converge, and are inherently stochastic so may not find the global optimum (Eiben and Smith, 2003).

Greedy algorithms are a widely used paradigm for optimising functions by making the locally optimal choice at each decision point in an attempt to reach a globally optimal solution. Greedy algorithms are widely used in combinatorial optimisation problems, especially for solving NP-hard problems (Vince, 2002). They are applied across diverse fields such as communication systems (Mileounis et al., 2010), biology (Zhang et al., 2000), social networks (Goyal et al., 2011), and machine learning (Bengio et al., 2006). In transport, greedy algorithms have been used for applications such as logistics scheduling (Chang et al., 2014), vehicle routing (Bastani et al., 2011; Dijkstra, 1959), and traffic signal control (Aziz et al., 2018; He et al., 2011). He et al. (2011) used a greedy algorithm to manage priority requests for phases at an intersection. A greedy algorithm was used as finding a near-optimal solution quickly was deemed preferable exhaustively searching for all possible solutions. Aziz et al. (2018) used a greedy algorithm to select control actions which optimise the intersection reward function. Greedy algorithms do not guarantee an optimal solution, but often they yield a solution which is close to optimal (Cormen et al., 2009). Greedy algorithms work by making the choice that appears optimal at the moment and continuously solve proceeding sub-problems in the same way. Therefore, greedy algorithms are highly suitable for stage sequence optimisation in the presence of CV data, as they can make the decision that best manages the perceived traffic demand at an intersection at the time.

Machine learning or Artificial Intelligence (AI) is a class of methods that use statistical approaches to allow algorithms to learn how to perform specific functions such as classify images (Xiaoxu Ma and Grimson, 2005), drive cars (Urmson et al., 2008), and control traffic (Box et al., 2010; Mannion et al., 2016). For traffic signal control, reinforcement learning such as in Box et al. (2010), Xiang and Chen (2016), and Liu et al. (2017) or Markov methods such as in Aziz et al. (2018). The approach is to iteratively reward actions that result in good traffic signal control decisions and penalise those that do not so that the algorithm learns to control traffic signal well. The issue with machine learning approaches is that they are comparatively complex to implement, require significant training so that they learn to perform their task well, and are often black boxes due to their so-called ‘hidden layers’ so problems may be difficult to diagnose (Mannion et al., 2016).

4.2 Signal Coordination

Coordination is a method of synchronising traffic signals to minimise the number of red lights a vehicle encounters as it travels through multiple intersections. Establishing coordination is usually beneficial when two or more intersections that handle high volumes of traffic are close to one another (Koonce et al., 2008). Figure 4.1 is a time-distance plot illustrating the progression of two vehicles V1 and V2, through two intersections J1 and J2.Time-distance plots are useful for assessing coordination as a vehicle whose time-distance line is straight proceeded through the intersection unimpeded. The more vertical the line (perpendicular to the x-axis) is, the faster it is travelling, the more horizontal the line (perpendicular to the y-axis) is, the slower its speed. Other traffic causes a vehicle's time distance line to shift to the right if the vehicle cannot achieve its target speed. A vehicles' time-distance line plateaus if the vehicle stops due to time progressing but the vehicle being stationary (no increase in distance travelled). A vehicle in a well-coordinated system stops infrequently, such as V1 in Figure 4.1. In a well-coordinated system, the green times for matching stages synchronise, creating a 'green-wave' which allows vehicles to progress with minimum interference. If the traffic signals are poorly coordinated, vehicles stop more frequently, like V2 in Figure 4.1. There are two methods of coordinating traffic signals, explicit and implicit coordination. Explicit coordination is where signals are deliberately timed relative to one another. Implicit coordination is where signals use data from a nearby intersection to promote coordination locally.

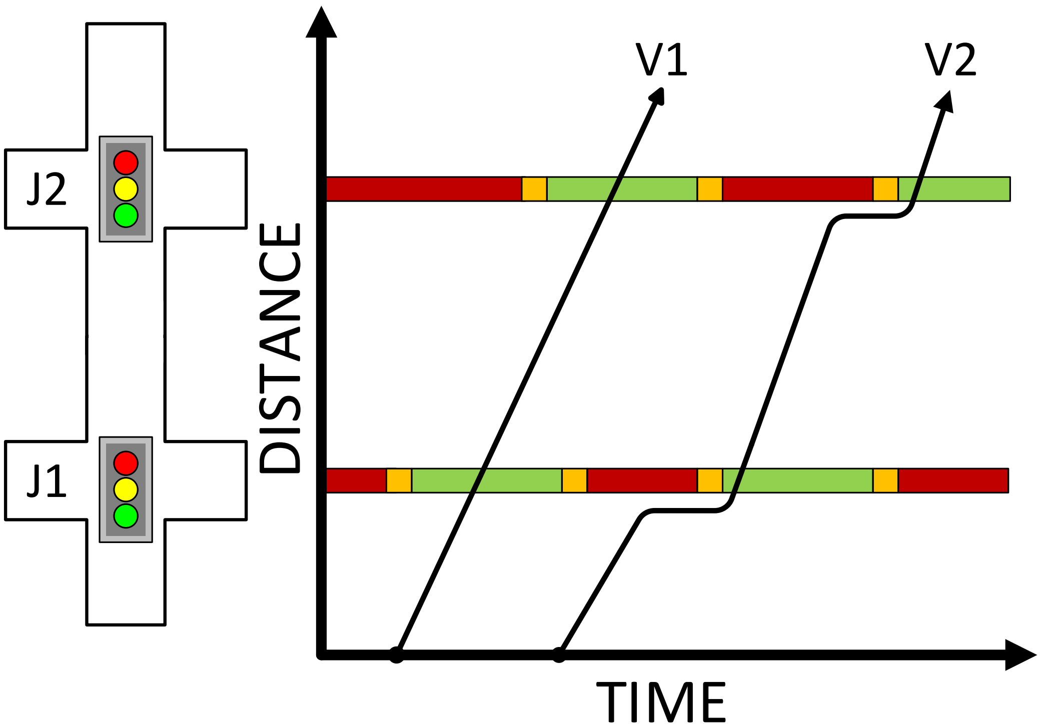


Figure 4.1: Time-distance diagram illustrating the effects of coordination and lack of coordination on vehicles attempting to travel through two junctions J1 and J2.

4.2.1 Coordinating traffic stages

4.2.1.1 Explicit Coordination of Traffic Signals

Historically, explicit coordination has been the most widely used approach to coordinating traffic signals. Coordinated traffic signal controllers such as SCOOT (Hunt et al., 1981) and SCATS (Lowrie, 1990) work through a centralised controller coordinating several local sub-controllers. For example, SCOOT works by optimising splits, offsets, and cycle times in increments of 4 to 16 seconds (UK Govt. Dept. Transport, 1995). Similarly, SCATS optimises cycle times, splits and offsets for the next cycle based on data from the previous three cycles.

In recent literature, Goodall et al. (2013) presented the PMSA, which used CV data to optimise traffic signals over a 15s rolling horizon. Islam and Hajbabaie (2017) achieved signal coordination through decentralised controllers communicating with each other to coordinate signals in a distributed approach over a prediction interval of $60\ \mathrm{s}$. Intersections locally optimise for the delay and queue lengths while factoring in demand levels that have been sent from neighbouring intersections. In Liang et al. (2019), coordination was achieved through rolling-horizon optimisation of vehicle platoon departures such as to minimise the total number of stops made. Signal phase and timing plans are joined across intersections and vehicles proceed through the network with the assistance of speed advisories.

The characteristic features of explicit coordination algorithms are that they predict the behaviour of the network over some time-horizon and optimise the traffic signals for the predicted scenario rather than dealing with traffic in real-time.

4.2.1.2 Implicit Coordination of Traffic Signals

The issue with explicitly coordinated systems is that they are all predictive, and therefore not dynamic enough to integrate into a real-time decision-making process such as the greedy stage sequence algorithm proposed in Chapter 4. To achieve coordination in a highly-adaptive and isolated control strategy, coordination must be achieved implicitly, i.e. as a decision during the optimisation process. Few studies have addressed the issue of coordination for highly adaptive systems. The first was Porche and Lafortune (1997), who proposed ALLONS-D. In ALLONS-D, coordination is implicit and uses data from as far upstream as the adjacent intersection as input to a rolling horizon optimisation. The implicit features did not guarantee optimal network-level performance, so a weighting scheme was introduced to specify the relative importance of stages to one another across multiple intersections, and achieve good signal progression.

In RHODES (Mirchandani and Head, 2001), a decentralised approach was also used for signal coordination. Similarly to ALLONS-D, coordination is implicit as RHODES does not have a fixed cycle time. Data from stop bar and upstream loop detectors are used to minimise the delay of vehicles passing through the intersection. An internal prediction model estimates vehicle flows to adjacent intersections and sends it to those intersections, resulting in implicit coordination.

Waterson and Box (2012) proposed a bid based algorithm of the form:

$$B_{\mathrm{Wi}} = B_{\mathrm{Wi}} + CB_{\mathrm{Ei}} \tag{4.1}$$

where B_{Wi} and B_{Ei} are bids for the west and east approaches respectively, and C is a scaling factor. Rather than explicitly coordinating the stages, Equation 4.1 allowed the probability of the west bid being selected to be increased based on the bid from the adjacent east bid. This implicit coordination strategy was shown to be more effective than the industry-leading MOVA algorithm (Vincent and Peirce, 1988) in their case study.

4.3 Real-time Stage Sequence Optimisation

Traffic signal timing is known to be an NP-complete problem (Wünsch, 2008); however, finding the true optimal solution for an entire network is prohibitively time-consuming. In the previous section, five methods for stage sequence optimisation were presented: rolling-horizon optimisation, platoon scheduling, genetic algorithms, greedy algorithms, machine learning. Additionally, in the previous chapter, the following objectives for the developed traffic signal controller were outlined:

1. To perform as well as or better than a state-of-practice traffic signal control algorithm.
2. To use control logic, and optimisation/heuristic procedures that are practical in deployment scenarios.
3. To respond to connected vehicles in real-time.
4. To integrate with existing systems.
5. To preserve driver privacy by not tracking them through the network.

Objective 3 eliminates rolling-horizon approaches as they are not real-time due to the predictive nature of their operations. In this research, the signal control decisions are to be made within 1 s of receiving data, i.e. the maximum period of a CAM message. As rolling horizon methods perform multiple sub simulations over a window of several seconds, the computational overhead is too great. Platoon scheduling is eliminated by Objectives 3 and 4 as vehicles may need to be tracked in order to monitor platoons/clusters through the corridor. It was also identified in the literature review that platooning require high levels of connectivity and algorithmic complexity in order to reliably identify and schedule platoons which makes them incompatible with existing systems, particularly at low levels of CV penetration. Genetic algorithms and machine learning approaches may also not be real-time due to their iterative convergence and need for training. Genetic algorithms obfuscate some of there operations during the fitness selection and mutation process, similarly machine learning algorithms obscure their operations. The complexity of genetic and machine learning algorithms may be seen as prohibitive to transport planners so may not be practical in a deployment scenario and puts the approaches in conflict with objective 2. Greedy algorithms are the most suitable approach for traffic stage optimisation here. As greedy algorithms require only evaluating a decision vector or matrix once as they are computationally efficient as a single-stage mathematical operation. Compared with genetic algorithms which have a time complexity of $O(n^3)$ to $O(n^5)$ (Nopiah et al., 2010), and reinforcement learning approaches which have a complexity of $O(n^3)$ in the learning phase and $O(n^2)$ on evaluation, greedy algorithms are more efficient with complexities in the region of $O(n \log n)$ (Silvestri et al., 2017). Greedy algorithms are also an inspectable process, and therefore more intuitive to understand than the alternative methods which is useful for transport planners attempting to deploy a greedy algorithm which is why they are selected here. Furthermore, the greedy algorithm developed here could serve as a base for a genetic optimisation or machine learning approach, making it a useful point of expansion for future research.

In their standard form, greedy algorithms continuously select the largest value from given a selection and add it to their construction of a solution, never going back on a previous decision (Curtis, 2003). A limitation of the standard greedy algorithm is their assumption that the optimal solution is analogous to the largest solution. A variant of the greedy algorithm called the ϵ-greedy algorithm introduces some randomness into the algorithm. The random choices occur at random with probability ϵ at each decision point, allowing for the exploration of alternative options (Sutton and Barto, 2011). The ϵ-greedy algorithm overcomes the short-sightedness of standard greedy approaches by allowing a certain percentage of decisions which may be regrettable.

The benefits of greedy algorithms for optimisation is that they are not iterative, meaning they are less computationally intensive than more involved iterative approaches such as evolutionary algorithms like the genetic algorithm (Koza, 1997; Yao et al., 2019) and numerical objective function minimisation methods such as the Simplex (Nelder and Mead, 1965) and Powell (Powell, 1964) methods. Greedy algorithms also do not require the training and pre-processing involved with machine learning approaches (Mannion et al., 2016). It has already been acknowledged that traffic flow is stochastic, so it is prohibitively complex to solve for every possible traffic configuration at an intersection. As the traffic demand at an intersection can differ significantly with time, the greedy algorithm's ability to assess the demand dynamically and make a fast decision that best manages the traffic signal stage sequence in that instant is advantageous.

4.4 Optimisation Problem

4.4.1 Performance Indicator

The main PIs for this research are delay and number of stops. As was seen for the TRANSYT PI in Equation 2.1, minimising a PI that considers both stops and delay creates the scenario where the smaller the PI value, the closer each vehicle is to making its journey under free-flow conditions. The following multi-objective global performance indicator was used to rank the performance of each combination of data points:

$$P_{\mathrm{i}} = \frac{1}{2}\left(\frac{T_{\mathrm{delay,\,i}}}{T_{\mathrm{delay,\,max}}} + \frac{N_{\mathrm{stops,\,i}}}{N_{\mathrm{stops,\,max}}}\right), \quad 0 \leq P_{\mathrm{i}} \leq 1 \tag{4.2}$$

where P_{i} is the performance indicator for data point combination i, $T_{\mathrm{delay,\,i}}$ and $N_{\mathrm{stops,\,i}}$ are the delay time and average number of stops for data point combination i respectively, and $T_{\mathrm{delay,\,max}}$ and $N_{\mathrm{stops,\,max}}$ are the maximum delay and number of stops across all data point combinations respectively. The lower the value of P_{i}, the better the combination of data points is at reducing delay and stops at signalised intersections. In Equation 4.2, delay and stops are considered equally important, future research may explore this balance.

4.4.2 Constraints

In order to ensure the balanced performance of the algorithms, the following constraints are considered;

1. If the data necessary for a part of the decision process is unavailable, that part does not influence the decision.
2. No stage may occur twice in succession. This condition prevents a particularly busy approach from dominating the others
3. An intersection must have three or more stages in order for the stage sequence to be optimised. This constraint ensures that at each decision point and considering Constraint 2, the algorithm has two or more options from which to choose.
4. Each stage must appear once every two cycles. In case a stage has unconnected vehicles or cyclists waiting, each stage can only be skipped in one cycle. This is known as double-cycling.
5. If a pedestrian stage is present, it occurs within one cycle to prevent long waiting times for pedestrians. Waiting until the end of a double cycle may result in pedestrians becoming frustrated by long waiting times and crossing unsafely (Crabtree, 2017).
6. Any ties at a decision point are broken at random.

4.5 Greedy Stage Sequence Optimisation with Implicit Coordination

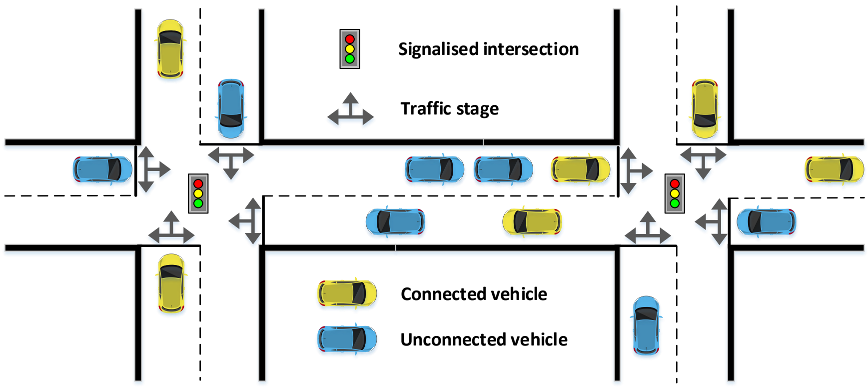


Figure 4.2: Diagram illustrating a traffic scenario to which the algorithm can be applied.

Table 4.1: List of nomenclature used in this chapter.

M	The number of rows (data points) in the utility matrix
N	The number of columns (stages) in the utility matrix
U_{ij}	The greedy algorithm utility matrix of size $M \times N$
$\widehat{U}_{\mathrm{ij}}$	The normalised utility matrix
ω_i	Weighting column vector
S_{j}	The utility aggregate row vector
S^*_{j}	The coordinated utility aggregate row vector
α	The coordination scaling factor
c_{j}	The stage coordination row vector
x_{i}	The stage index at decision point i
T_{j}	The stage time for stage j
T_{elapsed}	The time elapsed since the beginning of the current stage

4.5.1 Utility Matrix Formation

Figure 4.2 illustrates the type of scenario that is considered in this research. Two signalised intersections are shown with connected and unconnected vehicles approaching and departing the intersections. The intersections are neighbouring each other, so the control decisions of one may impact the performance of the other. Each intersection has a set of stages comprising a combination of traffic signals. The aim is to use data from connected vehicles to optimise the sequence of traffic stages. The nomenclature for variables and parameters used in this chapter is summarised in Table 4.1. The relationship between data and stages is given by:

$$U_{\text{ij}}, \quad \text{where} \quad i, j \in \{i, j \in \mathbb{Z} \mid 0 \leq i < M \mid 0 \leq j < N\} \tag{4.3}$$

where U_{ij} is the utility matrix of size $M \times N$. M is the integer number of rows corresponding to each received data point considered, and N is the integer number of stages.

4.5.2 Utility Matrix Normalisation and Weighting

As the data that form the utility matrix may not be of the same unit or magnitude, a procedure for normalising the disparate data is introduced. It is assumed there exists a mapping:

$$U_{\text{ij}} \mapsto \widehat{U}_{\text{ij}} \quad \forall \quad U_{\text{ij}} \in \mathbb{R}_{\geq 0} \tag{4.4}$$

where $\widehat{U}_{\text{ij}}$ is the normalised utility matrix, and $\mathbb{R}_{\geq 0} = \{x \in \mathbb{R} \mid x \geq 0\}$. Subject to the conditions in (4.4), the mapping is given by:

$$\widehat{U}_{\text{ij}} = \frac{U_{\text{ij}}}{\max\limits_{0 \leq j \leq N\text{-}1} U_{\text{ij}}} \tag{4.5}$$

The mapping in Equation 4.5 results in each row of U_{ij} being divided by the maximum value in that row to give the normalised utility matrix $\widehat{U}_{\text{ij}}$. Therefore, the elements of the normalised utility matrix are subject to $0 \leq \widehat{U}_{\text{ij}} \leq 1 \; \forall \; i, j$.

In its present form, the normalised utility matrix considers each data source equally. For a discrete number of data points, it may be beneficial to introduce a column vector of weights that would allow finer adjustment of the contributions of each data point. The adjusted utility matrix calculation is given by:

$$\widehat{U}_{\text{ij}} = \omega_i \frac{U_{\text{ij}}}{\max\limits_{0 \leq j \leq N\text{-}1} U_{\text{ij}}} \tag{4.6}$$

where ω_i is the column vector of size N of weights to be applied to the utility matrix.

4.5.3 Utility Aggregation

The normalised utility matrix $\widehat{U}_{\mathrm{ij}}$ from Equation 4.5 allows for comparison of multiple types of data, as all the data are now on the same scale. It is important to note here that all data sources are considered equally.

To compare the utility for each stage, the normalised utility matrix is aggregated to form the row vector:

$$S_{\mathrm{j}} = \sum_{\mathrm{i}=0}^{M-1} \widehat{U}_{\mathrm{ij}} \tag{4.7}$$

The utility aggregate S_{j} is a row vector containing the sum of normalised utility contributions for each stage.

4.5.4 Coordination as a Utility Parameter

The study by Waterson and Box (2012) was limited by the fact that their algorithm only considered coordinating stages that sink vehicles from the upstream intersection (a sink receives vehicles from an upstream intersection). Here, stages that source vehicles to the downstream intersection are also considered (a source send vehicles to a downstream intersection). In order to know whether to source vehicles or whether to sink vehicles, the intersection must be able to estimate the expected stage time at the adjacent intersection(s). Therefore, each intersection must record the mean stage time over a rolling time interval. The expected stage time is given by $\mathbb{E}(T_{\mathrm{j}})$. Where T_{elapsed} is the time that has elapsed since the current stage of the adjacent intersection began. The intersection adapts its utility to source vehicles to the adjacent intersection if:

$$T_{\mathrm{elapsed}} \leq \mathbb{E}(T_{\mathrm{j}})/2$$

i.e. the adjacent intersection is less likely to change so send it vehicles. The intersection sinks vehicles from the adjacent intersection if:

$$T_{\mathrm{elapsed}} > \mathbb{E}(T_{\mathrm{j}})/2$$

i.e. the adjacent intersection is more likely to change.

With the direction of coordination has been determined, a coordination row vector c_{j} can be formed by:

$$c_{\mathrm{j}} = \begin{cases} 1 & \textbf{if } j \in s_{\{\mathrm{source,\,sink}\}} \textbf{ and } \text{vehicles present} \\ 0 & \text{otherwise} \end{cases} \tag{4.8}$$

where $s_{\{\mathrm{source,\,sink}\}}$ is the set of stages at the adjacent intersections that source or sink vehicles to the target intersection respectively. Vehicle presence is determined from position and turn signal data from CVs. Vehicles displaying no turn signal are assumed to be travelling straight ahead. The sets of coordinating stages $s_{\{\mathrm{source,\,sink}\}}$ should also contain information about the directions vehicles are turning on their approach to arrive at the source/sink intersection to which the turn signals can be matched.

Given the utility aggregate in Equation 4.7, the utility aggregate S_j can be modified to a form similar to the bid modification proposed by Waterson and Box (2012) in Equation 4.1 to get:

$$S^*_\mathrm{j} = S_\mathrm{j} + \alpha M c_\mathrm{j}, \quad \alpha \in \{\alpha \in \mathbb{R} \mid 0 \leq \alpha \leq 1\} \tag{4.9}$$

where S^*_j is the coordinated utility aggregate. The parameter α is an empirically calibrated variable introduced to scale the impact of the coordination vector c_j which only has unit or zero values. The α parameter scales the impact of c_j relative to the number of data points considered M. Scaling the impact is important, as the contribution of c_j to S^*_j would otherwise diminish with increasing numbers of data points (M).

4.5.5 Optimal Stage Selection

As the goal of the greedy algorithm is to select the stage that maximises the utility at a given intersection, the index of the next stage is obtained by:

$$x_i = \arg\max_\mathrm{j} S^*_\mathrm{j} \tag{4.10}$$

where x_i is the stage index that maximises utility (minimises the PI) of the intersection at the decision point i. The operation $\arg\max$ returns the argument of the maximum utility in the utility aggregate S_j which corresponds to the stage index which maximises utility. In the event of a tie, one of the maxima is picked at random.

4.5.6 Greedy Algorithm Constraints

The greedy algorithm is subject to the constraints outlined in Section 4.4.2, to ensure fair operation at low penetrations of connected vehicles. The constraints are applied to the greedy algorithm as follows.

Constraint 1

$$U_\mathrm{ij} \leftarrow 0 \;\; \textbf{if} \;\; \text{no data}$$

U_ij is set to 0 for a given i,j-pair if there is no corresponding CV or input data. Constraint 1 ensures that when there is no CV data available on a given stage, there is no contribution to that utility aggregate from that data point.

Constraint 2

$$U_{\mathrm{ij}} \leftarrow 0 \quad \forall \quad j = x_{i-1}$$

Constraint 2 ensures that the previous stage x_{i-1} is not selected multiple times successively. Through negating successive selection, the stage selection process is less biased against drivers associated with stages that have less traffic or provide less information.

Constraint 3

$$x_i \leftarrow ((x_{i-1} + 1) \bmod N) \quad \text{if} \quad N < 3$$

A signalised junction must have 3 or more stages to switch between to use the greedy stage sequence optimisation. If there are only two stages, this constraint avoids the utility optimisation and cycles between the 2 available stages.

Constraint 4

$$x_i \leftarrow j \quad \text{if} \quad j \notin \{x_{i\text{-}(2N\text{-}1)}, ..., x_{i\text{-}1}\}$$

Double cycling is a common approach for allocating stages at intersections (Chaudhary et al., 2002) and has been shown to improve performance at intersections with unbalanced loads (Zhou et al., 2017). Constraint 4 imposes that if the stage j has not appeared in the last two cycles ($2N$), then it should occur next. Constraint 4 ensures that even at an intersection with a heavily unbalanced load, each stage is guaranteed green time. However, if the load is balanced, this is reflected in the utility matrix by uniformly increasing the utility of each stage, which results in a balanced distribution of stages.

Constraint 5

$$x_i \leftarrow \text{pedestrian-stage if pedestrian-stage} \notin \{x_{i\text{-}(N\text{-}1)}, ..., x_{i\text{-}1}\}$$

To ensure service to pedestrians, a pedestrian stage should occur no less than after every N stages if the pedestrian has called for one. Waiting until the end of a double cycle may result in pedestrians becoming frustrated by long waiting times and crossing unsafely (Crabtree, 2017).

Constraint 6

$$x_i \sim \arg\max_{\mathrm{j}} S_{\mathrm{j}} \text{ if } \mathit{count}(S_{\mathrm{j}} = \max S_{\mathrm{j}}) > 1$$

In the event of a tie (multiple values in S_{j} equal to the maximum value), the tie is broken by selecting one of the indices j in S_{j} at random. Although the choice may not be optimal, it adds an ϵ-greedy element to the algorithm, perturbing it away from its current optimum and allowing it to find a new one.

4.5.7 Algorithm Summary

Figure 4.3 shows a flowchart which summarises the theory described in Section 4.5 highlighting the progression from forming the utility matrix to returning the stage index with the highest utility. Bringing together the equations from Sections 4.5 the full greedy algorithm for stage selection with implicit coordination:

$$x_i = \arg\max_{\mathrm{j}} \left(\sum_{\mathrm{i}=0}^{M-1} \frac{U_{\mathrm{ij}}}{\max\limits_{0 \le j \le N\text{-}1} U_{\mathrm{ij}}} + \alpha M c_{\mathrm{j}} \right) \tag{4.11}$$

Equation 4.11 generalises for any data that can be added to the utility matrix such that the higher its value, the higher its utility contribution. Equation 4.11 also generalises to isolated intersections when $\alpha = 0$.

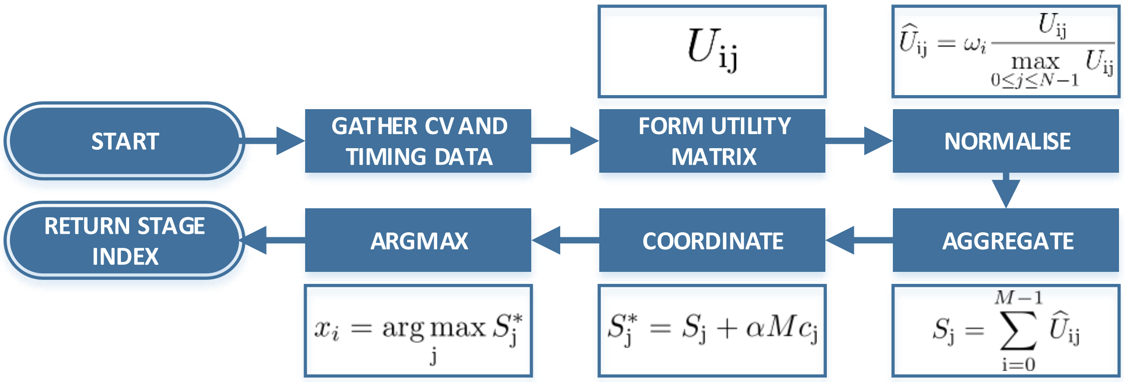


Figure 4.3: A flowchart summarising the greedy stage optimisation and coordination algorithm. Each process element in the algorithm flowchart is accompanied by its corresponding equation.

4.6 Conclusions and Future Work

This chapter proposed a greedy stage sequence optimisation algorithm that abstracts for multiple CV data sources. The greedy algorithm forms a utility matrix from available CV data then normalises the data contributions to make them comparable. The utility matrix is then aggregated, and a term for facilitating implicit coordination was developed. Finally, the stage with the highest utility is selected in order to minimise the global PI in Equation 4.2.

The previous chapter showed how traffic signal control could be performed using data from CVs, this chapter took an alternative approach, investigating what CV data can reveal about how it should be used for traffic signal control. This chapter has shown how a greedy algorithm can be used to provide a heuristic for stage sequence optimisation using multiple CV data sources, not just speed and position measurements as is common in other algorithms. Future work might explore the utility, and stage time information can be used to self-tune the signal controller parameters. Other more specific data points such as emissions, or bus/emergency service vehicle priority could be investigated to meet the transit priority needs of specific local authorities. An investigation into what data from CVs (if any) could be used to further optimise the green times calculated by the underlying algorithm would be useful. Further work could be done to apply a similar greedy process to a corridor with 100% CV penetration with autonomous drivers and a signal-less intersection as the greedy stage sequence optimisation algorithm has applications as a priority-based scheduling system. Finally, future research should investigate modifying the greedy algorithm approach for genetic algorithm or machine learning formulations.

4.7 Summary of Chapter Findings

1. A greedy algorithm can be used as a heuristic for acyclic stage sequence optimisation.
2. Multiple data from disparate sources can be combined in a single stage sequence optimisation process. Indeed, the algorithm can combine arbitrary inputs from data sources as long as they can be formulated in a way that they can be compared across stages, and that the greater its value (utility), the more likely it would be to minimise the global PI.
3. The stage sequence optimisation process allows the algorithm to determine which available data are best for optimising a given objective function.
4. A coordination term for the greedy stage sequence optimisation algorithm was developed to achieve coordination implicitly.

Chapter 5

Research Methodology

In order to achieve the objectives outlined in Section 1.4, the impact of CVs on the transportation network had to be evaluated. This chapter discusses the various methods that can be used to evaluate the impact of CVs in the transportation network and the specific approaches used in this research. Section 5.1 overviews the simulation description and summarises the workflow for this research. Section 5.2 outlines and justifies the simulation methods that were used to perform the core research. Section 5.3 discusses the tools that will be used to evaluate traffic signal control algorithms this research while Section 5.4 selects the models that will be used in the evaluation. Section 5.5 introduces and develops the realistic case study to which the research is applied. Section 5.6 discusses the tests that are conducted on the traffic signal control algorithms developed by research. Section 5.7 discusses how the performance of the traffic signal control algorithm proposed in this research will be assessed relative to other traffic signal controllers.

5.1 Testing Methodology Workflow

Figure 5.1 shows how the testing methodology outlined in this section is built and provides the framework on which to develop research. First, simulation was chosen as the method for evaluating the traffic signal controllers, SUMO was selected as the most appropriate simulation software, and the Krauß car-following model was chosen as the best for modelling mixed-vehicle traffic. The case study based on the Selly Oak area of Birmingham was developed from available data, and the parameters for the simulations were defined. These steps set the methodology for evaluating traffic signal control algorithms in this research. The steps after that are to develop and test a traffic signal control strategy, analyse the PIs and refine the algorithm where possible to improve its results. The rationale behind selecting this methodology is developed in the subsequent sections.

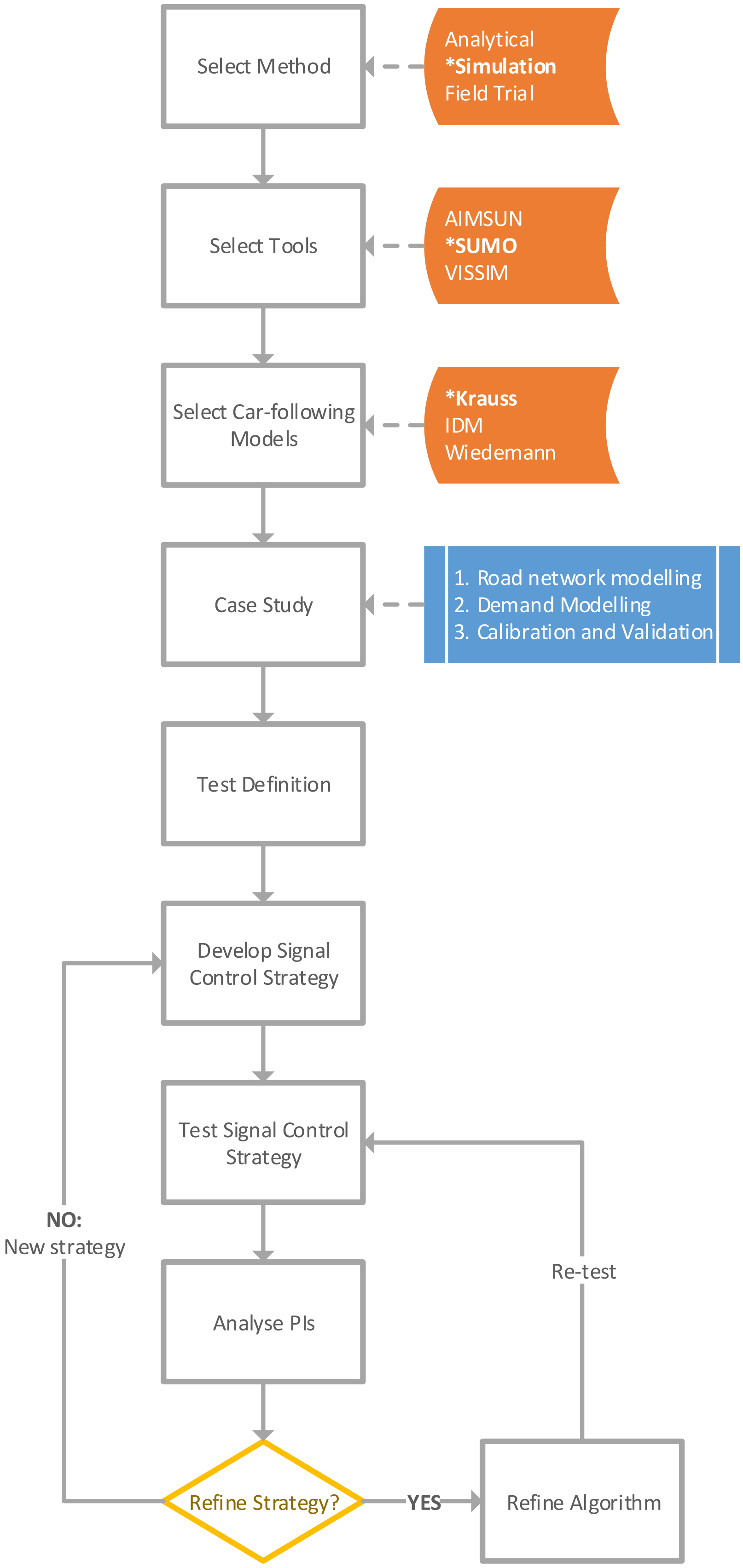


Figure 5.1: Research methodology flowchart.

5.2 Introduction to Research Methodologies for Traffic Analysis

This section discusses the three approaches that could be used to perform this research and identifies which is most suitable.

5.2.1 Analytical Evaluation

Analytical models involve expressing a system and its dynamics using mathematical equations. For example, many car-following models (e.g. Krauß (1997); Treiber et al. (2000); Wiedemann and Reiter (1992)) are developed using an analytical approach to determine equations that model car-following behaviour.

The advantage of analytical methods is that they allow the derivation of mathematical models that describe the behaviour of a system such as car-following. The mathematical models can be created either from empirical data, such as from recorded vehicle headways for a car-following model or through derivation from the physical properties of the system.

While analytical models are well suited to describing specific problems, it becomes increasingly difficult to describe a system using mathematical equations as its size and complexity (number of agents and variables) increases. The issue with analytical methods for this research is that although the traffic signal control algorithms will have specific behaviours, they need to be evaluated in a network. An urban corridor is a network consisting of multiple vehicles, vehicle types, road conditions, and signalised intersections. It is too broad a problem to be solved with a single analytical system. The review of traffic signal control in Chapter 2, showed that none of the algorithms reviewed used analytical methods to evaluated their research.

5.2.2 Simulation

Simulations allow systems to be modelled by describing the system using a computer programming language and then evaluating the code using a computer. The advantage of modelling systems using simulation is that simulations allow many different elements to be incorporated into a single model. Providing the models and underlying assumptions of the model are reasonable, good system-level results can be obtained. Simulations are also useful as the model codes can be altered to test new scenarios, and outputs can be generated and analysed in the same computing environment. Simulations can be limited if the model assumptions abstract the system too far from reality, in which case the results produced by the simulation would not be valid.

Simulation is the most common method for evaluating traffic signal control strategies. All of the traffic signal control strategies reviewed in Section 2.4 were tested using simulation methods to determine the performance of the strategy.

5.2.3 Field Trials

Field trials involve creating a physical system and observing results obtained from testing the system in specific scenarios. Field testing is highly practical as it provides direct evidence of how a system performs under specific conditions. Current field testing projects were reviewed in Chapter 2 Section 2.5.6.

The advantage of field trials is that they can yield results closest to the actual impact the system will have In the case of studying CAVs, field trials can provide good results but are limited in scope. The scope of CAV field trials is the cost of the equipment, and obtaining permissions to perform the trials due to the safety implications surrounding interactions between the technology and other road-users/pedestrians. The field trials discussed above were limited in that they only tested a limited number of vehicles, and did not assess their corridor network-level effects.

5.2.4 Discussion

The purpose of this research is to determine how to integrate CVs into the transport network through traffic signal control. As CVs are not heavily present on roads, there are limited opportunities to study them directly. The three methodologies for analysing vehicle traffic have been discussed.

Analytical solutions were found to be useful for analysing specific behaviours but were limited in the analysis of corridor network-level behaviours. Analytical solutions are accessible if a suitable experiment can be created to obtain empirical data, or the behaviour can be derived from the physical properties of the system. Traffic networks are highly complex systems comprising many vehicles and signalised intersections, so a purely analytical solution to the problem would be far too complex to solve for an entire network. To illustrate the complexity of attempting an analytical solution, vehicle dynamics, traffic signal control, the communication system, and the interactions between them would have to be assessed in a single solution. To analyse any one of these areas would represent a significant undertaking. The unsuitability of analytical methods for modelling traffic was reflected in the traffic signal control literature reviewed in Chapter 2, as none of the studied traffic signal control algorithms were evaluated analytically.

Field trials were found to be a useful method for assessing the real-world impacts of a target technology. The cost of field trials limits their scope, for example, the Smart Mobility Living Lab project (Smart Mobility Living Lab, 2020) is run by a consortium of universities, local authorities, industry partners with a £20 million budget. It is not practical to study CVs in the field for this research, as it would be too costly and disruptive to acquire and instrument a large enough fleet of CVs to study the effect of different levels of CV penetration in the transport network. Additionally, the results would be bound to a specific locality, affecting how transferable the results would be.

Both in this research and the literature, simulation is the preferred method for modelling scenarios involving CVs and C-ITSs, requiring only data about the system, not the physical system itself as in a practical study. The simulations can also be designed in a modular way to compare the performance of a variety of traffic control strategies in the transport network while isolating other variables. At Southampton University, there are the IRIDIS4 and IRIDIS5 High-Performance Computing (HPC) clusters, which allow for simulations to be conducted on a scale not accessible to many other institutions as long as the simulations can be conducted in a Linux based operating environment.

5.3 Simulation Tools for Modelling the Impacts of CVs in a Mixed Traffic Stream

In Section 5.2 simulation was selected as the most appropriate method to evaluate the problems of traffic signal control in the presence of CVs raised by this research. In this section, the type of simulation that is most applicable to the research is determined in Section 5.3.1 and the comparison and selection of simulation software for this research is made in Section 5.3.2.

5.3.1 Types of Simulation

There are three types of simulation that can be done to evaluate road network performance, namely microscopic, mesoscopic, and macroscopic. Table 5.1 summarises three types of road network simulation and compares their outputs, advantages and disadvantages. Microscopic simulations consider the behaviour of individual vehicles in the road network, e.g. individual speeds, positions, and emissions quantities. Macroscopic simulations consider the properties of the road network as a whole, or in zones, e.g. vehicle flows between areas, average speeds, total emissions. Mesoscopic simulations are a relatively new type of simulation with resolutions between that of microscopic and macroscopic simulations (Burghout et al., 2006). Rather than considering the entire urban corridor network as in macroscopic simulation, or individual vehicles as in microscopic simulation, mesoscopic simulation determines small groups of transportation elements in which traffic behaviour is homogeneous. For example, mesoscopic simulations may report results on a per lane basis, e.g. flows, average speeds, or total emission in each lane. The advantage of this middle level of reporting resolution is that it is less computationally intensive than microscopic simulations but more detailed than macroscopic. Mesoscopic simulation is limited in that few simulation platforms implement it.

From Table 5.1 it is evident that microsimulation offers more flexibility than mesoscopic or macroscopic simulations, despite being more computationally intensive. Microsimulation allows both microscopic and macroscopic quantities to be calculated by aggregating the results for individual vehicles. Analysing both microscopic and macroscopic values is important, as this research aims to understand the impacts of traffic signal control in the presence of

CVs. Microsimulation is also necessary as the communication systems in the C-ITS need to be considered in addition to the vehicle dynamics and traffic signal control strategy. As microsimulation tools allow the quantities of mesoscopic and macroscopic simulations to be determined, and the IRIDIS HPC resources are available to mitigate the increased computational cost, microsimulation is used to evaluate this research.

Table 5.1: Summary and comparison of the three types of road network simulation.

	SIMULATION TYPE		
	Microscopic	**Mesoscopic**	**Macroscopic**
Summary	Simulates the individual behaviours and movements of vehicles and other agents in the network	Simulates at an accuracy less than microscopic simulation but greater than macroscopic simulation by forming small logical groups	Simulates the net properties of vehicles in lanes or sections as a whole rather than individually
Outputs	Travel times, emissions, stops, routes, positions, and lane-changes for individual vehicles	Flows, routes and travel times for groups of vehicles	Collective system dynamics such as flow, density, and average velocity for a target region
Advantages	• Provides detailed results • Macroscopic quantities can be inferred	• More detailed than macroscopic simulations • Less computationally expensive than microscopic simulations	• Less computationally expensive than microscopic or mesoscopic simulations
Disadvantages	• More computationally expensive than macroscopic or mesoscopic simulation	• Cannot infer all microscopic values from mesoscopic results • Less detailed than microscopic simulations • More computationally expensive than macroscopic simulations	• Cannot infer microscopic values from macroscopic results

5.3.2 Microsimulation Software Available for this Research

In Section 5.3.1 microsimulation was identified as the road network simulation method most appropriate to this research project as it offers the highest resolution results. There are many microsimulation packages available for modelling traffic networks. The criteria that a microsimulation package must meet to be considered in this research are:

- The software must be actively developed by a funded team of software developers.
- The software must be used in industry projects.
- The software must be used in at least one traffic signal control modelling paper reviewed in Chapter 2.
- The software must have a scripting feature though which the simulation and modelled traffic signals can be controlled.
- The software must advertise connected environments as a use case.
- The software must have accessible documentation.

Three software packages were identified as meeting the traffic microsimulation software criteria, namely Aimsun (Barceló and Casas, 2005), SUMO (Krajzewicz et al., 2006), and VISSIM (Fellendorf, 1994). Notably, the Paramics software package (Cameron and Duncan, 1996) does not advertise CVs as a modelling case and does not make its documentation accessible. The Paramics software is most commonly used to model changes to existing roadways, So it is not suitable for assessing the impacts of CVs on urban traffic signal control being researched in this thesis.

Table 5.2, reviews the three microsimulation software packages that are suitable for this research (Aimsun, SUMO, and VISSIM) under the following criteria:

License: Software can be classified as being open-source or commercial. Software is open-source if it is freely available, its source code is publicly accessible, and may be redistributed and modified. Commercial software implies that the software is distributed under license, typically for a fee, to end-users, and its functionality is restricted to applications dictated by the developer.

Operating System: An operating system defines the software that manages a computer's underlying operations. Common operating systems include Windows, Linux, and Mac OSX.

Visualisation: This defines the software packages ability to render graphical representations of the road network in 2 or 3 dimensions.

Scripting: Defines the software package's ability to be interfaced with and controlled using computer code. Internal scripts are those added to a simulation from within the software to interface with the road network model. External scripts can interface with the simulation from outside the running software.

Parallel Simulations: Defines the software package's ability to run several simulations at the same time.

Vehicles: The types of vehicles supported by the software.

Mixed-Traffic: Support for traffic with mixed compositions of various vehicle types.

Pedestrians/Cyclists: Support for pedestrians and cyclists.

Roundabouts: Support for roundabout type road structures.

V2X Communications: Support for the simulations of V2X communications and other connected systems.

Scope: Size of the geographical region the software can simulate.

GIS: Support for importing road networks from map data.

Other Features: Additional modelling tools of interest to this research project such as traffic signal and demand modelling tools.

Table 5.2: Comparison features in the three available microsimulation software packages. Adapted and updated from Saidallah et al. (2016) and Maciejewski (2010)

Feature	SOFTWARE PACKAGE		
	Aimsun	**SUMO**	**VISSIM**
License	Commercial	Open-source	Commercial
Operating System	Windows	Windows/Linux	Windows
Visualisation	2D/3D	2D	2D/3D
Scripting	Yes (internal)	Yes (external)	Yes (external)
Parallel Simulations	Yes (extra cost)	Yes (via scripting)	4 instances/license
Vehicles	Car, bus, truck	Any	Car, bus, truck
Mixed-Traffic	Yes	Yes	Yes
Pedestrians/ Cyclists	Yes	Yes	Yes
Roundabouts	Yes	Limited	Yes
V2X Comms.	Yes	External Package/ Scripting	Yes
Scope	Regional/Country	City/Region	City/Region
GIS	Yes	Yes	Yes
Other Features	SCOOT and SCATS Traffic Control, Demand Modelling	Fully accessible source code	TRANSYT-VISSIM Link, Demand Modelling

5.3.3 Aimsun

Aimsun (Barceló and Casas, 2005) is a commercial microsimulation package for the Windows operating system that uses the Gipps safety distance car-following model (Gipps, 1981). Aimsun allows scripting from within the console, which limits users' ability to automate their testing procedure. Aimsun also only models three types of vehicle. Aimsun has built-in support for vehicular communications which supports the research on CVs conducted in this thesis. Aimsun has the largest scope of the microsimulation packages compared as it can manage region to country-level simulations. Aimsun has the benefit of being able to support the SCOOT and SCATS adaptive traffic signal controllers which could be used as benchmarks and has built-in demand modelling features to simplify road network modelling. The disadvantage of Aimsun is that its scripting interface requires the simulation to be running before the script can interface with it. Aimsun also requires an extra fee to be able to run simulations in parallel.

5.3.4 Simulator of Urban MObility (SUMO)

SUMO (Krajzewicz et al., 2006) is an open-source microsimulation package developed by the German Aerospace Centre, that support the Windows and Linux operating systems, and uses the Krauß (Krauß, 1997), IDM (Treiber et al., 2000), or Wiedemann (Wiedemann and Reiter, 1992) car-following models. The advantage of SUMO is that as open-source software, simulations can be fully customised through scripting, meaning all aspects of the simulation can be controlled, including the vehicle types and traffic signals. The disadvantage of SUMO is that it does not have links with other traffic signal controllers as the other two packages have due to its open-source license. As SUMO runs natively on Linux, it is the most appropriate choice for running on the IRIDIS HPC, so the benefits of parallel simulations can be realised.

5.3.5 VISSIM

VISSIM is (Fellendorf, 1994) is a Windows-based microsimulation package that uses the Wiedemann car-following model (Wiedemann and Reiter, 1992). Like Aimsun, VISSIM only supports the simulation of cars, buses and trucks. VISSIM has the benefit of a TRANSYT link, which would be useful as a benchmark traffic signal controller. Like Aimsun, VISSIM also has demand modelling tools to assist with road network building. Similarly to Aimsun, VISSIM scripting interface is disadvantaged by the fact it requires the simulation to be running before the script can interface with it. VISSIM also has a highly restrictive parallelisation policy of 4 simulations per license, which could slow computation down considerably.

5.3.6 Selection of the Microsimulation Software for this Research

From the comparison between the available software packages drawn in Table 5.2, SUMO is the most suitable choice for this research project. SUMO is open-source, meaning it is free to use, and its source code can be inspected and edited. Being able to inspect and edit the source, combined with its robust scripting interface TraCI, offer improved options for reproducibility over commercial software. SUMO's scripting interface is superior to VISSIM and Aimsun's interfaces, as it allows simulations to be started from the script itself. In VISSIM and Aimsun, the simulation must first be running before the script can connect to the simulation. SUMO's approach to scripting means that it is significantly easier to manage parallel instances, which is invaluable in reducing the time needed to simulate the parameter space of this research and perform repeated experiments. SUMO also supports more vehicle types than Aimsun or VISSIM, meaning the modelled traffic flows will be more representative of real traffic. SUMO is the best microsimulation package to use for this research as the parallelisation conditions are too restrictive with the other packages, and SUMO runs natively on the IRIDIS HPC. As the parameter space for this research includes multiple intersections, multiple traffic demands, and varying level of CVs, the number simulations needed to evaluate this research is large, so SUMO is the best package to explore the parameter space.

5.3.7 Reproducible Research Software

When developing simulation software, it is important to ensure the simulations, and therefore the results, are reproducible by other researchers. Reproducibility here is that if another researcher ran the codes used for this research under the same software conditions, the same output would be achieved. In order to ensure the results are reproducible, the following systems are used while developing codes and running simulations for this research:

Version Control with Git
Software development is an iterative procedure, and as the code-base expands and is revised, it is necessary to track the changes between successive versions of the code. Git (Torvalds and Hamano, 2010)(https://git-scm.com/) is a free and accessible version control system that is used to track changes to the software developed by this research.

Software containers
Software containers can be used to provide an operating environment with a known configuration. Therefore, all software run within that environment draws on software dependencies whose exact configuration are known, ensuring reproducibility. Singularity (Kurtzer et al., 2017)(https://singularity.lbl.gov/) and Docker (Merkel, 2014)(https://www.docker.com/) are free container management and provisioning tools that are used in this research to ensure all simulations are performed within a known software environment.

5.4 Selecting a Car-following Model

Microscopic traffic-flow models are needed to simulate vehicles in the road network. In Section 5.3.2 SUMO was selected as the most appropriate simulation package for this research. SUMO implements several of the best validated traffic-flow models, namely the Krauß Model (Krauß, 1998), the IDM (Treiber et al., 2000), and the Wiedemann Model (Wiedemann and Reiter, 1992).

Microsimulations typically use a 1 s time step. This time-step is due to the fastest dynamic considered in the simulation being the driver reaction time, which for human drivers, the literature suggests is ≈ 1 s. In this research, V2X communications are the system with the fastest dynamics to be simulated. In this research, the ETSI CAM standard (see Section 2.3), is used to model CV communications. The ETSI CAM standard is used over the SAE standard as the ETSI standard is open-source, and its documentation describes its implementation in details. Section 2.3 identified that both the ETSI and SAE standards are similar due to effort to harmonise the standards (EU-US ITS Task Force Standards Harmonization Working Group, 2012). As the ETSI CAM standard was used, a time step at least as small as 0.1 s is required to capture the 10 Hz CAMP packet frequency. The Wiedemann model has a minimum threshold of 0.1 s (Fellendorf and Vortisch, 2010), so is not appropriate for simulations with dynamics faster than the minimum threshold. The Krauß model is stable as long as the simulation time steps are smaller than the driver's reaction time (Krauß, 1998), and the IDM has been studied at time steps as low as 0.1 s (Treiber et al., 2006).

For this study, the Krauß model is most suitable as it produces stable collision-free traffic flow and is well validated Krauß (1998). The Krauß model has been shown to outperform the other traffic-flow models in mixed traffic scenarios (Mathew and Ravishankar, 2011). The IDM can cope with mixed traffic flows but must be adapted.

The formulation of the Krauß model is as follows (Krauß, 1998):

$$\nu_{\text{safe}}(t) = \nu_{\text{l}}(t) + \frac{g(t) - g_{\text{des}}(t)}{\tau_{\text{b}} - \tau} \tag{5.1}$$

$$\nu_{\text{des}}(t) = \min\left(\nu_{\max},\ \nu(t) + a(\nu)\Delta t,\ \nu_{\text{safe}}(t)\right) \tag{5.2}$$

$$\nu(t + \Delta t) = \max\left(0,\ \nu_{\text{des}}(t) - \sigma\right) \tag{5.3}$$

$$x(t + \Delta t) = x(t) + \nu \Delta t \tag{5.4}$$

Where: The Equations for the Krauß car-following model, and the parameter descriptions

ν_{safe}	is the safe velocity	ν_{des}	is the vehicle's desired velocity
ν_{l}	is the lead vehicle's speed	$\nu_{\max}$	is the vehicle's max velocity
x	is the vehicle position	g	is the vehicle's gap distance
g_{des}	is the vehicle's desired gap	τ	is the driver reaction time
a	is the vehicle's acceleration	σ	is the driver imperfection
t	is the simulation time	Δt	is the time step
$\tau_{\text{b}} = \bar{\nu}/b$	is the time scale (where $\bar{\nu}$ is the vehicle's mean speed and b its typical deceleration)		

are given in Equation 5.1. The Krauß car-following model updates a vehicles velocity based on its desire to maintain a safe headway with the vehicle ahead. A vehicle will not exceed its max speed or the road speed limit, and will speed up or down according to its defined acceleration characteristics. The Krauß model includes the driver imperfection parameter σ, which varies the driving behaviour of each vehicle slightly. The driver imperfection makes the traffic flow more realistic as it better captures the differences between aggressive (high acceleration, high speed) and timid (slower acceleration and moderate speed) driving styles.

The review of microsimulation packages in Section 5.3.2 showed that SUMO is capable of modelling any type of vehicle. The UK Government issues licences based on vehicle types (UK Government, 2019). Here it is assumed that tractors are not present in urban road networks and that trailers are not modelled as microsimulation packages do not support them. In that case, the five licensed vehicle types in the UK are cars, motorcycles, buses, Light Goods Vehicles (LGVs), and Heavy Goods Vehicles (HGVs). Table 5.3 describes the parameters for the Krauß car-following model for the five types of vehicles that are used in this research. The car-following parameters for CVs and unconnected vehicles are the same. As distinguished in Chapter 1, it is assumed that vehicle connectivity does not affect how cars interact with each other, as connectivity and autonomous driving are separate functions.

Table 5.3: The Krauß car-following model parameters for the modelled vehicle types (DLR, 2018).

Parameter (*unit*)	**Car**	**MC**	**LGV**	**HGV**	**Bus**
Acceleration $(\mathrm{m/s^2})$	2.6	5.0	2.0	1.3	1.0
Deceleration $(\mathrm{m/s^2})$	4.5	9.0	4.0	3.5	3.5
Driver Imperfection - σ	0.5	0.5	0.5	0.5	0.5
Reaction Time - $\tau(\mathrm{s})$	1.0	1.0	1.0	1.0	1.0
Length (m)	4.3	2.2	6.5	7.1	12.0
Min. Gap (m)	2.5	2.5	2.5	2.5	2.5
Max. Speed $(\mathrm{km/h})$	180	200	160	130	85

L/HGV: *Light/Heavy Goods Vehicle*
MC: *Motorcycle*

5.5 Case Study Model Building

In order to validate the usefulness of any traffic signal control strategies developed by this research, a realistic case study modelling a real-world urban corridor was undertaken. Several ongoing CV trials were reviewed in Section 2.5.6. However, the majority of trials covered highway traffic rather than the urban corridors, which are the focus of this thesis. Furthermore, this thesis is focused on integrating CV data with traffic signal control with a focus on the UK. At the time of case study creation, the UK trials were still emerging, and the data from their trials was unready, or not publicly available. The main benefit of existing trials was providing insights into which communication systems and standards were being seriously considered for C-ITS applications. The most accessible and comprehensive UK traffic data that covers urban corridors at the time of model creation was the Birmingham and West Midlands real-time traffic data (Birmingham City Council, 2016) provided by Birmingham City Council.

This section outlines the chosen case study, the datasets used to model it, and the road network building and traffic assignment procedure. Finally, the strengths and limitations of the case study model are discussed.

5.5.1 Study Location

The road section chosen for the case study was from Selly Oak (latitude/longitude: 52.439177, -1.940248), to the Warwickshire Country Cricket Club (latitude/longitude: 52.455288, -1.907067), in Birmingham, UK. The main urban corridor is highlighted in red on the map in Figure 5.2. Birmingham was selected as it is the second-largest city in the UK, and the Birmingham Urban Traffic Management Centre also makes its data open to the public, making it the most accessible, current, and comprehensive source of traffic data in the UK. Southampton was also considered as the Transportation Research Group has access to the loop detector data for the city centre. Southampton was ultimately not chosen as the loop detector coverage is too degraded to reproduce the traffic flows in the area with sufficient accuracy.

The Selly Oak area was the best candidate in the Birmingham dataset for study as it had the highest density of working loop detectors and traffic signals than any other location in the city for the length of the route. It also receives high volumes of traffic due to the following features:

1. Warwickshire Country Cricket Club
2. Several supermarkets
3. Two train stations
4. A 1000+ bed hospital
5. University of Birmingham
6. Several park areas
7. Large residential areas
8. A retail park

Figure 5.2: Map of the case study location from Selly Oak to the Warwickshire County Cricket Club. The features in the numbered list in Section 5.5.1 are represented on the map by their number.

5.5.2 Data Used for the Case Study

Here the datasets used to build the urban corridor road network and traffic flows for the case study are detailed.

Manual Site Survey

A manual traffic survey of the target urban corridor was conducted over two days in February 2019. The traffic survey consisted of:

1. 10-20 minute traffic counts for the approaches at each signalised intersection in the target area.
2. 15 minute video recordings of each signalised intersection in the urban corridor.
3. Observation of the stage patterns at each signalised intersection.
4. 15 minute counts of passing vehicles by vehicle type.

The information gathered is included in Appendix C, and was used to ensure the data collected from the datasets are consistent with the real state of the traffic in Selly Oak.

OpenStreetMap Data

The OpenStreetMap (OSM) Foundation (OpenStreetMap Foundation, n.d.*a*) is an international not-for-profit organisation that provides open-source geographic data (Haklay and Weber, 2008). Access to the data is provided under the Open Data Commons Open Database License (ODbL) (Open Data Commons, n.d.). Geofabrik GmbH provides larger portions of the dataset under the ODbL and Creative Commons BY-SA 2.0 (Creative Commons, n.d.). The OSM data provided the base information from which the physical urban corridor was modelled in SUMO. The OSM dataset contains data about road geometry, road type (e.g. motorway, residential), numbers of lanes, locations of traffic signals, and speed limits.

Birmingham Urban Traffic Management and Control Centre Data

Birmingham City Council provides the Birmingham and West Midlands real-time traffic data (Birmingham City Council, 2016) under the UK Open Government License (National Archives, n.d.). An explanation of the full Urban Traffic Management and Control (UTMC) dataset can be found on GitHub (Radford and Rafter, n.d.). The specific UTMC dataset that was used in this research is the inductive loop dataset, from the city's traffic control system. The inductive dataset is drawn from roadside loop detectors, and average values aggregated over 5 minutes are reported. The dataset contains the following data (descriptors adapted from (Radford and Rafter, n.d.)):

SCN: System Code Number, a unique value that identifies each loop detector.

Date: The date (YYYY-MM-DD) and time (HH:MM:SS) the observation was recorded. The time indicates the beginning of the interval the data are aggregated over.

Description: Additional information about the loop site.

Northing and Easting: Ordnance Survey Grid reference based on the British National Grid, that identifies the exact position of the loop detector on the rod section.

Flow: The flow in vehicles per hour travelling over the link derived from the loop detectors.

Speed: Information about the average vehicle speed on a link over the preceding five minutes, derived from link length, a pre-measured cruise time for the link and vehicle delay.

Time: Information about the travel time over a link. An estimate of the time a typical vehicle takes to travel along a link at an average speed. The Time value is obtained by adding vehicle delay (an estimate of delay encountered by vehicles on a link) to the pre-measured 'cruise' time of vehicles between a loop detector and stop line.

Time_Status: Numeric, typically 0. Unclear what this represents.

Time_Type: Numeric, either 0 or 1. Unclear what this represents.

5.5.3 Developing the Simulated Urban Corridor in SUMO

SUMO has a variety of tools for building road network models. The approach taken here is to import OSM data into SUMO and then edit the network. The exact steps for the road building process are:

1. Download the OSM data containing for the target area from a portal such as Geofabrik. Geofabrik allows the download of regional OSM data for analysis.
2. Use the Osmosis (OpenStreetMap Foundation, n.d.*b*) tool to extract the target area from the larger dataset.
3. Use the osmfilter tool to extract only the OSM data concerning roadways
4. Use SUMO's NETCONVERT tool to map the filtered OSM data to a SUMO format road network.
5. Use SUMO's NETEDIT tool to fix any connections that did not import correctly. SUMO will not connect roads when it cannot automatically calculate a connection for them. SUMO warns the user of these locations so they may manually form the connections.
6. Use NETEDIT to remove any unwanted features from the road network model. Unwanted features could include roads that were not removed during the filtering process, or house or signage objects that have no bearing on the road network. For this model, only roads labelled as highway/motorway, primary, or secondary roads were kept. Only residential roads connecting to the A38 and B384, and B4217 were were kept. This selection of roads ensures that all roads that can contribute to the origin-destination flows in the model are included.
7. Using NETEDIT, specify which intersections are signalised, and which are priority junctions.
8. Use the Northing and Easting information from the Birmingham UTMC loop data to add inductive loops into the road network at their actual locations. The inductive loops can then be used by the traffic signal control algorithms developed by this research to assess how they behave with existing infrastructure.

This process yields the urban corridor road network model for the Selly Oak area of Birmingham city as depicted in Figure 5.3.

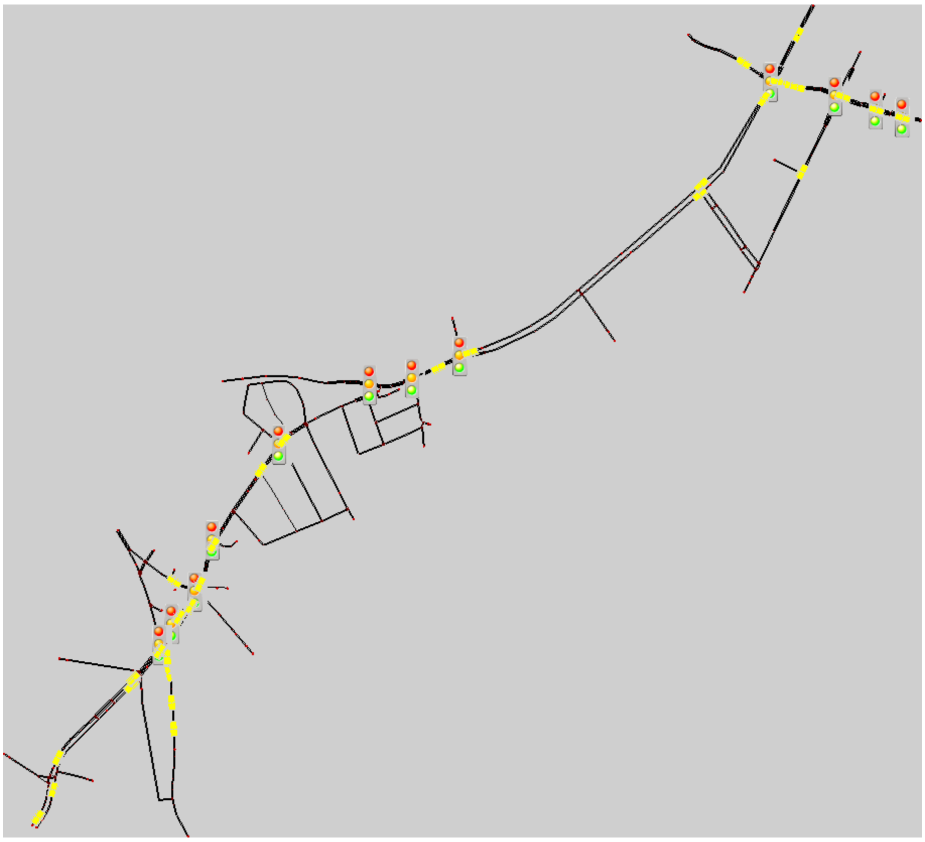


Figure 5.3: SUMO representation of the Selly Oak urban corridor. Intersections with traffic signals are highlighted with the red-amber-green light block (12 in total), The SUMO model is a 1:1 replica of the urban corridor it represents. The locations of the inductive loops are marked with yellow rectangles (loop size not to scale for visualisation).

5.5.4 Demand Modelling

With the urban corridor road network built the next stage in the model development was to model the traffic demand on the corridor. The most ubiquitous approach to demand modelling is the Four-Step Model (FSM)(De Dios Ortúzar and Willumsen, 2011; Hensher and Button, 2007). The inputs to the FSM are road user activity data and information regarding the layout and usage of the transport network. The modelling process for the FSM is:

1. **Trip Generation:** From the activity data, the frequency of use for each origin and destination point in the corridor can be determined. The trip frequencies indicate the likelihood of travel from each point in the corridor at a given time.
2. **Trip Distribution:** With the number of trips at each origin and destination known, the trips can be distributed between origin-destination (OD) pairs that are connected, forming an OD matrix.
3. **Mode Choice:** With the trips determined the next step is to allocate each trip a mode of travel, e.g. car/truck/bus.
4. **Route Choice:** With the trips and travel modes determined the routes used for each trip can be calculated.

The steps, inputs, and outputs for the FSM are summarised in Figure 5.4.

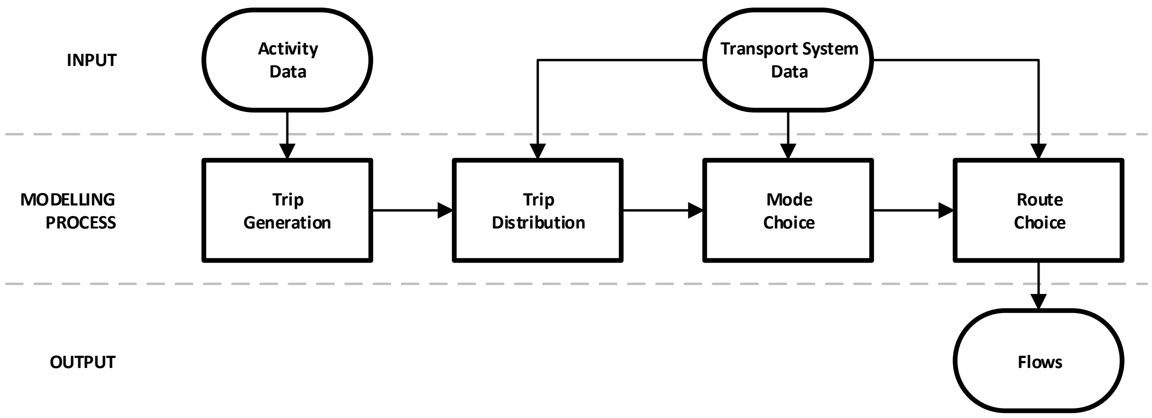


Figure 5.4: A graphical representation of the FSM demand modelling approach.

In this research, the ability to model the urban corridor is restricted by the availability of suitable data. The data available are a combination of geographical map data from OSM, and flow information for specific points in the corridor from the Birmingham UTMC dataset. The process detailed below builds as accurate a representation of traffic flow for the Selly Oak corridor as possible with the available data.

The methods used at each stage in the FSM procedure for this case study is discussed in the following sections.

5.5.4.1 Trip Generation

For this model, trips were generated based on the known flow values from the Birmingham UTMC SCOOT data. Before generating trips from the data, the following steps to pre-process the data were taken:

1. Inductive loop data were downloaded, as described in Section 5.5.2, for the entire corridor for the years 2016 and 2017. Due to the construction of a 'Cycle Superhighway' through Selly Oak from 2018 onward, there were a high number of loop outages, so these data were not used.
2. The data were converted from the XML to CSV file format for ease of manipulation.
3. Any entries not concerning the SCNs of loops not in the Selly Oak model were filtered out.
4. The data aggregation interval was increased from 5 minutes to 15 minutes to normalise the time intervals between detectors (not all detectors has synchronised clocks). The clock skew was of the order of 1 s and uniform, so increasing the binning interval ensured three entries per bin after the first bin. Increasing the binning interval simplified the route calibration while traffic flow level remains unaffected.
5. The case considered in this model is the average weekday traffic. Therefore, data for weekends were removed, and the data averaged for each 15 minute time interval. Weekends were removed as they significantly reduced the morning and evening traffic flow peaks compared to only considering the weekday data. The effects of weekends are illustrated in Figure 5.7 and discussed further below.
6. During the averaging process, the minimum, maximum were extracted. The average flow $\pm 20\%$ were extracted as indicators of high and low traffic volumes. The 20% limit was found empirically as the value beyond which the traffic deviates so far from the underlying TRANSYT plan that gridlock occurs in the corridor. As TRANSYT has no gating strategy, it cannot mitigate gridlock.

Figure 5.5 illustrates the locations and IDs of the loops used for vehicle source and sink data for the origin-destination traffic flow calculations. Figure 5.6 depicts the flow information obtained for a single loop detector. Each inductive loop counts the flow for one lane only. *Flow* is the average flow at each 15-minute interval. *Fmax* and *Fmin* are the maximum and minimum flows respectively, and *Fhi* and *Flo* are the average flow $\pm 20\%$ respectively. The 20% limit was found empirically as the value beyond which the traffic deviates so far from the underlying TRANSYT plan that gridlock occurs in the corridor. As TRANSYT has no gating strategy, it cannot mitigate gridlock. Figure 5.7 illustrates the difference in the mean flows if only weekday flows are considered, only weekends are considered, and both are considered together. The flows are compared for the same single lane loop detector as in Figure 5.6. The mean flow for weekdays exhibits the characteristic peaks for weekday rush hours at 08:00 and 17:00. The weekend flow does not exhibit the same flow characteristics as weekday traffic, there are no rush hour peaks, the overall traffic volume is lower than during the week, and the traffic mostly occurs between 12:00 and 18:00. It can be seen that when weekend flows are considered with the weekday flows, the resulting flow characteristic does not exhibit rush hour peaks, and its shape is not representative of either weekends or weekdays. Weekdays are considered in the research as the overall traffic demand is higher during the week than at weekends, and so is the more challenging traffic demand to manage.

Each detector is matched to its corresponding origin or destination lane in the urban corridor road network model. The flow information then becomes the total trips per hour going to/from the corresponding lane.

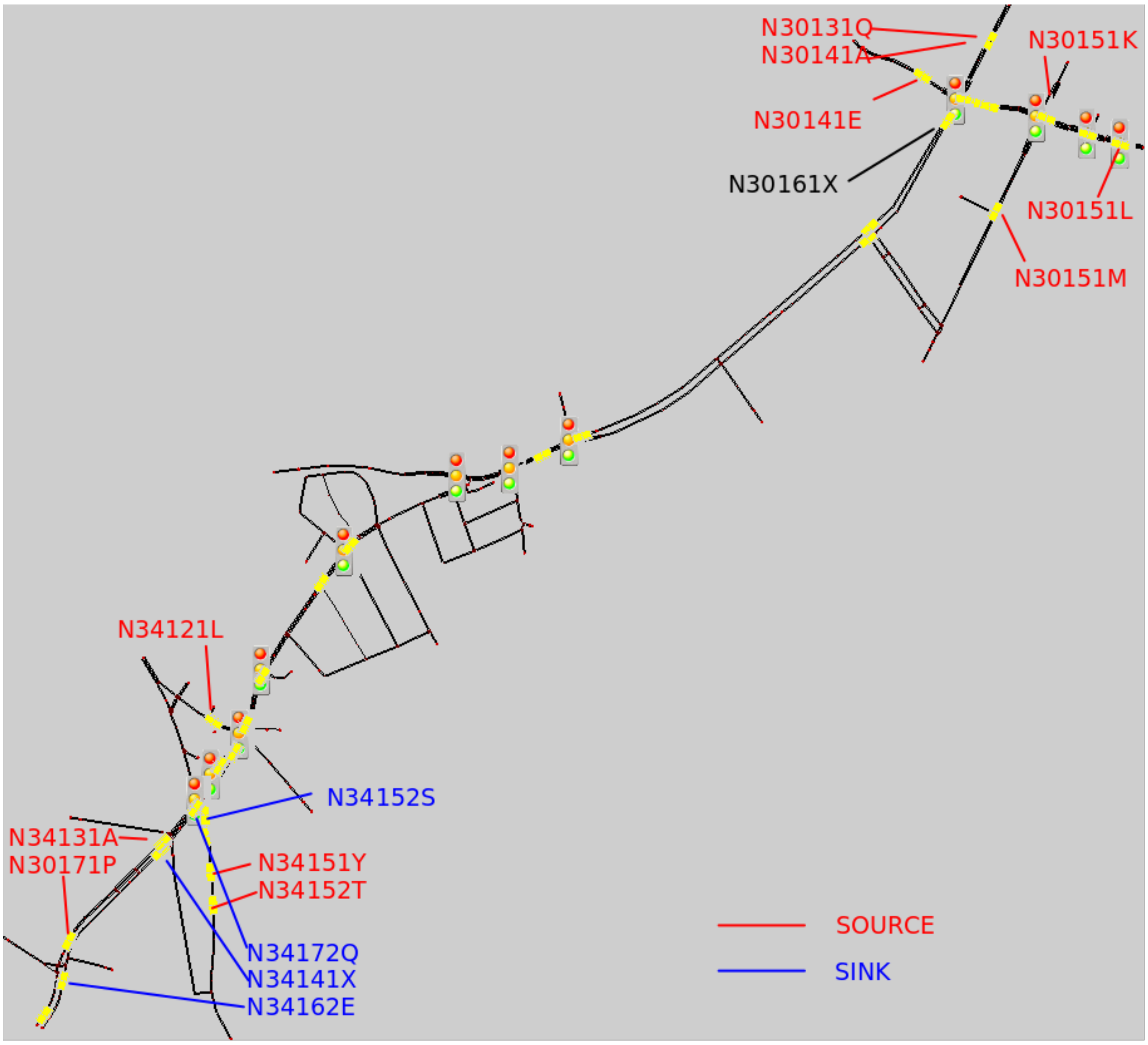


Figure 5.5: A illustration of the locations of the inductive loops and their IDs that form the source and sink calculation data for the urban corridor road network model. Loop N30161X is also labelled as it is used for examples in this section.

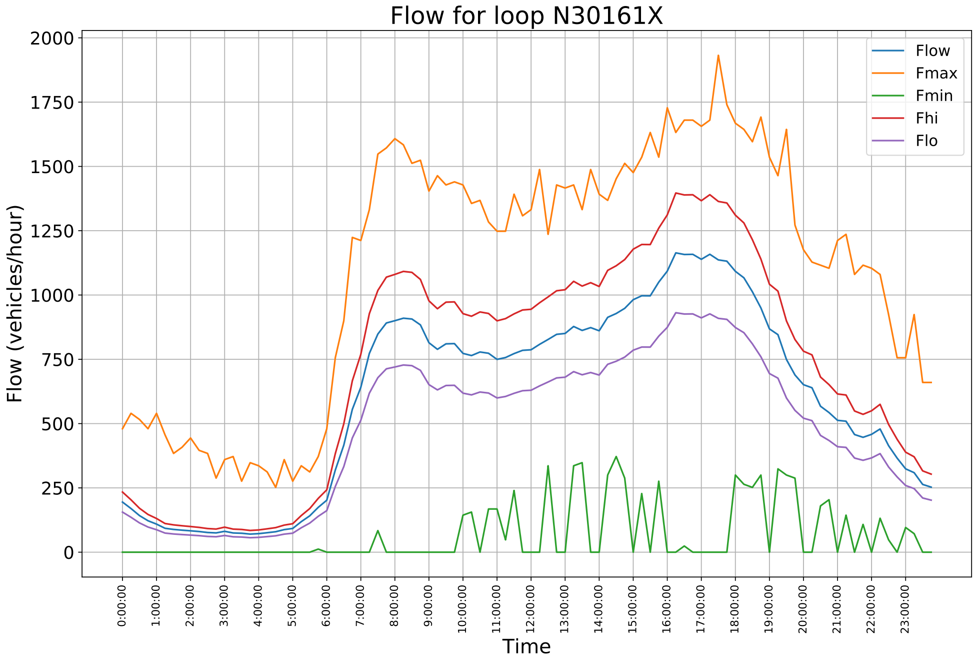


Figure 5.6: An example of the flow information for one inductive loop detector. Flow is the average flow in vehicles per hour at each 15 minute interval. Fmax and Fmin are the maximum and minimum flows respectively, and Fhi and Flo are the average flow $\pm 20\%$ respectively.

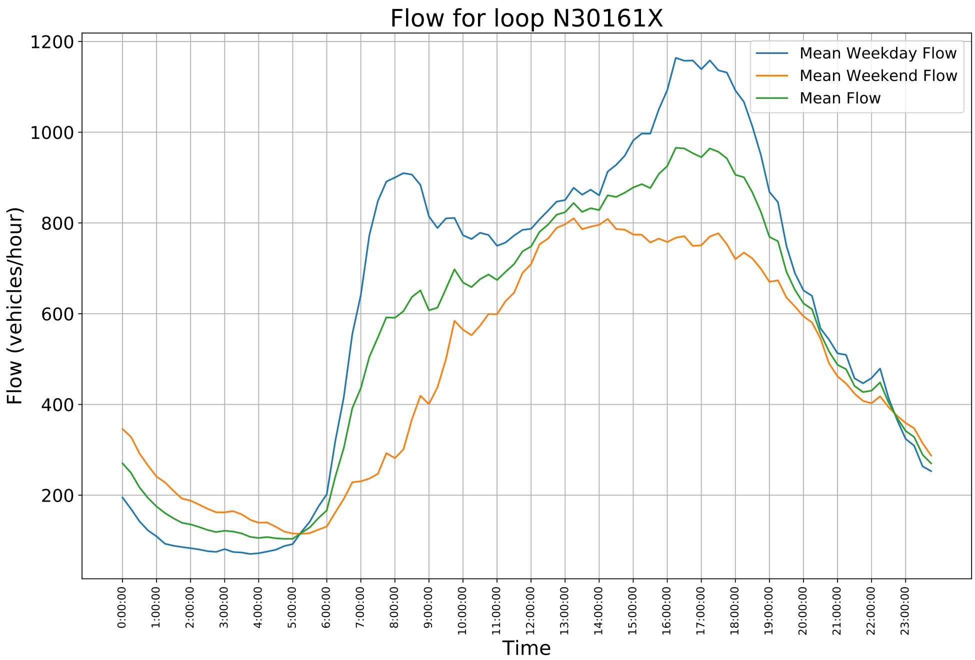


Figure 5.7: An example of the difference in weekday and weekend flow information for one inductive loop detector. Flows are in vehicles per hour.

5.5.4.2 Trip Distribution

In this section, the method for distributing the generated trips amongst the origins and destinations. First, the notation is introduced, then the methods for the initial assignment and calibration of the OD matrix are described.

Notation

Let m and n be the number of origin and destination lanes in the road network respectively. The OD or trip matrix is defined as T_{ij}, a matrix of size $m \times n$ denoting the number of vehicles per hour making the trip from origin i (rows) to destination j (columns). Furthermore, let:

$$O_i = \sum_j T_{ij} \tag{5.5}$$

$$D_j = \sum_i T_{ij} \tag{5.6}$$

where O_i is the column vector summation of all trips originating from each origin lane, and D_j is the row vector summation of trips travelling to each destination. Finally, let T_{total} be the total number of trips given by:

$$T_{\text{total}} = \sum_i \sum_j T_{ij} \tag{5.7}$$

Enforcing the condition that all vehicles entering the network must eventually leave the network, the following equality must be true:

$$\sum_i O_i = \sum_j D_j = T_{\text{total}} \tag{5.8}$$

Table 5.4 describes the general format of the trip matrix given by the definitions above.

Table 5.4: The general form of the trip matrix system T_{ij}, O_i, and D_j

	Destinations					
Origins	1	2	3	$\cdots$	n	O_i
1	T_{11}	T_{12}	T_{13}	$\cdots$	T_{1n}	O_1
2	T_{21}	T_{22}	T_{23}	$\cdots$	T_{2n}	O_2
3	T_{31}	T_{32}	T_{33}	$\cdots$	T_{3n}	O_3
$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\ddots$	$\vdots$	$\vdots$
m	T_{m1}	T_{m2}	T_{m3}	$\cdots$	T_{mn}	O_m
D_j	D_1	D_2	D_3	$\cdots$	D_n	T_{total}

Initial Trip Assignment

The column vector O_i and row vector D_j are determined from the trip information generated from the collected flow data. As there is no prior travel survey information or turn counts available for the corridor, the most sensible method to use for the initial traffic assignment is a proportional assignment technique of the form initially proposed by Robillard (1975). Details of other assignment techniques can be found in De Dios Ortúzar and Willumsen (2011).

Proportional assignment distributes the origin flows amongst the destinations, or destination flows amongst the origins. Trips are assigned based on the likelihood a vehicle departs an origin for a destination or arrives at a destination from an origin. The trip matrix entries can be assigned from origin flows by:

$$T_{ij} = O_i \mathbb{P}(j|i) \tag{5.9}$$

or from destination flows by:

$$T_{ij} = D_j \mathbb{P}(i|j) \tag{5.10}$$

where $\mathbb{P}(j|i)$ is the probability that a vehicle travels to destination j given that it originated from origin i. $\mathbb{P}(i|j)$ is the probability a vehicle arriving at destination j originated from origin i. Since no prior information regarding trip numbers was available, trips were initially assigned with weighted probabilities based on the number of lanes at each origin/destination point scaled by the speed limit of the road as an indicator of capacity and usage. The probabilities are defined as 0 for U-turns ($i = j$), and for cases where the route from i to j does not exist. The probabilities are therefore given by:

$$\mathbb{P}(j|i) = \begin{cases} 0 & i = j \\ 0 & \nexists \text{ route } i \to j \\ \dfrac{\omega_j N_{\text{lanes},j}}{\sum_j \omega_j N_{\text{lanes},j}} & \text{Otherwise} \end{cases} \tag{5.11}$$

$$\mathbb{P}(i|j) = \begin{cases} 0 & i = j \\ 0 & \nexists \text{ route } i \to j \\ \dfrac{\omega_i N_{\text{lanes},i}}{\sum_i \omega_i N_{\text{lanes},i}} & \text{Otherwise} \end{cases} \tag{5.12}$$

where $\omega_{\{i,j\}}$ is the speed limit at destination j or origin i. $N_{\text{lanes},\{i,j\}}$ is the number of lanes at destination j or origin i, and its sum is the total number of lanes from valid origins/destinations. The following equality holds for the trip distribution:

$$\sum_j \mathbb{P}(j|i) = \sum_i \mathbb{P}(i|j) = 1 \tag{5.13}$$

Trip Matrix Calibration

The initial trip assignment provides an estimate of the trip matrix's values. However, in this study, both origin and destination flows are known and assigned. Double assignment may lead to trips to be over or under assigned. Therefore the matrix needs to be calibrated after assignment. Two widely used approaches for trip matrix calibration are Growth-factor methods, and Gravity models (De Dios Ortúzar and Willumsen, 2011).

In growth factor methods, trip matrix adjustments of the following form are applied:

$$T_{ij,\text{new}} = \tau T_{ij,\text{old}} \tag{5.14}$$

where τ is the expansion ratio (growth-factor). The simplest expression of a gravity model has the form:

$$T_{ij} = \frac{\alpha P_i P_j}{d_{ij}^2} \tag{5.15}$$

where P_i and P_j are the populations at locales i and j, α is a proportionality factor, and d_{ij} is the distance between locales i and j.

There is insufficient data available for a gravity model approach, so a growth-factor approach is taken. Growth-factor methods can be singly constrained if only the origin flows or destination flows need to be adjusted, or doubly constrained if both flows need to be adjusted. Here, both the origin and destination flows need to be calibrated, so a doubly constrained growth-factor method is necessary.

The Furness method (Furness, 1965) is the best known of the doubly-constrained growth factor methods. The updates for the Furness method have the form:

$$T_{ij,\text{new}} = a_i b_j T_{ij,\text{old}} \tag{5.16}$$

where a_i is the column vector of origin growth-factors, and b_j is the row vector of destination growth-factors. given a target origin vector $O_{i,\text{target}}$, and target destination vector $D_{j,\text{target}}$ such that:

$$\sum_i O_{i,\text{target}} = \sum_j D_{j,\text{target}} = T_{\text{total,target}} \tag{5.17}$$

The updated matrix for the Furness method is given in Table 5.5. The solution to the matrix system given in Table 5.5 is found by performing the following steps:

1. Initialise all $b_j = 1$
2. Solve for a_i such that the target origin criteria $O_{i,\text{target}}$ are satisfied.
3. Using a_i from the previous step, Solve for b_j such that the target destination criteria $D_{j,\text{target}}$ are satisfied
4. Repeat steps (2) and (3) until the system convergence criteria are met.

Table 5.5: The general form of the matrix system for the Furness method.

	Destinations							
Origins	1	2	3	$\cdots$	n	O_i	a_i	$O_{i,\text{target}}$
1	T_{11}	T_{12}	T_{13}	$\cdots$	T_{1n}	O_1	a_1	$O_{1,\text{target}}$
2	T_{21}	T_{22}	T_{23}	$\cdots$	T_{2n}	O_2	a_2	$O_{2,\text{target}}$
3	T_{31}	T_{32}	T_{33}	$\cdots$	T_{3n}	O_3	a_3	$O_{3,\text{target}}$
$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\ddots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$
m	T_{m1}	T_{m2}	T_{m3}	$\cdots$	T_{mn}	O_m	a_m	$O_{m,\text{target}}$
D_j	D_1	D_2	D_3	$\cdots$	D_n	T_{total}	–	–
b_j	b_1	b_2	b_3	$\cdots$	b_n	–	–	–
$D_{j,\text{target}}$	$D_{1,\text{target}}$	$D_{2,\text{target}}$	$D_{3,\text{target}}$	$\cdots$	$D_{n,\text{target}}$	–	–	$T_{\text{total,target}}$

5.5.4.3 Mode Choice

With the trip matrix defined, the modes of transport used to make the trips were determined. The UK Department for Transport provides information about the distribution of different vehicle types on a per-region basis in the VEH0104 dataset (UK Govt. Dept. Transport, 2017). Figure 5.8 shows the distribution of vehicles registered in the West Midlands area of the UK, where Birmingham is located. The values derived from the VEH0104 dataset (UK Govt. Dept. Transport, 2017) are compared with results from the manual traffic survey (see Appendix C). The comparison shows that the VEH0104 dataset is consistent with the observed vehicle type counts. The data from the VEH1014 dataset are used to assign types to inserted vehicles based on the proportion of each type of vehicle in the network as it is representative of the entire West Midlands fleet, not just the traffic observed during the survey.

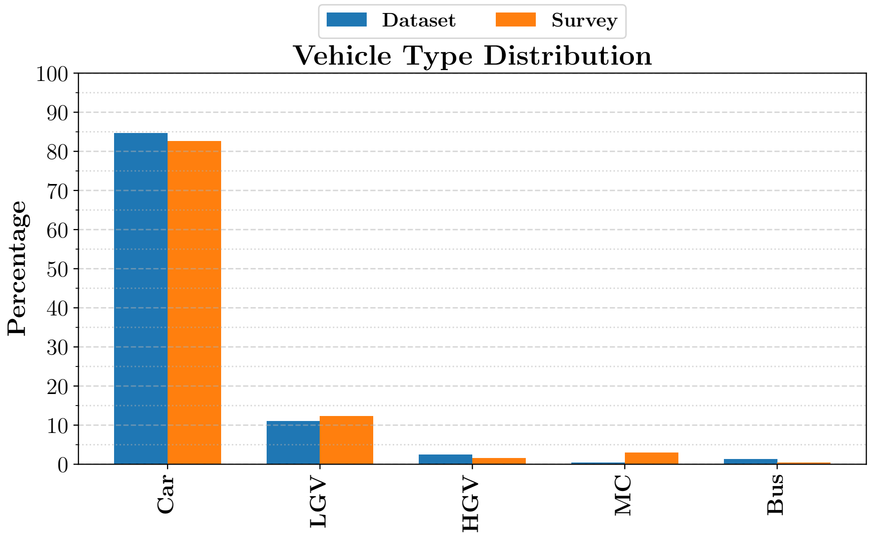


Figure 5.8: The distribution of vehicles by type in the West Midlands region of the UK. The proportions derived from the VEH0104 dataset (UK Govt. Dept. Transport, 2017) are compared with the results from the manual traffic survey. LGV (Light Goods Vehicle), HGV (Heavy Goods Vehicle), MC (Motorcycle).

5.5.4.4 Route Choice

The Selly Oak corridor is a local area with very few alternative paths between origins and destinations. It is reasonable to assume that drivers in the corridor follow the shortest path to their destination. Dijkstra's algorithm (Dijkstra, 1959) for finding the shortest path between two nodes is the best choice for the localised urban corridor studied here. Dijkstra's algorithm is implemented in SUMO's routing tool DUAROUTER. With the trip matrix calculated, the values can be passed to DUAROUTER for routing. All vehicle flows are uniformly distributed across their 15-minute intervals.

5.5.4.5 Model Calibration and Validation

In order to validate and calibrate traffic models, (Transport for London, 2010) recommends using the GEH-statistic to determine in the traffic flows within the model match traffic counts to an acceptable level of accuracy. The GEH-statistic correlates observed traffic flows with simulated traffic flows using the following equation:

$$GEH = \sqrt{\frac{(V_{\mathrm{sim}} - V_{\mathrm{obs}})^2}{\frac{V_{\mathrm{sim}}+V_{\mathrm{obs}}}{2}}} \tag{5.18}$$

where V_{sim} is the volume of traffic in the simulation, and V_{obs} the traffic volume from the observed data. For the simulation to be representative of real-world traffic, it is recommended that the GEH statistic be $<$5% for more than 85% of cases (Katrakazas et al., 2019).

For this research, the model flows were calibrated to the average demand case (see Section 5.5.4.1), and the low and high demand cases were scaled accordingly. For each detector, and for each 15-minute aggregation period, the GEH-statistic was captured. This research uses the more strict criteria that the max GEH-statistic for any detector in each period is less than 5%. If the model did not meet the strict criteria, the observed flows were fed back to the FSM, and the Furness method (Equation 5.16) used to recalibrate the trip distributions. The convergence criteria for the calibration and validation step was that the average change in GEH statistic values was less than 0.5% between iterations. Convergence was achieved after 13 iterations.

Figure 5.9 shows the result of the model calibration and validation. It can be seen that the GEH-statistics for each time period in the calibrated model meet the strict $<$5% criteria. In Figure 5.9 it can be seen that the highest error occurs between 00:00:00 and 06:00:00, and is around 2%. for all other times, the error is around 1%. As the GEH-statistics are all $<$5% the traffic flow is satisfactorily representative of the real traffic flow.

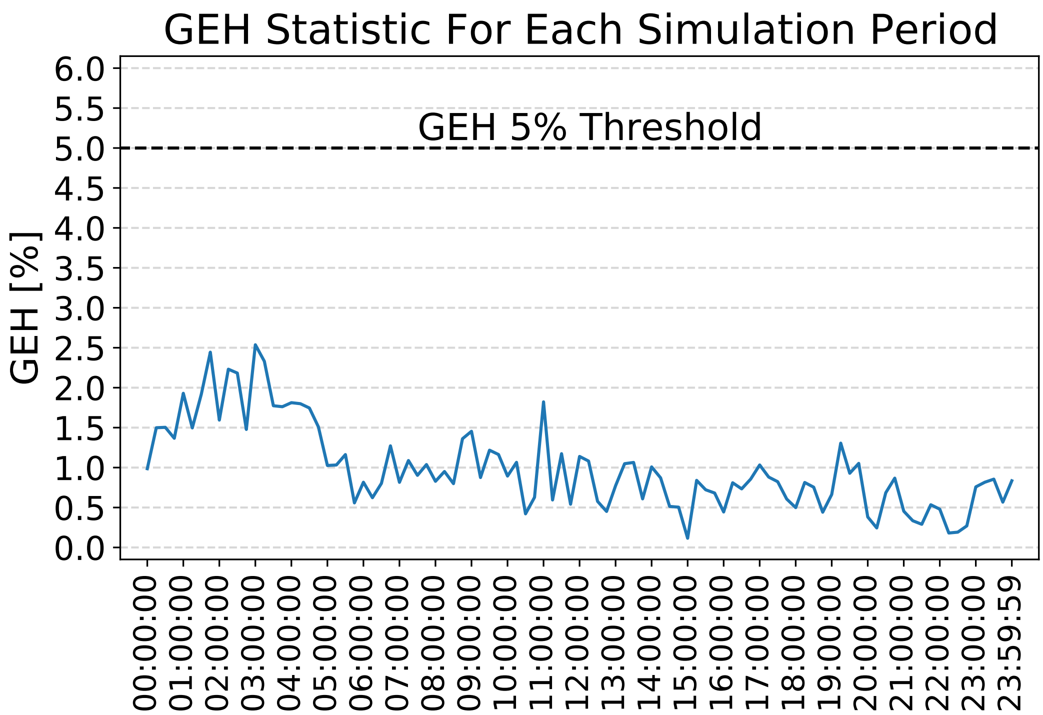


Figure 5.9: The maximum GEH-statistic for each 15-minute interval from 00:00:00 to 23:59:59. The 5% error threshold is shown by the black dashed line.

5.5.4.6 Estimating Passenger Counts

As CVs can transmit any information, a traffic signal control system can use data about numbers of passengers in the vehicle as inputs to it control actions. The number of passengers is a data point that is not directly available from the microsimulation or signal controller. The occupancy of passenger cars is determined by:

$$n_{\text{p,car}} \sim \{x \in [1,4] \mid x \in \mathbb{Z} \mid \sigma = 1.6\} \tag{5.19}$$

where it is assumed all passenger cars have 1 to 4 passengers, $n_{\text{p,car}}$ is the integer number of passengers drawn from a distribution with mean $\sigma = 1.6$. The mean is based on the average car occupancy in the UK (UK Govt. Dept. Transport, 2019*a*).

For buses, correspondence with the local bus operator in Birmingham, National Express West Midlands, revealed that their fleet is composed of 70% double-decker Alexander Dennis E400 buses (86 person capacity (Alexander Dennis, 2019*b*)), and 30% single-decker Alexander Dennis E200 buses (45 person capacity (Alexander Dennis, 2019*a*)).

It is assumed that the bus passengers are uniformly distributed integer values drawn from the time-dependent distribution $n_{\mathrm{p,bus}}$. Where a 24-hour day is divided into off-peak (00:00-06:00, 20:00-00:00), inter-peak (11:00-16:00), and peak (06:00-11:00, 16:00-20:00) traffic periods, $n_{\mathrm{p,bus}}$ is given by:

$$n_{\mathrm{p,bus}} \sim \begin{cases} \left\{x \in \left[0,\ \frac{N_{\mathrm{cap}}}{3}\right] \,\middle|\, x \in \mathbb{Z}\right\} & OFFPEAK \\ \left\{x \in \left[\frac{N_{\mathrm{cap}}}{3},\ \frac{2N_{\mathrm{cap}}}{3}\right] \,\middle|\, x \in \mathbb{Z}\right\} & INTERPEAK \\ \left\{x \in \left[\frac{2N_{\mathrm{cap}}}{3},\ N_{\mathrm{cap}}\right] \,\middle|\, x \in \mathbb{Z}\right\} & PEAK \end{cases} \tag{5.20}$$

where N_{cap} is the capacity of the single-decker or double-decker bus. The case study does not model bus stops as National Express West Midlands were not forthcoming with their transport data. As a result the bus passenger count is static for the duration of the buses journey in the simulation. The passenger counts for motorcycles, LGVs, and HGVs are assumed to be 1.

5.5.4.7 Estimating Pedestrian Usage

The computational overhead of simulating the corridor with a large number of controllers at several flow levels and CV penetrations is considerable. Modelling individual pedestrians would incur a significant additional computational overhead. Furthermore, pedestrian count and movement data are not available for the Selly Oak area. To address this issue, pedestrians are modelled indirectly by modelling the impact of the pedestrian stage being triggered at intersections with a pedestrian stage for every cycle. This approach is consistent with the approach of Chang and Park (2013), who were the only researchers to simulate pedestrians in any of the C-ITS signal control strategies reviewed in Section 2.4.

5.6 Traffic System Simulation Test Cases

In this section, the tests to be performed on any developed signal control strategies are outlined. The variable space for this research is large; the factors that need to be tested include:

1. Corridor Road network model.
2. Percentage of CVs (CV penetration).
3. Level of flow applied to the corridor.
4. Control strategy used.
5. Stochastic effects.
6. Communication errors and delays.
7. Error in communicated measurements.

5.6.1 CV penetration

In order to understand how the number of CVs present in the corridor affects the transport network simulations need to be run at a spectrum of CV penetration. In this research, the CV presence in the corridor is incremented from 0% to 100% in steps of 10%. The 10% increment was chosen as it provides finer resolution than the 20%–25% increments used in the literature reviewed in Table 2.7. The incremental coverage of CV penetrations allows the emergent behaviour of CVs to be assessed during the analysis of the results, allowing for better insights into the impact of CVs and the penetration of CV technology needed for beneficial results.

5.6.2 Flow Levels

The amount of traffic in the corridor is a contributory factor in determining how effective a traffic signal control strategy is. By testing the urban corridor at, low, average, and high flow levels, the change performance of the signal control strategies at varying demand levels can be assessed. For the Selly Oak study, the traffic levels are defined from the average and percentile data, as shown in the example in Figure 5.6.

5.6.3 Control Strategies

In order to validate the performance of the developed signal control strategies, they must be compared to existing methods. In this study, the developed traffic control strategies are compared against a calibrated TRANSYT timing plan. The control specification for the algorithms is described below.

In this research, traffic stages are defined as the traffic light's configuration at an intersection. Table 5.6 defines the possible phases a traffic light can have and their meanings. Here, a stage comprises the set of traffic phases that give priority green to a single lane of an intersection. The lane showing priority green is referred to as the 'active lane', the others are considered 'inactive'. Inactive lanes display permissive green on routes that are not in conflict with any priority green streams, and red on streams that conflict with priority stream(s). Pedestrians are not considered in this study, so the stages only account for vehicle movements.

Table 5.6: Traffic light phase definitions.

Phase	Description
Red	Vehicles must stop
Yellow	Vehicles stop if it is safe to do so
Permissive Green	Vehicles proceed if the road is unoccupied by vehicles in a priority green stream
Priority Green	Vehicles proceed if it is safe to do so

All of the algorithms presented in this thesis make control decisions every 1 s unless otherwise specified. All intergreen times are derived from the UK Government guideline intergreen times (UK Govt. Dept. Transport, 2006) presented in Table 5.7.

Table 5.7: UK Government guideline intergreen times (UK Govt. Dept. Transport, 2006).

Distance (m)	<10	10-18	19-27	28-37	38-46	47-55	56-64	>65
Intergreen (s)	5	6	7	8	9	10	11	12

5.6.3.1 TRANSYT Plan Generation

In a fixed-time control algorithm, each lane in the intersection is set active for a predetermined amount of time, and the controller cycles through the stages sequentially. Algorithm 1 is the pseudocode description of a fixed-time control process. TRANSYT (Robertson, 1969) is one of the most widely deployed fixed-time optimisation packages still in modern usage. TRANSYT uses historic flow measurements to generate optimum signal timing plans for both isolated and networked intersections. TRANSYT calculates the optimal signal timings for a given road network model by minimising a performance function consisting of the delay, number of stops, and economic factors. TRANSYT has been shown to reduce delay up to 24% over pre-existing signal timing plans in the New England region of the USA (Agbolosu-Amison et al., 2004).

Here, TRANSYT signal timing plans are produced using the TRANSYT 15 software (Binning et al., 2013). Separate timing plans are calibrated for off-peak (00:00-06:00, 20:00-00:00), peak (06:00-11:00, 16:00-20:00) and inter-peak flows (11:00-16:00). The optimisation is unconstrained and uses the standard economic factors so that the TRANSYT plans are best optimised for the provided flows. In this research, TRANSYT is used as the benchmark with which the other signal controllers are tested. The TRANSYT plans, which are given in Appendix D, have been kindly verified been verified by traffic engineers at the Transportation Research Laboratory (TRL), UK who maintain the TRANSYT software.

Algorithm 1: Fixed-Time Control Algorithm Pseudocode

```
begin Fixed-time control
    if elapsedTime < stageDuration then
        elapsedTime ← elapsedTime + timeStep
    else
        DO: change to next traffic stage
        elapsedTime ← 0
```

5.6.3.2 MATS Configuration

The MATS algorithm (Algorithm 2) was configured with an extension interval of 2 s for the inductive loop actuation per the work of Bonneson and McCoy (2005).

As the stage times are optimised with the cycle time unconstrained, the minimum and maximum green times for each stage were 2 and 10 times the intergreen time for the intersection, respectively. For intersections with high numbers of stages, this may result in effective cycle lengths exceeding the 120 s maximum cycle length recommendation from the Department of Transport (UK Govt. Dept. Transport, 2006). Here, an unconstrained approach is taken, as the TRANSYT software suggests cycle lengths greater than 120 s (see Appendix D) for high volume junctions. In other studies, Synchro suggests cycle lengths of up to 180 s for high demand intersections (Goodall et al., 2013).

When actuating based on CV data, the MATS algorithm considers vehicles within a 4-second time headway from the intersection. As the standard guidance is for drivers to leave 2 seconds time-headway between cars (Highways Agency and Driver and Vehicle Standards Agency, n.d.), and the HEOMM (Highways England, 2019) defines a reliable journey time as 1.67 times the free-flow travel, the MATS algorithm will "catch" a vehicle within $2 \times 1.67 = 3.34s$ of the intersection, which is rounded up to 4 s control only occurs on integer second intervals.

The junction control region was defined as a circle with radius 250 m (Hameed Mir and Filali, 2014) centred on the intersection. The check interval for the MATS algorithm was $5\ \mathrm{s}$, not $1\ \mathrm{s}$, to allow sufficient time for decisions in the event of long communication latencies and high levels of packet loss.

To establish how the performance of the MATS algorithm differs depending on the quality and availability of input data, three varieties of the MATS algorithm are defined and compared:

- **MATS-FT**: The MATS algorithm combining data from fixed-time plans and CVs
- **MATS-HA**: The MATS algorithm with hybrid actuation, combining data from fixed-time plans, inductive loops, and CVs
- **MATS-ERR**: MATS-FT but under the non-ideal communication channel conditions outlined in Section 5.6.5.

The fixed time plan was derived from the TRANSYT plan. The times given by the TRANSYT plan were truncated in the MATS algorithm if they exceed the junction's maximum green time value. Furthermore, during initial testing, it was found that the use of loop data was detrimental to the performance of the MATS-HA variant at 0% CV penetration so at 0% CV penetration, the fixed-time mode is used. The negative behaviour was due to placing the algorithm in a network with imperfect coverage, and placement for a system other than MATS.

5.6.3.3 CDOTS Configuration

To test the greedy stage optimisation algorithm, it is combined with the MATS algorithm. The MATS algorithm implementation uses speed, position, and heading data from CVs for adaptive signal control, and the calibrated TRANSYT plan for its base signal timings the same as the configuration of MATS-FT.

For the sake of distinction, the combined algorithm is hereafter referred to as Connected Data Optimised Traffic Signals (CDOTS). The CDOTS algorithm benefits from the MATS algorithms green time calculations but enhances stage selection with the greedy stage optimisation algorithm. Previously, the MATS algorithm used cyclic stage selection. Figure 5.10 shows the flowchart for the operation of the CDOTS algorithm, highlighting how the greedy stage optimisation logic from Figure 4.3 integrates with the MATS algorithm's control logic.

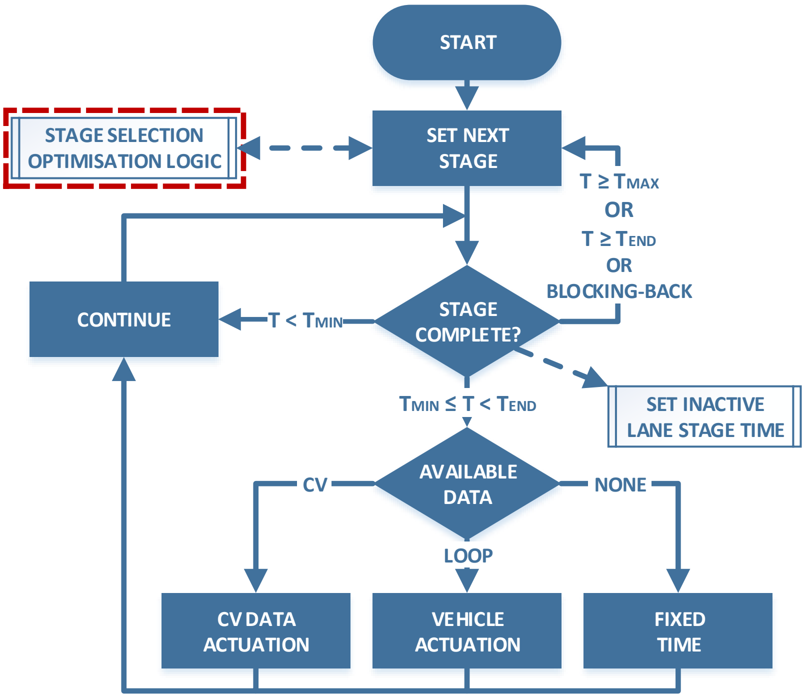


Figure 5.10: The flow chart for the CDOTS algorithm. The greedy stage optimisation algorithm integrates with the MATS algorithm at the stage selection process indicated with the red dashed box.

5.6.4 Accounting for Stochastic Effects in the SUMO Simulations

Many of the processes within the simulation rely on randomness to generate values, especially the traffic generation process. All random number generators used in the codes for this research are drawn from seeded distributions so that the results are repeatable. As the system is stochastic, each simulation must be repeated to create a sample space, and the results averaged in order to determine the typical performance of the underlying systems.

In order to determine the nature of the hypothesis test to be used the data are first tested for normality using both D'Agostino's K^2 test (D'Agostino, 1971) and the Shapiro-Wilk test (Shapiro and Wilk, 1965). Depending on the results for each tests and their distribution, a suitable hypothesis testing regime is chosen to test a null-hypothesis H_0 and an alternative hypothesis H_1. Analysis of the results shows that due to the size and scope of the simulation, only $N = 3$ samples need to be taken to achieve a p-value of $p < 0.05$ (i.e. the samples within in each run are similarly distributed). However, for statistical robustness, $N = 50$ is recommended and was used for this research.

5.6.5 Modelling Communication Errors and Delays in C-ITS Wireless Channels

In the literature review, Table 2.7 identified that the majority of the proposed signal controllers are tested with ideal data. Others only tested one or two of the three possible sources of communication errors. Here, an error model that tests GPS measurement noise, packet loss, and delay is used.

The open-source ETSI CAM (ETSI, 2011) (see Section 2.3 also) standard is used over the proprietary SAE J2735 for this research. The ETSI CAM standard is used over the SAE standard as the ETSI standards are open-source, and its documentation describes its implementation in details. Section 2.3 identified that both the ETSI and SAE standards are similar due to effort to harmonise the standards (EU-US ITS Task Force Standards Harmonization Working Group, 2012). Under ideal conditions, CVs send data at a rate of $10\ \mathrm{Hz}$. Messages are sent over an lossless IEEE 802.11p (IEEE, 2010) Dedicated Short-Range Communication (DSRC) channel. Research on IEEE 802.11p networks shows that signal strength within a $250\ \mathrm{m}$ range is high enough that messages can be received correctly (Hameed Mir and Filali, 2014; Msadaa et al., 2010), and that packet latencies of approximately $50\ \mathrm{ms}$ are achievable at vehicles speeds up to $90\ \mathrm{km/h}$ (Msadaa et al., 2010). In the ideal case, CAMs are received by the intersection controller with ideal data content, but with a delay of $100\ \mathrm{ms}$.

In order to assess the lower-bound performance of the proposed algorithms, they are tested under adverse communication channel conditions. In the adverse case, the algorithms are tested with the lower-bound CAM generation rate of $1\ \mathrm{Hz}$ instead of the usual $10\ \mathrm{Hz}$. The packet loss in the system was set to 50%, i.e. half of the data is not received (at random). Tonguz and Zhang (2019) showed that 50% packet loss was a reasonable level to test to assess how dependent an algorithm is on received data. Finally, Gaussian noise of the form $X \sim \mathcal{N}(\mu, \sigma^2)$, with mean $\mu = 0$ and variance $\sigma^2 = 2.79$, is added to GPS measurements (i.e. the position $\pm 5\ \mathrm{m}$ in both the x and y coordinates, typical for differential GPS systems (Box and Waterson, 2010)).

5.6.5.1 Alternative CV Modelling Options

As this research considers CVs, it is worth noting the VEINS vehicle simulation framework (Sommer et al., 2011). VEINS combines SUMO with the communication network simulator OMNeT++ (Varga, 2010). The objective of this research is to study the performance of the traffic signal control systems in a connected environment, not the underlying communication systems. While VEINS would be an appropriate vehicle simulator, initial tests with SUMO (on which VEINS is based) found that simulating the case study used in this research while implementing a traffic signal control interface is already close to the maximum compute time afforded by the HPC resource available. To simplify the model, rather than implementing the simulation at the network layer (see OSI stack (ISO/IEC JTC 1 Information Technology, 1994)) for a specific communication system, the problem was abstracted to the transport layer. That way, the underlying communication is modelled as any system that satisfies the upper and lower bounds of acceptable performance as outlined in the message set standard. This abstraction is beneficial as it means the system can support DSRC and 5G communications without committing to either. If the research can accommodate the computational resources VEINS is recommended; however, this was not the case for this research.

5.6.6 Determining System Fairness to Unconnected Vehicles

In Chapter 1, the ethics of transport were discussed, and the point was made that transportation is used by everyone, and therefore changes in access to transport can disadvantage vulnerable groups such as the elderly, disabled, and low-income communities if not planned correctly (Public Health England, 2019). Systems which rely on CV data, such as the CDOTS algorithm, risk disadvantaging those without access to a CV.

For this test, the average delay per kilometre and average stops per kilometre results will be compared on the case study, for all three demand levels, with and without pedestrians, and for 10%–90% CV penetration. Unlike the previous chapters, the results for connected and Unconnected Vehicles (UVs) are plotted separately to observe if one group is disadvantaged by the presence of the other. The CDOTS algorithm, as defined in Chapter 4, is used as it was the best form of the algorithm for the case study corridor. The algorithm is tested with ideal and non-ideal communications and the performance of CVs and UVs compared.

5.6.7 Comparison of the Developed Algorithms with a Vehicle Actuation Strategy

The case study compared the algorithms developed in this study with TRANSYT. Ideally, as the research aims to develop a coordinated method for controlling traffic signals, SCOOT would be used to benchmark the algorithm. Due to the open-source license used by SUMO, it is not presently possible to create a SCOOT integration with SUMO without exposing the intellectual property of its maintainers, the Transportation Research Laboratory (TRL). Alternative state-of-practice coordinated signal controllers were considered, but unavailable for SUMO at the time of testing due to similar licensing issues.

As the algorithm extends the principles of operation of the MOVA algorithm, MOVA was deemed an appropriate alternative signal controller with which to compare the developed MATS and CDOTS algorithms. As with SCOOT, due to the open-source license used by SUMO, it is not presently possible to create a MOVA integration with SUMO without exposing the

MOVA kernel and therefore the intellectual property of its maintainers TRL. In order to compare the MATS and CDOTS algorithms with MOVA, the case study from Waterson and Box (2012) was reproduced, and the CDOTS and MATS algorithms tested on them. Waterson and Box (2012) compared MOVA to their bid based algorithm on a single intersection road network model.

In this section, the road network model used to compare the algorithms is defined.

5.6.7.1 Network Model

Figure 5.11 illustrates the T-junction type intersection used to assess the performance of the MOVA algorithm in Waterson and Box (2012). The traffic signal stages for the intersection are given in Figure 5.12. Finally, the OD matrix for the model is given in Table 5.8. The OD matrix was reported to yield flows that operate the intersection close to its saturation point.

The MATS algorithm variants from Chapter 3, and the CDOTS algorithm from Chapter 4 were tested with ideal and non-ideal data. As TRANSYT was unavailable for this model, the default behaviour of the MATS and CDOTS algorithms is fixed-time with timings for each stage approximated from Webster's formula for optimal signal timings (Webster, 1958). The experiment simulated one hour of traffic flow and was repeated 50 times. The mean delay was calculated as the performance indicator for comparison with the MOVA results.

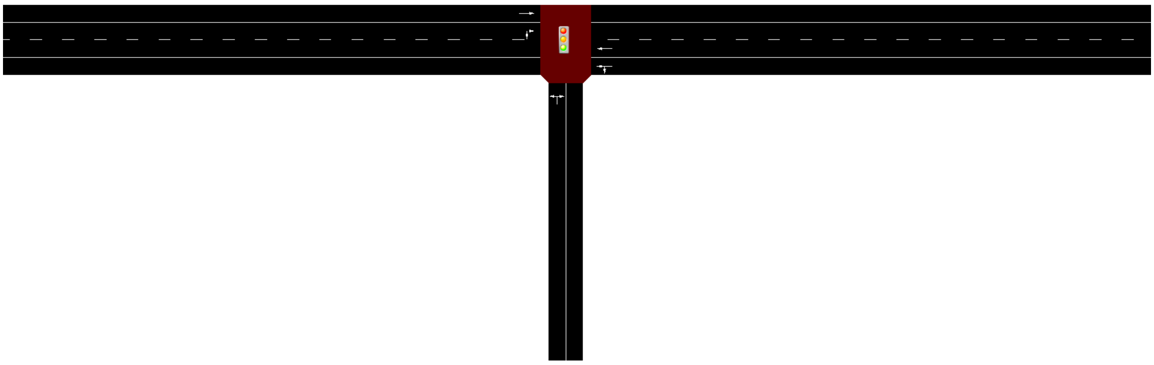


Figure 5.11: SUMO model of the T-junction type intersection used in Waterson and Box (2012).

Table 5.8: OD matrix for the T-junction model. Rows denote origins and columns denote destinations. Flows are in vehicles per hour.

	East	West	South
East	–	948	48
West	750	–	198
South	162	162	–

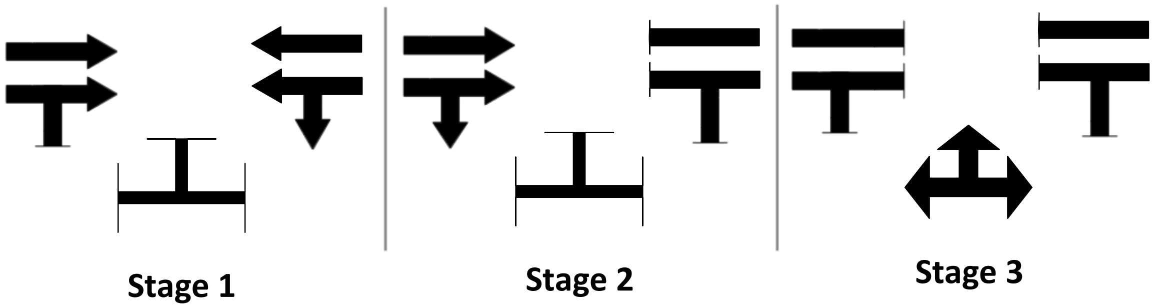


Figure 5.12: Stage diagram for T-junction traffic signals as defined in Waterson and Box (2012).

5.6.8 Computation Challenges in Traffic Signal Control Systems

One of the challenges in developing a traffic signal control algorithm is determining the hardware necessary to run the algorithm on the timescales it requires. The more computationally intensive the algorithm is, the longer it will take a computer to execute it. The computational resources of algorithms, especially those with a hierarchical or centralised approach to control, can be high depending on their complexity.

The algorithms developed here are decentralised. In a decentralised system, each controller requires one controlling processor, or control instance. The CDOTS algorithm also achieves coordination in a decentralised way, as the decisions at each intersection remain independent rather than having the overhead of a master controller. As the CDOTS algorithm only deals with information from the adjacent intersections, this limits the amount of additional computation it must perform. A controlling processor if the controller computations are performed locally, and a control instance if the control is performed on a remote server. Here, the time necessary to compute the control actions of increasing numbers of controllers in the case study model will be determined.

5.6.8.1 Test

The time to execute the controller processes in the case study was monitored for a single core of a computer running: SUMO v0.30.0, Python 2.7.12, Ubuntu 16.04 64-bit OS, and an Intel Core i7-6700 3.4 GHz processor. The case study contains a group of 12 controllers, so they were run 1–100 times (12–1200 controllers) every 15 simulation minutes for ten separate simulation runs, and the execution time of their control decisions recorded. The CDOTS algorithm from Chapter 4 was used to assess the timings as it was the best performing algorithm of this research. TRANSYT was also timed for reference.

5.7 Performance Indicators for Evaluating Intersection Control Strategies

Developing intersection control strategies is the main focuses of this research. In order to establish the effectiveness of the proposed strategies using simulation, their performance must be compared to others.

Performance Indicators (PIs) define significant, calculable values for measuring a system's effectiveness. In signalised traffic networks, the mean delay and number of stops are useful quantities to compare. In this chapter, PIs are defined for comparing the effectiveness of intersection control strategies against one another. The Highways England Operational Metrics Manual (HEOMM) (Highways England, 2019) outlines many PIs for assessing road network performance. When considering PIs for road traffic, the HEOMM describes two important considerations to make when assessing the data, validity and reliability.

Validity

Validity considers the data source and their generation/collection/supply from a third party until the point where it is used to calculate the PI. Validity is determined based on two components:

Representativeness: How representative the data are of the entire road network. For example, the delay experienced by a single vehicle is not representative of the entire road network. In contrast, the average delay of every vehicle in the network better represents the overall efficiency of the transport network.

Accuracy: Correctness and accuracy of the collected data. For example, a person manually counting traffic may not be as accurate due to human error, as an inductive loop that can count cars automatically.

The most meaningful data are highly representative of the entire road network and very accurate. Representative data are important when comparing two intersection control strategies. Representativeness is important for understanding the impact of a control strategy not only on individual vehicles but the wider road network.

Reliability

Reliability is concerned with the process used to capture the data and calculate the PI. Data from automated processes such as GPS, accelerometers, and vision systems are considered reliable as they are gathered in a specified way at regular intervals, and often have well-defined error bands. Manually gathered data can be more error-prone compared to electronic data due to human error during collection and transcription.

In this research, the data are gathered from V2I data streams, which as can be seen in Table 2.1, is generated by electronic systems. Therefore, the data considered in this research are both accurate and reliable. The limiting factor is on how to use and report the data to maximise their representativeness.

5.7.1 Key Performance Indicators in the Literature

5.7.1.1 Traffic Signal Control Performance Metrics

Table 5.9 describes the most common PIs used to evaluate traffic systems, and the PIs deemed most valid and reliable in Highways England (2019) that are relevant to ITS intersection management. Table 5.9 also outlines the general procedure for calculating each of the described PIs. Table 5.9 illustrates that many PIs that can be used to quantify the performance of traffic systems. The PIs are broadly concerned with assessing the efficiency of the transport network, the environmental impacts of the traffic system, and the state of the infrastructure.

Efficiency metrics aim to quantify how well the transport network is operating. Mean travel time, mean delay, throughput, flow, and acceptable journeys are examples of PIs that can be used to assess the efficiency of the transport network as they indicate how reliably users are making journeys through the network and can be used to identify when the network becomes congested.

Environmental metrics, such as CO_2 and NO_x emissions, are used to evaluate how changes to the transport network impact the environment, and in turn, affect public health.

PIs for infrastructure include Road Network Availability, Technology Asset Availability, and Robustness to Lane Closure. These Pis are useful for assessing how well provisioned the transport network is for the current demand, and how resilient the transport network is to a sudden loss of infrastructure.

Table 5.10 reviews the ways the performance of a subset of the algorithms in Section 2.4.3 was assessed. Table 5.10 cites the papers discussing an ITS intersection control algorithm, summarises the data used by the algorithm and its assumed accuracy, and how it works. Thirdly, the table lists the performance indicators chosen by the authors to measure the effectiveness of their algorithms. Table 5.10 is used as an indicator of the most frequently used PIs for assessing the performance of traffic signal controllers.

It can be noted that the PIs commonly used in the literature (Table 5.10) and defined in the HEOMM (Table 5.9) are highly economic in their focus, i.e. there is financial merit in their optimisation. Economic PIs are primarily quantitative, which is sensible given that the research method used for assessing the PIs was computer simulations for all the literature discussed. However, optimising traffic control based on economic PIs does not capture the full range of dynamics present in a road network. Psychological factors such as driver frustration and societal factors such as safety and fairness are more qualitative than economic PIs and are not well represented in the literature. As this research aims to anticipate the impact of CVs interspersed with unconnected vehicles, a complete representation of the transport network is needed. There may exist PIs that are more representative of the interplay between CV and unconnected vehicles and C-ITS performance than is currently used in common practice, and that have been discussed in the literature. Therefore, this research is aware of the possibility of new, relevant PIs in its analysis.

Based on the synthesis of PIs in Table 5.9, and the literature reviewed in Table 5.10, the metrics that are used as the PIs for this research are the mean travel time delay, mean number of stops, and vehicle emissions. Distance vs Time plots are used where it is necessary to determine if the system is coordinated.

Table 5.9: Description of PIs for traffic systems, adapted from the Highways England (2019).

PI	**Description**	**Calculation**
Mean Travel Time*	The time it takes a vehicle to get from its point of origin to its destination	Start Time − End Time
Travel Time Reliability*	The variation in travel time along a particular route or road segment	Variance, standard deviation, percentile range, or a confidence interval of travel times
Free-flow Travel Time*	The time it takes a vehicle to travel from its origin to its destination, as fast as is allowed by the speed limit, unobstructed by traffic lights, other vehicles, or any other obstacle	Travel time on an unobstructed route
Mean Delay*	The time in excess of the free-flow travel time a vehicle spends completing its journey	Travel time − free-flow travel time on the same route
Acceptable Journeys*	The percentage of journeys completed faster than $4/3$ of the free-flow travel time	Count cars that complete their journey faster than $4/3 \times$ the journey free-flow time, divide by the total number of cars, and multiply by 100
Mean Velocity*	The mean speed a vehicle is observed travelling at while not queuing. Will ideally be close to the speed limits on the routes travelled by the vehicle	Measure vehicle velocities directly, or infer from two position updates and the time between them
Mean Queuing Time	The amount of time a vehicle spends in a queue. The exact definition of a queue is ill-defined for road traffic.	Define queuing, measure time spent in a queue for each vehicle
Mean Number of Stops	Count of the number of times a vehicle stops throughout its journey	Count a stop each time the vehicles' velocity reduces to 0 before it reaches its destination.
Distance vs. Time	A graphical representation of the total distance travelled by a vehicle in time	Create a distance, time pair for each vehicle at each time step, plot the pair for each vehicle
Throughput	The number of vehicles that clear the road network or a junction per unit time	Count the number of vehicles leaving the simulation per unit time
Flow*	The number of vehicles that enter or travel along a particular road segment per unit time	Count the number of vehicles entering the simulation per unit time
CO_2/NO_x Emissions*	The volume of greenhouse gasses produced by road network users	Use an emission model to determine the emissions per vehicle and aggregate the result
Road Network Availability*	The percentage of the road network that is unoccupied over time	$100 \times$ length of road / length of all vehicles on the road, average overall roads
Technology Asset Availability*	The percentage of roadside devices, and control and communication systems in working operation	$100 \times$ available assets / total assets
Robustness to Lane Closure	Network robustness is the observation of how a lane closure effects any of the above metrics. The metric will, ideally, not change significantly for minor disruptions	Measure the difference in performance of any of the above with lane closures, accidents, or more traffic present

** Reported as a valid, reliable PI in the HEOMM (Highways England, 2019).*

Table 5.10: Summary of the performance indicators used in a subset of the ITS traffic control strategies in Table 2.7.

Key Literature	Algorithm Summary	Performance Metrics Used
Goodall et al. (2013); Smith et al. (2011)	Position (SAE J2735), Queue length (inferred). Determines vehicle queue length using GPS data from vehicles	• Distance vs. time • Mean delay • Mean velocity • Mean queuing time • Number of Stops • Throughput
Au et al. (2015); Fajardo et al. (2011)	Position, speed, steer angle trajectory mapping, ideal communications Vehicles make reservations with a central server that directs them through the intersection	• Mean delay
HomChaudhuri et al. (2016)	SPaT, ideal communications. Uses V2X communication to relay signal phase and timing (SPaT) information to vehicles	• Distance vs. Time • Velocity vs. Time
He et al. (2012, 2014)	Platoon identification, position, speed, ideal communications. An intersection manager receives travel mode, position, speed, and desired phase information from the vehicle	• Cycle Length vs. Saturation Rate • Throughput • Mean delay
Priemer and Friedrich (2009)	Position, loop, ideal communications. Optimisation procedure attempts to reduce the queue length over 20 forecasted seconds	• Distance vs. time • Velocity vs. Time
Datesh et al. (2011)	Position, speed, ideal communications. Uses k-mean clustering (of vehicle time-to-intersection) to determine when the phase should change	• Mean delay • Mean travel time • Mean queuing time • Miles per gallon • CO_2 emissions
Lee and Park (2012); Lee et al. (2013)	Cumulative Travel Time (CTT) (IEEE 802.11p, 50 and 100 ms broadcast, ideal communications). Sets the signal phase and green time based on the phase with the highest total CTT	• Mean delay • Mean velocity • Cumulative travel time • Mean queuing time • Throughput • Fuel consumption • CO_2 emissions
Yang et al. (2016)	Traffic velocity, inter-vehicle distance. Vehicles synchronise their approaches so as to pass through the intersection without collision	• Distance vs. Time

SPaT: Signal Phase and Timing
RSU: Roadside Unit

5.7.1.2 Traffic Safety Performance

In addition to assessing the performance of a traffic signal control system, it is also desirable to assess the system's safety. Time-to-collision (TTC) is a common metric for determining the safety of traffic control systems (Vogel, 2003). TTC describes the time it would take for a vehicle to collide with the proceeding vehicle if they were both to continue travelling at the same speed (Hayward, 1972). Small TTC values are associated with a higher risk of accidents (Svensson, 1998), with times less than 1 s considered near-misses (Hayward, 1972).

The formula for calculating TTC is given by (Minderhoud and Bovy, 2001):

$$TTC_{\mathrm{i}} = \frac{X_{\mathrm{i}-1}(t) - X_{\mathrm{i}}(t) - l_{\mathrm{i}}}{\dot{X}_{\mathrm{i}-1}(t) - \dot{X}_{\mathrm{i}}(t)} \quad \forall \quad \dot{X}_{\mathrm{i}}(t) > \dot{X}_{\mathrm{i}-1}(t) \tag{5.21}$$

Where $\dot{X}$ is speed, X is position, l is vehicle length, t is time, $i-1$ is the index of the lead-vehicle, and i is the index of the following vehicle.

As can be seen from Equation 5.21, to accurately determine the TTC between vehicles, information about every vehicle is required at every time step. As the scale of the simulation scale runs over 24-hours and considers a large number of vehicles at sub-second time-resolution, it was found that tracking TTC during the simulation increased the computation time beyond the HPC resources limits. Additionally, exporting the sub-second vehicle traces for all experiments exceeded the HPC storage allocation. Due to these limitations, TTC was not considered for this research, but a safety analysis including TTC has been included in the thesis' future work.

5.7.2 Definitions of the Performance Indicators Calculations Used in this Research

Mean travel time delay and mean stops, and emissions were selected as the performance indicators for this research. Delay and stops are the primary components of the objective function which TRANSYT optimises to generate its signal timings (Binning et al., 2013), and so are useful metrics to compare across algorithms here. Delay and stops were also chosen as they do not require output at every time step which was a concern for TTC. Emissions were chosen as they are important to monitor to address environmental concerns associated with vehicle traffic.

5.7.2.1 Delay

Travel-time delay characterises the excess time a vehicle takes to complete its journey compared to the free-flow travel time for the same journey. Delay indicates the amount of time saved compared to the total journey time and highlights the performance limitations of each method.

The travel-time delay is calculated by:

$$T_{\text{delay}} = T_{\text{out}} - T_{\text{in}} - T_{\text{freeflow}} \tag{5.22}$$

Where T_{delay} is the time delay experienced, T_{in} and T_{out} are the times at which the vehicle enter and exit the simulation respectively, and T_{freeflow} is the freeflow travel time for that vehicles' route.

In this study, free-flow travel time is established by setting all intersection lights to green and passing a vehicle along each route in all the models. The average free-flow travel time for each route is then established. The vehicle departures are spaced in time so that the vehicles do not interact. Additional time is added between the calculation of a subsequent route's free-flow time to allow vehicles from the previous test to clear the network.

5.7.2.2 Stops

A vehicle is defined as having come to a stop if its speed is less than 0.01 $\mathrm{m/s}$. The total number of stops a vehicle makes on its journey are recorded here. The simulation script was configured to monitor vehicle speeds in every time-step, and count how many times a vehicle stopped on its journey.

5.7.2.3 Emissions Modelling

The SUMO microsimulation package comes with two methods of modelling vehicle emissions, the Handbook Emission Factors for Road Transport (HBEFA) v3.1 model, and the Passenger car and Heavy-duty Emission Model light (PHEMlight) model. PHEMlight is a simplified version of the full PHEM model (Hausberger et al., 2009) which is a proprietary algorithm. PHEM models emissions instantaneously on a per-second basis using vehicle engine power, and speed. The HBEFA emissions model (Hausberger et al., 2009) is based on the PHEM model and provides a database of emissions factors for a variety of vehicle types. The HBEFA model looks up emissions quantities relating to common vehicle types for use in the simulation. The HBEFA emissions model is used here, as the while it is an abstracted model it is based on the full PHEM model rather being simplified like the PHEMlight model.

The emissions quantities that can be extracted from the HBEFA model are:

CO_2: Carbon dioxide [mg]
CO: Carbon monoxide [mg]
HC: Hydrocarbons [mg]
NO_x: Nitrogen oxide [mg]
PM_x: Particulate matter (x $\leq 10\ \mu m$) [mg]
FUEL: Gasoline and diesel [ml]

In this simulation set up, all the emissions were recorded in the SUMO simulations.

5.7.2.4 Result normalisation and errors

In order to compare the results of vehicles travelling different journey lengths, the mean delay and mean stops are represented per kilometre. The 90% prediction interval of the data are used as error bands on the mean to indicate the degree of variability in the results.

5.7.2.5 Percentage reduction

To compare the delay and stop results of the tested algorithms the percentage difference with respect to a benchmark traffic signal control algorithm is used. The percentage reduction between a value x and its reference or benchmark value x_{ref} is given by:

$$100\left(1-\frac{x}{x_{\mathrm{ref}}}\right) \tag{5.23}$$

5.8 Summary of Chapter Findings

1. Simulation was identified as the best approach for this research.
2. The most appropriate software (SUMO) and models (Krauß) were identified.
3. A real urban corridor based on the Selly Oak area of Birmingham was modelled for use in testing the algorithms developed by this research.
4. The test cases needed to evaluate this research were defined.
5. The workflow for evaluating traffic signal controller in this research was defined.
6. Tests for determining system fairness, performance against and adaptive traffic signal control systems, and computational efficiency were defined.
7. The performance indicators used for this research were identified (delay, stops, and emissions).

Chapter 6

Results and Discussion

In this chapter, the results of the tests described in Chapter 5 are presented and discussed. In Section 6.1, the results of testing the MATS algorithm against TRANSYT on the case study are presented and discussed. Section 6.2 shows results from determining the data to provide the CDOTS algorithm. Section 6.3 shows how the coordination factor for the CDOTS algorithm was determined. In Section 6.4, the results of testing the CDOTS algorithm against TRANSYT and the MATS algorithm on the case study are presented and discussed. Section 6.5 compares the performance experienced by connected and unconnected vehicles under the CDOTS and MATS algorithms. Section 6.6 compares CDOTS and MATS against MOVA. Section 6.7 compares the computational efficiency of the MATS and CDOTS algorithms with that of the TRANSYT algorithm.

6.1 Testing the MATS Algorithm on the Case Study Model

In this section, the results for the simulations of the MATS algorithm on the case study model are compared with those of TRANSYT. As discussed in Section 5.7, mean travel time delay and mean stops were selected as the performance indicators for this research. Delay and stops are primary components on which TRANSYT optimises signal timings (Binning et al., 2013) and allow comparison. In this section, the delay results are discussed in Section 6.1.1 and the stops results are compared in Section 6.1.2. Hypothesis testing on the stops and delay results are presented in Section 6.1.4. Additionally, the impact of the MATS algorithm on vehicle emissions is assessed in Section 6.1.3. Finally, the impact of the MATS algorithm on intersection stage intervals for selected junctions is described in Section 6.1.5. It should be noted that the TRANSYT results do not vary with CV penetration, as TRANSYT controls traffic independently of CV data.

6.1.1 Delay

In Figures 6.1 and 6.2, the results comparing the TRANSYT and MATS algorithms' performance in terms of mean delay per kilometre for are shown. The algorithms are compared for each of the three demand levels, and both with and without pedestrians present. In Tables 6.1 and 6.2, the percentage reduction in mean stops and mean delay of the MATS algorithm with respect to TRANSYT are presented. The comparisons are made across CV penetration rates and demand levels.

In Figure 6.1 and 6.2 (a) and (b), under low traffic demand, the MATS algorithm does well at reducing delay compared with TRANSYT. Mean delay is reduced by over 75% under ideal communication conditions with CV penetrations as low as 10% regardless of pedestrian presence in the corridor. From Tables 6.1 and 6.2, it can be seen that with non-ideal communications, the delay reduction is about 40% at 10% CV penetration, but by 50% CV penetration the MATS algorithm reduced mean delay to within 5% of the ideal cases regardless of pedestrians. The addition of loop detectors does not significantly improve the performance of the MATS algorithm over just using CV data and fixed-time data, even at low CV penetrations. Non-ideal communication channel conditions reduce the performance of the algorithm at low CV penetrations, but these negative effects are largely mitigated by 30% CV penetration. In both plots, there is a notable reduction in the 90% prediction interval for CV penetrations above 10%, indicating that the MATS algorithm makes travel times significantly more reliable. As expected, the TRANSYT results are static with increasing CV penetration as the algorithm does not rely on CV data.

Figures 6.1 and 6.2 (c) and (d) compare the MATS algorithm with TRANSYT for average traffic demand. The effects of non-ideal communications are more pronounced under the increased traffic demand, with the delay not settling until closer to 40% CV penetration. However, Tables 6.1 and 6.2 show that the effects of non-ideal communications are offset for this demand case by 50% CV penetration. Inductive loops do not significantly impact the performance of the algorithm when there are low penetrations of CVs and no pedestrians. However, inductive loops reduce delays help the MATS algorithm reduce delays at 10% CV penetration when pedestrians are present. The benefits inductive loops provide in this case are largely redundant above 20% CV penetration. The plots also show a significant reduction in delay variability compared with TRANSYT, with the 95th percentile data being much less than the mean TRANSYT delay reduction by 30% CV penetration.

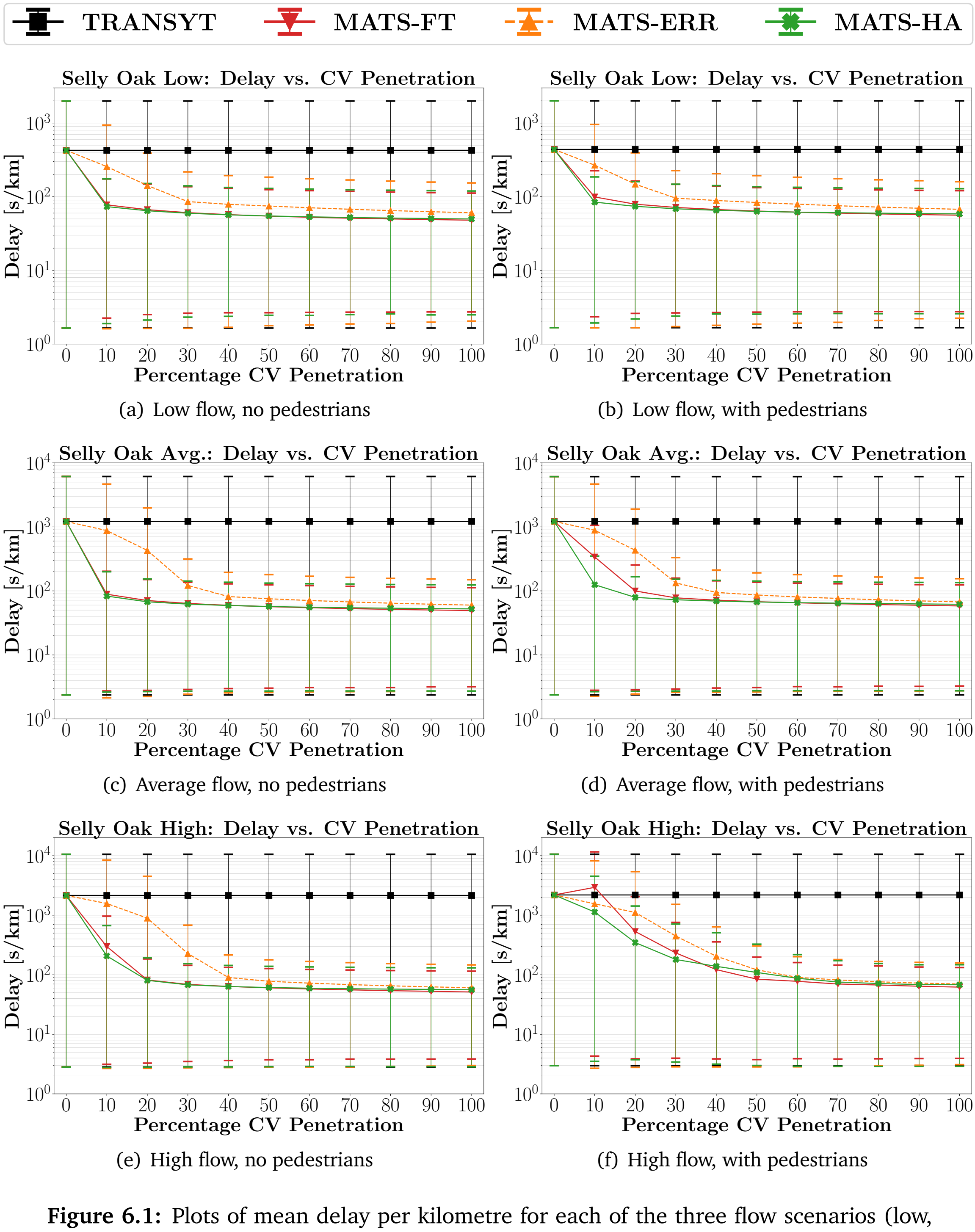
In the plots for the high demand case shown in Figures 6.1 and 6.2 (e) and (f), it can be seen again that non-ideal communications inhibit the MATS algorithm's ability to reduce delays. But, similarly to the lower demand cases, Tables 6.1 and 6.2 the effects of non-ideal communications are overcome by 50% CV penetration. The most interesting development in the results for high traffic demand is that when pedestrians are present, the MATS-FT algorithm variant performs worse than TRANSYT at 10% CV penetration. The reduced performance of MAT-FT under high traffic demand can be attributed to increased switching between modes. It can be seen that under non-ideal conditions, the MATS-ERR variant does not suffer the same issues with mode switching as the data are ten times less frequent. In both the cases with and without pedestrians, inductive loops do not provide significant benefit. Inductive loops may only be useful in busy corridors at low CV penetrations to compensate for the mode-switching issues that occur.

Overall, from Figures 6.1 and 6.2 and Tables 6.1 and 6.2 it can be seen that the MATS algorithm offers significant reductions in delay in most cases at all levels of traffic demand for CV penetrations above 10%. The average delay can be reduced by more than 85% with CV penetrations as low as 50%. Furthermore, the MATS algorithm reduces delay variability to a similar level regardless of the traffic demand. Notably, as CV penetration increases the lower bound of the 90% prediction interval increases, increasing delay for vehicles on shorter routes marginally, to decrease delay for vehicles on longer routes significantly. The reduction in delay variability emphasises that the MATS algorithm allows road users to make their journeys more reliably, and indicates the algorithm is robust to fluctuations in traffic demand. Across all the results, some delay variability remains even at high CV penetrations due to the varied route lengths in the corridor resulting from its large size. Under non-ideal communication conditions, although improvements are possible, they are less significant until the CV penetration is at least 30% where after they amount to only about a 10 s/km difference. The discrepancy between MATS-ERR and the other MATS algorithm variants can be attributed to MATS-ERR overestimating or underestimating the queue clearance time and stage extensions due to the noise, error, and delay in the communication channel. However, the MATS algorithm still offers reductions in mean delay and variability compared with TRANSYT. Inductive loops are beneficial at improving the performance of the MATS algorithm at low CV penetrations, even if they only partially cover the network as in the case study corridor. However, the results suggest that in the presence of CV data, the data from inductive loops does not significantly improve the performance of the algorithm.

6.1.2 Stops

In Figure 6.3, the results comparing the TRANSYT and MATS algorithms' performance in terms of mean stops per kilometre for are shown. The algorithms are compared for each of the three demand levels, and both with and without pedestrians present. In Tables 6.1 and 6.2, the percentage reduction in mean stops and mean delay of the MATS algorithm with respect to TRANSYT are presented. The comparisons are made across CV penetration rates and demand levels.

Figures 6.3 (a) and (b) show the mean stops per kilometre, for the low demand case. It can be seen in both plots that while the mean reduction in stops is relatively small in comparison to the delay reductions, by 30% CV penetration, the 95th percentile number of stops is substantially reduced. The addition of loop data does not aid the MATS algorithm in reducing stops significantly. As with the delay results, they provide modest improvements at 10-20% CVP. Here, errors in the communication channel do not affect the reduction of stops as significantly as in the delay results. In the case where pedestrians are present, at 10% CV



(a) Low flow, no pedestrians

(b) Low flow, with pedestrians

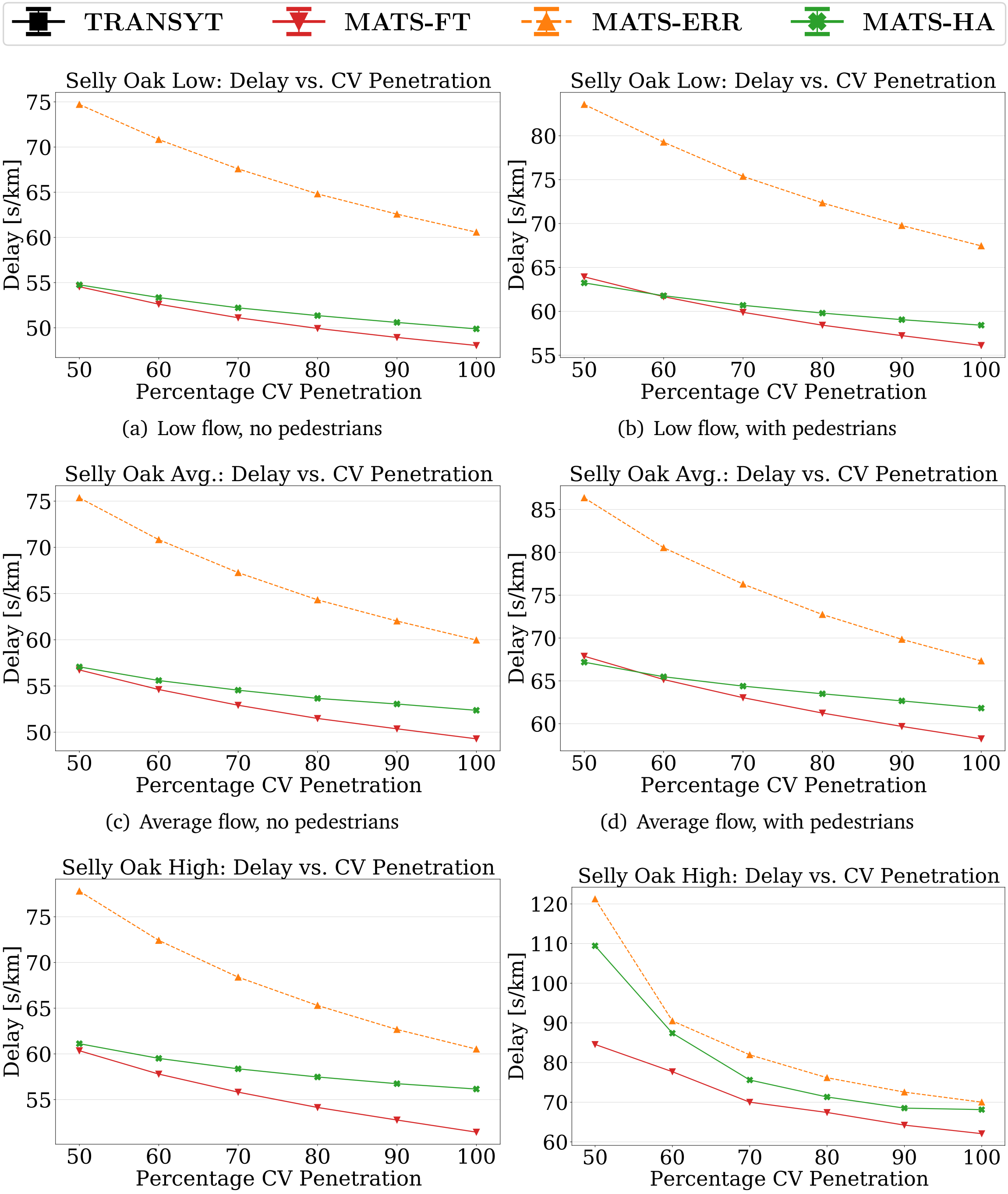
(c) Average flow, no pedestrians

(d) Average flow, with pedestrians

(e) High flow, no pedestrians

(f) High flow, with pedestrians

Figure 6.1: Plots of mean delay per kilometre for each of the three flow scenarios (low, average, high), with and without pedestrians. Each plot compares the performance of the MATS algorithm with and without loop information (MATS-FT), and the MATS algorithm with errors (MATS-ERR), to TRANSYT. The bands on the data represent the 5th and 95th percentiles of the data as indicators of variability.



(a) Low flow, no pedestrians

(b) Low flow, with pedestrians

(c) Average flow, no pedestrians

(d) Average flow, with pedestrians

(e) High flow, no pedestrians

(f) High flow, with pedestrians

Figure 6.2: Plots of mean delay per kilometre for each of the three flow scenarios (low, average, high), with and without pedestrians. Each plot compares the performance of the MATS algorithm variants at CV penetrations above 50% so that the differences can be more clearly observed.

Table 6.1: The benchmarking of the tested MATS algorithm instances against TRANSYT for the low (A), average (B), and high (C) demand cases without pedestrians. The results show the percentage reduction in the average delay and average number of stops at 10%, 50%, and 100% CV penetration.

A: Low Traffic Demand (80% of Average)						
Algorithm	**CV Penetration**					
	10%		**50%**		**100%**	
	Delay	**Stops**	**Delay**	**Stops**	**Delay**	**Stops**
MATS-FT	82%	7%	87%	19%	89%	24%
MATS-HA	83%	19%	87%	23%	88%	26%
MATS-ERR	40%	4%	82%	20%	86%	25%
B: Average Traffic Demand						
Algorithm	**CV Penetration**					
	10%		**50%**		**100%**	
	Delay	**Stops**	**Delay**	**Stops**	**Delay**	**Stops**
MATS-FT	93%	3%	95%	26%	96%	32%
MATS-HA	93%	20%	95%	32%	96%	35%
MATS-ERR	28%	9%	94%	25%	95%	33%
C: High Traffic Demand (120% of Average)						
Algorithm	**CV Penetration**					
	10%		**50%**		**100%**	
	Delay	**Stops**	**Delay**	**Stops**	**Delay**	**Stops**
MATS-FT	86%	-29%	97%	40%	98%	47%
MATS-HA	90%	-1%	97%	46%	97%	49%
MATS-ERR	27%	13%	96%	37%	97%	47%

penetration it can be seen from Table 6.2 that the MATS-FT algorithm variant does worse on average than TRANSYT at reducing delays but has lower variability. As with the delay results, the degraded performance at low CV penetrations can be attributed to the increased switching between modes of operation.

Figures 6.3 (c) and (d) compare the MATS algorithm with TRANSYT for average traffic demand. The reductions in the mean number of stops are marginally greater than in the low demand case, but still not as significant as the decreases in delay. As in the low demand case, inductive loops do not significantly improve the MATS algorithms ability to reduce the mean number of stops per kilometre. In both plots, the variability in the number of stops does not decrease significantly, below 40% CV penetration. The effects pedestrians have on the algorithm are more pronounced for the average demand case than in the low demand case. At 10% the MATS-FT and MATS-HA algorithm variants perform worse then TRANSYT due to the increased switching between control modes and the loss of signal synchronisation due to pedestrian stages. The MATS-ERR variant is the only form of the MATS algorithm that is not

Table 6.2: The benchmarking of the tested MATS algorithm instances against TRANSYT for the low (A), average (B), and high (C) demand cases with pedestrians. The results show the percentage reduction in the average delay and average number of stops at 10%, 50%, and 100% CV penetration.

A: Low Traffic Demand (80% of Average)						
Algorithm	**CV Penetration**					
	10%		**50%**		**100%**	
	Delay	**Stops**	**Delay**	**Stops**	**Delay**	**Stops**
MATS-FT	77%	-4%	85%	17%	87%	23%
MATS-HA	81%	17%	86%	22%	87%	24%
MATS-ERR	39%	4%	81%	19%	85%	25%
B: Average Traffic Demand						
Algorithm	**CV Penetration**					
	10%		**50%**		**100%**	
	Delay	**Stops**	**Delay**	**Stops**	**Delay**	**Stops**
MATS-FT	72%	-72%	94%	25%	95%	32%
MATS-HA	90%	-15%	94%	31%	95%	33%
MATS-ERR	27%	6%	93%	23%	94%	33%
C: High Traffic Demand (120% of Average)						
Algorithm	**CV Penetration**					
	10%		**50%**		**100%**	
	Delay	**Stops**	**Delay**	**Stops**	**Delay**	**Stops**
MATS-FT	-34%	-192%	96%	39%	97%	51%
MATS-HA	48%	-115%	95%	14%	97%	52%
MATS-ERR	29%	20%	94%	28%	97%	52%

substantially affected by pedestrians, indicating that making less frequent control decisions may be beneficial at low CV penetrations.

Figures 6.3 (e) and (f) show the comparison between the MATS algorithm and TRANSYT for high traffic demand. As with the average demand case, the high demand on the intersections causes an increased level of stopping at CV penetrations below 20% in the non-pedestrian case, and 50% in the pedestrian case, even when inductive loops are present. The degradation in performance at low CV penetrations highlights that TRANSYT's ability to coordinate signals outweighs the reactive properties of the MATS algorithm under high demand when it comes to reducing stops, suggesting that the MATS algorithm may benefit from an acyclic stage sequence. Tables 6.1 and 6.2 show that there are still reductions in stops that can be achieved between 50% and 100% CV penetration, unlike for delay where after 50% CV penetration the gains were marginal. The benefits of less frequent control causing a reduction in stops seen in the average demand case are also seen here but are of little benefit overall. As demand increases, the MATS algorithms ability to reduce delays at low CV penetrations appears to come at the expense of increasing the number of times vehicles stop.

Overall, from Figures 6.3 and Tables 6.1 and 6.2 it can be seen that the MATS algorithm offers slight reductions in the number of stops vehicles make per kilometre for CV penetrations above 20% above 20% under low and average demand, and above 50% during high traffic demand. The most significant reductions in stop variance are achieved when there is high demand in the corridor and high penetrations of CVs. The instability of the algorithm may be addressed by using an acyclic stage sequence (Bretherton, 2003), to compensate for missing CV and loop data, and achieve better coordination than TRANSYT. The effects communication errors have on the average number of stops are smaller in magnitude than for the delay results, and showed that in some low CV penetration cases at high demands that receiving data less frequently can be beneficial.

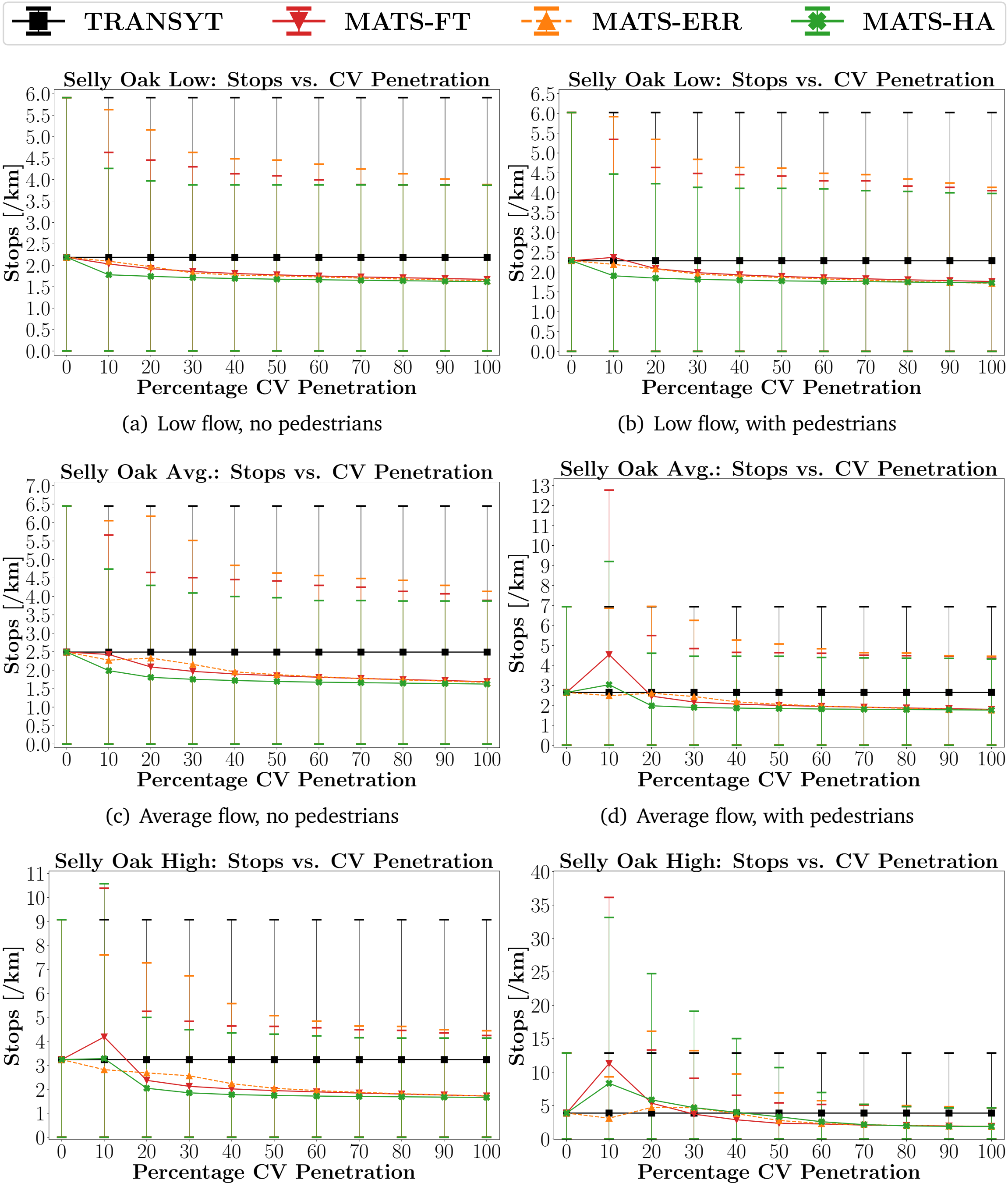
6.1.3 Emissions

Figure 6.4 shows how the MATS and TRANSYT algorithms impact on the mean total emissions over the experimental runs. The emitted particles studied are CO_2, CO, NO_x, PM_x, and Fuel, as described in Chapter 5.5. The total emissions are presented for each CV penetration, and each of the three traffic demands cases. Only the results for the pedestrian case are shown as, as the algorithm is more susceptible to perturbations when pedestrians were included.

Figures 6.4 (a), (d), (g), (j), and (m) show the total emission results for the MATS algorithm compared with TRANSYT for low traffic demand. The trends in each of the plots appear similar regardless of the emitted particle. At low demand and CV penetrations less than 30%, the supplemental information from the inductive loops is beneficial for reducing emissions than with CV and fixed-time plan data only. Errors in the communication channel cause a much slower reduction in emissions than in the ideal case, and the trend does not converge on a similar point to the ideal cases like in the delay and stop results.

Figures 6.4 (b), (e), (h), (k), and (n) show the total emission results for the MATS algorithm compared with TRANSYT for average traffic demand, and Table 6.3 shows the percentage difference between the MATS algorithm variants and TRANSYT at 10%, 50%, and 100% CV penetration. Similarly to the stops results, the increased mode switching of the algorithm at low CV penetrations causes an increase. From Table 6.3 the MATS-FT variant is worse across all emissions at 10% CV penetration but has converged by 50%. Under ideal conditions and CV penetrations below 30%, loop detectors are beneficial at keeping the emissions below the levels TRANSYT achieves. Similarly, the reduced data rate in the non-ideal case improves the algorithm's performance at 10%. Unlike the ideal case, the non-ideal communication channel reduces the rate of improvement above 10% CV penetration.

Figures 6.4 (c), (f), (i), (l), and (o) show the total emission results for the MATS algorithm compared with TRANSYT for high traffic demand. As with the average demand case, the increasing traffic demand worsens the performance of the MATS algorithm both with and without loops data, for CV penetrations below 40%. In the non-ideal case, it can be seen that the lower mode-switching frequency is beneficial at 10% CV penetration. However, those



(a) Low flow, no pedestrians

(b) Low flow, with pedestrians

(c) Average flow, no pedestrians

(d) Average flow, with pedestrians

(e) High flow, no pedestrians

(f) High flow, with pedestrians

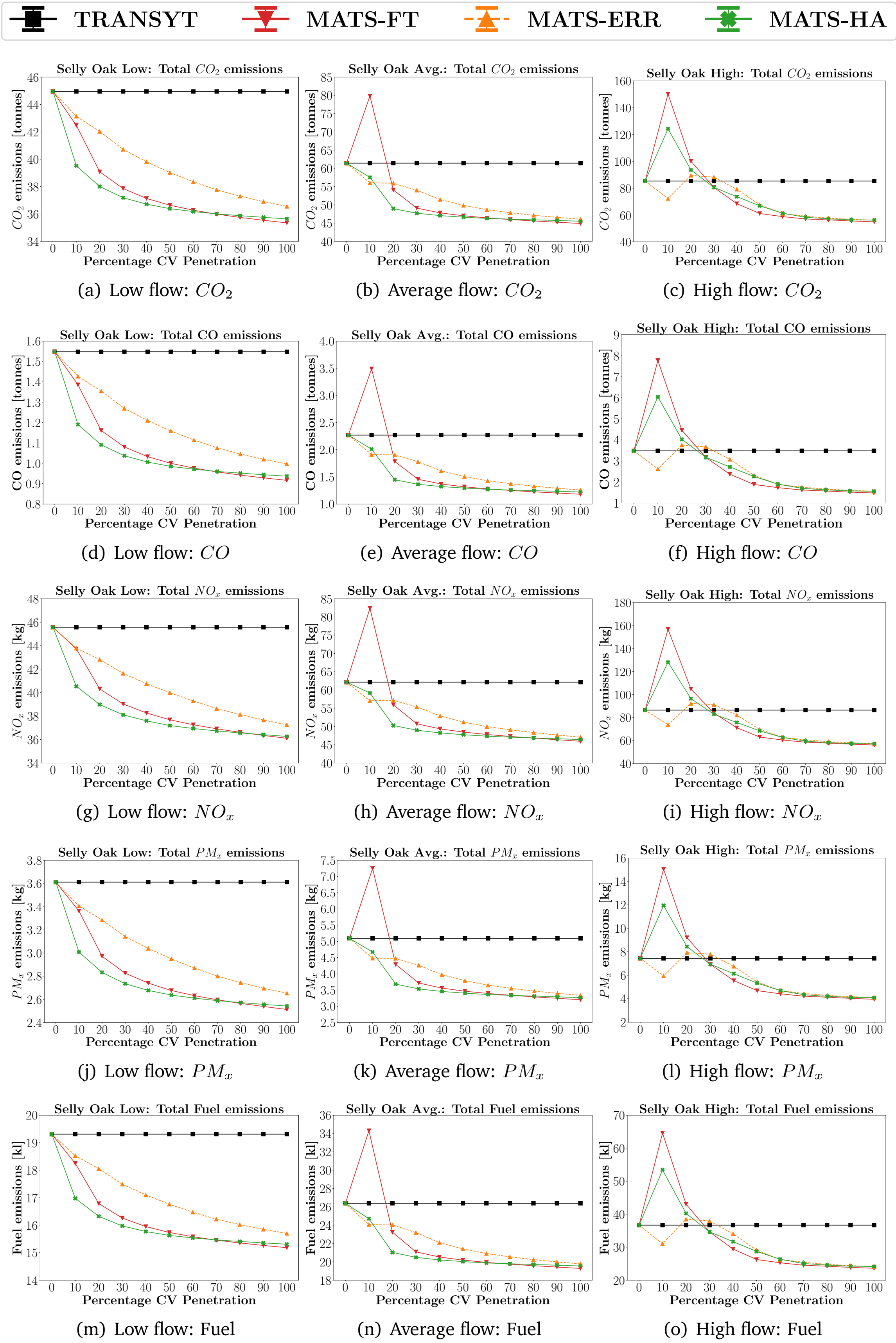
Figure 6.3: Plots of mean stops per kilometre for each of the three flow scenarios (low, average, high), with and without pedestrians. Each plot compares the performance of the MATS algorithm with and without loop information (MATS-FT), and the MATS algorithm with errors (MATS-ERR), to TRANSYT. The bands on the data represent the 5th and 95th percentiles of the data as indicators of variability.

Table 6.3: The benchmarking of the tested MATS algorithm instances against TRANSYT at 10%, 50%, and 100% CV penetration with pedestrians on the average demand case. The results show the percentage reduction in mean total vehicle emissions for each variant of the MATS algorithm.

A: MATS-FT					
CVP	**Emission**				
	CO_2	CO	NO_x	PM_x	$Fuel$
10%	-30%	-54%	-33%	-42%	-30%
50%	23%	42%	22%	32%	23%
100%	27%	48%	26%	37%	27%
B: MATS-HA					
CVP	**Emission**				
	CO_2	CO	NO_x	PM_x	$Fuel$
10%	6%	11%	5%	8%	6%
50%	24%	43%	23%	33%	24%
100%	26%	46%	25%	36%	26%
C: MATS-ERR					
CVP	**Emission**				
	CO_2	CO	NO_x	PM_x	$Fuel$
10%	9%	16%	8%	12%	9%
50%	19%	34%	18%	26%	19%
100%	25%	45%	24%	34%	24%

benefits are lost above 10% CV penetration as the behaviour converges more strongly towards the ideal cases.

Overall, the MATS algorithm is most beneficial at reducing emissions under low demand scenarios. As with the case of the stop results, the coordination TRANSYT provides is more beneficial at higher demand and low CV penetration than the adaptive properties of the MATS algorithm. Another observation that applies to the plots for the low and average demand cases is that the total emissions line for MATS-FT intersects with and then dip below the line for the MAT-HA variant at 70% CV penetration, for the high demand case MATS-FT supersedes MATS-HA by 40% CV penetration. This shows that there is a threshold, for emissions reduction, that loop detectors become redundant when there is sufficient CV data. The MATS algorithm is unique in that it is multi-mode; its mode of operation differs depending on what data are available.



(a) Low flow: CO_2 (b) Average flow: CO_2 (c) High flow: CO_2

(d) Low flow: CO (e) Average flow: CO (f) High flow: CO

(g) Low flow: NO_x (h) Average flow: NO_x (i) High flow: NO_x

(j) Low flow: PM_x (k) Average flow: PM_x (l) High flow: PM_x

(m) Low flow: Fuel (n) Average flow: Fuel (o) High flow: Fuel

Figure 6.4: Plots of the mean total emissions expelled in each of the three flow scenarios (low, average, high) with pedestrians. Each plot compares the performance of the MATS algorithm with and without loop information (MATS-FT), and the MATS algorithm with errors (MATS-ERR), to TRANSYT.

6.1.4 Hypothesis Testing

As the simulations were stochastic, hypothesis tests were performed on the delay, stop, and emissions data in order to assess its statistical independence across the $N = 50$ experimental runs, and incremental increases in CV penetration. Here, the following hypotheses were tested:

- The null hypothesis H_0 was that the mean stops, delay, and emissions data at CV penetrations greater than 0% were drawn from the same distribution as the mean delay for 0% CV penetration.
- The alternative hypotheses H_1 was that the mean delay, stops, and emissions data for all simulated CV penetrations greater than 0% CV penetration is different to the data for 0% CVP.

In order to determine the nature of the hypothesis test to be used the data were first tested for normality using both D'Agostino's K^2 test (D'Agostino, 1971) and the Shapiro-Wilk test (Shapiro and Wilk, 1965). The results of the normality tests only reject the hypothesis that the data is normal with $p < 0.01$ in less than 10% of cases. This indicates that while many of the results follow a normal distribution, a normal distribution is not guaranteed.

As proposed in Watkins (2019), for two independent samples (runs are independent of one another and independent across CV penetration) that may not be normally distributed, a Mann-Whitney U test (Mann and Whitney, 1947) was performed between H_0 and each H_1, and the U-statistic and p-value was determined. The hypothesis testing results for all delay and emissions cases rejected the null hypothesis in favour of the alternative hypothesis with $U = 0$ and significance $p < 0.001$. The stops results rejected the null hypothesis in favour of the alternative hypothesis with $U = 0$ for most cases and significance $p < 0.001$ for all cases. Table 6.4 lists the exceptions where the U-statistic was greater than 0. Most of the U-statistics in Table 6.4 satisfy $U \ll N^2$ and reject the null hypothesis in favour of the alternative hypothesis with $p < 0.001$. Only 1 case fails to reject the null hypothesis, and that is MATS-FT under average demand at 10% CVP, indicating a higher CVP is required for this control mode to distinguish its performance from TRANSYT.

The hypothesis testing results show that the addition of connected vehicles into the transport network changes the MATS algorithm such that it meaningfully impacts the delays and number of stops experienced by road users in all but one of the cases where CVs were present. The rejection of the null hypothesis also confirms that there was a significant reduction in delay in all case for CV penetrations as low as 10%, which address the gap from previous research.

Table 6.4: Table of stop result hypothesis tests for which the U-statistic was greater than 0.

Demand	**Controller**	**CVP**	U	p
Low	MATS-ERR	10	16	< 0.001
Average	MATS-FT	10	1067	0.104
Average	MATS-ERR	20	16	< 0.001
Average	MATS-FT	10	200	< 0.001
High	MATS-ERR	10	91	< 0.001
High	MATS-ERR	20	46	< 0.001
High	MATS-HA	10	350	< 0.001

6.1.5 Signal Timings

Unlike TRANSYT, the MATS algorithm does not operate a fixed cycle time with optimised splits and offsets. Instead, the MATS algorithm provides a heuristic for optimising stage times in an unconstrained way. As the cycle length is not directly comparable, the stage interval, the time between the end of a stage and its next occurrence, is observed as an analogue to the cycle length. Figure 6.5 compares the stage interval distributions of TRANSYT, to those of the MATS-FT algorithm at 100% CV penetration for each of the three traffic demand cases. The pedestrian case is used as the stage intervals are longer than in the non-pedestrianised case. The comparisons are made for junctions 3, 5, and 9 (refer to the model in Appendix B), as they are the busiest intersections in the top, middle, and lower thirds of the model. Table 6.5 compares the mean and 95% prediction intervals of the stage interval distributions for the TRANSYT and MATS algorithms.

For the TRANSYT results, it can be seen that the histogram only has 4 or 5 columns. This compact distribution is expected, as the plan is fixed-time, there are only discrete values the stage interval can hold. In comparison, the MATS algorithm stage intervals are more spread out due to its flexible stage time optimisations. For all of the junctions, Table 6.5 indicates that TRANSYT also yields higher average stage intervals compared with the MATS algorithm. As demand increases, large stage intervals occur more often when the signals are controlled with TRANSYT, and in the cases of junctions 3 and 5, frequently exceed the 120 s recommended cycle length limit.

In contrast, the MATS algorithm infrequently exceeds the 120 s recommended limit as it can have intermediate stage lengths that better satisfy the traffic demand. Due to its ability to extend stage times flexibly, the MATS algorithm histogram only shifts marginally to the right as traffic demand increases. However, the frequency of the higher stage times decreases due to the capacity maximising effects of the stage extension. Table 6.5 for junction 5 shows that the mean increases, but the upper bound of the 95% prediction interval decreases with increasing traffic demand.

Overall, there is no need to add a stage time restriction to the MATS algorithm as the 95% prediction intervals in Table 6.5 show that it seldom violates the recommended 120 s cycle length limit, and never exceeds 180 s limit for highly saturated intersections. It may be necessary to add a limiting constraint for environments that become highly oversaturated on all approaches.

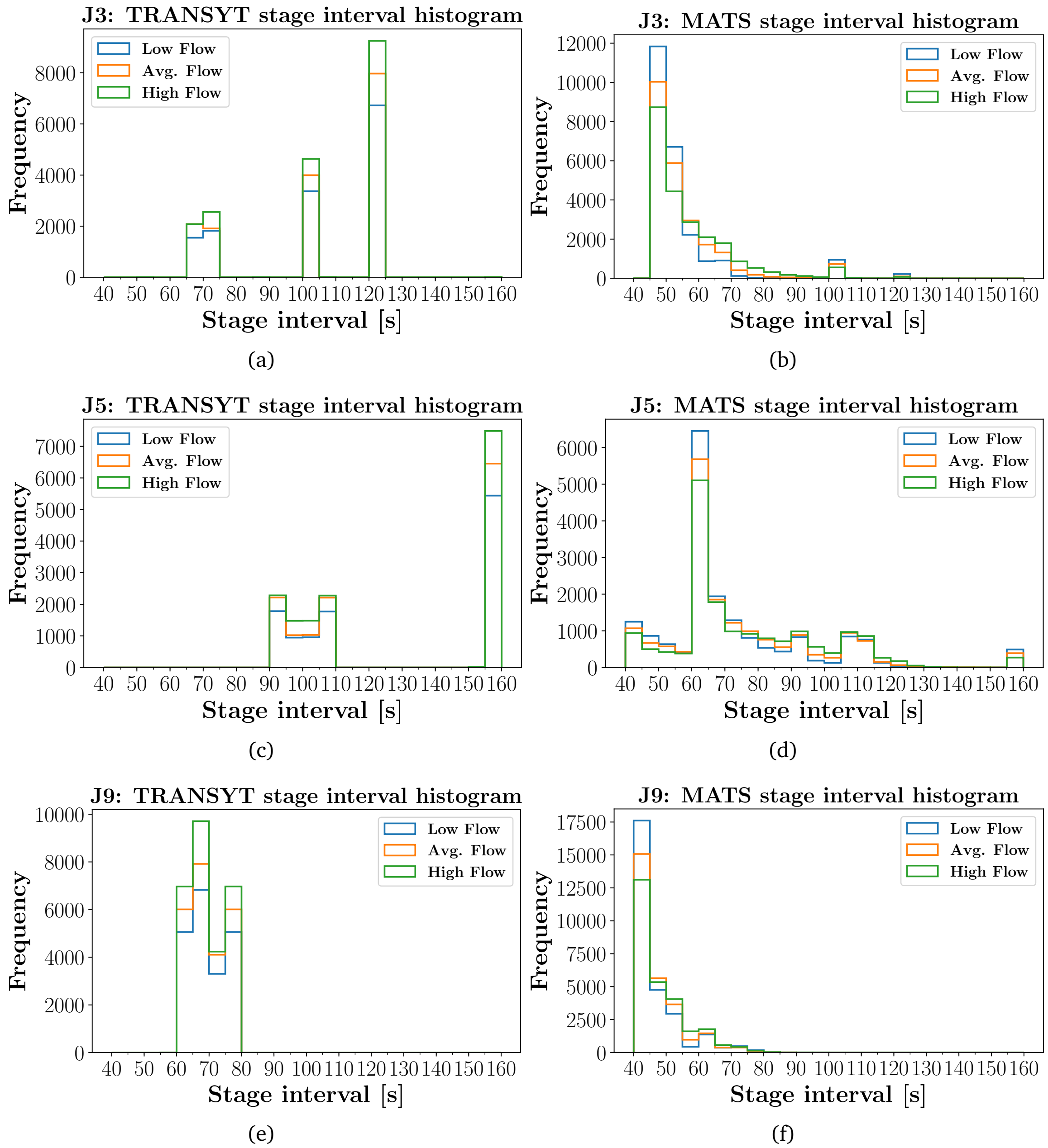


Figure 6.5: Histograms comparing the distribution of stage intervals for the MATS-FT (at 100% CV penetration) and TRANSYT algorithms. The data are in 5 second bins, and each plot shows the histograms for the stage intervals at low, average, and high traffic flow levels for Junctions 3 (J3), 5 (J5), and 9 (J9).

Table 6.5: The stage interval mean and 95% prediction interval comparison between the MATS algorithm at 100% CV penetration and TRANSYT. The metrics are compared for junctions 3, 5, and 9, for each of the three demand cases with pedestrians.

A: Mean Stage Intervals [s]						
	TRANSYT			**MATS-FT**		
Junction	**Traffic Flow**			**Traffic Flow**		
	Low	Avg.	High	Low	Avg.	High
J3	103.61	103.63	103.61	54.43	55.36	57.39
J5	103.02	103.03	103.03	72.07	73.81	76.17
J9	69.00	69.00	69.00	46.32	47.50	48.04
B: 95% Prediction Intervals [s, s]						
	TRANSYT			**MATS-FT**		
Junction	**Traffic Flow**			**Traffic Flow**		
	Low	Avg.	High	Low	Avg.	High
J3	[67, 122]	[67, 122]	[67, 122]	[48, 103]	[48, 103]	[48, 103]
J5	[92, 157]	[92, 157]	[92, 157]	[42, 157]	[42, 129]	[42, 122]
J9	[60, 78]	[60, 78]	[60, 78]	[42, 68]	[42, 68]	[42, 69]

6.2 CDOTS Greedy Algorithm Data and Parameters

The core issue with creating an algorithm that uses multiple data sources lies in determining which data to use to optimise the level of service it provides. In this section, the data that are available to an algorithm of this type are outlined, and the optimal dataset is determined.

6.2.1 Optimal Data Points for the Greedy Algorithm

6.2.1.1 Data Points

A CV has the potential to broadcast any of the data it has available to its internal sensors and navigation systems. Considering the sensors in a vehicle (Urmson et al., 2008) and the data available internally to the signal controller, a set of data points that can be used in the greedy algorithm have been identified in Table 6.6. Table 6.6 compiles the information that is suitable for the normalisation and aggregation steps of the greedy algorithm based on the timing and map data available to a signal controller, and the data can be inferred from vehicle position, speed, and heading measurements.

In Table 6.6, it can be seen that some of the data must be normalised on a per vehicle. Normalisation is necessary as lanes that can accommodate more vehicles would bias the values in the utility matrix. Normalisation is achieved by taking the average value per vehicle of the data to be normalised. Furthermore, the queue length must be considered as a percentage of its capacity to mitigate bias from lanes that can accommodate longer queues. It should be noted that in the algorithm implementation 'number of stages since last call' was not used in the utility matrix as it functionally the same as the 'time since the stage was last called' but with less granularity. Instead, the 'number of stages since last call' is used to enforce Constraint 4 from Section 4.5.

Table 6.6: The data points available to the stage optimisation algorithm as inferred from CV data and signal controller internal data.

Data	**Unit**	**Normalised Unit**
Time since stage last called	s	–
Number of stages since last call	$stages$	–
Number of vehicles	$vehicles$	–
Number of passengers	$passengers$	$passengers/vehicle$
Percentage of vehicles not turning	%	–
Number of stops this journey	$stops$	$stops/vehicle$
Waiting time this journey	s	$\mathrm{s}/vehicle$
Queue Length	m	*% max queue length per lane*

6.2.1.2 Determining the Optimal Data Points

With the data available to the greedy algorithm determined, each permutation of the data points is tested to see which results in the lowest delay and number of stops. In order to maintain standard cyclic operation in the absence of CV data, 'time since stage last called' is constant among each data point combination. With six remaining discretionary data points, $N = 2^6 = 64$ tests are performed on the average demand scenario for CV penetration from 0% to 100% in steps of 10%. The multi-objective global performance indicator defined by Equation 4.2 in Chapter 4 was used to determine the performance of each configuration.

In order to determine which strategies were most successful, each data point combination was tested at CV penetration were compared for the CDOTS and CDOTS-ERR algorithms on the average demand case. The value of the weighting vector ω_i was held constant as a column vector of N ones. In Figure 6.6, the ten strategies with the lowest P_{i} values are compared, and the data points that appeared most frequently were ranked. In Figure 6.6 it can be seen that time since last green is always first as it is in every strategy. However, the importance of the other data points varies depending on the penetration of CVs. Overall, it can be seen that the 'number of vehicles', and the 'average number of stops per vehicle' are the most valuable data points for stage optimisation. It was found that the mean number of data points in the top 10 strategies was 3.55 points. For further testing, the data combinations with the top 3 and 4 data points (time since last green, number of vehicles, number of stops, and number of passengers/not turning ratio) from Figure 6.6 (a) and (b) were compared. The difference in P_{i} for the top 3 and 4 data combinations is less than 10^{-3}. Consequently, the more parsimonious 3 data point strategy is used for all further testing.

Data importance (CDOTS)							CVP
0	1	5	4	3	6	2	10
0	1	5	3	6	4	2	20
0	1	3	5	6	4	2	30
0	1	3	6	5	4	2	40
0	1	3	6	5	2	4	50
0	1	3	6	5	2	4	60
0	1	3	6	2	5	4	70
0	1	3	6	2	5	4	80
0	1	3	6	2	5	4	90
0	1	3	6	2	5	4	100

(a) CDOTS

Data importance (CDOTS-ERR)							CVP
0	1	5	4	3	6	2	10
0	1	5	4	3	6	2	20
0	1	4	3	5	6	2	30
0	1	3	4	5	6	2	40
0	3	1	4	5	2	6	50
0	3	1	4	5	2	6	60
0	3	1	4	5	2	6	70
0	3	1	4	5	2	6	80
0	3	1	2	5	4	6	90
0	3	1	2	6	5	4	100

(b) CDOTS-ERR

```
0: Time since last green
1: # vehicles
2: # passengers
3: Stops per vehicle
4: Wait per vehicle
5: Queue length ratio
6: Not turning ratio
```

(c) Data source key

Figure 6.6: The data sources in order of most to least frequently appearing in the 10 results for the CDOTS and CDOTS-ERR algorithms with the lowest P_i value for each CV penetration (percent).

6.2.2 Adjusting the Weighting Vector

When determining the optimal data points, the weighting vector ω_i was held constant as a column vector of N ones. Determining the optimal data points optimises the configuration of the greedy algorithm to minimise the global performance indicator in Equation 4.2 coarsely. Here, the optimal data points are kept constant. However, the weights are adjusted to see if finely adjusting the utility contributions of each data point further minimises the global performance indicator.

The problem here is to find the set of weights ω_i that minimise the global objective function in Equation 4.2 which in its general form is a multivariable optimisation of a single objective. The function to be optimised is a single run on the average demand case for 10%, 50% and 100% CV penetration. Rather than the full 24-hour simulation, 2 hours of the simulation from 07:30-09:30 capturing the morning rush hours are used to reduce the computation time. As the function is non-trivial to differentiate, a multivariable optimisation procedure for non-differentiable equations is needed. The two most widely used optimisation procedures for non-differentiable multivariable problems are the Simplex Method (Nelder and Mead, 1965) (also known as the Nelder-Mead Method), and the Powell Method (Powell, 1964).

Table 6.7 shows the results of the optimisations on the various network configurations. The weights are initialised as ones, and the mean delay and mean stop values from the first run are used as the maximum values in the PI calculation so that the optimisation procedure produces a result ≤ 1. Table 6.7 compares the global performance indicator (PI) and final weight vector for each combination of CV penetration (CVP), optimisation method, with and without pedestrians. The weights correspond to the 'time since last green', 'number of vehicles', and 'mean number of stops per vehicle' data points respectively. The results show that adjusting the weighting vector can improve the performance of the algorithm a small amount. The results show that the greedy stage optimisation algorithm can be improved by up to 5.1% compared to the non-optimised case, but only 2.1% on average. The Powell method generally achieved better optimisation than the Simplex method. Fine-grained optimisation of a system as large as the case study is challenging and computationally time-consuming, and the weights differ with CV penetration which is a difficult metric to calculate. The weights may also be specific for improving performance for the given model configuration and may be overfitted for the greedy stage optimisation of other configurations. Given the incremental gains achieved by the optimisation process, and the dependence of the results on CV penetration, the benefits do not outweigh the computational effort needed to obtain optimised weights, so unit weights are used in the final tests.

Table 6.7: The weights and final PI, and configuration for the optimisation process on the average demand case.

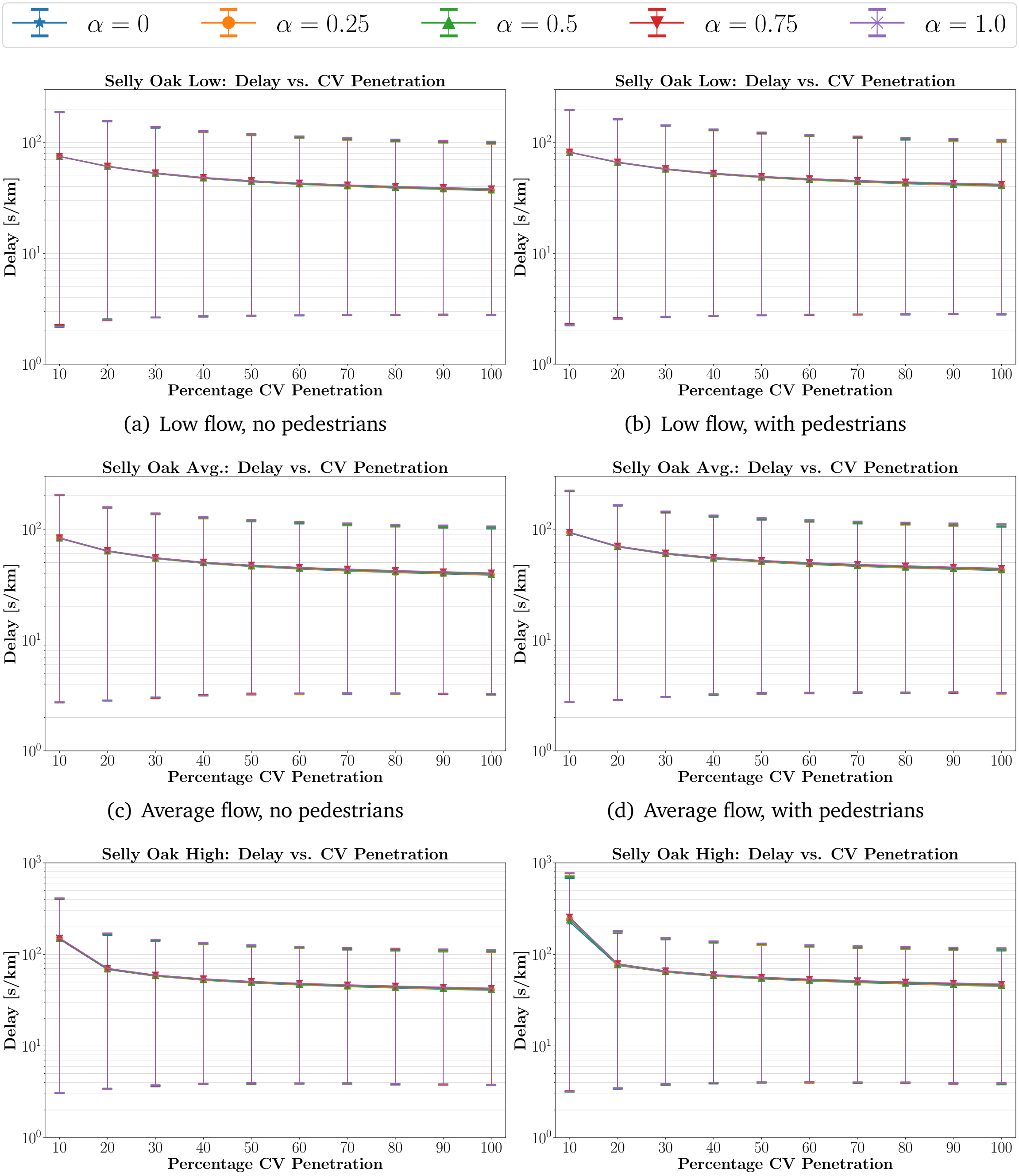
CVP	Method	Pedestrians	Weights	PI
10%	Simplex	False	$(1.05, 1.0, 1.0)^{\mathrm{T}}$	0.999
		True	$(1.0, 1., 1.05)^{\mathrm{T}}$	0.976
	Powell	False	$(0.994975,\ 1.14589803,\ 0.97986267)^{\mathrm{T}}$	1.0
		True	$(0.8974141,\ 1.01950437,\ 0.99784458)^{\mathrm{T}}$	0.976
50%	Simplex	False	$(1.0, 1.0, 1.0)^{\mathrm{T}}$	1.0
		True	$(1.0, 1.0, 1.0)^{\mathrm{T}}$	1.0
	Powell	False	$(1.99999979,\ 2.00703878,\ 1.00000018)^{\mathrm{T}}$	0.972
		True	$(-0.62187276,\ 2.00957817,\ 1.05963046)^{\mathrm{T}}$	0.949
100%	Simplex	False	$(1.03333333, 1.01666667, 1.0)^{\mathrm{T}}$	0.979
		True	$(1.05, 1.0, 1.0)^{\mathrm{T}}$	0.989
	Powell	False	$(-1.17553325,\ 2.51357372,\ 2.30595775)^{\mathrm{T}}$	0.956
		True	$(-0.75467399,\ 1.38196603,\ 1.35184209)^{\mathrm{T}}$	0.96

6.3 Determining the Greedy Algorithm Coordination Factor

In addition to the set of optimal data points for the it is necessary to find the optimal value for α in Equation 4.9. In the tests to determine the optimal dataset $\alpha = 0$, here $\alpha \in \{0, 0.25, 0.5, 0.75, 1\}$ are tested for 10–100% CV penetration at each traffic demand level.

6.3.1 Delay

Figure 6.7 and 6.8 shows the results for average delay per kilometre bounded by the 90% prediction interval for CV penetrations from 10–100% for each demand level and both with and without pedestrians. Each of the plots depicts the same situation, varying the coordination factor α does not further reduce delay to any visible extent. The difference between the mean delays per kilometre is less than 2 s in all cases.



(a) Low flow, no pedestrians

(b) Low flow, with pedestrians

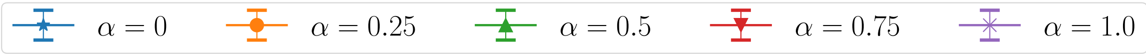
(c) Average flow, no pedestrians

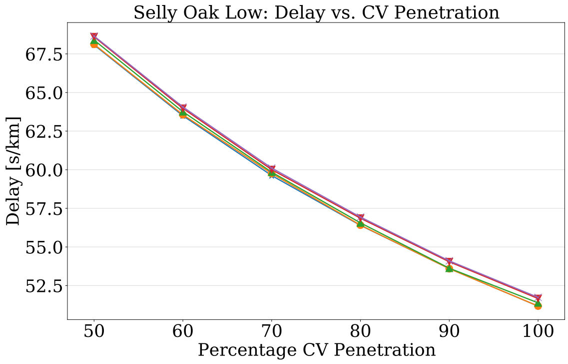
(d) Average flow, with pedestrians

(e) High flow, no pedestrians

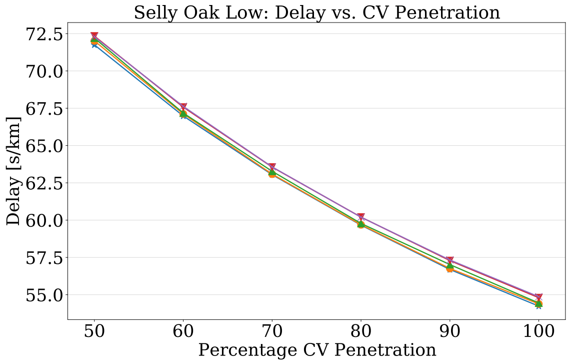
(f) High flow, with pedestrians

Figure 6.7: Plots of mean delay per kilometre for each demand level, with and without pedestrians, at CV penetrations from 10%-100%. Each plot compares the performance of the CDOTS algorithm with varying α values. The bands on the data represent the 90% prediction interval.

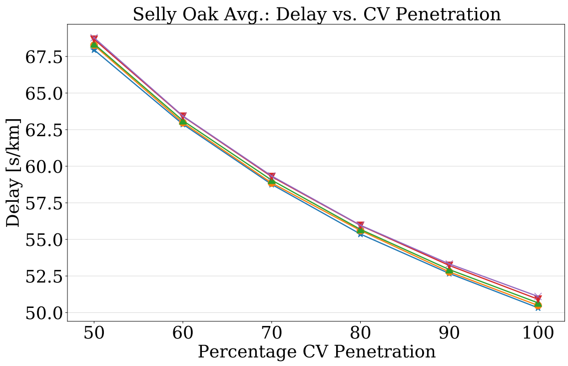




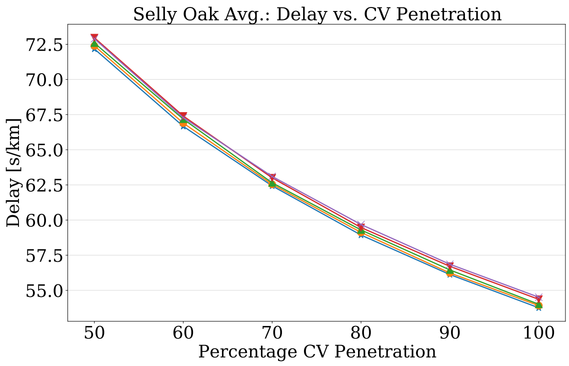
(a) Low flow, no pedestrians



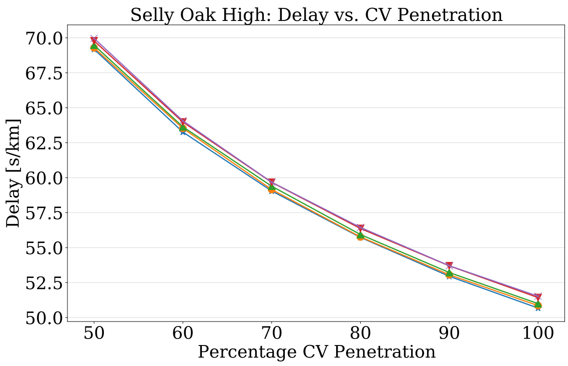
(b) Low flow, with pedestrians



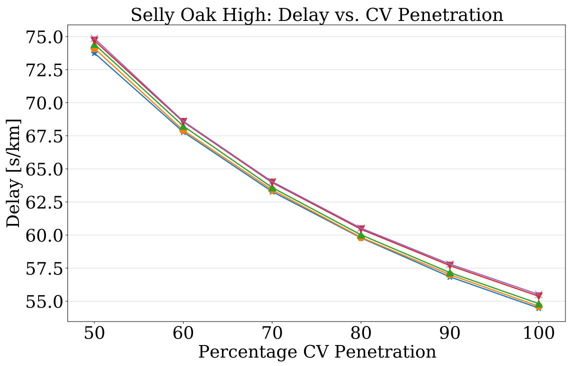
(c) Average flow, no pedestrians



(d) Average flow, with pedestrians



(e) High flow, no pedestrians



(f) High flow, with pedestrians

Figure 6.8: Plots of mean delay per kilometre for each demand level, with and without pedestrians, at CV penetrations from 50%-100%. Each plot compares the performance of the CDOTS algorithm with varying α values.

6.3.2 Stops

Figure 6.9 shows the results for average delay bounded by the 90% prediction interval for CV penetrations from 10–100% for each demand level and both with and without pedestrians. Each of the plots depicts the same situation, varying the coordination factor α does not further reduce stops to any visible extent. The difference between the mean stops per kilometre is less than 0.1 stops in all cases. The only notable difference is at 10% CV penetration under high traffic demand, with pedestrians. In this case, the upper bound of the 90% prediction interval is slightly lower for $\alpha = 0.5$ than for the other values of α.

6.3.3 Hypothesis Testing

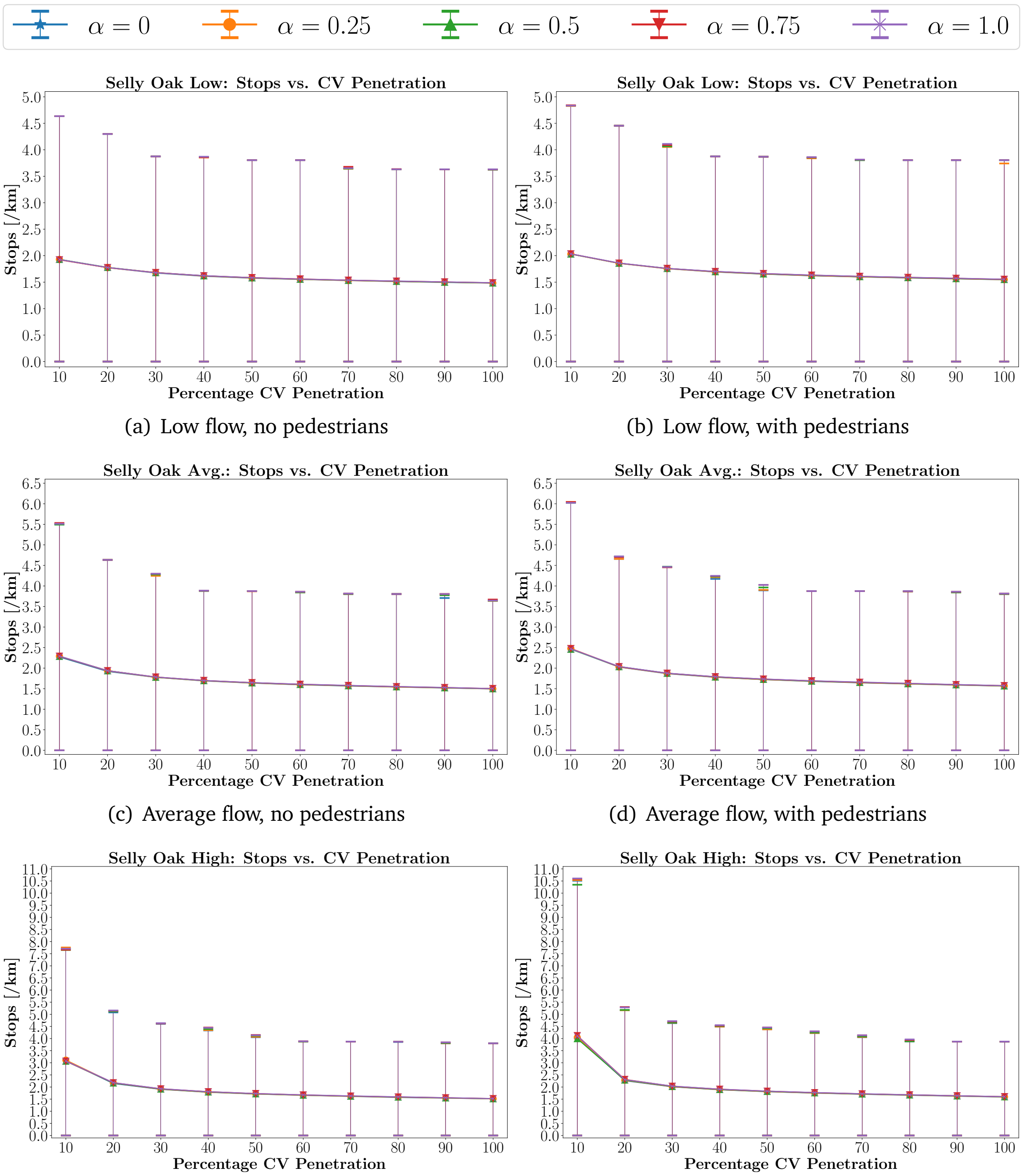
As the simulations were stochastic, hypothesis tests were performed on the delay, and stop data in order to assess its statistical independence across the $N = 50$ experimental runs, and incremental increases in CV penetration. As this is a calibration test, emissions were not tested as delay and stops are representative of the system behaviour and are the PI's begin optimised. Here, the following hypotheses were tested:

- The null hypothesis H_0 was that the mean stops and delay data at $\alpha > 0$ were drawn from the same distribution as the data for $\alpha = 0$.
- The alternative hypotheses H_1 was that the mean stops and delay data at $\alpha > 0$ were drawn from a different distribution as the data for $\alpha = 0$.

As in Section 6.1, D'Agostino's K^2 test (D'Agostino, 1971) and the Shapiro-Wilk test (Shapiro and Wilk, 1965) were used to test for normality. The results of the normality tests only reject the hypothesis that the data is normal with $p < 0.01$ in less than 10% of cases. This indicates that while many of the results follow a normal distribution, a normal distribution is not guaranteed. As proposed in Watkins (2019), for two samples that may not be normally distributed and are independent of each other, a Mann-Whitney U test (Mann and Whitney, 1947) was performed between H_0 and each H_1, and the p-value was determined.

Table 6.8 shows the results of the hypothesis testing for the delay and stops results at each demand level. The hypothesis testing results show that for $\alpha < 0.5$ and low traffic demand, the results do not conclusively reject the null hypothesis for all CVPs. The cases that fail to reject the null hypothesis were for CVP$< 30\%$ indicating that a certain level of traffic and CVs are required for the coordination term to have a significant effect. For the hypothesis testing results for the stops data, only the high demand case with $\alpha = 1$ rejected the null hypothesis with $p < 0.05$ for all cases. For the rest of the case, most failed to reject the null hypothesis for more than 50% of cases.

The hypothesis testing results show that using a coordination term in the greedy algorithm does not provide a significant change in behaviour to the system for the case study corridor.



(a) Low flow, no pedestrians

(b) Low flow, with pedestrians

(c) Average flow, no pedestrians

(d) Average flow, with pedestrians

(e) High flow, no pedestrians

(f) High flow, with pedestrians

Figure 6.9: Plots of mean stops per kilometre for each demand level, with and without pedestrians, at CV penetrations from 10%-100%. Each plot compares the performance of the CDOTS algorithm with varying α values. The bands on the data represent the 90% prediction interval.

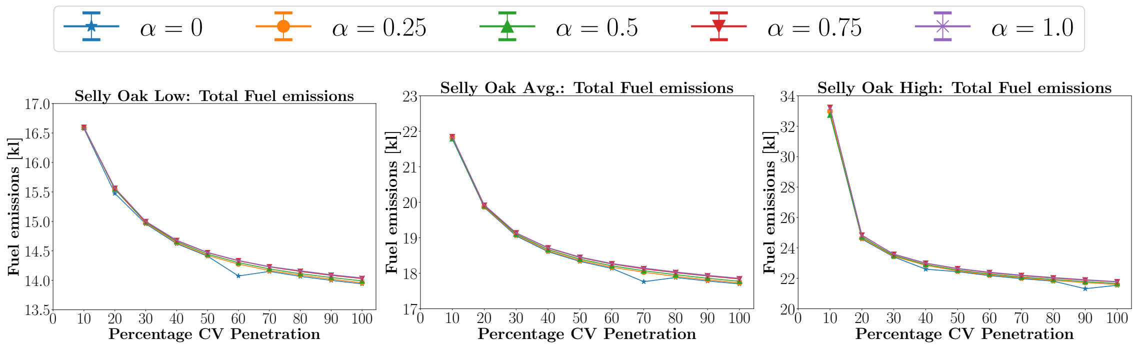
Table 6.8: The results of the hypothesis testing on the delay and stops results of α calibration. The results show the percentage of cases that reject the null hypothesis in favour of the alternative hypothesis with $p < 0.05$ for each demand level at each value of α.

	Demand	α			
		0.25	0.5	0.75	1
Delay	Low	30%	70%	80%	80%
	Avg.	50%	80%	90%	100%
	High	40%	70%	90%	80%
Stops	Low	10%	0%	20%	30%
	Avg.	20%	30%	60%	60%
	High	30%	60%	90%	90%

Most notably, the results for the stops did not show significant change for most cases, indicating the coordination term either does not work or that it is made redundant by other mechanisms in the algorithm. These assertions are tested in the next section.

6.3.4 Emissions

Figure 6.10 shows the results for mean total fuel consumption for CV penetrations from 10–100% for each demand level and both with and without pedestrians. Only fuel consumption is used as the emission trends have been consistent across each pollutant in previous sections, so the trend in fuel consumption is representative of the rest. Each of the plots depicts the same situation, varying the coordination factor α does not further reduce stops to any visible extent. Emissions slightly increase when coordination is added. The difference between the mean total fuel consumption is less than 250 litres in all cases.



(a) Low flow: Fuel (b) Average flow: Fuel (c) High flow: Fuel

Figure 6.10: Plots of mean total fuel consumption for each demand level at CV penetrations from 10%-100%. Each plot compares the performance of the CDOTS algorithm with varying α values.

6.3.5 Discussion of the PI results

The invariance of the stage selection algorithm to coordination is not an unexpected outcome given the case study. As the stage optimiser is formed from CV data, the vehicle is factored into the utility calculation within seconds of entering a lane controlled by an intersection. Box et al. (2012) and Goodall et al. (2013) suggested that if an intersection controller has sufficient advanced warning of approaching vehicles vehicle, and can respond quickly enough to the oncoming traffic, then deliberate coordination may not be necessary. Furthermore, in Chapter 2, the discussion of the TRANSYT PI highlighted that if delays and stops are minimised then the closer, the PI gets to zero the closer to a free-flow state the traffic is. As the greedy stage sequence optimisation operates locally to minimise a PI that seeks the global reduction of delay and stops, the results are confirmation that the stage sequence optimisation process is sufficiently self-coordinating to make deliberately promoting coordination unnecessary.

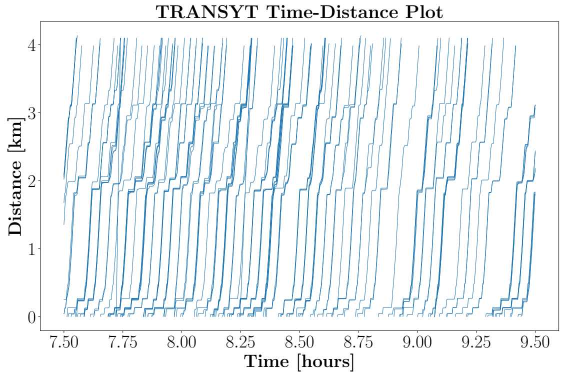
These findings are evidence that there is enough space between the intersections case study urban corridor such that the intersections can locate CVs quickly enough to make coordination redundant. For the final set of tests, $\alpha = 0$ is used as the other values for α offer little further benefit for the intersections in the case study. It should be noted that for road networks with more closely spaced intersections, a larger α parameter may be beneficial. The final tests determine if the CDOTS algorithm is sufficiently self-coordinating that the addition of the coordination term is not necessary.

6.3.6 Coordination Testing

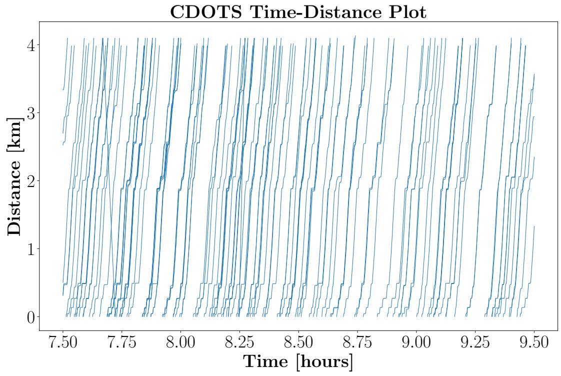
In the previous section, adding a coordination term to the stage sequence optimisation for the CDOTS algorithm with a coordination factor did not improve on the CDOTS algorithm with no coordination factor for the case study corridor. In this section, it is investigated if the greedy stage algorithm can react quickly enough in response to the CV data that it self-coordinates.

To assess the level of coordination, time-distance plots are used to inspect vehicle progression through the corridor. Vehicles that enter the corridor travelling westbound on the Edgbaston Road (B4217), and then exit the corridor after Junction 10 (see Appendix B) on the Bristol Road (A38). This route was chosen as vehicles travelling it encounter every signalised intersection in the corridor during their journey.

Figure 6.11 shows compares vehicle flows for the target route when the TRANSYT (Figure 6.11(a)) and CDOTS (Figure 6.11(b)) algorithms with 100% CV penetration are used for high traffic demand. The time-distance data is collected during the morning peak demand hours (07:30–09:30). The results for the CDOTS algorithm are significantly smoother than those for TRANSYT, indicating vehicles are less delayed. The results for the CDOTS algorithm also less pronounced stopping around kilometre 2 and 3 than in the TRANSYT results.



(a) TRANSYT



(b) CDOTS

Figure 6.11: Time-distance plots for vehicles travelling southbound through all intersections during the morning peak hours. The same vehicles are compared for TRANSYT and the CDOTS algorithm for high traffic demand and 100% CV penetration.

Figure 6.12 compares a subset of the vehicles departing between 07:30–08:00 under both TRANSYT control and the CDOTS algorithm. By looking more closely at specific vehicle traces the algorithm's impacts on their progression can be better assessed. It can be seen that all vehicles begin their journeys at the same time, regardless of the signal control algorithm. As in Figure 6.11, the vehicles make faster progress when signals are controlled using the CDOTS algorithm. When the CDOTS algorithm is used, vehicles stop less frequently and for shorter amounts of time (shorter plateaus) than with TRANSYT.

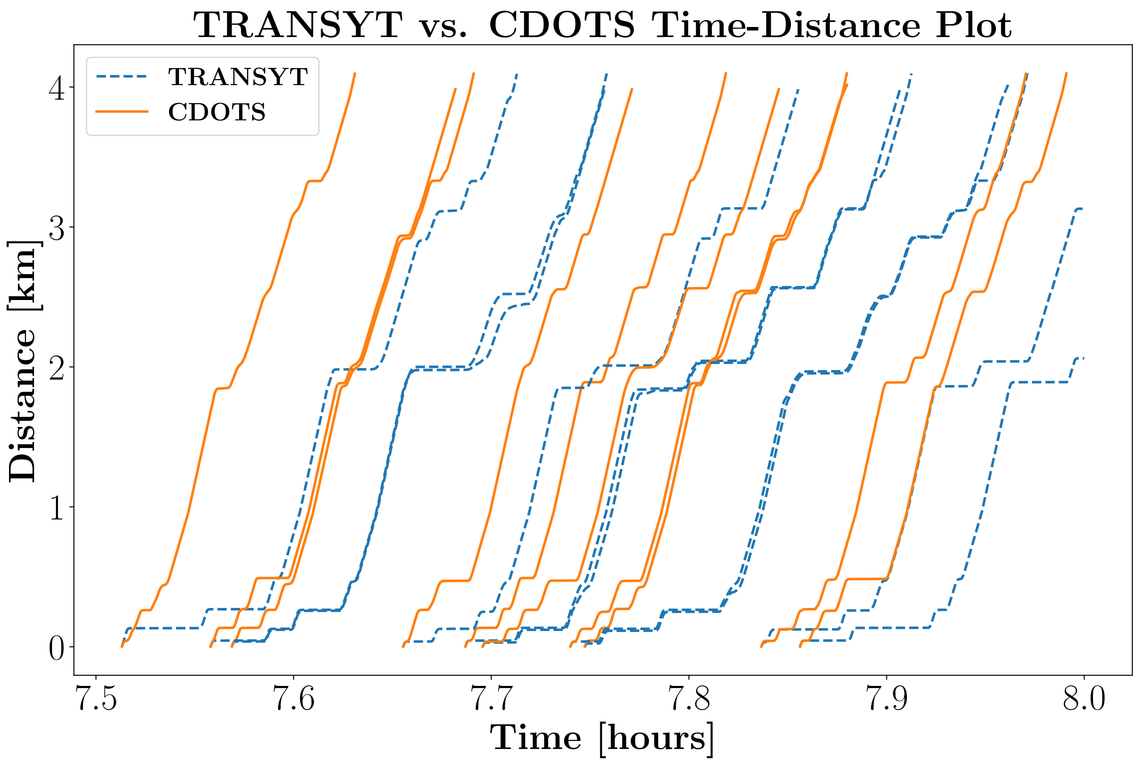


Figure 6.12: Time-distance plot comparing the vehicle traces with TRANSYT against those with the CDOTS algorithm.

As vehicles in a transport network desire different destinations, their interactions often come into conflict. As it is the role of the traffic signal controller to resolve these conflicts, there are inevitable compromises made to favour one set of road users over another. Under high traffic demand, it is unlikely that a vehicle never stops. However, the CDOTS algorithm demonstrates it is possible to manage traffic signals to make vehicles stop less frequently and achieve better progression. A key finding of these results, and indeed this research, is that the CDOTS algorithm demonstrates that coordination is redundant if vehicles can be detected early enough, and their presence responded to quickly enough. This finding is important as it demonstrates that using CV data and having a responsive traffic signal controller makes signal coordination unnecessary under certain conditions. A departure from deliberate signal coordination in connected environments represents an important change from where research efforts have been placed for unconnected traffic signal control.

6.4 Testing the CDOTS Algorithm on the Case Study Model

In this section, the results for the simulations of the CDOTS algorithm on the case study model are compared with those of the TRANSYT and MATS algorithms. As discussed in Section 5.7, mean travel time delay and mean stops were selected as the performance indicators for this research. Delay and stops are primary components on which TRANSYT optimises signal timings (Binning et al., 2013) and allow comparison. In this section, the delay results are discussed in Section 6.4.1, and the stops results are compared in Section 6.4.2. Hypothesis testing on the stops and delay results are presented in Section 6.4.4.

Additionally, the impact of the CDOTS algorithm on vehicle emissions is assessed in Section 6.4.3. Finally, the impact of the CDOTS algorithm on intersection stage intervals for selected junctions is described in Section 6.4.5. It should be noted that the TRANSYT results do not vary with CV penetration, as TRANSYT controls traffic independently of CV data.

6.4.1 Delay

In Figures 6.13 and 6.14, the results comparing the CDOTS algorithm with the TRANSYT and MATS algorithms' performance in terms of mean delay per kilometre for are shown. The algorithms are compared for each of the three demand levels, and both with and without pedestrians present. In Tables 6.9 and 6.10, the percentage reduction in mean stops and mean delay of the MATS algorithm relative to TRANSYT are presented. The comparisons are made across CV penetration rates and demand levels.

In Figure 6.13 and 6.14 (a) and (b), under low traffic demand, the CDOTS algorithm does marginally better than the MATS algorithm does at reducing delay compared with TRANSYT. Mean delay is reduced by over 80% under ideal communication conditions with CV penetrations as low as 10% regardless of pedestrian presence in the network. From Tables 6.9 and 6.10, it can be seen that with non-ideal communications, the delay reduction is above 55% at 10% CV penetration compared with 40% for the MATS algorithm, but by 50% CV penetration the CDOTS algorithm reduced mean delay to within 6% of the ideal cases regardless of pedestrians. Non-ideal communication channel conditions reduce the performance of the CDOTS algorithm at low CV penetrations, but the plots show the negative effects are largely mitigated by 30% CV penetration. In both plots, there is a notable reduction in the 90% prediction interval for CV penetrations above 10%, and the lower bound of the prediction interval for the CDOTS algorithm is lower than that of the other two algorithms. The compressed prediction intervals indicate that the CDOTS algorithm makes travel times significantly more reliable. Under ideal communication conditions, the CDOTS algorithm does not perform significantly better than the MATS algorithm at low CV penetrations, except when there are pedestrians. Under non-ideal communication conditions, the CDOTS algorithm does up to 18% better than the MATS algorithm at mitigating delay, and by 100% CV penetration the CDOTS algorithm performs better than the MATS algorithm under ideal conditions.

Figures 6.13 and 6.14 (c) and (d) compare the CDOTS algorithm with the MATS and TRANSYT algorithms for average traffic demand. The effects of non-ideal communications are more pronounced under the increased traffic demand, with the delay not settling until closer to 40% CV penetration. However, Tables 6.9 and 6.10 show that the effects of non-ideal communications are offset for this demand case by 50% CV penetration and that the CDOTS algorithms perform as well as or better than the MATS algorithm above 50% CV penetration. As with the low demand case stage optimisation is of little benefit when there are no pedestrians, but significantly increase the rate of delay reduction at low CV penetrations when there are pedestrians present. The plots also show a significant reduction in delay variability compared with TRANSYT, with the 95th percentile data being much less than the mean TRANSYT delay reduction by 30% CV penetration. Furthermore, the lower bound of the prediction interval is less for the CDOTS algorithm than it is for the MATS and TRANSYT algorithms.

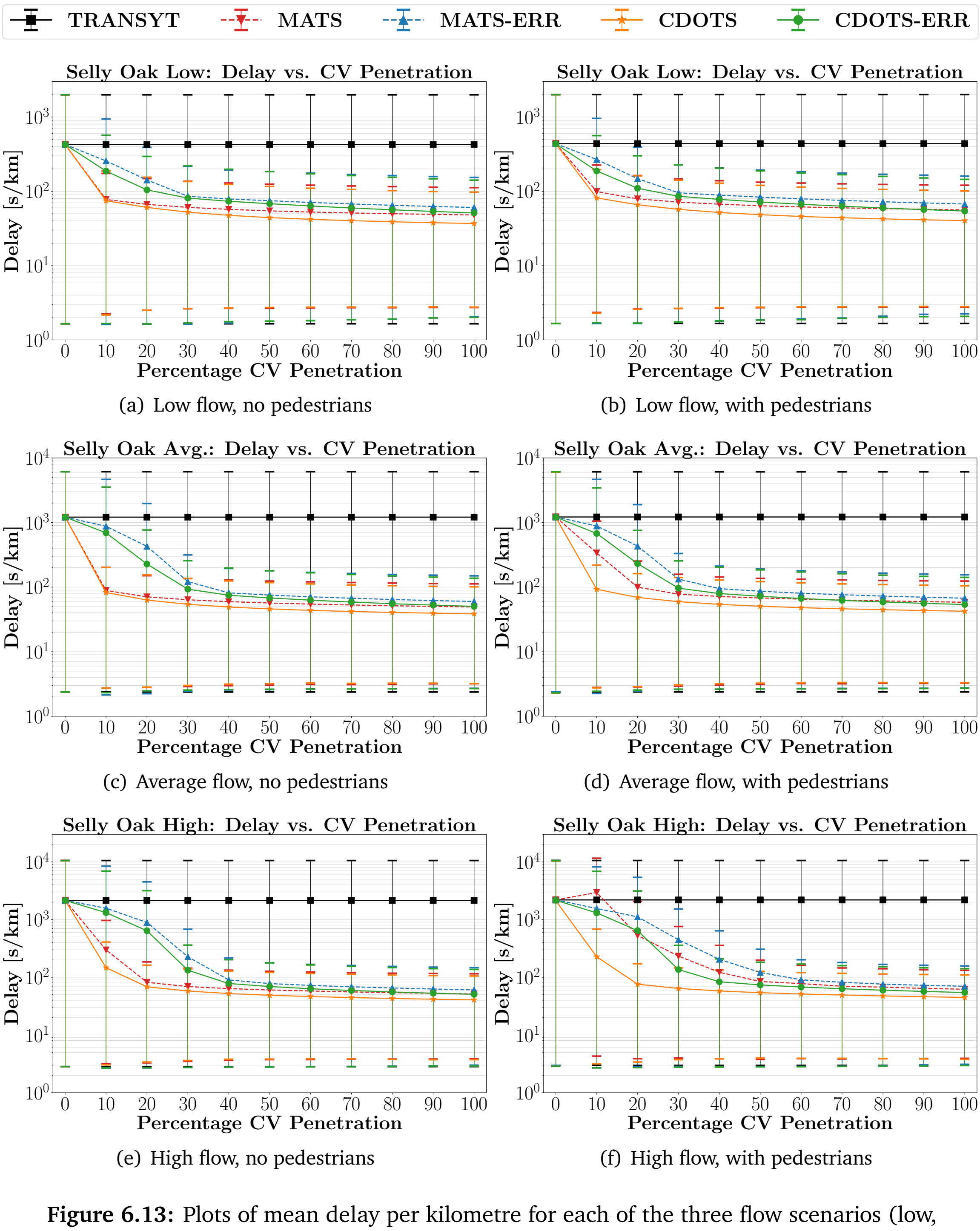
In the plots for the high demand case shown in Figures 6.13 and 6.14 (e) and (f), it can be seen again that non-ideal communications inhibit the CDOTS and MATS algorithm's ability to reduce delays. Similarly to the lower demand cases, Tables 6.9 and 6.10 the effects of non-ideal communications are overcome by 50% CV penetration, and the CDOTS algorithm outperforms the MATS algorithm above 50% CV penetration. The CDOTS algorithm also reduces delay better with increasing CV penetrations under non-ideal communication conditions. Under high traffic demand, and when pedestrians are present, the MATS algorithm performs worse than TRANSYT at 10% CV penetration. The CDOTS algorithm mitigates this spurious behaviour as it is better able to distribute the demand at the intersection. As with the MATS algorithm, the lower bound of the 90% prediction interval increases marginally with increasing CV penetration. In contrast, the CDOTS algorithm does not increase the lower bound of the prediction interval as much as the MATS algorithm does.

Overall, from Figures 6.13 and 6.14 and Tables 6.9 and 6.10 it can be seen that the CDOTS algorithm offers significant reductions in delay at all levels of traffic demand for CV penetrations above 10%. The mean delay can be reduced by more than 94% with CV penetrations as low as 50% under average conditions. Furthermore, the CDOTS algorithm reduces delay variability to a similar level regardless of the traffic demand, which corresponds to more reliable journeys for drivers. The reduction in delay variability emphasises that the CDOTS algorithm allows road users to make their journeys more reliably, and indicates the algorithm is robust to fluctuations in traffic demand. The CDOTS algorithm reduces delay better than its parent MATS algorithm when there are pedestrians present, highlighting the CDOTS algorithm's ability at redistributing traffic demand intelligently. Across all the results, some delay variability remains even at high CV penetrations due to the varied route lengths in the corridor resulting from its large size. Under non-ideal communication conditions, although improvements are possible, they are less significant until the CV penetration is at least 30%. The discrepancy between the results for the CDOTS algorithm and the CDOTS-ERR algorithm can be attributed to the CDOTS-ERR algorithm overestimating or underestimating the queue clearance time and stage extensions due to the noise, error, and delay in the communication channel. However, the CDOTS algorithm still offers reductions in mean delay and variability compared with TRANSYT. Compared to the MATS algorithm variant with loop data in Chapter 3 Tables 6.1 and 6.2, the CDOTS algorithm is better at reducing delay on average, indicating that loops are of little benefit when traffic can be controlled in real-time with high-resolution data. Given the degraded state of the case study urban corridor, the CDOTS algorithm would be a good alternative to installing new loop detectors if CV penetrations of above 10% can be achieved.

6.4.2 Stops

In Figure 6.15, the results comparing the CDOTS algorithm with the TRANSYT and MATS algorithms' performance in terms of mean stops per kilometre for are shown. The algorithms are compared for each of the three demand levels, and both with and without pedestrians present. In Tables 6.9 and 6.10, the percentage reduction in mean stops and mean delay of the CDOTS and MATS algorithms relative to TRANSYT are presented. The comparisons are made across CV penetration rates and demand levels.

Figures 6.15 (a) and (b) show the mean stops per kilometre, for the low demand case. It can be seen in both plots that while the mean reduction in stops is relatively small in comparison to the delay reductions, by 30% CV penetration, the 95th percentile number of stops is substantially reduced. Here, errors in the communication channel do not affect the ability of the CDOTS algorithm to reduce of stops as significantly as in the delay results, and there is little difference between the ideal and non-ideal results. The CDOTS algorithm is better at reducing stops than the MATS algorithm even in the presence of non-ideal communication conditions in all cases where CVs are present. In the case where pedestrians are present,



(a) Low flow, no pedestrians

(b) Low flow, with pedestrians

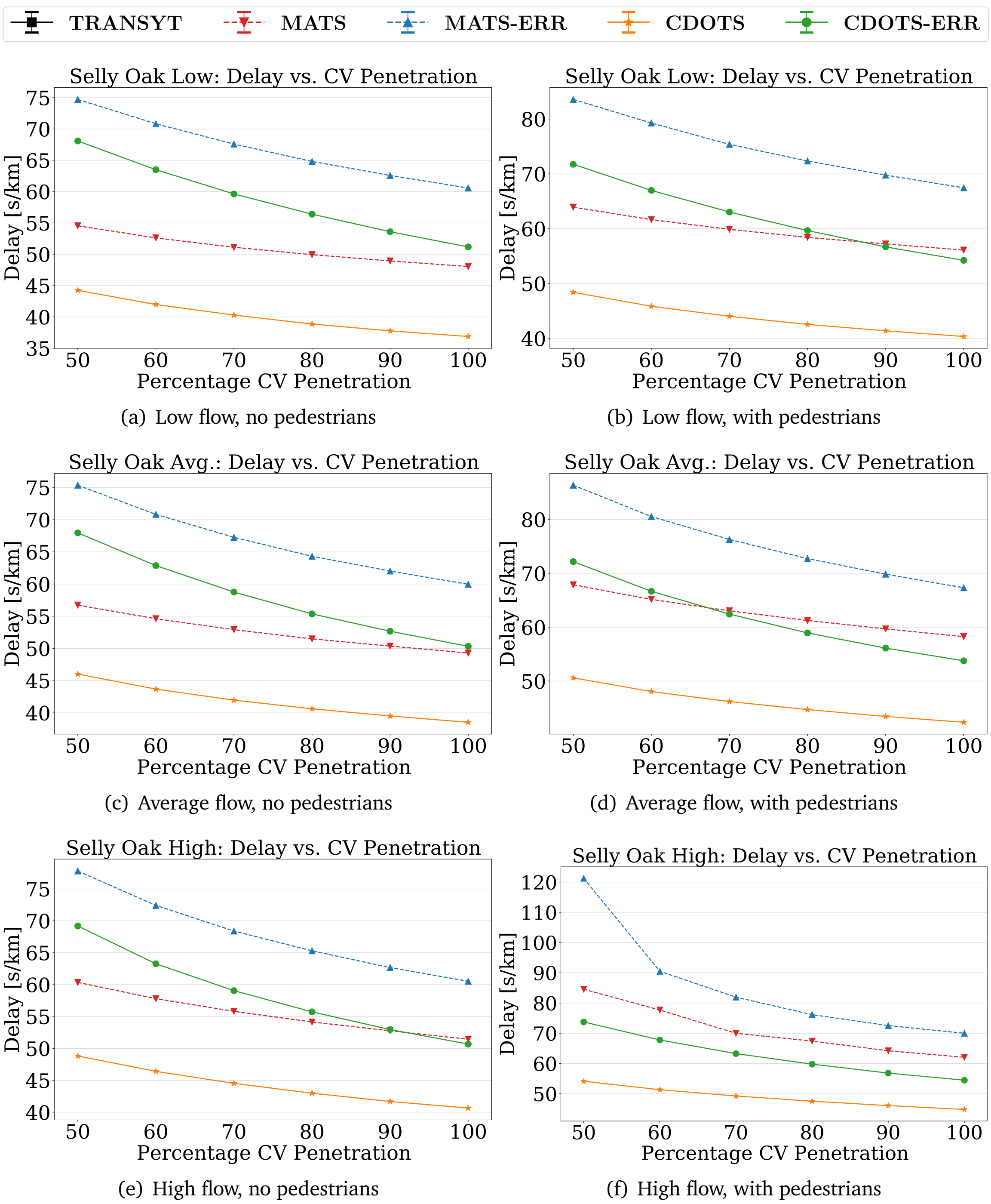
(c) Average flow, no pedestrians

(d) Average flow, with pedestrians

(e) High flow, no pedestrians

(f) High flow, with pedestrians

Figure 6.13: Plots of mean delay per kilometre for each of the three flow scenarios (low, average, high), with and without pedestrians. Each plot compares the performance of the CDOTS algorithm is compared with the MATS algorithm with and without errors, to TRANSYT. The bands on the data represent the 5th and 95th percentiles of the data as indicators of variability.



(a) Low flow, no pedestrians

(b) Low flow, with pedestrians

(c) Average flow, no pedestrians

(d) Average flow, with pedestrians

(e) High flow, no pedestrians

(f) High flow, with pedestrians

Figure 6.14: Plots of mean delay per kilometre for each of the three flow scenarios (low, average, high), with and without pedestrians. Each plot compares the performance of the CDOTS algorithm variants at CV penetrations above 50% so that the differences can be more clearly observed.

Table 6.9: The benchmarking of the tested CDOTS algorithm instances against the MATS algorithm and TRANSYT for the low (A), average (B), and high (C) demand cases without pedestrians. The results show the percentage reduction in the average delay and the average number of stops at 10%, 50%, and 100% CV penetration.

A: Low Traffic Demand (80% of Average)						
Algorithm	**CV Penetration**					
	10%		**50%**		**100%**	
	Delay	**Stops**	**Delay**	**Stops**	**Delay**	**Stops**
MATS	82%	7%	87%	19%	89%	24%
MATS-ERR	40%	4%	82%	20%	86%	25%
CDOTS	82%	12%	90%	28%	91%	32%
CDOTS-ERR	56%	8%	84%	26%	88%	32%
B: Average Traffic Demand						
Algorithm	**CV Penetration**					
	10%		**50%**		**100%**	
	Delay	**Stops**	**Delay**	**Stops**	**Delay**	**Stops**
MATS	93%	3%	95%	26%	96%	32%
MATS-ERR	28%	9%	94%	25%	95%	33%
CDOTS	93%	9%	96%	34%	97%	40%
CDOTS-ERR	43%	10%	94%	31%	96%	40%
C: High Traffic Demand (120% of Average)						
Algorithm	**CV Penetration**					
	10%		**50%**		**100%**	
	Delay	**Stops**	**Delay**	**Stops**	**Delay**	**Stops**
MATS	86%	-29%	97%	40%	98%	47%
MATS-ERR	27%	13%	96%	37%	97%	47%
CDOTS	93%	5%	98%	47%	98%	53%
CDOTS-ERR	39%	24%	97%	44%	98%	53%

Table 6.10 shows that the CDOTS algorithm is better at reducing stops than the MATS algorithm in all cases.

Figures 6.15 (c) and (d) compare the CDOTS algorithm with TRANSYT and the MATS algorithm for average traffic demand. The reductions in the mean number of stops are greater than in the low demand case, particularly at low CV penetrations. In both plots, the variability in the number of stops does not decrease significantly below 30% CV penetration. The effects pedestrians have on the algorithm are more pronounced for the average demand case than in the low demand case. At 10% the MATS-FT and MATS-HA algorithm variants perform worse than TRANSYT due to the increased switching between control modes and the loss of signal coordination due to pedestrian stages. In contrast, the CDOTS algorithm is unaffected by the increase in demand or non-ideal communication conditions. When

Table 6.10: The benchmarking of the tested CDOTS algorithm instances against the MATS algorithm and TRANSYT for the low (A), average (B), and high (C) demand cases with pedestrians. The results show the percentage reduction in the average delay and the average number of stops at 10%, 50%, and 100% CV penetration.

A: Low Traffic Demand (80% of Average)						
Algorithm	**CV Penetration**					
	10%		**50%**		**100%**	
	Delay	**Stops**	**Delay**	**Stops**	**Delay**	**Stops**
MATS	77%	-4%	85%	17%	87%	23%
MATS-ERR	39%	4%	81%	19%	85%	25%
CDOTS	81%	11%	89%	28%	91%	32%
CDOTS-ERR	57%	10%	84%	27%	88%	33%
B: Average Traffic Demand						
Algorithm	**CV Penetration**					
	10%		**50%**		**100%**	
	Delay	**Stops**	**Delay**	**Stops**	**Delay**	**Stops**
MATS	72%	-72%	94%	25%	95%	32%
MATS-ERR	27%	6%	93%	23%	94%	33%
CDOTS	92%	7%	96%	35%	97%	41%
CDOTS-ERR	44%	12%	94%	33%	96%	41%
C: High Traffic Demand (120% of Average)						
Algorithm	**CV Penetration**					
	10%		**50%**		**100%**	
	Delay	**Stops**	**Delay**	**Stops**	**Delay**	**Stops**
MATS	-34%	-192%	96%	39%	97%	51%
MATS-ERR	29%	20%	94%	28%	97%	52%
CDOTS	90%	-5%	98%	53%	98%	59%
CDOTS-ERR	40%	33%	97%	51%	98%	59%

non-ideal communications are present, the CDOTS algorithm performs slightly better than the ideal case at 10% CV penetration, showing that as with the MATS algorithm, relaxing the mode switching frequency may be beneficial.

Figures 6.15 (e) and (f) show the comparison between each control algorithm for high traffic demand. As with the average demand case, the high demand on the intersections causes an increased level of stopping in the MATS algorithm at CV penetrations below 20% in the non-pedestrian case, and 50% in the pedestrian case, even when inductive loops are present. The degradation in performance at low CV penetrations is overcome by the stage sequence optimisation provided by the CDOTS algorithm. The CDOTS algorithm does show signs of performance beginning to degrade in the pedestrianised case at 10% CV penetration under ideal conditions, indicating that a further increase in traffic demand may destabilise the algorithm. Tables 6.9 and 6.10 show that there are still reductions in stops that can be achieved between 50% and 100% CV penetration, unlike for delay where after 50% CV penetration the gains were marginal. The benefits of less frequent control reducing stops are seen in the average demand case are also seen here but are of little benefit overall.

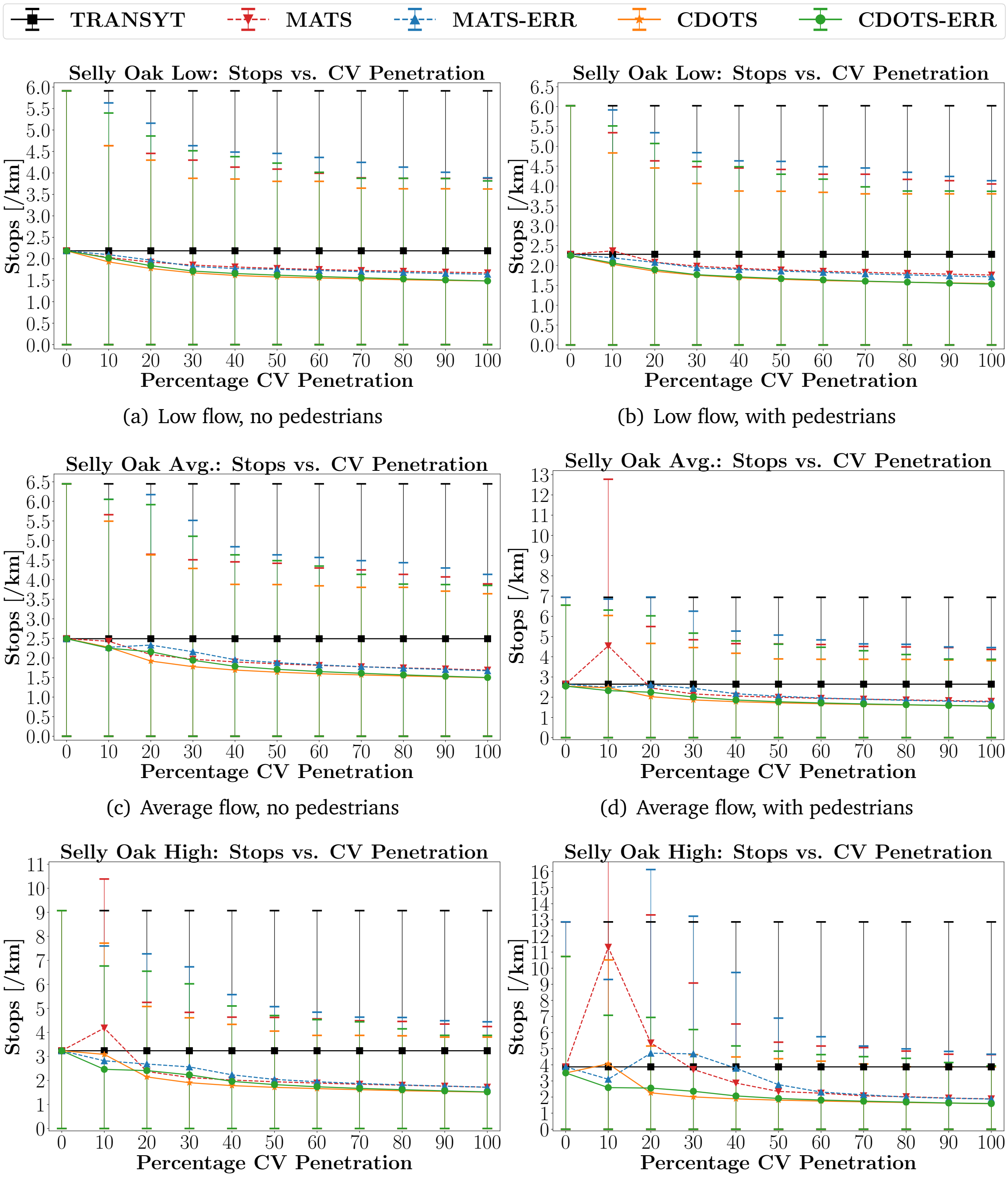
Overall, from Figures 6.15 and Tables 6.9 and 6.10 it can be seen that the CDOTS algorithm offers reductions in the number of stops vehicles make per kilometre in all cases where CVs are present for all traffic demands. The greatest reductions in stop variance are achieved when there is high demand in the corridor and high penetrations of CVs. The greedy stage optimisation heuristic effectively addresses the instability of the MATS algorithm in the CDOTS algorithm. The effects communication errors have on the average number of stops are negligible, and showed that in some high CV penetration cases at high demands that receiving data less frequently can be beneficial. Compared to the MATS algorithm variant with loop data in Chapter 3 Tables 6.1 and 6.2, the CDOTS algorithm is better at reducing stops on average, indicating that loops are of little benefit when traffic can be controlled in real-time with high-resolution data.

6.4.3 Emissions

Figure 6.16 shows how the CDOTS, MATS, and TRANSYT algorithms impact on the mean total emissions over the experiment runs. The emissions studied are CO_2, CO, NO_x, PM_x, and Fuel, as described in Chapter 5.5. The total emissions are presented for each CV penetration, and each of the three traffic demands cases. Only the results for the pedestrian case are shown as, as the algorithms are more susceptible to perturbations when pedestrians were included.

Figures 6.16 (a), (d), (g), (j), and (m) show the total emission results for the CDOTS and MATS algorithms compared with TRANSYT for low traffic demand. The trends in each of the plots appear similar regardless of the emission. The CDOTS algorithm is better than the MATS algorithm in all cases where CVs are present under ideal conditions. Errors in the communication channel cause a slower reduction in emissions than in the ideal case, and the trend does not converge on a similar point to the ideal cases like in the delay and stop results. Furthermore, the CDOTS algorithm under non-ideal conditions outperforms the MATS algorithm under ideal conditions at 10%, and above 50% CV penetration.

Figures 6.16 (b), (e), (h), (k), and (n) show the total emission results for the CDOTS and MATS algorithms compared with TRANSYT for average traffic demand, and Table 6.11 shows the percentage difference between the MATS algorithm and TRANSYT at 10%, 50%, and 100% CV penetration. It can be seen that as with the stops results, the increased mode switching of the MATS algorithm at low CV penetrations causes an increase. The CDOTS algorithm entirely mitigates the spurious behaviours as a result of its ability to schedule stages. From Table 6.11, the CDOTS algorithm reduces emissions 6.8% further on average than the



(a) Low flow, no pedestrians

(b) Low flow, with pedestrians

(c) Average flow, no pedestrians

(d) Average flow, with pedestrians

(e) High flow, no pedestrians

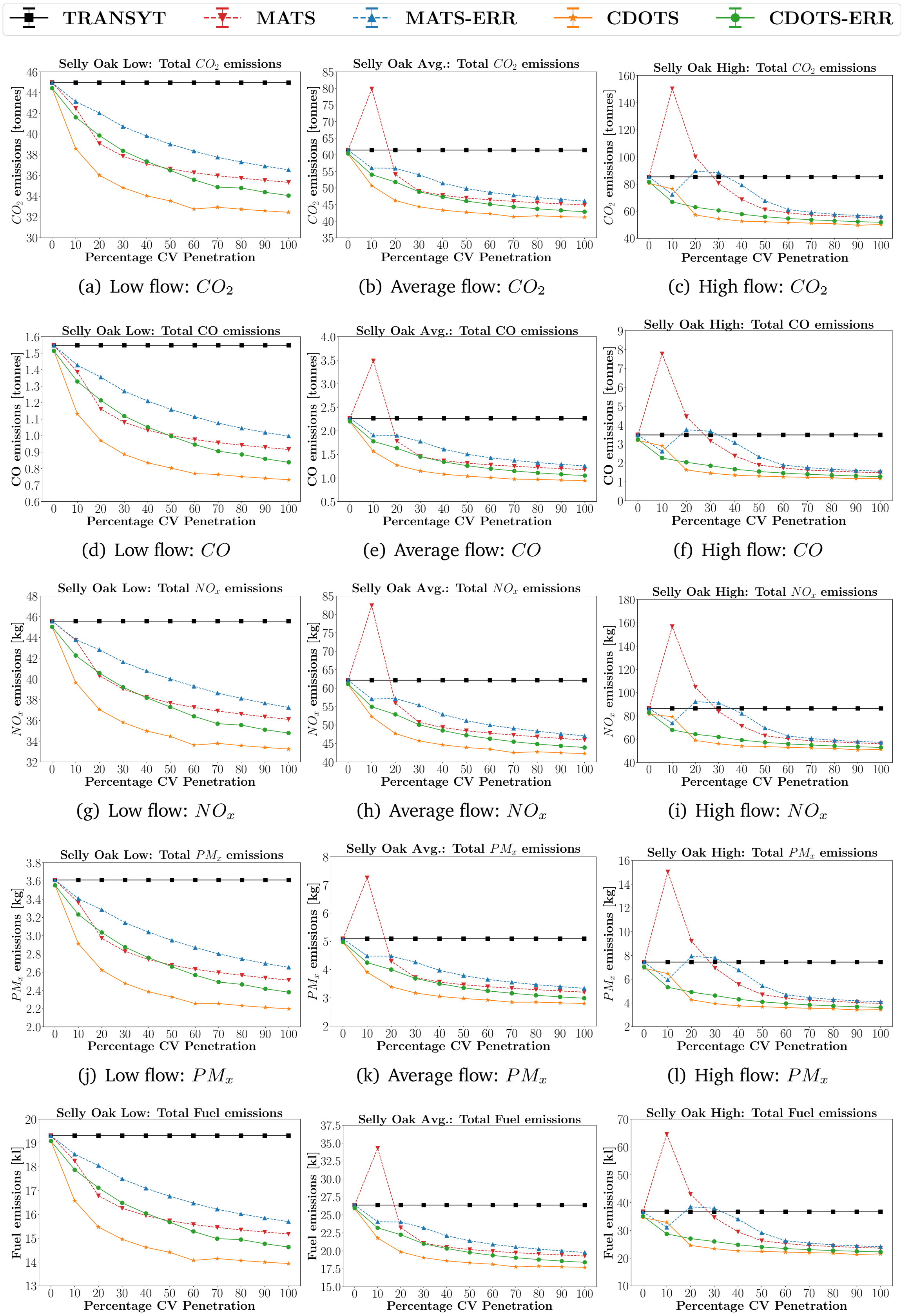
(f) High flow, with pedestrians

Figure 6.15: Plots of mean stops per kilometre for each of the three flow scenarios (low, average, high), with and without pedestrians. Each plot compares the performance of the CDOTS algorithm is compared with the MATS algorithm with and without errors, to TRANSYT.. The bands on the data represent the 5th and 95th percentiles of the data as indicators of variability.

MATS algorithm compared with TRANSYT. Under non-ideal communication conditions, the CDOTS algorithm only performs 5.3% worse on average than the ideal case.

Figures 6.16 (c), (f), (i), (l), and (o) show the total emission results for the CDOTS and MATS algorithms compared with TRANSYT for high traffic demand. As with the average demand case, the increasing traffic demand worsens the performance of the MATS algorithm for CV penetrations below 40%. By optimising the stage sequence, the CDOTS algorithm mitigates the increase in emissions caused by the MATS algorithm at low CV penetrations. In the non-ideal case, it can be seen that the lower mode-switching frequency is beneficial at 10% CV penetration. However, those benefits are lost above 10% CV penetration as the behaviour converges more strongly towards the ideal cases but still remains close to the ideal behaviour.

Overall, the CDOTS algorithm is most beneficial at reducing emissions under low demand scenarios but can reduce total emissions better than the MATS algorithm or TRANSYT. The CDOTS algorithm is robust to changes in traffic demand and CV penetration. It can reduce emissions better under non-ideal communication conditions than the MATS algorithm can under ideal conditions.



(a) Low flow: CO_2 (b) Average flow: CO_2 (c) High flow: CO_2

(d) Low flow: CO (e) Average flow: CO (f) High flow: CO

(g) Low flow: NO_x (h) Average flow: NO_x (i) High flow: NO_x

(j) Low flow: PM_x (k) Average flow: PM_x (l) High flow: PM_x

(m) Low flow: Fuel (n) Average flow: Fuel (o) High flow: Fuel

Figure 6.16: Plots of the mean total emissions expelled in each of the three flow scenarios (low, average, high) with pedestrians. Each plot compares the performance of the MATS algorithm with and without loop information (MATS-FT), and the MATS algorithm with errors (MATS-ERR), to TRANSYT.

Table 6.11: The benchmarking of the tested MATS algorithm instances against TRANSYT at 10%, 50%, and 100% CV penetration with pedestrians on the average demand case. The results show the percentage reduction in mean total vehicle emissions for each variant of the MATS algorithm.

A: MATS-FT					
CVP	**Emission**				
	CO_2	CO	NO_x	PM_x	$Fuel$
10%	-30%	-54%	-33%	-42%	-30%
50%	23%	42%	22%	32%	23%
100%	27%	48%	26%	37%	27%
B: MATS-ERR					
CVP	**Emission**				
	CO_2	CO	NO_x	PM_x	$Fuel$
10%	9%	16%	8%	12%	9%
50%	19%	34%	18%	26%	19%
100%	25%	45%	24%	34%	24%
C: CDOTS					
CVP	**Emission**				
	CO_2	CO	NO_x	PM_x	$Fuel$
10%	17%	31%	16%	23%	17%
50%	30%	54%	29%	42%	31%
100%	33%	58%	32%	45%	33%
D: CDOTS-ERR					
CVP	**Emission**				
	CO_2	CO	NO_x	PM_x	$Fuel$
10%	12%	22%	12%	17%	12%
50%	25%	44%	24%	34%	25%
100%	30%	54%	29%	41%	30%

6.4.4 Hypothesis Testing

As the simulations were stochastic, hypothesis tests were performed on the delay, stop, emissions data in order to assess its statistical independence across the $N = 50$ experimental runs, and incremental increases in CV penetration. Here, the following hypotheses were tested:

- The null hypothesis H_0 was that the mean stops, delay, and emissions data at CV penetrations greater than 0% were drawn from the same distribution as the mean delay for 0% CV penetration.
- The alternative hypotheses H_1 tested was that the mean delay, stops, and emissions data for all simulated CV penetrations greater than 0% CV penetration is different to the data for 0% CVP.

In order to determine the nature of the hypothesis test to be used the data were first tested for normality using both D'Agostino's K^2 test (D'Agostino, 1971) and the Shapiro-Wilk test (Shapiro and Wilk, 1965). The results of the normality tests only reject the hypothesis that the data is normal with $p < 0.01$ in less than 10% of cases. This indicates that while many of the results follow a normal distribution, a normal distribution is not guaranteed.

As proposed in Watkins (2019), for two independent samples (runs are independent of one another and independent across CV penetration) that may not be normally distributed, a Mann-Whitney U test (Mann and Whitney, 1947) was performed between H_0 and each H_1, and the U-statistic and p-value was determined. The hypothesis testing results for all delay, stops, and emissions cases rejected the null hypothesis in facour of the alternative hypothesis with $U = 0$ and significance $p < 0.001$ in all but one case. The exceptional case was under high demand, with the CDOTS controller at 10% CVP. In this case the U-statistic was $U = 362$, as $U \ll N^2$ the null hypothesis is still rejected in favour of the alternative hypothesis with $p < 0.001$.

The hypothesis testing results show that the addition of connected vehicles into the transport network changes both the MATS and CDOTS algorithms such that it meaningfully impacts the delays and number of stops experienced by road users in all cases where CVs were present. The rejection of the null hypothesis also confirms that there was a significant reduction in delay in all case for CV penetrations as low as 10%, which address the gap from previous research.

6.4.5 Signal Timings

Unlike TRANSYT, the MATS and CDOTS algorithms do not operate a fixed cycle time with optimised splits and offsets. Instead, the MATS algorithm provides a heuristic for optimising stage times in an unconstrained way, and the CDOTS algorithms add a stage sequence optimisation heuristic. As the cycle length is not directly comparable, the stage interval, the time between the end of a stage and its next occurrence, are observed as an analogue to the cycle length. Figure 6.17 compares the stage interval distributions of the MATS and CDOTS algorithms at 100% CV penetration for each of the three traffic demand cases. The pedestrian case is used as the stage intervals are longer than in the non-pedestrianised case. The comparisons are made for junctions 3, 5, and 9 (refer to the model in Appendix B), as they are the busiest intersections in the top, middle, and lower thirds of the model. Table 6.12 compares the mean and 95% prediction intervals of the stage interval distributions for the TRANSYT and MATS algorithms.

Figure 6.17 shows that the stage interval distributions for the CDOTS algorithm are much wider than those for the MATS algorithm. Table 6.12 shows that despite the difference in distributions widths, the mean stage intervals for the MATS and CDOTS algorithms are similar for each junction and demand level. The key difference between the MATS and CDOTS algorithm stage distributions are in the 95% prediction interval. The lower bound of the 95% prediction interval is much lower for the CDOTS algorithm than for the MATS algorithm indicating that stages for which there is high demand can be called more frequently. In contrast, the upper bound of the 95% prediction interval is much higher for the CDOTS algorithm than for the MATS algorithm indicating that stages for which there is low demand are called less frequently. As with the MATS algorithm stage distributions, the distributions for the CDOTS algorithms skew towards the mean as the traffic demand increases.

The issue with the spread in stage intervals is that the CDOTS algorithm frequently violates the 120 s recommended cycle length limit (UK Govt. Dept. Transport, 2006). Increases in cycle time are a known side effect of having acyclic stage sequencing (Bretherton, 2003). Further investigation into the stage interval data showed that for Junctions 3, the stage intervals typically only exceed a 120 s stage interval before 5 A.M. when traffic is at its lowest. For Junction 5, the 120 s stage interval is routinely exceeded. However, the stage being skipped corresponds to the minor roads that join the intersection which provides side access to the University of Birmingham and a small residential area so are rarely used. For Junction 9, the stage intervals only exceed 120 s for a single stage that provides access to an infrequently travelled to an industrial unit. The delay and stop results show that despite large stage intervals, vehicles are still experiencing reductions in delay and stops. This indicates that although some stages may wait up to 5 minutes for activation, there are no vehicles waiting at those stages being delayed for that long.

Overall, there is no need to add a stage time restriction to the CDOTS algorithm in this case as the 95% prediction intervals as the violations of the recommended 120 s cycle length limit do not disadvantage road users.

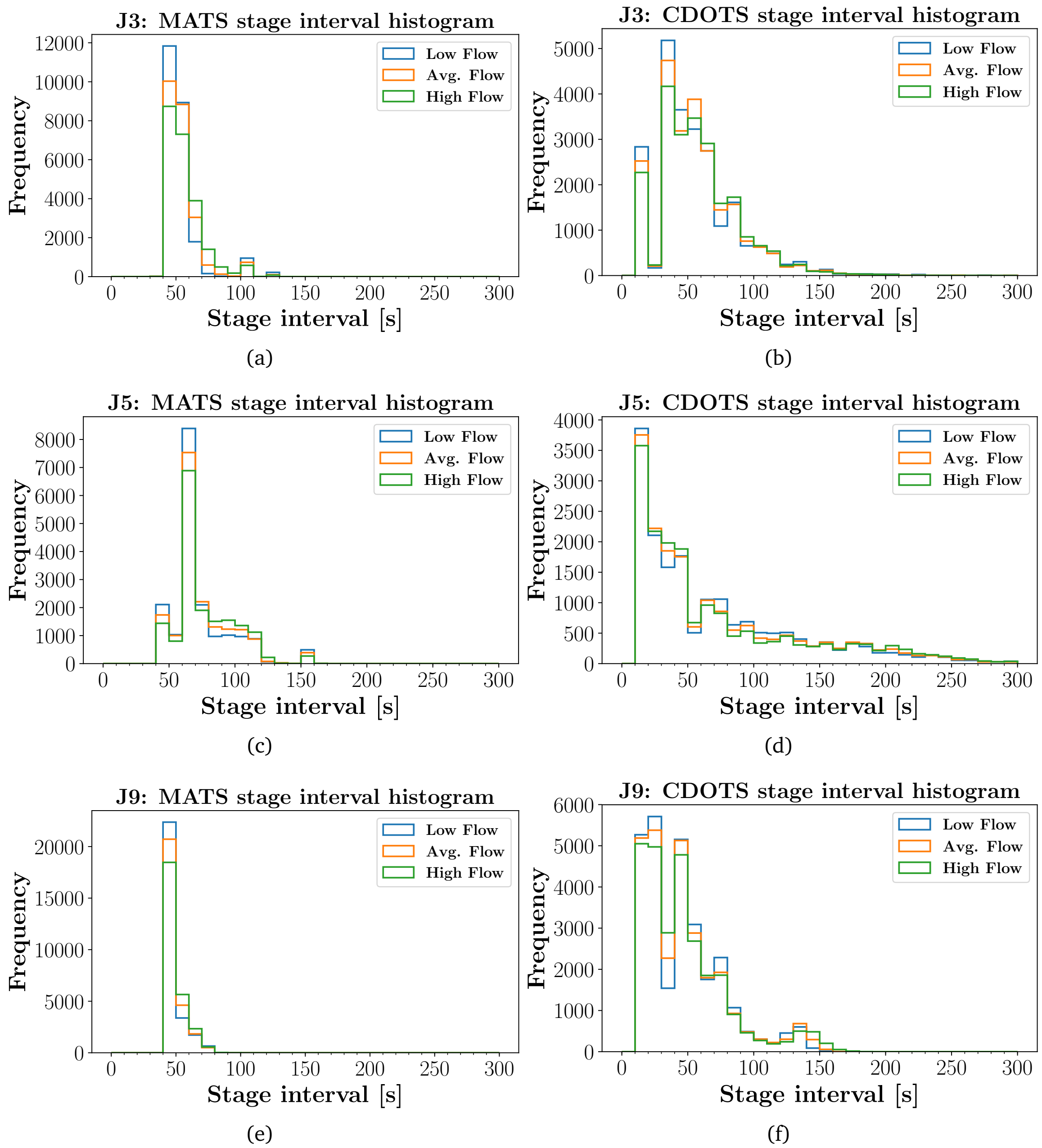


Figure 6.17: Histograms comparing the distribution of stage intervals for the MATS and CDOTS algorithms at 100% CV penetrations. The data are in 10 second bins, and each plot shows the histograms for the stage intervals at low, average, and high traffic flow levels for Junctions 3 (J3), 5 (J5), and 9 (J9).

Table 6.12: The stage interval mean and 95% prediction interval comparison between the CDOTS and MATS algorithms at 100% CV penetration. The metrics are compared for junctions 3, 5, and 9, for each of the three demand cases with pedestrians.

A: Mean Stage Intervals [s]						
Junction	**MATS**			**CDOTS**		
	Traffic Flow			**Traffic Flow**		
	Low	Avg.	High	Low	Avg.	High
J3	54.43	55.36	57.39	54.43	55.36	57.39
J5	72.07	73.81	76.17	72.88	72.96	76.17
J9	46.32	47.50	48.04	46.45	46.72	47.46
B: 95% Prediction Intervals [s, s]						
Junction	**MATS**			**CDOTS**		
	Traffic Flow			**Traffic Flow**		
	Low	Avg.	High	Low	Avg.	High
J3	[48, 103]	[48, 103]	[48, 103]	[16, 135]	[16, 135]	[16, 132]
J5	[42, 157]	[42, 129]	[42, 122]	[14, 241]	[14, 240]	[14, 247]
J9	[42, 68]	[42, 68]	[42, 69]	[14, 130]	[14, 134]	[14, 141]

6.5 Determining System Fairness to Unconnected Vehicles

In this section, the results of the fairness tests defined in Section 5.6.6 are presented. The average delay per kilometre and average stops per kilometre results will be compared on the case study, for all three demand levels, with and without pedestrians, and for 10%–90% CV penetration. Unlike the previous sections, the results for connected and Unconnected Vehicles (UVs) are plotted separately to observe if one group is disadvantaged by the presence of the other. The results of TRANSYT are not included on the results plots as TRANSYT operates independently of CV data and as seen in Sections 6.1 and 6.4, create a difference in scale that makes it challenging to differentiate between the trends.

6.5.1 Delay

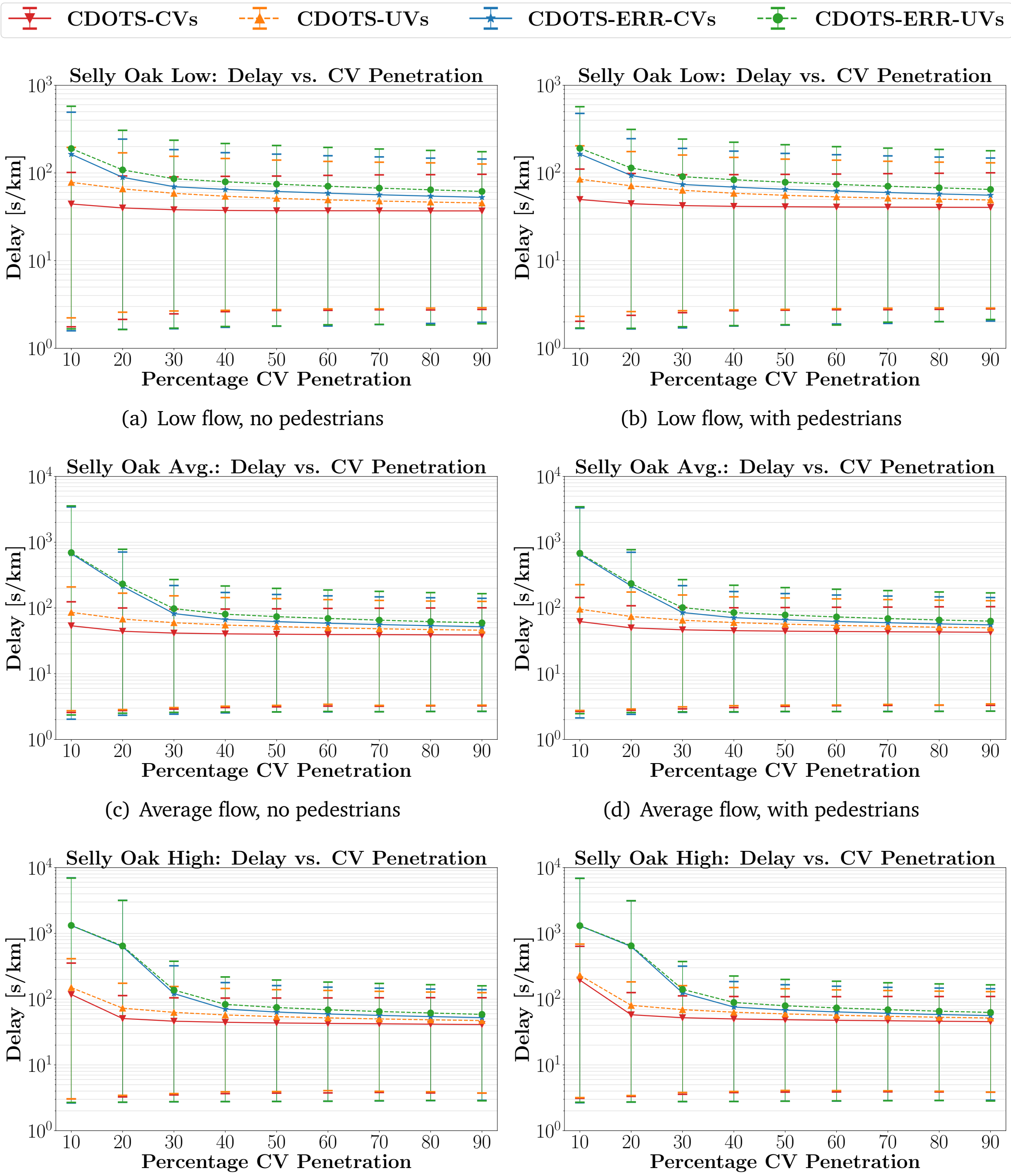
In Figures 6.18 and 6.19, the results comparing the performance of CVs and UVs under the CDOTS algorithm in terms of mean delay per kilometre for are shown. The performance of CV and UVs are compared on the case study for the three demand levels, and with and without pedestrians present. In Table 6.13(A) and (B), the percentage difference in mean delay between the CVs and UVs are shown for the CDOTS algorithm with and without communication error. The comparisons are made across CV penetration rates and demand levels. The figures in Figure 6.18 and 6.19 show that regardless of the demand case, or pedestrian presence UVs experience more delay on average compared with UVs. The results for the CDOTS algorithm with non-ideal communications are worse than under the ideal conditions.

Table 6.13(A) and (B), it can be seen that under low demand and ideal conditions, UVs perform up to 76.5% worse than CVs under the CDOTS algorithm at 10% CV penetration. At 90% CV penetration, the difference is lowered as far as 21.3% difference. The decreasing percentage difference in mean delay shows that CVs benefit from the CDOTS algorithm being able to detect their presence and that for us to benefit in under low demand, a significant proportion of them must be connected. Under average traffic demand, the percentage difference in delay rages between 60.14% at 10% CV penetration, and 16.7% at 90% CV penetration. The average demand results emphasise that increasing connectivity mitigates the disparity in performance between CVs and UVs. For the high demand case, when pedestrians are present, it can be seen that the percentage difference in the mean delay is higher at 50% CV penetration than at 10% or 90%. The increase in the 50% CV penetration case is also mirrored across all the non-ideal communication cases, indicating that having dominance of one type over the other is beneficial under high demands and when the received data is non-ideal. In the cases for the CDOTS algorithm with non-ideal data, the results show that the differences in CV and UV performance are smaller than those under ideal communication conditions despite being worse overall.

6.5.2 Stops

In Figure 6.20, the results comparing the performance of CVs and UVs under the CDOTS algorithm in terms of mean stops per kilometre for are shown. The performance of CVs and UVs are compared for each of the three demand levels, and both with and without pedestrians present. In Table 6.13(C) and (D), the percentage difference in mean delay between the CVs and UVs are shown for the CDOTS algorithm with and without communication error. The comparisons are made across CV penetration rates and demand levels. The figures in Figure 6.20 show that regardless of the demand case, or pedestrian presence UVs experience more stops on average compared with UVs.

Table 6.13(C) and (D), it can be seen that under all conditions the percentage difference between CVs and UVs is not greater than 6.22%, and as low as 1.31%. These results show that UVs are not significantly affected by the CDOTS algorithm. Similarly to the delay results, the difference in performance between CVs and UVs is less under non-ideal communication conditions.



(a) Low flow, no pedestrians

(b) Low flow, with pedestrians

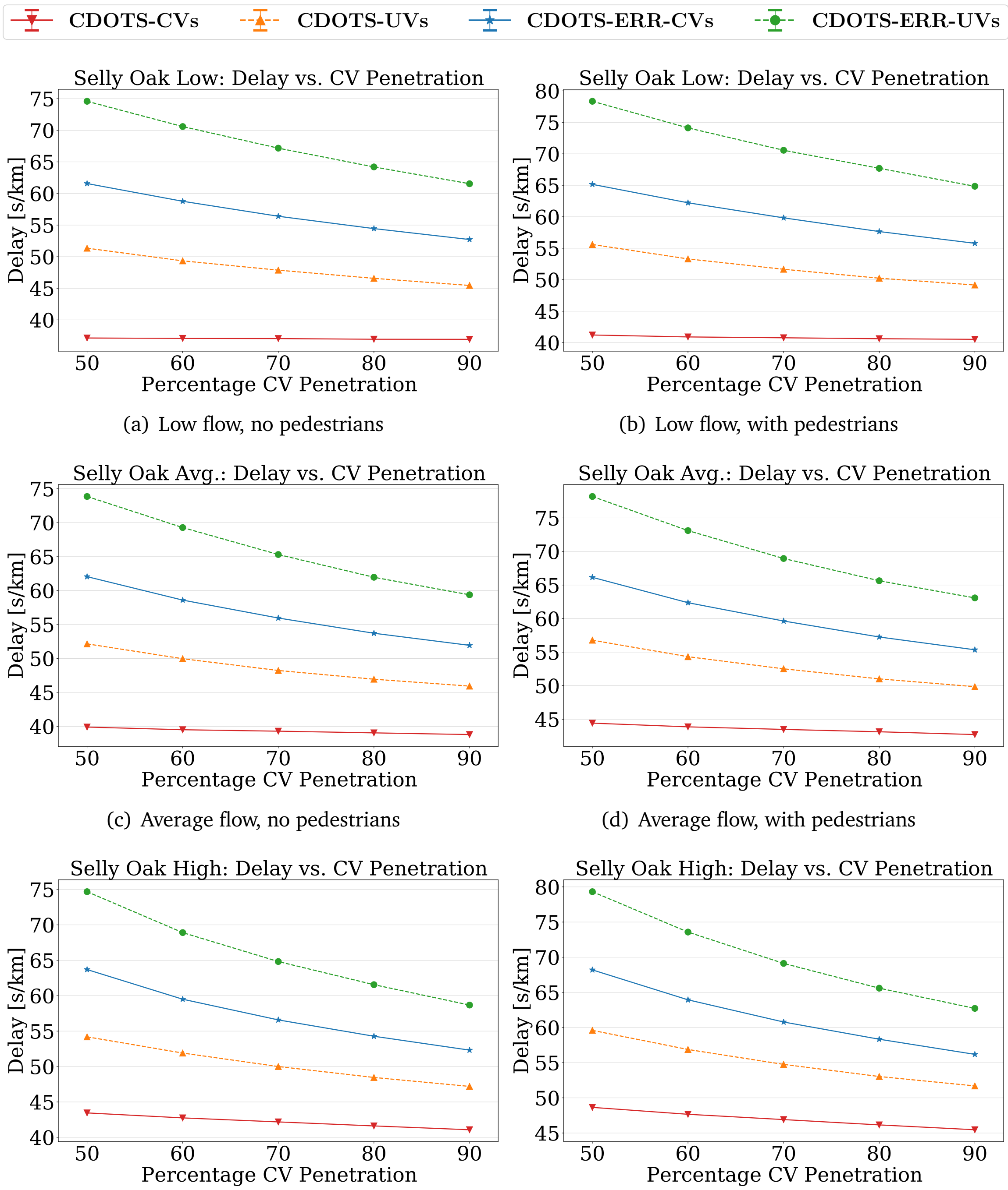
(c) Average flow, no pedestrians

(d) Average flow, with pedestrians

(e) High flow, no pedestrians

(f) High flow, with pedestrians

Figure 6.18: Plots of mean delay per kilometre for each of the three flow scenarios (low, average, high), with and without pedestrians. Each plot compares the performance of CVs and UVs under the CDOTS algorithm with and without errors. The bands on the data represent the 5th and 95th percentiles of the data as indicators of variability.

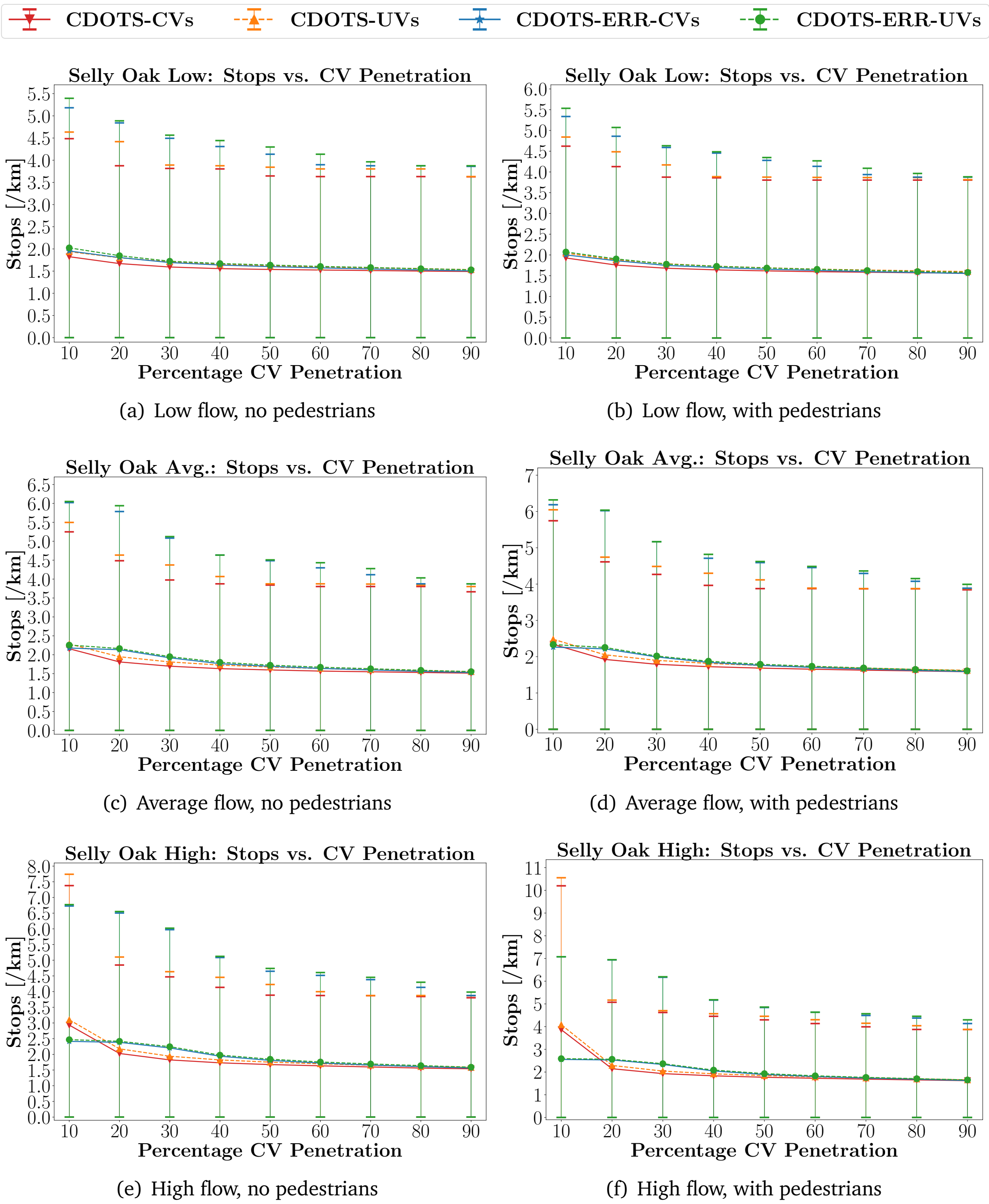


(a) Low flow, no pedestrians
(b) Low flow, with pedestrians
(c) Average flow, no pedestrians
(d) Average flow, with pedestrians
(e) High flow, no pedestrians
(f) High flow, with pedestrians

Figure 6.19: Plots of mean delay per kilometre for each of the three flow scenarios (low, average, high), with and without pedestrians for CVPs from 50%–100%. Each plot compares the performance of CVs and UVs under the CDOTS algorithm with and without errors.

Table 6.13: The percentage difference in mean delays and mean stops between the CVs under the CDOTS algorithm and the UVs under the CDOTS algorithm at 10%, 50% and 90% CV penetration (CVP).

A: Delay, no pedestrians						
CVP	**CDOTS**			**CDOTS-ERR**		
	Traffic Flow			**Traffic Flow**		
	Low	Avg.	High	Low	Avg.	High
10%	-76.52%	-60.14%	-27.66%	-16.04%	-3.16%	-0.286%
50%	-38.27%	-30.73%	-24.72%	-21.15%	-19.03%	-17.26%
90%	-23.1%	-18.4%	-14.9%	-16.75%	-14.34%	-12.16%
B: Delay, with pedestrians						
CVP	**CDOTS**			**CDOTS-ERR**		
	Traffic Flow			**Traffic Flow**		
	Low	Avg.	High	Low	Avg.	High
10%	-70.62%	-54.43%	-18.46%	-16.27%	-3.18%	-0.41%
50%	-34.89%	-27.84%	-22.51%	-20.26%	-18.21%	-16.3%
90%	-21.3%	-16.7%	-13.71%	-16.24%	-13.97%	-11.64%
C: Stops, no pedestrians						
CVP	**CDOTS**			**CDOTS-ERR**		
	Traffic Flow			**Traffic Flow**		
	Low	Avg.	High	Low	Avg.	High
10%	-6.22%	-5.8%	-5.78%	-3.66%	-3.63%	-2.23%
50%	-5.07%	-4.8%	-4.59%	-2.21%	-1.85%	-2.07%
90%	-2.72%	-2.66%	-2.77%	-1.69%	-1.68%	-1.85%
D: Stops, with pedestrians						
CVP	**CDOTS**			**CDOTS-ERR**		
	Traffic Flow			**Traffic Flow**		
	Low	Avg.	High	Low	Avg.	High
10%	-6.02%	-5.98%	-5.67%	-3.56%	-3.09%	-1.31%
50%	-4.58%	-4.35%	-4.19%	-1.91%	-1.71%	-2%
90%	-2.65%	-2.51%	-2.25%	-1.79%	-1.37%	-1.61%



(a) Low flow, no pedestrians

(b) Low flow, with pedestrians

(c) Average flow, no pedestrians

(d) Average flow, with pedestrians

(e) High flow, no pedestrians

(f) High flow, with pedestrians

Figure 6.20: Plots of mean stops per kilometre for each of the three flow scenarios (low, average, high), with and without pedestrians. Each plot compares the performance of CVs and UVs under the CDOTS algorithm with and without errors. The bands on the data represent the 5th and 95th percentiles of the data as indicators of variability.

6.5.3 Hypothesis Testing

As the simulations were stochastic, hypothesis tests were performed on the delay, stop data in order to assess its statistical independence across the $N = 50$ experimental runs, and incremental increases in CV penetration. Here, the following hypotheses were tested:

- The null hypothesis H_0 was that the mean stops and delay data for unconnected vehicles are from the same distribution as the mean delay for CVs at each CV penetration.
- The alternative hypotheses H_1 were that the mean stops and delay data for unconnected vehicles are from a different distribution as the mean delay for CVs at each CV penetration.

As in Section 6.1, D'Agostino's K^2 test (D'Agostino, 1971) and the Shapiro-Wilk test (Shapiro and Wilk, 1965) were used to test for normality. The results of the normality tests only reject the hypothesis that the data is normal with $p < 0.01$ in less than 10% of cases. This indicates that while many of the results follow a normal distribution, a normal distribution is not guaranteed.

The difference between this set of tests and the test in previous sections is that while the data is independent across runs, the data for the CV and UV groups may not be independent due to vehicle interactions. As proposed in Watkins (2019), for samples that are not normally distributed and exhibit grouping, a Wilcoxon signed-rank test (Wilcoxon, 1945) was performed between H_0 and each H_1, and the p-value was determined. The hypothesis testing results for all but three delay result cases rejected the null hypothesis in favour of the alternative hypothesis with significance $p < 0.001$, demonstrating the difference in stops is statistically significant despite being visually similar. Table 6.14 shows the cases where the null hypothesis was not rejected in favour of the alternative hypothesis. Table 6.14 shoes that under non-ideal communication conditions, average to high traffic demand, and CVP less than 30%, the delay experienced by CVs and UV is not significantly different.

Table 6.14: Table of delay result hypothesis tests for which did not reject the null hypothesis in favour of the alternative hypothesis with $p < 0.001$.

Demand	**Controller**	**CVP**	p
Average	CDOTS-ERR	10	0.007179
High	CDOTS-ERR	10	0.775819
High	CDOTS-ERR	20	0.019739

The hypothesis testing results show that unconnected vehicles do not experience the same travel times as connected vehicles in the majority of cases above 20% CVP.

6.5.4 Discussion

The results comparing the performance of CVs and UVs under the CDOTS algorithm show that the performance of UVs is worse than for CVs in terms of mean delay per kilometre. The disparity is not desirable, but challenging to avoid as the performance benefits of the CDOTS algorithm derives from its use of CV data. Despite the difference in mean delay between CVs and UVs, the UVs still benefit from reduced delays compared with TRANSYT when compared with the results from Section 6.4 (see Figure 6.13–6.15 (pages 177 and 182)). For the mean stops per kilometre results, UVs also fare worse than CVs, but by a smaller margin. Further study is needed to investigate whether the disadvantage of increased delays faced by users of UVs is at an acceptable level and if they have broader impacts for vulnerable groups.

6.6 Comparison of the Developed Algorithms with a Vehicle Actuation Strategy

In this section, the results test defined in Section 5.6.7 to compare the MATS and CDOTS algorithms against MOVA are discussed.

6.6.1 Results and Discussion

The MATS and CDOTS algorithms are compared to the state-of-the-art vehicle actuated signal controller of MOVA using the single intersection case study developed by Waterson and Box (2012). In that study, it was demonstrated that MOVA the average delay was 20.3 s, on the single intersection for traffic conditions just below saturation, and with ideal loop detector data. Figure 6.21 shows the difference in delay between MOVA and the MATS and CDOTS algorithms for CV penetrations from 0%–100%. Table 6.15 shows the percentage difference in delay between the MATS and CDOTS algorithms and MOVA.

Under the same traffic conditions and ideal communication conditions, the MATS-FT algorithm showed lower mean delay than MOVA above 20% CV penetration, with mean delay reductions of 20%-28% above 30% CV penetration. Under non-ideal communication conditions, the MATS algorithm reduces mean delay better than MOVA above 40% CV penetration, with reductions in mean delay between 19%-29% above 40% CV penetration. When both inductive loop and CV data are used in the MATS-HA algorithm, the MATS-HA algorithm reduces mean delay between 12%-15% compared with MOVA for CV penetrations $\geq$10%. The MATS-FT and MATS-ERR variants are worse than MOVA at 0% CV penetration as they fall back to fixed-time plans. The MATS-FT and MATS-ERR algorithms also show that respective CV penetration thresholds of 10% and 20% are needed before CV data is useful to this model. The MATS-HA algorithm does the best at 0% CV penetration as it can use loop detectors to actuate signal timings, but is worse than MOVA as its actuation strategy is not as sophisticated. The results show that the MATS algorithm is better than the state-of-the-art vehicle actuation strategy MOVA, and that loop detector data is useful at low CV penetrations but can limit performance at high CV penetrations.

The results for the CDOTS algorithm show that under ideal conditions, the CDOTS algorithm can reduce the mean delay by 18%-26% for CV penetrations above 30%. Under non-ideal conditions, the CDOTS algorithm reduces the mean delay between 22%-26% for CV penetrations above 40%. The CDOTS-FT and CDOTS-ERR algorithms also show that respective CV penetration thresholds of 10% and 20% are needed before CV data is useful to this model. The CDOTS algorithm performs worse overall than the MATS algorithm for this single intersection case study but was better in the testing on the realistic case study. This difference is due to the MATS algorithm locally optimising delays and stops, whereas the CDOTS algorithm was calibrated to optimise a global objective. Therefore, the CDOTS algorithm does better at the corridor level, whereas the MATS algorithm is better for individual intersections. Future work could investigate calibrating the CDOTS algorithm for individual intersections.

The results show that the MATS and CDOTS algorithms are better than the state-of-the-art vehicle actuation strategy MOVA for CV penetration above 30%. The results also show that loop detector data is useful at low CV penetrations but can be detrimental at high CV penetrations.

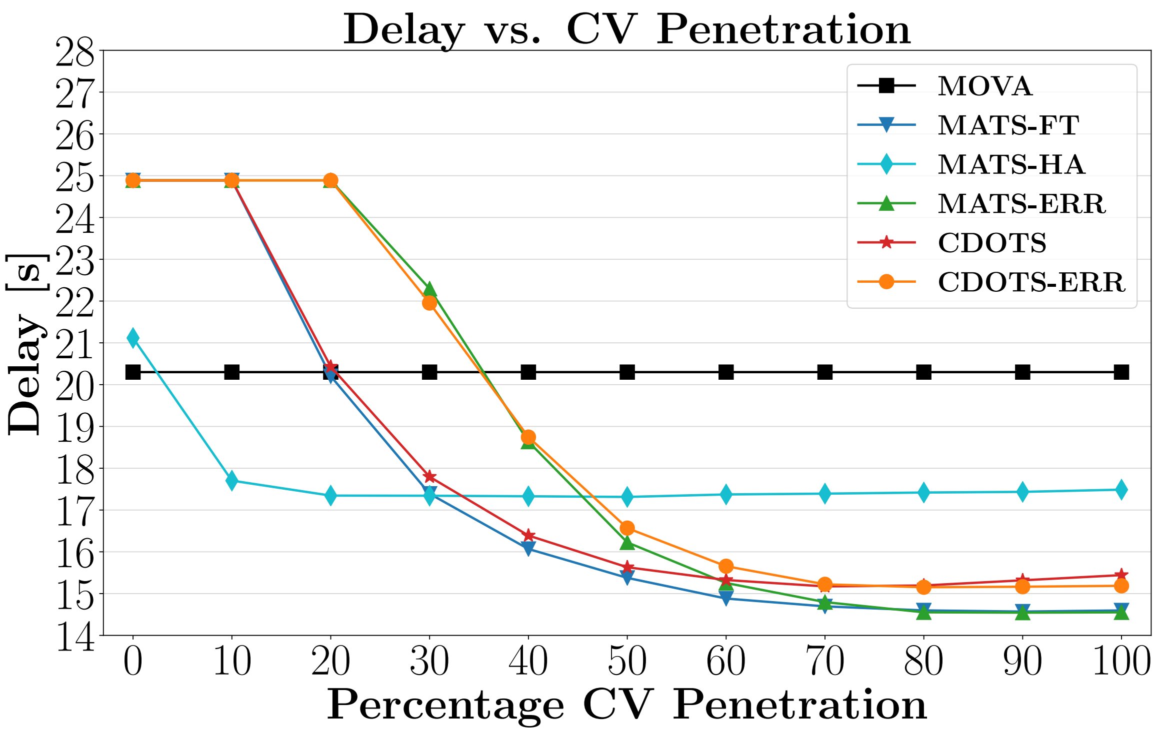


Figure 6.21: Comparison of the mean delay of the MATS algorithm with MOVA on the first case study.

Table 6.15: Percentage difference in mean delay between MOVA and each of the tested control algorithms on the T-junction network.

CVP	MATS-FT	MATS-HA	MATS-ERR	CDOTS	CDOTS-ERR
0%	-22.6%	-4.02%	-22.6%	-22.6%	-22.6%
10%	-22.6%	12.79%	-22.6%	-22.6%	-22.6%
20%	0.48%	14.56%	-22.6%	-0.64%	-23.28%
30%	14.34%	14.57%	-9.83%	12.34%	-8.14%
40%	20.85%	14.64%	8.2%	19.26%	7.66%
50%	24.25%	14.71%	20.07%	23.0%	18.38%
60%	26.69%	14.42%	24.86%	24.51%	22.88%
70%	27.61%	14.33%	27.11%	25.26%	25.01%
80%	28.09%	14.19%	28.32%	25.15%	25.36%
90%	28.23%	14.12%	28.35%	24.54%	25.3%
100%	28.09%	13.86%	28.32%	23.93%	25.19%

6.6.2 Hypothesis Testing

As the simulations were stochastic, hypothesis tests were performed on the delay data in order to assess its statistical independence across the $N = 50$ experimental runs, and incremental increases in CV penetration. Here, the following hypotheses were tested:

- The null hypothesis H_0 was that the mean delays data at CV penetrations greater than 0% were drawn from the same distribution as the mean delay for 0% CV penetration.
- The alternative hypothesis H_1 was that the mean delays data at CV penetrations greater than 0% were drawn from a different distribution as the mean delay for 0% CV penetration.

As the MOVA results are a single value from the results in Waterson and Box (2012), they are not suitable for use in hypothesis tests. The MATS and CDOTS algorithms are used as in Sections 6.1 and 6.4. As in Section 6.1, D'Agostino's K^2 test (D'Agostino, 1971) and the Shapiro-Wilk test (Shapiro and Wilk, 1965) were used to test for normality. The results of the normality tests only reject the hypothesis that the data is normal with $p < 0.01$ in less than 10% of cases. This indicates that while many of the results follow a normal distribution, a normal distribution is not guaranteed.

As proposed in Watkins (2019), for two independent samples (runs are independent of one another and independent across CV penetration) that are not normally distributed, a Mann-Whitney U test (Mann and Whitney, 1947) was performed between H_0 and each H_1, and the U-statistic and p-value was determined. The hypothesis testing results for all cases rejected the null hypothesis in favour of the alternative Hypothesis with $U = 0$ and significance $p < 0.001$ except for CDOTS and MATS-FT at 10% CVP, and CDOTS-ERR and MATS-ERR at 10% and 20% CVP where the null hypothesis is not rejected. The null hypothesis is not rejected in these cases as the same fixed-time behaviour as the 0% CVP case was exhibited due to insufficient CV data. The values in The hypothesis testing results show that the addition of connected vehicles into the transport network changes both the MATS and CDOTS algorithms such that it meaningfully impacts the delays and number of stops experienced by road users in cases where CVs were present at CVPs of 30% or greater. It also demonstrates the algorithm achieves statistically significant changes in delay for multiple road models.

6.7 Computation Challenges in Traffic Signal Control Systems

One of the challenges in developing a traffic signal control algorithm is determining the hardware necessary to run the algorithm on the timescales it requires. The more computationally intensive the algorithm is, the longer it will take a computer to execute it. The computational resources of algorithms, especially those with a hierarchical or centralised approach to control, can be high depending on their complexity.

This section presents the results for comparing the compute times of CDOTS against TRANSYT defined in Section 5.6.8.

6.7.1 Results and Discussion

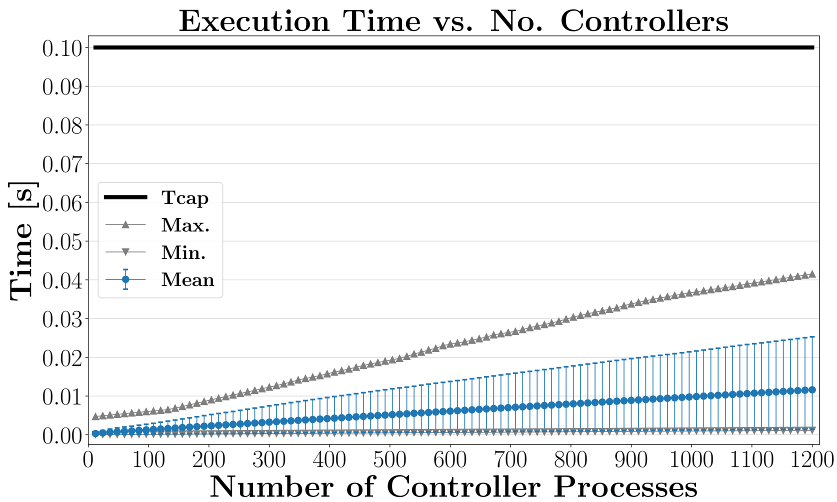
The results in Figure 6.22 show the timing plots for TRANSYT and the CDOTS algorithm. The trends appear linear, which is consistent with increasing numbers of processes running on a single processor. Table 6.16 shows the number of controllers that can be processed before reaching the execution cap for a variety of points in the timing data (rounded down to the nearest integer number of processes). The execution cap is the maximum time allowed to complete all processing tasks. The maximum CAM packet frequency is 10 Hz, or one packet every 0.1 s. Ideally, the data would be processed at least that quickly, in time for the next incoming data. In Table 6.16, the intercept for data that crosses the execution cap is calculated by T_{cap}/m, where T_{cap} is the execution cap, and m is the slope between the points in the timing data either side of the execution cap assuming a y-intercept of 0. If the timing data does not intercept the execution cap for the data range tested, an ordinary least squares linear regression is used to predict the intercept.

It can be seen from Table 6.16 and Figure 6.22 that one to two orders of magnitude more TRANSYT controllers can be processed before hitting the 0.1 s execution cap than with CDOTS. TRANSYTs reduced computational load is expected as it is not as complex as the CDOTS algorithm. TRANSYT does not have to process CV data in real-time as the CDOTS algorithm does. The CDOTS algorithm can process approximately 324 controllers on average before hitting the execution cap at the processor speed used.

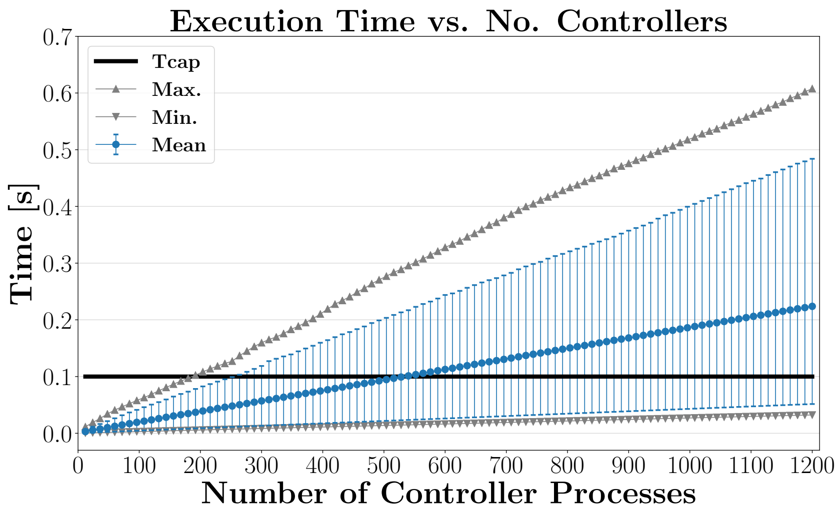
The worst-case scenario is when the CDOTS algorithm has the overhead of processing non-ideal CV data. In the worst case, only 81 controllers are processed before hitting the execution cap. The 81 controllers-per-processor cap is suitable for the case study, but if a centralised system were needed in a large city such as London or New York, more resources would be needed. In London, there are an estimated 6000 traffic signals (Transport for London, 2018), approximately half of which control traffic (the others are pedestrian crossings only) (Transport for London, 2018). To deploy the CDOTS algorithm for 3000 intersections, a central system operating at least 10 Intel Core i7-6700 3.4 GHz processors would be needed. Each Intel Core i7-6700 processors has four physical cores and four virtual cores. The virtual cores can be used to process additional controllers, or manage background data processing. Extra processors may be desirable for redundancy. An alternative approach is to deploy a small micro-controller at every intersection, or for clusters of intersections. A hybrid system may also add redundancy where there are some microprocessor-controlled intersections and others that are controlled centrally. The central system could then have the facility to compensate for failures in local micro-controllers. The memory requirements are negligible as the system does not track vehicles, so it does not need a large cache to store their information. Overall, the CDOTS and by extension MATS algorithm, present an efficient solution for minimising a multi-objective PI for large numbers of intersections.

Table 6.16: The number of controllers that can be processed on the testing set up before exceeding the 0.1 s execution cap T_{cap} for the minimum, mean, maximum, and 95% prediction interval values from the data.

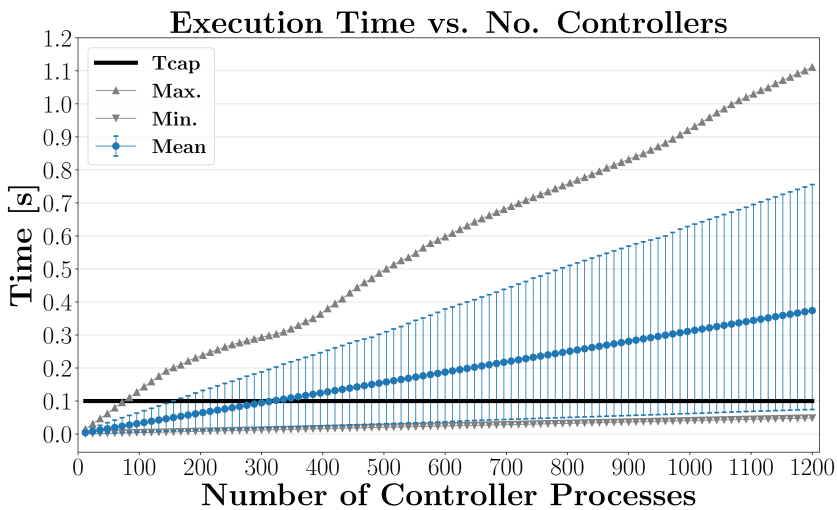
	TRANSYT	CDOTS	CDOTS-ERR
Lower Bound	2893	217	81
97.5th Percentile	4821	286	155
Mean Intercept	10587	581	324
2.5th Percentile	86745	2333	1605
Upper Bound	108053	3742	2476



(a) TRANSYT, high demand, with pedestrians



(b) CDOTS, high demand, with pedestrians



(c) CDOTS-ERR, high demand, with pedestrians

Figure 6.22: The number of controllers processed against execution time on the testing set up for high traffic demand with pedestrians. The timing plots for TRANSYT (a), CDOTS (b) and CDOTS-ERR (c) are shown. The 0.1 s execution cap T_{cap} is plotted for reference. The mean trend is bound by the 95% prediction interval.

6.8 Summary of Chapter Findings

1. MATS Tests:
   a) achieves real-time, unconstrained, isolated signal control in corridors with existing infrastructure.
   b) develops intuitive heuristics for optimising stage times using data from multiple data sources based on the principles used in state-of-practice algorithms such as MOVA.
   c) does not require any data that would track or uniquely identify road users.
   d) can detect blocking back at an isolated intersection using CV data.
   e) is capable of reducing delays by up to 95% on average.
   f) is capable of reducing stops and emissions both by up to 33% on average but is hindered at low CV penetrations and in the pedestrianised situation by frequent mode-switching.
   g) is highly flexible and reduces waiting times on average when compared with TRANSYT.
   h) Inductive loops offer little benefit over CV data above 20% CV penetration.
   i) The inclusion of non-ideal wireless communications show that the quality of data significantly affects performance, but can usually be compensated for with increased quantity of data and that frequent control actions at low CV penetrations are not necessarily better.

2. CDOTS Tests:
   a) Multiple data sources from CVs can be applied to the stage sequence optimisation process.
   b) The stage sequence optimisation process allows the algorithm to determine which data are best for optimising a given objective function.
   c) Fine-tuning the contributions of each data point to the stage sequence optimisation algorithm is of little benefit, and prohibitive due to the computational effort involved in determining the weights, and the dependence of the weights on CV penetration.
   d) The CDOTS algorithm reduces delay by up to 93% and stops by up to 8% with CV penetrations as low as 10% and can reduce delay and stops up to 97% and 41% respectively with CV penetrations above 50% when compared to the industry-leading TRANSYT algorithm.
   e) Acyclic stage sequencing increases stage interval times but does not necessarily incur longer waiting times.
   f) Adding stage sequence optimisation to the MATS algorithm to form the CDOTS algorithm is beneficial for further reducing delays, stops, and emissions.

g) Adding stage sequence optimisation to the MATS algorithm to form the CDOTS algorithm is also beneficial for improving the stability of the algorithm at low CV penetrations and in the presence of pedestrians.

h) A coordination term for the greedy stage sequence optimisation algorithm was developed.

i) Deliberate coordination is redundant if the traffic signal can react to vehicles in real-time ($\leq$1 s), and is aware of them sufficiently far in advance.

j) The CDOTS algorithm reacts to vehicles sufficiently quickly that it is pseudo-coordinated.

3. Fairness Tests:

   a) Unconnected vehicles benefit from the presence of CVs but do not benefit from delays reductions as significant as CVs experience.

   b) There is little difference in the number of stops an unconnected and connected vehicle makes.

   c) Further investigation is needed to determine if the disadvantage experienced by the drivers of unconnected vehicles causes wider inequity.

4. MOVA Tests:

   a) The MATS and CDOTS algorithms outperform MOVA on an isolated intersection for CV penetrations above 30% under ideal conditions, and 40% under non-ideal conditions.

   b) As the MATS algorithm outperforms the CDOTS algorithm for the isolated intersection as the global optimisation objective in the CDOTS algorithm compromises local optimisation marginally.

5. Compute Time Tests:

   a) The CDOTS algorithm incurs higher computational overhead than TRANSYT.

   b) The CDOTS algorithm can process 324 intersections on average before exceeding the 0.1 s execution cap needed to handle high-speed CAM packets.

   c) The lower bound performance on the CDOTS algorithm is 81 controller processes per processor.

Chapter 7

Impacts and Implementation Issues

The technical work completed in Chapters 3–6 show how CV data can be used for traffic signal control in an urban environment. The discussion in this section covers outstanding information relating to the impacts of a traffic signal control system that uses data from CVs on users, transport planning, and government policy.

Section 7.1 explores how users perceive sharing their data with traffic management services. Section 7.2 discussed the issues transport planners would need to be aware of when implementing the CDOTS algorithm in practice. Finally, Section 7.3 introduces policy recommendations based on the findings of this research.

7.1 User Attitudes to Sharing Data with Urban Traffic Management Services

In Chapter 3, the identified roadside and CV data were used to augment existing traffic signal infrastructure with CV data to reduce delays and stops. In Chapter 4, a method for determining the most useful CV data points to use for optimising a given PI was developed alongside a method for adding deliberate coordination to a highly adaptive traffic signal controller using CV data.

The key difference between data gathered from roadside infrastructure and data gathered from CVs is that the data from roadside infrastructure belong to the authority who own the loops and the traffic signal control infrastructure. Conversely, the data produced by a CV belongs to the driver/occupant of the vehicle. Using CV data raises the issue that the owner of the data is no longer the operator of the traffic signals. As a result, the owner of the CV data must elect to share it with traffic management systems that wish to use it, and the traffic management service must use it securely, privately, and per the owners' wishes. If users do not see the benefit in sharing their CV data with a traffic management system, then algorithms that use data from connected vehicles will be challenging to deploy.

In this chapter, Section 7.1.1 discusses the findings of surveys on user attitudes towards connected vehicles, and Section 7.1.2 discusses the impact traffic management with CV data will have on users.

7.1.1 Background

Many surveys seek to determine user perception on CAV driving technologies, but there is significantly more interest in gauging attitudes towards AV over CVs (Litman, 2019). In this section, the findings of surveys investigating user perceptions towards CVs are discussed.

Schoettle and Sivak (2014) surveyed participants in the US, UK, and Australia about their opinions on connected vehicles (questionnaire, $N = 1596$). Before the survey, 78% of participants had not heard of CVs, but 62% had a positive sentiment towards them. Participants were most confident about CVs being able to reduce crashes (86%), and least confident about CVs being able to reduce driver distraction (61%). Participants were most concerned about the security of the vehicle from hacking, the privacy of their data, and drivers coming to rely too much on CV technologies. Overall, the majority of respondents thought that safety was the most critical area for CVs to focus on, that a CV should integrate with their smartphone, and that they have a desire to have CV technology in their vehicles.

Shin et al. (2015) surveyed user acceptance and willingness to pay for CV technologies (questionnaire, $N = 529$). Respondents reported price, collision avoidance, and travel assistance as the three most important considerations when considering the value of a CV. The survey found that the more educated participants were about CVs, the more willing to pay for a CV they were.

Owens et al. (2015) conducted a cross-generational study to assess user acceptance of CV technologies based on respondent age (questionnaire, $N = 1019$). The generations considered were Millenials (born 1983-2001), Generation X (born 1965-1982), Baby Boomers (born 1946-1964), and the Silent Generation (born 1929-1945). The study found that younger generations favoured the adoption of CV technologies compared with older generations, who were less interested in CV technologies, and less comfortable with advanced technology in general. Younger generations were also more likely to use smartphones to access music and navigation service in their cars. All participant reported equal interest in safety applications and equal disinterest in infotainment applications. Respondents were also equally concerned about the privacy and security of their data.

Bird (2016) surveyed consumer uses of connected technologies and applications in their vehicles (questionnaire, $N = 1003$). The survey found that Millenials would be more willing on average to pay for connected services such as Wi-Fi and in-vehicle streaming than the average respondent. The study also highlighted that Millenials use smartphone navigation software more often than any other generation.

Sahebi and Nassiri (2017) studied user acceptance of CVs based on their impact in a Usage-Based Insurance (UBI) policy (questionnaire, $N = 244$). The study found that only 13% of the drivers' surveys would reject a UBI for CVs despite multiple levels of incentives being offered. Safer drivers were predominantly for a UBI policy for CV insurance, whereas younger, more reckless drivers were more reluctant to agree.

Foley and Lardner LLP (2017) surveyed automotive and technology executives to determine their perceptions of CVs (questionnaire, $N = 83$). The respondents thought that the three most significant barriers to CV adoption were: cyber-security and privacy concerns, safety concerns, and uncertainty regarding CV capabilities. Respondents strongly believed that regulatory frameworks for CAV development and deployment should come from the government.

The Federation Internationale de L'Automobile (2017) surveyed respondents across 12 European countries to assess their perceptions of CVs (questionnaire, $N = 12000$). On average, 33% of participants were previously aware of CVs. France, Germany and Italy had the highest levels of respondents with prior knowledge, whereas the UK, Poland, and Denmark had the lowest levels. The respondents reported being most interested in buying a CV if it increased their safety and fuel efficiency, and reduced congestion in the traffic network. The survey is the first to assess user perception of sharing specific data points. The respondents were more comfortable sharing general information regarding their vehicle maintenance status, driving profile (speed, acceleration, braking), dashboard usage, and location. Respondents were less comfortable sharing information about their infotainment usage, use of connected features, information that would personally identify them, and their call/text information. 76% of the respondents felt that data should be shared with time-limited access, and over 95% felt that there should be legislation protecting their data privacy.

The Society of Motor Manufacturers and Traders (2017) conducted a survey to assess how CAVs will impact user mobility with an emphasis on users with disabilities (questionnaire, $N = 3641$ (total), $N = 1012$ (disabled)). The survey observed that 50% of respondents felt that current transport modes restrict their mobility. Disabled people were most excited (56%) by the increased mobility that the introduction of CAVs can offer. Generally, 95% of respondents felt that CAVs would provide more opportunities for them to socialise outside their homes. The survey identified that there is a clear need for CAVs and the current perception of CAVs is positive, but that much more needs to be done to improve awareness of CAVs in the UK and to improve the UK's connected infrastructure.

The Centre for Connected and Autonomous Vehicles (2019) conducted a focus group based survey in the UK to gauge user perceptions of CAV technologies through discussions with local communities (focus group, $N = 158$). The survey found that CAVs should:

1. Be proven to be safe and secure.
2. Be equally accessible to all citizens.
3. Provide societal benefits and promote job growth.
4. Be the opportunity for people to remain in control of their transport choices.
5. Be subject to clear guidance on who is accountable in the event of CAV accidents.
6. Be subject to independent oversight.

In parallel to this research, there was research investigating the willingness of transport users to share their data with traffic management services (See Appendix F for the questionnaire details, $N = 113$). The preliminary findings of the survey suggest that almost 20% of people are travelling in a connected way already through smartphone use. Respondents appeared to be more willing than unwilling to share their data with a traffic management service. Respondents were more willing than not willing to share the data required by the MATS algorithm. It should be noted that this study is still incomplete and requires further analysis.

7.1.2 Discussion

The literature on surveys about CV perceptions shows that the general trends in user perceptions of CVs are well understood. CV users would be reluctant to share personal information and are very concerned about the security and privacy of their data. Additionally, younger generations are more comfortable adopting advanced technologies and are the groups most likely to adopt CVs. The study by the Federation Internationale de L'Automobile (2017) was the most detailed investigation into how users feel about sharing different types of CV data. However, there are no complete studies addressing user attitudes towards sharing their CV data for the specific purpose of enhancing traffic signal control.

There is a gap in the literature for a survey to be done that more accurately assesses the willingness of users to share specific data from their CVs with traffic management services. Such a survey should determine the willingness of users to share specific data with traffic management services. Furthermore, there needs to be research done to investigate the ownership of data in connected environments.

7.2 Transport Planning and Implementation Recommendations

In this section, points relevant to transport planners looking to implement or commercialise the algorithms developed in this research are discussed.

7.2.1 Algorithm Implementation Recommendations

7.2.1.1 Stage Timings and Sequences

In Chapters 3 and 4, it was shown that the stage times exceeded the 120 s maximum cycle length guidelines under low demand conditions or when the traffic demand on the approaches to an intersection is unbalanced to the point where the double cycle-constraint is triggered. The results showed that exceeding the 120 s cycle time guideline did not increase vehicles' delays as CV data allows sufficient detection to avoid this case. If it is desirable to maintain a 120 s cycle time, the recommendation is to develop a system for incrementally increasing and decreasing the maximum green time for each stage based on the prevailing traffic demand. The system would then be able to calibrate the maximum green times so that they are long on busy approaches, and short on quieter approaches.

Using an acyclic stage sequence was shown to be beneficial in the CDOTS algorithm for better reducing the mean number of stops compared to the MATS algorithm. Having complete control over the intersections' timing and stage sequence is also a critical factor that allows the CDOTS algorithm to achieve implicit coordination of the traffic signals. Bretherton (2003) showed that there are no safety implications to stage skipping, but further investigation is needed to determine how drivers interact with a system that has more autonomy over which stage is activated than current systems, and if they are safe.

7.2.1.2 CV Data Privacy

It has been identified throughout this thesis that there is a greater wealth of data that can be gathered from CVs than from roadside infrastructure. The primary concern is that data from CVs is more personal to the drivers than roadside infrastructure. The survey results in Section 7.1 identified that privacy is a significant concern for participants and that the more personal the data (e.g. the number of passengers in the vehicle), the less willing they were to share that information. The survey findings are important as they indicate that a continuous effort to educate users about the benefits of CV technologies may be needed to increase the acceptance and adoption of these new systems.

The MATS and CDOTS algorithms preserve driver privacy as they use instantaneous data in real-time to avoid needing to track vehicles through the road network. Therefore, the algorithms maintain the privacy of road users while still reducing the delays and stops they experience.

7.2.1.3 Unconnected Vehicles

In Section 6.5 the difference in performance between CVs and UVs in a corridor controlled by the CDOTS algorithms is analysed. It was found that UVs did not stop significantly more than CVs, but did experience more delay. The extra delay experienced by UVs meant that their journeys were longer on average, but still faster than in when the corridor is controlled with TRANSYT control. The difference in performance indicates that offline methods of detection may be needed to supplement data from CVs if the difference in delays causes disadvantages to vulnerable groups. The results also indicate that CV penetration level of 50% should be reached as quickly as possible to aid the deployment of the algorithm, and minimise the difference in delay experienced by UVs.

7.2.1.4 Pedestrians and Cyclists

The MATS and CDOTS algorithms serve pedestrians are served in much the same way as current traffic signal control strategies and are not disadvantaged by either algorithm. Cyclists may suffer the same lesser delay benefits as UVs as the system has no way to detect their presence. The issue could be addressed by allowing cyclists to share their data with a traffic management service using an app-based service. Cyclists' data could then be integrated into the MATS and CDOTS algorithms, allowing them to be factored into the stage extension and optimisation procedures.

7.2.1.5 Safety

One of the reasons MOVA is an industry-leading algorithm is that it can modify green times and inter-green times to avoid placing vehicles in the dilemma zone and allow them enough time to clear the intersection. These extension behaviours act as safety measures to reduce collisions. The MATS and CDOTS algorithms do not adjust signal timings in this way as vehicles do not violate red lights in SUMO. Therefore, collision avoidance mechanisms need to be introduced to the algorithms in a real deployment scenario.

7.2.2 System Implementation Recommendations

7.2.2.1 CV Equipment

The CV data provided to the MATS and CDOTS algorithms are essential to their performance. The ETSI CAM standard has a maximum data rate of 10 Hz, so all sensors in the vehicle should be able to update their measurements on at the same frequency. The GPS measurements are the most critical to the performance of the MATS algorithm as position information is used to determine the stage time extensions and queue lengths. Position information would also be needed to estimate vehicle speeds in an app or third-party hardware implementation as the system may not have direct access to data from the in-vehicle speedometer.

To achieve GPS accuracy below 1 m, the following systems are recommended:

Differential GPS (DGPS): DGPS is an enhancement to standard GPS that uses ground-based reference station to improve the accuracy of GPS position calculations (Monteiro et al., 2005). Reference stations could be deployed around urban areas, or at intersections to improve the accuracy of vehicle position measurements.

Inertial Management Units (IMUs): IMUs integrate accelerometers and gyroscopes to monitor the acceleration forces on a vehicle. IMU data can be used to correct DGPS measurements to improve accuracy further (Godha and Cannon, 2005). Accelerometers in smartphones can be used to achieve a similar effect (Lin et al., 2014).

Wi-Fi Positioning: Wi-Fi access points are ubiquitous in urban areas and can be used to enhance GPS location measurements (Zirari et al., 2010).

Map-matching: Map-matching is the process of combining position data with spatial road network data (Quddus et al., 2007). Map-matching is useful as it allows vehicles to be matched to their location in the physical road network rather than their absolute position as reported by the GPS measurements.

As there are no decided standards for C-ITS communication systems or message systems, a hybrid system that supports IEEE 802.11p and 5G is recommended to add redundancy to the system and distribute the demand on the communication system. The system should be re-programmable to support both ETSI and SAE message standards so that vehicles can change between regional implementations if necessary.

7.2.2.2 Infrastructure Equipment

The core components of traffic signalling hardware are the traffic signals themselves, the software license, and the computing hardware to operate the system. Adaptive traffic control systems such as SCOOT and SCATS were estimated to cost between \$16’000–\$120’000 per intersection to install, with annual maintenance costs between \$3’500–\$25’000 (Mladenovic and Abbas, 2013). In the UK, TRANSYT installations are estimated to cost £10’000–£15’000 per intersection (KonSULT, 2003), MOVA installations cost around £15’000–£25’000 per intersection (Hertfordshire County Council, 2011; Siddall, 2015), and SCOOT installations cost in the region of £20’000–£25’000 (Hertfordshire County Council, 2011; KonSULT, 2003). The costs for SCOOT and MOVA are considerably higher than for TRANSYT as they require maintenance and higher installation costs due to the use of inductive loops.

Inductive loops cost in the region of £150 per loop to install (Hertfordshire County Council, 2011). In contrast, a connected system would require a single antenna that supports DSRC or cellular communications, which cost between £50–£200 (Broadband Buyer, 2019; Solwise, 2019) depending on the signal strength required to cover the intersection and its surrounds. Multiple antennae may be needed in noisy urban environments with high levels of wireless data traffic and tall buildings which could cause multi-path effects.

To meet the computational needs of the algorithm, individual micro-controllers cost in the region of £100, and one could cover up to 10 intersections with a 1.5 GHz processor. For a centralised approach, a server rack would cost between £3'500–£10'000 to cover a metropolitan area with adequate up-time, and service planning (Manx Tech Group, 2019).

Software licensing and configuration would be up to the distributor or consultancy to price along with additional cabling and installation configuration costs. Overall, a CV based system such as CDOTS algorithm should cost less than a MOVA or SCOOT installation as it only requires calibration to the intersection, not the traffic demand, and uses comparatively cheaper infrastructure than loop based systems. The MATS and CDOTS algorithms also integrate over existing infrastructure, which mitigates the cost of an entirely new installation.

7.2.3 System Limitations

7.2.3.1 Communication Range

The range of the communication system was 250 m for the tests performed in this research. It needs to be determined if increasing or decreasing this range impact on the performance of the system significantly. Increasing the range of the system should not decrease performance, but there is likely a threshold at which the algorithm performance suffers or cannot function if the range becomes too small.

7.2.3.2 Data Availability

The MATS and CDOTS algorithms rely on data from CVs to be able to operate. The results of the test show that at CV penetrations below 50% data, quality is important and that for CV penetrations above 50%, high quantity of data is sufficient to provide good reductions in the mean delay and number of stops even if the quality is poor. Low noise should be easier to achieve at low CV penetrations as fewer communicating vehicles should correspond to lower channel congestion and noise.

7.2.3.3 Level-of-Service

The algorithms are tested for stages where vehicles only travel in one direction in each stage. If a stage allows vehicles to travel in different directions, a system for balancing service in each direction needs to be implemented to modify the stages in the scenario where many vehicles are travelling in one direction but not the other.

7.3 Public Policy Recommendations

Transport policy defines the frameworks for how the transport system should function, to realise specific social, economic, and environmental conditions (Rodrigue et al., 2016). Transport policy is towards making decisions on how transport resources should be allocated; in contrast, transport planning is towards realising those decisions. Effective transport policy facilitates the efficient, accessible movement of goods and people. Figure 7.1 from Rode et al. (2019), illustrates how transport policy integrates with spatial planning and social policy to improve accessibility for transport users.

In this section, the current trends in transport policy for connected vehicles are discussed based on geographic regions. Second, the overall state of policy for C-ITS is reviewed. Finally, the policy recommendations arising from this research are presented.

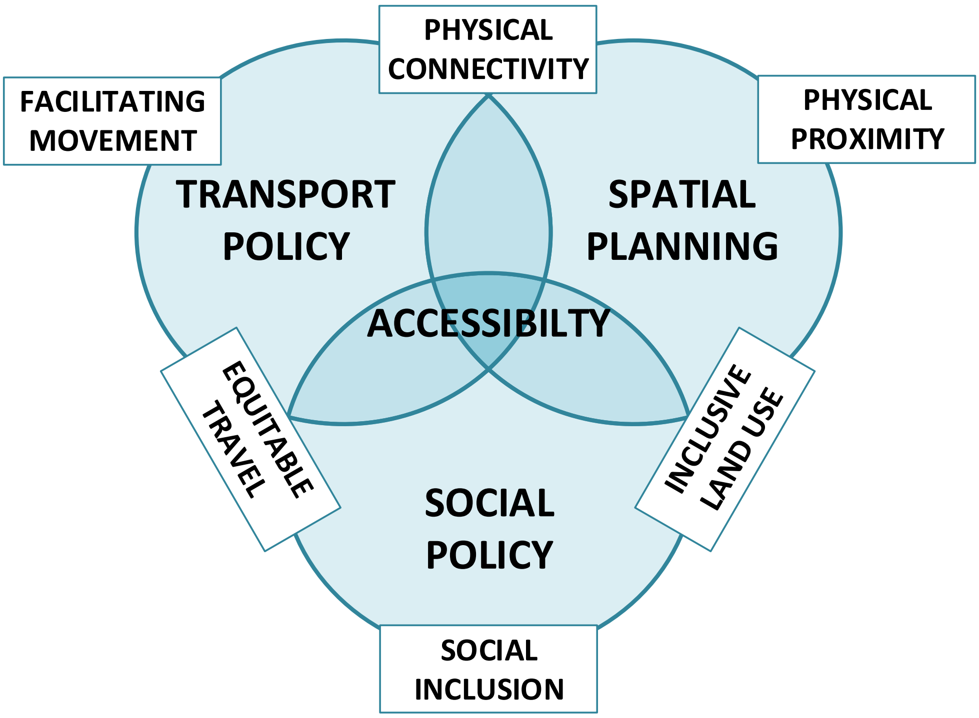


Figure 7.1: The urban policy nexus for accessibility, reproduced from Rode et al. (2019)

7.3.1 Current Policies for C-ITS

7.3.1.1 North America

In the USA, there are many ongoing field tests of CAV technologies to investigate the technological and policy needs of CAVs (Hallmark et al., 2019). The USA's current policy stance appears to be to allow testing of CAV technologies now, to allow future policies to be implemented based on the outcomes of the tests (Shladover, 2017). The National Cooperative Highway Research Program (NCHRP) most recent road-map for CAV research identifies several core policy needs for CVs in the USA (Booz Allen Hamilton, 2018):

Guidance standards for CV pilot testing: Guidelines for legislators and regulators about the requirements entities seeking to trial CV technologies should adhere.

Guidance on the implications of CVs for public agencies and public policy: Defining a research agenda to provide evidence-based recommendations to public agencies, on how to plan for CVs.

Developing public education and outreach information: Consumers and government officials have limited understanding of CV systems, and are often exposed to media hype rather than reality. Comprehensive public outreach material is needed to educate the public on the operational concepts of CVs in an easy to understand way.

Review of approaches to regulation and innovation: There is a need to understand what reforms could be made to promote innovation. The reforms could be to introduce new legislation or the revision or removal of outdated legislation.

Harmonisation of state regulations: Harmonising the legislation across the country affords the best opportunity to create interoperable infrastructure for CVs.

Workforce capability strategies: CVs may impact on many workforces. Detailed studies are needed to determine the roles of CV and infrastructure owners and operators and their training and capability development requirements.

Determining the minimum safety threshold: Public attitudes need to be assessed to determine how safe is safe enough for the public acceptance of CAV technologies.

Determining how CVs contribute to societal goals: Do CVs assist in improving mobility, safety, and equitable access to transport.

Framework for CV pilots and smart-city data analytics: How data from CVs should be used to inform governmental decision-making processes.

In Canada, there are also some field trials of CVs, but with a smaller set of objectives defined by the Policy and Planning Support Committee (PPSC) (PPSC, 2019). In PPSC (2019), six principles for CAV development and policy are outlined:

Safety: New regulation is needed to test and deploy CAVs safely. CAVs need to be demonstrated to be safe, both to severe Canadian weather, and cyber-attacks.

Information exchange: Information exchange between CAVs, infrastructure, and government agencies must be safe and secure. The government and law enforcement should have access to CAV data while protecting traveller privacy. Information should also be exchanged between the government, industry, and academia, to develop future legislation and leverage the full benefits of the new technology.

Policy alignment: Canada is committed to aligning its policy with partners in the US and internationally, as well as internally. Here, the objective is to create consistent operation of the network and testing procedures regardless of location.

Public awareness: The uncertainties of the public need to be addressed to deploy CAVs during the early stages of their adoption successfully. The safety and benefits of CAVs should form the primary information delivered to the public during the first phase.

Proactive preparation for CAVs on public roads: The government needs to prepare for the introduction of CAVs and understand their impact on safety, mobility, and land use. Being proactive allows government agencies to maximise the benefits of CAV technologies and mitigate potential negative effects.

Continuous collaboration: There are many entities involved in the developments and testing of CAVs. The government needs to actively collaborate with those entities that are developing strategies that align with Canadian interests.

7.3.1.2 Europe

The European Union (EU) are committed to developing the transport systems across its member states. Freedom of movement is one of the tenets of the EU, and the EU acknowledges that free movement is complicated without a reliable transport network (European Commission, 2019). The EU has several projects that seek to create a socially fair transition towards clean, competitive, and connected mobility. These projects include a Horizon 2020 programme to investigate the challenges associated with CAVs, and 'Europe on the Move'. The EU and its member states are accepting of CV trials, as they acknowledge the potential benefits of CVs, and the effort being invested by other countries (European Commission, 2016). One project that demonstrates the EU's commitment to CV adoption is the InterCor project. The InterCor project is an ambitious cross-border testbed for CV technologies in the UK, France, Belgium, and The Netherlands (InterCor, 2019).

In the UK, five CAV testbed projects have been established to investigate the implications of enhancing the road network with connected vehicles and infrastructure (Department for Transport, 2018). The UK Department for Transport has been proactive in managing its CAV research be setting up a dedicated centre to oversee CAV projects, and committed significant investment to study the feasibility of CAV technologies (Department for Transport, 2018). The motivation for such large-scale investments is that the UK government acknowledges the potential for CVs to change how the transport network is used at a fundamental level, and make urban spaces more desirable (Department for Transport, 2019). The principles underpinning UK innovation in transport (Department for Transport, 2019) are:

1. New transport modes must be safe and secure.
2. There should be equitable access to all mobility innovations.
3. Walking and cycling should be prioritised for short urban trips.
4. Mass transit is fundamental to the efficient operation of the transport network.
5. New mobility options should lead toward a zero-emission future.
6. Mobility innovation should reduce traffic congestion and efficiently use limited road space.
7. The mobility market should be open to stimulate innovation and give the best deal to consumers.
8. New mobility services should be designed to integrate into a multi-modal transport system.
9. Data from mobility services should be shared appropriately to improve the operation of the transport system.

7.3.1.3 Asia

In China, there is a significant investment in CAV technologies from both the government, and the large tech companies (e.g. BaiDu, Tencent, and Alibaba) (Zhao, 2019). Zhao (2019) reviewed the state of CVs in China. In their review, Zhao showed that while there are significant investments of money and person-hours being allocated to integrating CVs into Chinese roads, sanctions restrict access to the best technologies and that large numbers of competent software engineers, do not compensate for the lack of hardware design expertise in China. From the public, wide-scale disobedience of traffic ordinances in China makes testing CAVs more challenging than in countries where road users drive or cycle more cautiously. China has made its CV testing policy more liberal to stimulate growth, improve road safety, and to allow China to become a world leader in CV technology by 2030 (GIZ, 2018).

Japan is heavily invested in CV technology, due to the automotive manufacturers Toyota, Nissan, and Honda being located in Japan, and being heavily invested in CAV developments for 2020 (Jie, 2019). Although automotive manufacturers are active in CAV development in Japan, legislation is far more restrictive, with only partial automation permitted from May 2020 (Kyodo, 2019).

South Korea are the best poised to adopt CV technologies after the USA due to their preparedness for 5G, and highly-developed existing 4G infrastructure (SMMT, 2019). Government commitment to broader connectivity is supported by local manufacturers Hyundai and Kia, who are actively investing in CAV technologies (Business Wire, 2018).

7.3.2 State of C-ITS Policy

The review of countries policies on CV developments showed that many countries are taking the same approach of supporting testing CVs, then legislating based on the trial outcomes. Figure 7.2 illustrates how CV technology is strategised, delivered, and consumed. Figure 7.2 shows the feedback between consumers, industry, and the government, and how this drives policy development.

Table 7.1 shows a Strength Weakness Opportunity Threat (SWOT) analysis of current CV policy relating to the flow of information in Figure 7.2. The SWOT analysis identifies that CV policy is currently suitable for current CV trials, but as technology advances rapidly, lagging legislation and lack of clarity around CV standards will eventually stall CV development progress. Governments must be proactive to keep pace with the automotive and technology sectors if they are to realise the benefits of CVs in their road networks.

Table 7.1: SWOT matrix analysing the state of CV policy.

	POSITIVE	NEGATIVE
INTERNAL	**Strengths** • Many testing environments • Legislation supporting up to partial automation • International support for the adoption of CVs • Significant funding for CAV technologies	**Weaknesses** • Legislation lags development • Legislators are unfamiliar with CV technology • Legislation is slower to develop than technology • Guidance on standards is still vague
EXTERNAL	**Opportunities** • The automotive industry is making rapid advances in CV technology • Much of the vehicle fleet has the potential to be connected • There are opportunities for collaboration between government, academia, and industry • There are opportunities to harmonise standards across countries	**Threats** • Lack of public education could alienate the CV user base • Lack of standards could frustrate and disadvantage manufacturers • Lack of legislation could stall progress

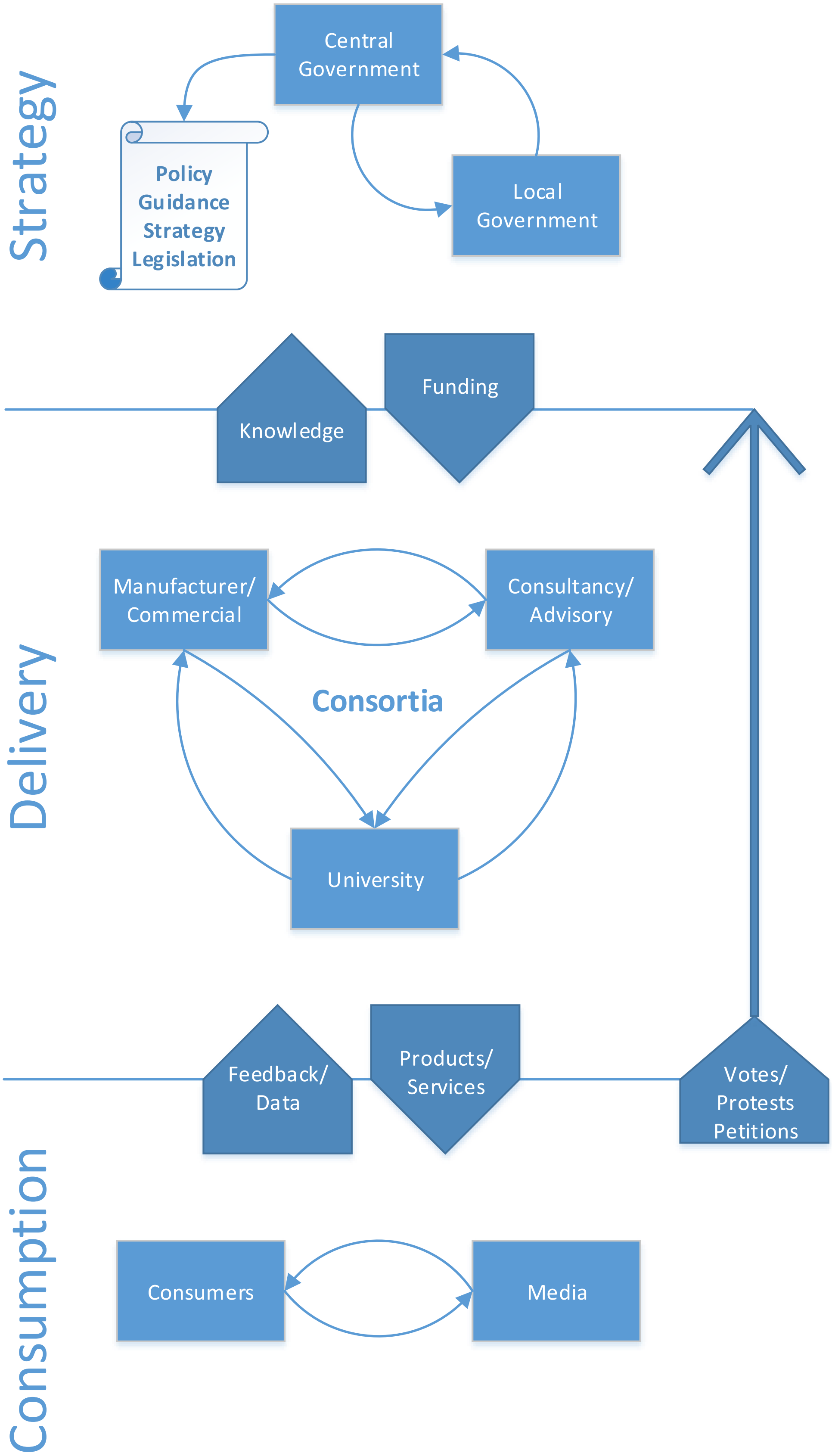


Figure 7.2: Hierarchy of entities with an interest in C-ITS technologies and their relationships.

7.3.3 C-ITS Policy Recommendations

This research has presented many findings suggesting that CVs are beneficial to the transportation network in many ways. The policy recommendations for information, transportation, and social policy are made based on the findings of this research.

7.3.3.1 Information Policy Recommendations

Communication system standards: IEEE 802.11p DSRC and 5G cellular have been identified as the most appropriate systems to support C-ITS. A system that supports both wireless standards improves the robustness of the system in case one fails. Supporting both systems also distributes the demand on each network so that neither is overloaded.

Message set standards: The ETSI and SAE have both defined message set standards for how information should be transferred between agents in a C-ITS. The recommendation is that the systems be developed to be interoperable, but that only one be chosen per geographic region to maximise interoperability.

Data sharing standards: Surveys of transport users consistently show that privacy is a primary concern regarding connected applications. Any C-ITS must be secure from cyber-attack, preserve user privacy, and manage data safely. It is the responsibility of the government to use the data appropriately to the benefit of the public and to improve transport and infrastructure.

Interoperability standards: Guidance must be offered to local authorities and manufacturers outlining the standards and technologies needed to implement C-ITS consistently across the country. The government should define the rules for how C-ITS should be implemented, and invite groups to develop C-ITS products within the scope of the guidance.

7.3.3.2 Transportation Policy Recommendations

Market penetration of CVs: The research in this thesis suggests that CV penetration in the vehicle fleet should be at least 30% to fully realise the benefits of CV data for traffic signal control. CV penetration of 30% is necessary to surpass the signal control benefits offered by actuated signal control systems. CV penetrations of 20% are acceptable if the CDOTS or MATS algorithms were to replace a fixed-time system.

Benefits for traffic congestion: The proposed MATS and CDOTS algorithms were demonstrated to reduce average delays by up to 96% and average stops by up to 34% over TRANSYT, with a CV penetration of 50% for typical traffic demand on a realistic case-study based in Birmingham, UK. These reductions correspond to significant reductions in emissions and fuel consumption, which benefit both the environment and the economy.

Benefits for the environment: The MATS and CDOTS algorithms both reduce particulate and gaseous emissions over TRANSYT. These reductions translate to cleaner air and better public health in cities.

Acyclic stage sequences: The CDOTS algorithm demonstrates that using acyclic stage sequences are beneficial for reducing delay and stops compared with using a cyclic stage sequence. Furthermore the literature review in Chapters 2 and 4 evidence that there is no safety implication in doing so. It is recommended that the UK reevaluate its prohibition of acyclic stage sequences.

Promoting CV adoption: The survey conducted in this research estimated that 20% of drivers already drive in a connected way. Provisions must be made to create a system that can exploit the data for improving the transport network and encourage other road users to drive in a connected way. New vehicles should be equipped with CV hardware built-in, and an app or third-party system should be subsidised to promote connected driving among those who cannot afford a new vehicle.

7.3.3.3 Social Policy Recommendations

Public outreach and education: Surveys show that public understanding of CV and C-ITS concepts is low, but that the public is accepting of solutions which will improve their travel. A comprehensive and easy to understand education campaign is needed to inform the public about CVs and C-ITS and how their lives will benefit from the introduction of these technologies. Education will be the key to promoting trust in CV and C-ITS technologies.

Equitable access: In line with the UK government's policy of having equitable access to all mobility innovations, traffic signal control is one way to get everyone on the road moving more efficiently. The CDOTS and MATS algorithms, do not significantly disadvantage UVs compared to CVs. However, efforts should still be made to bridge the gap by assisting everyone to access the connected system.

Data ownership: Data produced by a CV belongs to the driver/occupant of the vehicle. Using CV data raises the issue that the owner of the data is no longer the operator of the traffic signals. As a result, the owner of the CV data must elect to share it with traffic management systems that wish to use it, and the traffic management service must use it securely, privately, and per the owners' wishes. Policy needs to be determined to define who owns data produced by CVs, the conditions for sharing CV data, and what data are ethical to share and use for transport management.

7.4 Summary of Chapter Findings

Section 7.1: User Attitudes to Sharing Data with Urban Traffic Management Services

1. CV users would be reluctant to share personal information and are very concerned about the security and privacy of their data.
2. Younger generations are more comfortable adopting advanced technologies and are the groups most likely to adopt CVs.
3. There are no complete studies addressing user attitudes towards sharing their CV data for the specific purpose of enhancing traffic signal control.

Section 7.2: Transport Planning and Implementation Recommendations

4. Cycle time constraints may need to be investigated if the unconstrained cycle length causes significant delays to UVs and cyclists.
5. The MATS and CDOTS algorithms preserve driver privacy which was a major concern of respondents to surveys about CV technology.
6. Further investigation may be needed to include additional safety measures in the MATS and CDOTS algorithms.
7. The positioning hardware in CVs should focus on delivering location updates as accurately as possible at 10 Hz.
8. A hybrid system that supports both IEEE 802.11p DSRC and 5G cellular under both ETSI and SAE message sets is recommended for maximum interoperability.
9. New vehicles should include built-in hardware that supports sharing vehicular data. An app should also be developed to allow UVs and cyclists to access the system and boost CV penetration.
10. The MATS and CDOTS algorithms should be cheaper to install the MOVA or SCOOT as they do not necessarily require loop detectors, and can integrate with existing hardware.

Section 7.3: Public Policy Recommendations

11. Policy for CVs is currently open to CVs being tested but lags their development.
12. Policy for CVs is vague around the standards for CV technologies, which may slow progress in CV development.
13. CV technologies must be standardised to make systems interoperable both nationally, and internationally.
14. Traffic signal control should be done using CV data, as traffic signal controllers that use CV data are cheaper than existing systems, and are better at reducing delays, stops, and emissions.
15. The public need to be educated about CV and C-ITS technologies to promote trust and understanding in these new systems.

16. Policy needs to be implemented to determine who owns CV data and if it should be mandated that it be shared.

Chapter 8

Contributions, Conclusions, and Future Research

Connected vehicles are set to cause fundamental changes in how urban traffic management systems are operated. The richness of the dataset afforded by CVs is unmatched by infrastructure data sources and presents many new opportunities to operate the transport network more intelligently and efficiently. Within traffic signal control systems, the use of CV data represents a fundamental shift in traffic signal operations. The shift to connected traffic control systems from actuated and adaptive control systems is as significant as when actuated and adaptive systems superseded fixed-time plans when they were first introduced. New technology necessitates new methods to utilise its potential best. Old methods for hardware-based systems need to be updated and improved upon to make way for a new generation of dynamic, connected, real-time control systems whose software and algorithms are critical to their performance.

This research has developed a series of algorithms that utilise CV data to update existing infrastructure and perform traffic signal control that builds upon the principles of the state-of-the-art traffic signal control algorithms that have gone before it. The algorithms also sought to use data from CVs in innovative ways to investigate which sources are useful for traffic signal control, rather than accepting the status quo and only using CV data to replace data that could be obtained from roadside infrastructure. This research also determines if users would accept sharing their data with the system developed, rather than assuming users would want to share their data with a traffic management service.

The conclusions of the thesis are structured as follows. Section 8.1 discusses how the research conducted in this theses fulfils the objectives set out in the introduction. Section 8.2 discuses the topics identified as areas for future research. Finally, in Section 8.3, a summary of this thesis is given.

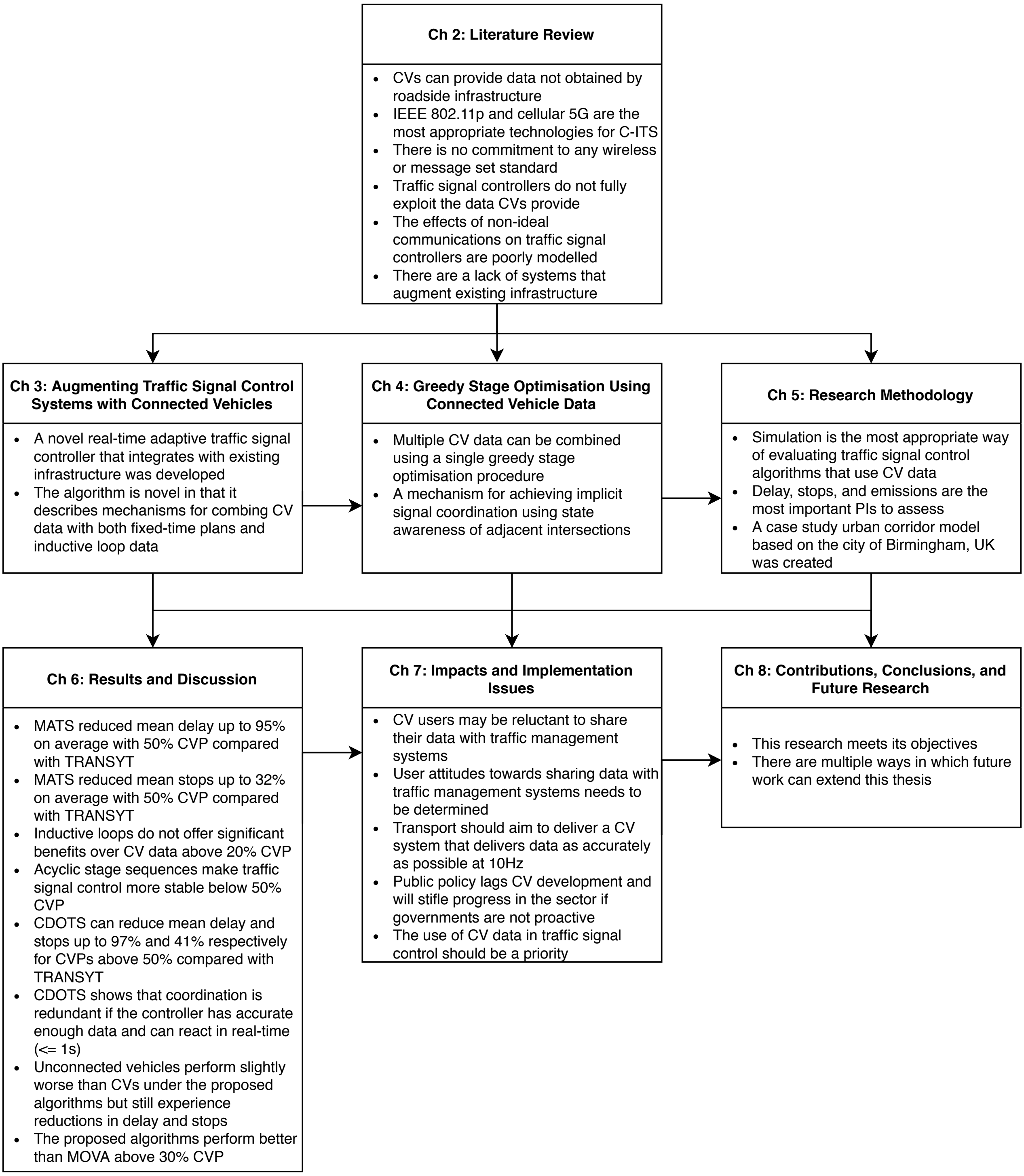


Figure 8.1: Key findings in each chapter of this thesis.

8.1 Fulfilment of the Research Objectives

In Chapter 1, five research objectives were given to motivate this research. Each of these objectives are discussed in turn and how the findings of this research fulfil them.

8.1.1 Determining which data are generated by CVs and evaluate their usefulness for urban traffic signal control through simulation.

In Chapter 2, the technologies that underpin C-ITS and CV operations were reviewed, and the data they produce determined. In Chapter 3, data from CVs were used to create the MATS algorithm whose operation is a functional extension of the principles of the MOVA algorithm using connected vehicle data. Position, speed, and heading information were used to achieve traffic signal control in the MATS algorithm. The MATS algorithm also had the benefit of being able to integrate with existing infrastructure systems. The results showed that the MATS algorithm offers typical reductions in the mean delay of up to 95% and the mean number of stops up to 33% over TRANSYT, for urban corridors with 0-100% connected vehicle presence. The results also confirm that significant reductions in delay can be achieved for CV penetrations as low as 10%, highlighting that all the vehicles in the corridor need not be connected to achieve delay reductions. The results also showed that the MATS algorithm is capable of reducing emissions by over 25% on average. Furthermore, inductive loops were shown to be redundant in the presence of CV data for CV penetrations above 20%. Overall, the results comparing the MATS algorithm with TRANSYT show that using CV data is beneficial for traffic signal control and can do better than existing state-of-practice strategies.

In Chapter 4, the MATS algorithm from Chapter 3 was extended to allow an acyclic stage sequence. Specific data from CVs were used to achieve control that was functionally similar to MOVA in Chapter 3, in Chapter 4 a method for considering multiple available CV data was developed. By considering multiple data sources in the greedy stage optimisation heuristic, different combinations of data could be tested to determine which were the most useful for globally reducing delay and stops in the case study corridor. It was found that knowing the number of vehicles in each lane, and how many times they had stopped on their current journey were the most useful quantities to use in the stage sequence calculation. The two data are interesting as they are more abstract than the speed and position data commonly used for traffic signal control using CVs (see Table 2.7). Moreover, determining the most suitable data for optimising the global PI, provided greater reductions in the mean number of stops, delay, and emissions over TRANSYT than were achieved by the MATS algorithm.

Finally, in Chapter 6, it was determined that explicit coordination of traffic signals is redundant if the system can react in real-time ($\leq$1 s) to the prevailing traffic demand in the transport network. This finding is interesting as methods that achieve signal coordination are the most prevalent strategies in urban corridors. What this research demonstrates is that with enough data, and a PI comprised of delay and number of stops, the traffic signals implicitly coordinate themselves. Where previously much effort has gone into coordinating signals, responsive control with accurate CV data presents the new opportunity for control with inherent coordination.

8.1.2 Quantifying how the presence of CVs in the vehicle fleet impacts on the efficiency of the transport network for increasing CV penetration from 0% to 100%.

In Chapter 6, the MATS and CDOTS algorithms were tested extensively on a realistic case study, at multiple traffic demand levels, and under ideal and non-ideal wireless communications. The algorithms were also benchmarked against the industry standard TRANSYT and MOVA algorithms.

The results of the tests show that the greater the traffic demand on the corridor, the better the MATS and CDOTS algorithms are at reducing delays, stops, and emissions in the corridor. Compared with TRANSYT, CV penetrations of 20% or greater are needed to realise the potential of CV data in the transport network. Compared with MOVA, CV penetrations of 30% or greater are needed to realise the benefits of traffic signal control using CV data.

The results showing reductions in the mean delay of up to 96% and mean stops of 34% over TRANSYT, with only 50% CV penetration under average traffic demand are significant. Under the CDOTS algorithm, traffic flow in the Birmingham case study was measurably more efficient. By reducing delays and stops so significantly, the capacity of the corridor is increased and mitigates the need for costly capacity enhancing measures such as adding lanes.

8.1.3 Formulating urban traffic signal control strategies based on state-of-practice and state-of-the-art knowledge that are beneficial for both connected and unconnected vehicles.

In Chapter 6, the results for connected and unconnected vehicles under the CDOTS algorithm were treated separately to determine if there was a difference between them. The results comparing the performance of CVs and UVs under the CDOTS algorithm show that the performance of UVs is 13%–60% worse than for CVs in terms of mean delay per kilometre. The disparity is not desirable, but challenging to avoid as the performance benefits of the CDOTS algorithm derives from its use of CV data. Despite the difference in mean delay between CVs and UVs, the UVs still benefit from reduced delays compared with TRANSYT when compared with the results from Chapter 4. For the mean stops per kilometre results, UVs also fare worse than CVs, but by a significantly smaller margin (1%–6%). Although using CV data for traffic signal control benefits both connected and unconnected vehicles, further study is needed to investigate whether the disadvantage of increased delays faced by users of UVs is at an acceptable level and if they have broader impacts for vulnerable groups.

8.1.4 Informing policymakers and transport planners on how to design better, safer urban corridors that are towards the integration of CVs using a state-of-the-art literature review combined with the findings of this research.

The impact of this research on transport planning and policy were discussed in detail in Chapter 7. From a transport planning perspective, the main concern is data quality and quantity. From Chapter 6, at CV penetrations below 50%, data quality is crucial to maintain efficient operation of the CDOTS algorithm. At CV penetrations above 50%, non-ideal data can be compensated for by the quantity of data in the network. The balance should be achievable as at lower CV penetrations, there are less connected devices, and therefore less noise to interfere with wireless communications. It is also essential that transport planners maintain road users' desire for data privacy and security when implementing the system. Transport planners should also implement the system to give the most users access to it. By making the system accessible, higher levels of CV penetration can be achieved earlier in the life-cycle of the algorithm so that it can realise the most significant benefits over its deployment. As the MATS and CDOTS algorithms integrate with existing infrastructure, the algorithms should be less expensive to deploy than loop based systems as computing and wireless communication infrastructure is cheaper to install than inductive loops.

In terms of government policy, there seems to be a global trend towards testing CV technologies to legislate their requirements as outcomes of the tests provide insights into the impact and requirements of connected technology. Although the testing regime is a useful exercise, CAV manufacturers are advancing their products rapidly, and policy is at risk of lagging the pace of the industry. The main issue for policymakers to address is the selection of wireless and message set standards. This research recommends IEEE 802.11p DSRC or cellular 5G as the most suitable communication standards for C-ITS. There are two message set standards for C-ITS, one is proprietary and maintained by the SAE, the other is open-source and maintained by ETSI. The two message set standards differ only slightly, and a CV could theoretically support both.

Policymakers should be actively pursuing the implementation of traffic signal control systems that use data from CVs. The proposed MATS and CDOTS algorithms significantly reduce mean delays, numbers of stops, and emissions which benefit the environment and save the economy billions of dollars per year in lost time and wasted energy. To realise the benefits of C-ITS, policymakers need to educate themselves and the general public about the benefits and operations of the new technology, so that trust and understanding are fostered, and the technology is seen as desirable and useful.

8.2 Future Work

8.2.1 Enhanced case study and benchmark

The Birmingham case study used in this research was produced from real data and represent a model significantly close to a real-world scenario than is common in the field of traffic signal control simulation. Some additions that were not possible in this research due to lack of data were cyclists, bus stops and time tables, and full benchmarking against MOVA and SCOOT.

Cyclists are a common presence in urban roadways, but modelling their interaction with cars can be challenging for microsimulation. With the construction of the Selly Oak Cycle Superhighway in Birmingham, there will likely be traffic surveys conducted to monitor the use of the new network. This cyclist traffic data could be integrated with the new road layout to assess the effects of the MATS and CDOTS algorithms on cyclists.

Buses as a vehicle class are included in the simulation, but the volume of bus stop information was too large to model in this study. If more time was available to build the road model, bus-stop dynamics could be worth including in the model.

Safety performance indicators such as TTC discussed in Chapter 5.7 should be considered to determine the safety impact of the control strategies on traffic safety in the network.

Finally, TRANSYT was used as the benchmark traffic signal controller for the case study. MOVA was comparable based on the results of other research but not on the case study due to licensing issues with SUMO as discussed in Chapter 5. In future, it would be worth implementing the MATS and CDOTS algorithms in a microsimulation software where they can be compared to the actuated and adaptive strategies MOVA and SCOOT. Benchmarking the proposed algorithms against MOVA and SCOOT would better reflect what improvements can be achieved against data-driven traffic signal control strategies.

8.2.2 Self-optimising/learning for control parameters

The results in Chapters 3 and 4 showed that the proposed MATS and CDOTS algorithms increased stage times compared to TRANSYT, and at times exceeded the 120 s maximum cycle length recommended in UK Govt. Dept. Transport (2006). Although these cycle time violations were shown not to interfere with road users' progress through the network, transport planners may find it desirable to set constraints that prevent the algorithm from exceeding the 120 s maximum cycle time recommendations.

One way constraints could be implemented is by reducing the number of stages that can occur before a stage occurs again, or by removing the double-cycle, and constraining the stage sequence optimisation to a single cycle. The other way the cycle time recommendations could be achieved is through self-optimising or reinforcement-learning, to increase or decrease the maximum green time for all stages or individual stages, incrementally. The second approach would allow each intersection to further tune its performance to the traffic flow characteristics of its lanes.

It would also be useful to investigate methods for estimating CV penetration reliably. Reliable CV penetration estimation would allow finer control over when the MATS algorithm uses CV data in its control actions, and improve performance at CV penetrations below 30%.

8.2.3 Transit priority

Transit priority is the ability to prioritise specific modes of transport such as buses and emergency vehicles, giving them preferential treatment in terms of reduced delays and stops at the expense of other road users. The next stage in this research would be to integrate a priority term into the greedy stage optimisation procedure in the CDOTS algorithm and add bonus green time extensions to the MATS algorithms' green time control. The system could be implemented using a graphical interface that allows the engineer implementing the algorithm to weight the priority of different vehicle or road user types against each other.

8.2.4 Neighbouring Junctions

In Chapter 6, the results showed that the CDOTS algorithm responds to traffic demand fast enough that explicit coordination is unnecessary. For the case study corridor, there is no network-level benefit of coordinating the traffic signals. The lack of a need for coordination, in this case, does not mean there are no cases where coordination is not useful. It may be the case that intersections with short separations ($< 100m$) could benefit from stage coordination for stages involving the short inter-junction lanes. It could be worth establishing a test with a corridor of N intersections, and running tests to assess the CDOTS algorithm with increasingly short inter-junction separation to determine if coordination is ever beneficial in a connected traffic signal control environment.

8.2.5 Signal-less traffic control

At the cutting-edge of traffic control, some strategies work for CAVs where there are no physical traffic signals, and vehicles are scheduled autonomously through an intersection. This research could be extended for CAV operation by using the greedy stage sequence optimisation algorithm in combination with speed advisories, and a clustering algorithm to schedule platoons of vehicles through the intersection without any traffic lights.

8.3 Closing Summary

This research proposed a traffic signal control algorithm that optimised traffic signal timings using CV data in a manner functionally similar to the MOVA algorithm. The algorithm was novel in its approach to traffic signal timing calculation and how it managed blocking-back conditions at isolated intersections. The algorithm is also novel in that it integrates with and over existing traffic signal control algorithms and infrastructure. The next phase of the algorithm was to optimise the stage sequence. Stage sequence optimisation was achieved through a greedy algorithm that could consider multiple data sources simultaneously, allowing the best data sources to be determined. This research also developed a method for adding implicit coordination to the stage optimisation procedure. The key finding of this research is that coordination was found to be unnecessary in a connected environment as the CDOTS algorithm could respond quickly enough to the prevailing traffic demand. Lastly, surveys of user perception of data sharing with traffic management systems, transport planning impacts, and government policy showed that there is a significant gap between CV technologies and their adoption at governmental, engineering, and users levels. This research has the potential to reduce the delays, stops, and emissions of vehicles in connected urban transport networks significantly, even under non-ideal communication conditions and connected vehicle penetrations below 50%. More effort from transport planners and policymakers is necessary to realise the benefit of a new generation of traffic signal controllers that exploit data from connected vehicles.

Chapter 9

Appendix

A Contributions to the Field

Significant sections of this thesis have been presented at conferences, published in journal articles, and discussed at industrial meetings and seminars. The following publications were produced throughout this research:

Rafter, C. B., & Box, S. (2016), Investigating the effects of mixed driver reaction times in the transport network, *in* 5th Symposium of the European Association for Research in Transportation (hEART).

Rafter, C. B., Anvari, B., & Box, S. (2017), Traffic Responsive Intersection Control Algorithm Using GPS Data, *in* 20th International IEEE Conference on Intelligent Transportation Systems (ITSC).

Rafter, C. B., Anvari, B., & Box, S. (2017), A hybrid traffic responsive intersection control algorithm using global positioning system and inductive loop data, *in* Proceedings of the Transportation Research Board 97th Annual Meeting.

Rafter, C. B., Anvari, B., Cherrett T. J., & Box, S. (2020), Augmenting traffic signal control systems for urban road networks, *IEEE Transactions on Intelligent Transportation Systems*.

Rafter, C. B., Anvari, B., Cherrett T. J., & Box, S. (2020), (*under review*) A Greedy algorithm for optimising traffic signal stages using arbitrary data from connected vehicles, *Transportation Research Part C: Emerging Technologies*.

The papers Rafter et al. (2017*a*,*b*, 2019*b*) form the basis of Chapter 3 and 5, and (Rafter et al., 2019*a*) forms the basis of Chapter 4.

B Selly Oak Traffic Model

In this section, the configuration of the Selly Oak SUMO model is given. The labels of each signalised intersection is described, the signal stages illustrated, and the groups of signals for coordination given.

B.1 Model labels

Figure B.1 illustrates the labels used to identify each of the intersections in the case study model.

B.2 Stages

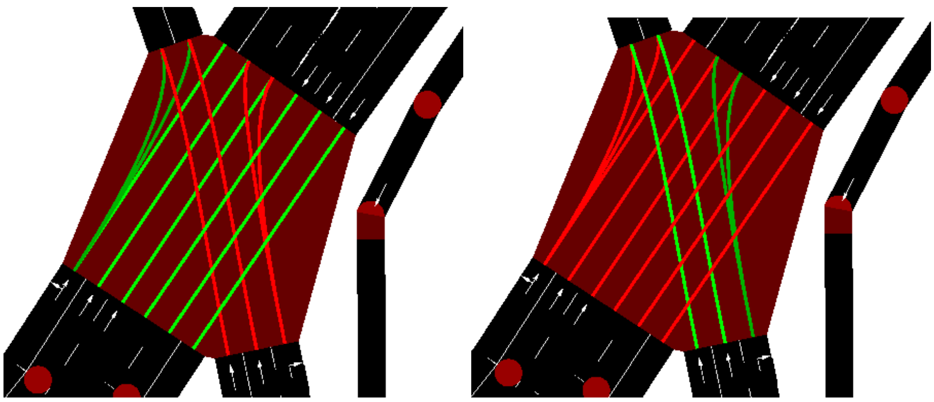
Figures B.2–B.12, illustrates the traffic signal stages at each of the intersections in the model. Red lines indicate a red traffic signal for the stage, green lines indicate a green light for the stage. The white arrows in each of the lanes indicate the movements a vehicle can make from that lane.

The intersections with pedestrian stages are *junc0*, *junc1*, *junc4*, *junc5*, *junc6*, and *junc7*. During a pedestrian stage all signals are red for the duration of the pedestrian stage.

B.3 Coordination Groups

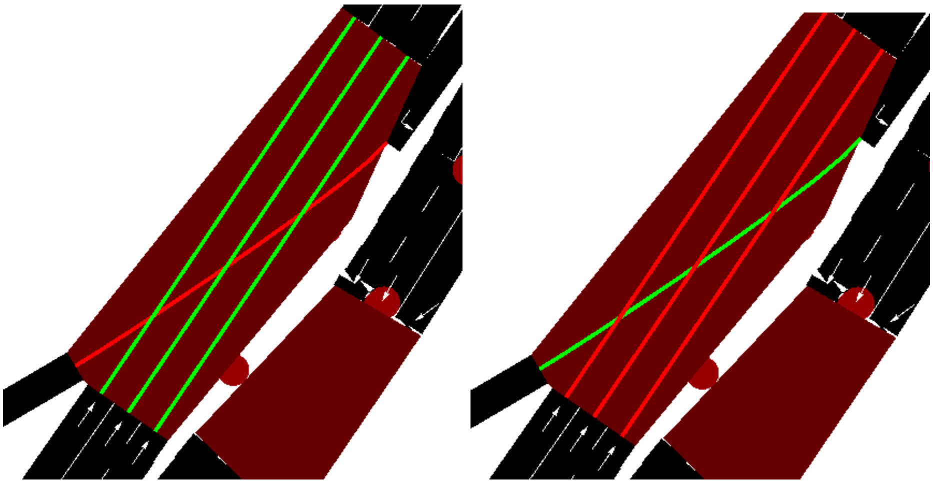
Figure B.13 illustrates which intersections are grouped for coordination in this research.

Figure B.1: An illustration of the road network model in SUMO with the junctions labelled with their IDs.



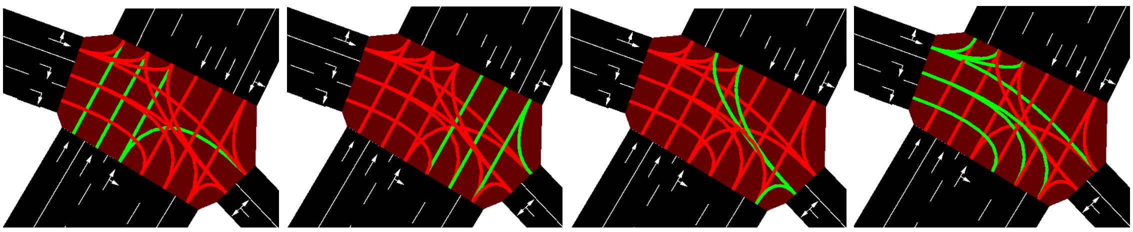
(a) Stage 1 (b) Stage 2

Figure B.2: The signal stages for junc10.



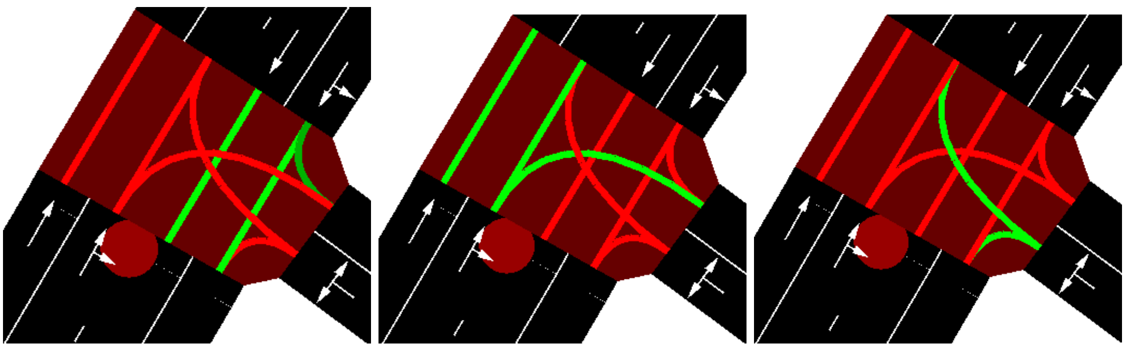
(a) Stage 1 (b) Stage 2

Figure B.3: The signal stages for junc11.



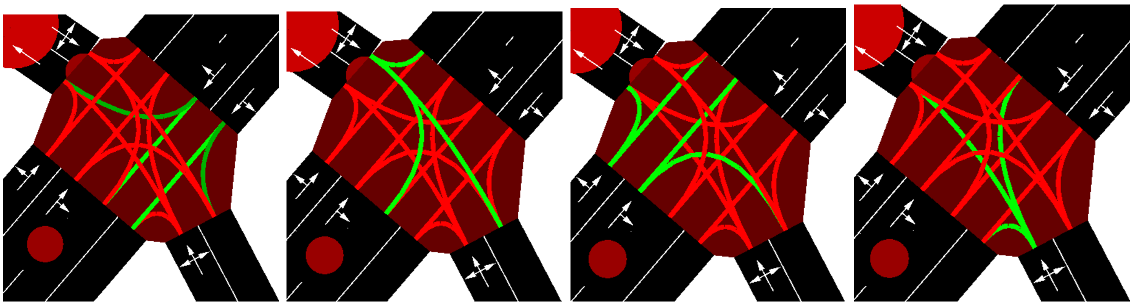
(a) Stage 1 (b) Stage 2 (c) Stage 3 (d) Stage 4

Figure B.4: The signal stages for junc9.



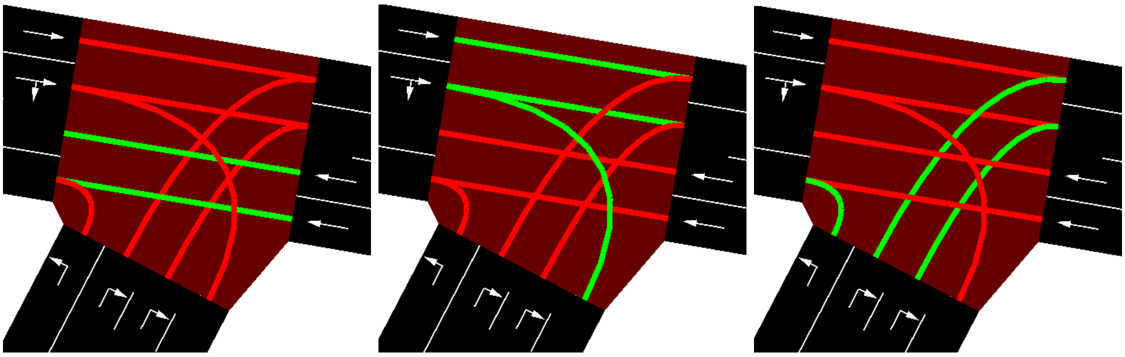
(a) Stage 1 (b) Stage 2 (c) Stage 3

Figure B.5: The signal stages for junc1.



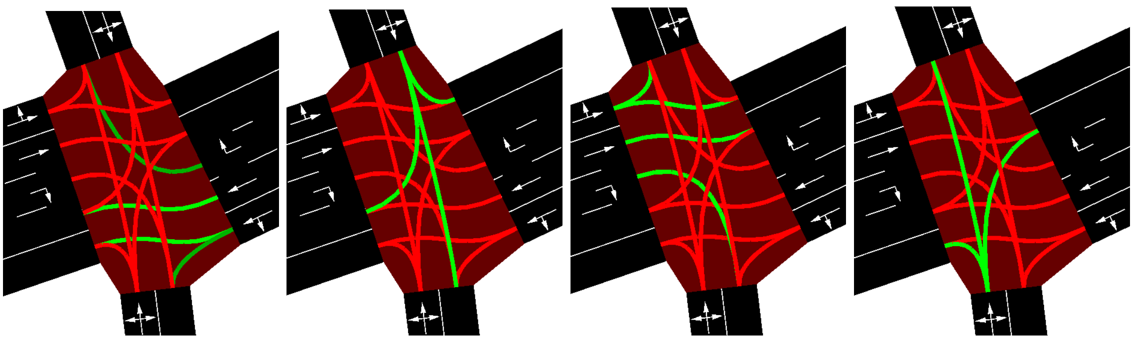
(a) Stage 1 (b) Stage 2 (c) Stage 3 (d) Stage 4

Figure B.6: The signal stages for junc0.



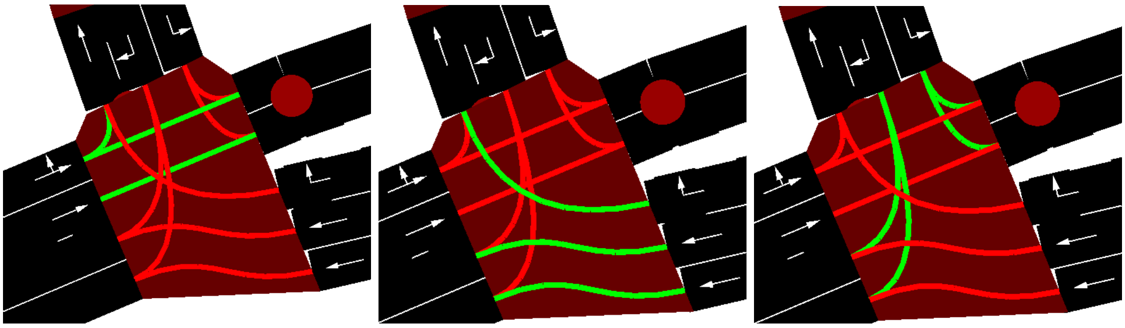
(a) Stage 1 (b) Stage 2 (c) Stage 3

Figure B.7: The signal stages for junc4.



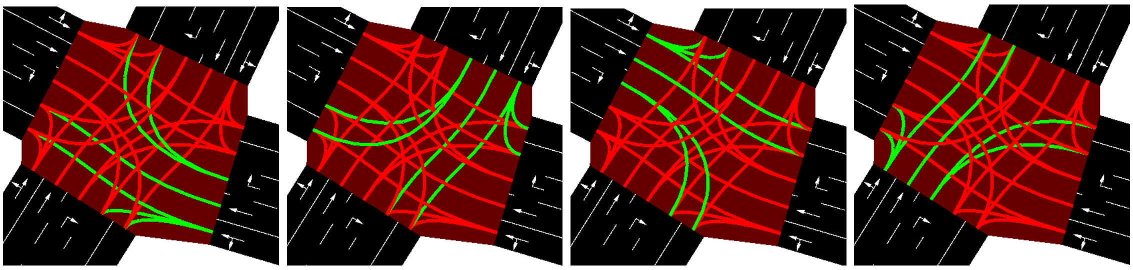
(a) Stage 1 (b) Stage 2 (c) Stage 3 (d) Stage 4

Figure B.8: The signal stages for junc5.



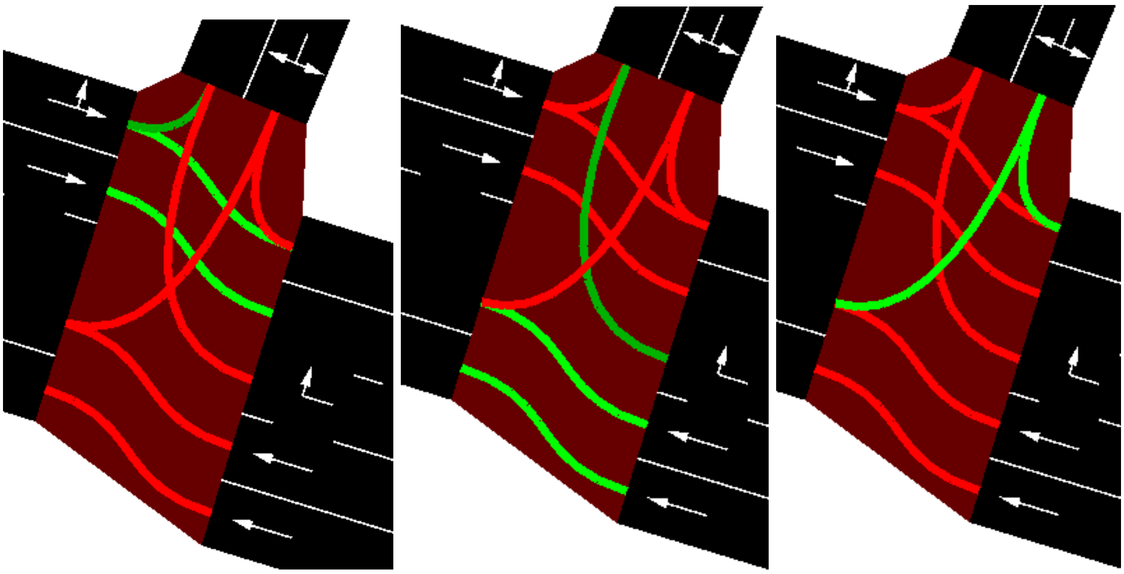
(a) Stage 1 (b) Stage 2 (c) Stage 3

Figure B.9: The signal stages for junc6.



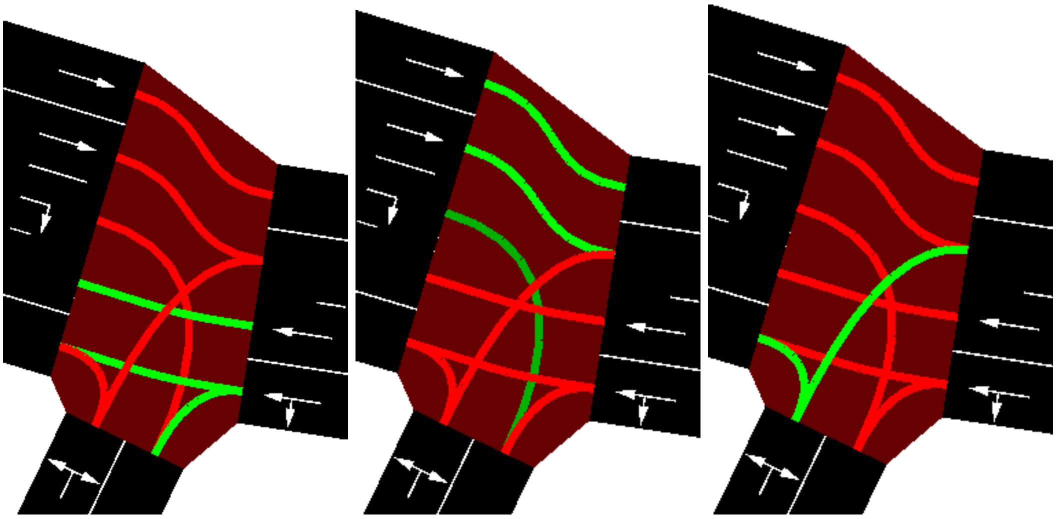
(a) Stage 1 (b) Stage 2 (c) Stage 3 (d) Stage 4

Figure B.10: The signal stages for junc3 and junc12.



(a) Stage 1 (b) Stage 2 (c) Stage 3

Figure B.11: The signal stages for junc7.



(a) Stage 1 (b) Stage 2 (c) Stage 3

Figure B.12: The signal stages for junc8.

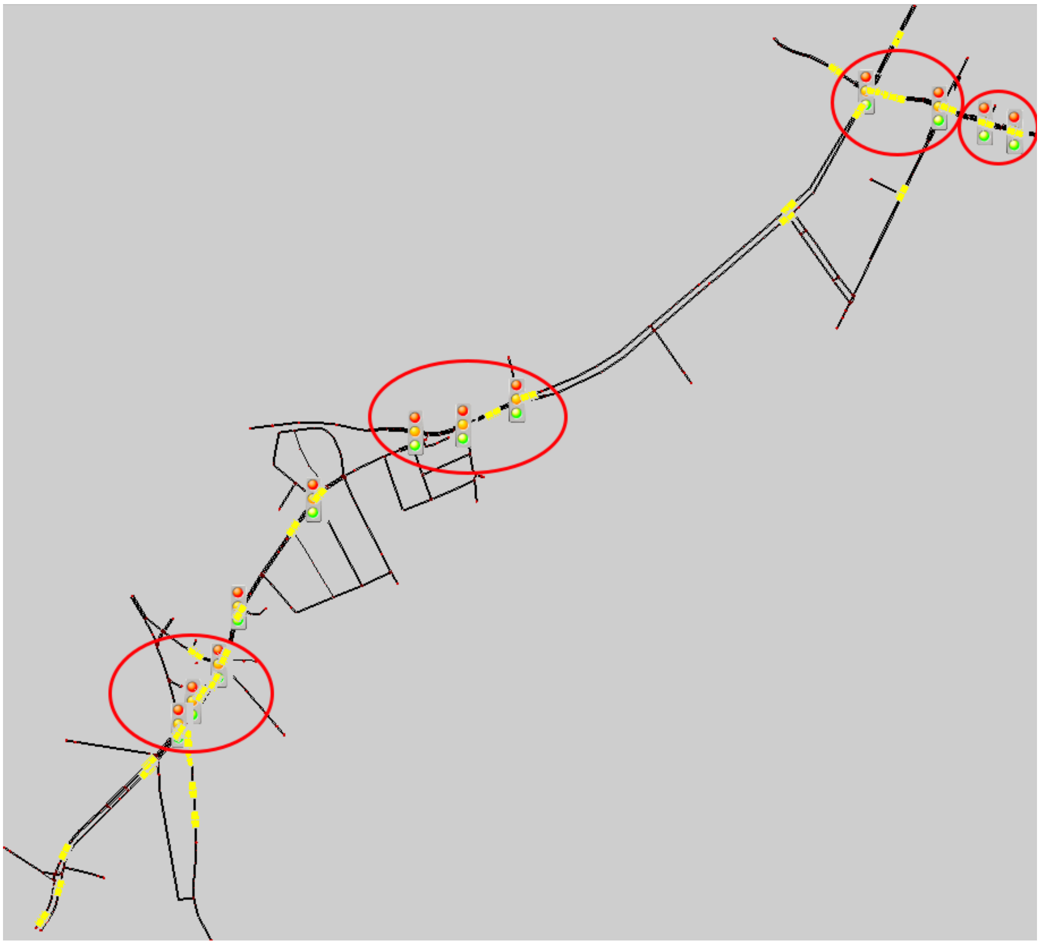


Figure B.13: An illustration of the road network model in SUMO. Signalised intersections are represented by the red-amber-green lamp icon, groups of signals which are coordinated are bound by red ellipses.

C Manual Traffic Survey in Selly Oak, Birmingham, UK

In order to validate the traffic flow levels, a manual traffic counts were performed over two days in February 2019. The area and intersection counted in the Selly Oak area of Birmingham, UK is shown in Figure C.14. Vehicle flows were counted for 10–15 minutes for each stage of each intersection. The flow levels are recorded in Table C.1, and were found to be consistent with the traffic flow levels provided by Birmingham Council used to model the road network. In Table C.1, the hourly vehicle flows are given as totals for each stage, and split into direction of travel at the intersection (straigh, left, or right). The types of passing vehicles were also recorded for 10 minutes at each intersection. The composition of the recorded vehicle fleet is given in Figure C.2, and is consistent with the values from the VEH0104 dataset (UK Govt. Dept. Transport, 2017) for vehicle registration in the West-Midlands.

Videos were also recorded for 15 minutes intervals of traffic flow at each intersection and can be found on YouTube with descriptions here:

https://www.youtube.com/playlist?list=PLDncUlj1fe7KcsBnT235Z9Q8ye_MLIkFE

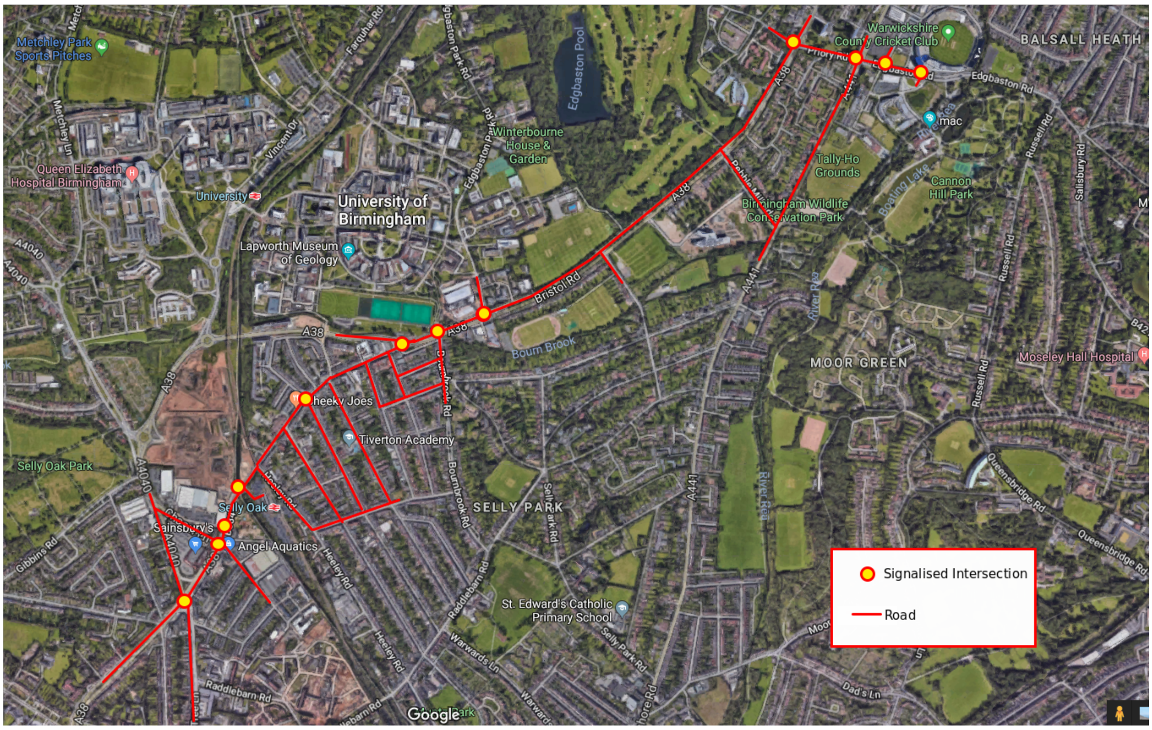


Figure C.14: A map of the area of Selly Oak, Birmingham, UK surveyed for the case study.

Table C.1: Vehicle flows in each direction of each stage of the network intersections. Flows in vehicles per hour

Junction ID	Stage ID	Straight	Left	Right	Total
junc10	1	1035	627	480	2142
	2	720	84	33	837
junc11	1	456	426	–	882
	2	–	–	192	192
junc9	1	610	–	65	675
	2	455	55	–	510
	3	–	65	–	65
	4	608	48	130	786
junc1	1	456	6	–	462
	2	588	–	30	618
	3	–	21	9	30
junc0	1	462	18	24	504
	2	30	48	42	120
	3	600	18	78	696
	4	18	6	12	36
junc4	1	444	402	–	846
	2	474	–	30	504
	3	468	18	–	486
junc5	1	786	132	0	918
	2	12	18	12	42
	3	888	0	84	972
	4	0	60	126	186
junc6	1	876	210	–	1086
	2	726	138	–	864
	3	–	234	186	420
junc3	1	678	246	66	990
	2	678	234	144	845
	3	66	18	150	234
	4	642	36	102	780
junc12	1	732	156	132	1020
	2	654	162	162	978
	3	666	108	174	948
	4	954	84	180	1218
junc7	1	1356	6	–	1362
	2	828	–	0	828
	3	–	48	72	120
junc8	1	597	42	–	639
	2	768	–	81	849
	3	–	138	144	282

Table C.2: Vehicle type counts from the survey of Selly Oak traffic.

Vehicle Type	Count	Fleet Share
Car	3574	84.68%
LGV	466	11.04%
HGV	107	2.53%
Motorcycle	19	0.45%
Bus	55	1.3%
Total	**4221**	**100%**

D TRANSYT Plans

The TRANSYT signal timing plans for the Selly Oak case study were produced using the TRANSYT 15 software (Binning et al., 2013). Separate timing plans are calibrated for off-peak (00:00-06:00, 20:00-00:00), peak (06:00-11:00, 16:00-20:00) and inter-peak flows (11:00-16:00). The optimisation is unconstrained and uses the standard economic factors so that the TRANSYT plans are best optimised for the provided flows.

Tables D.3–D.5 show the TRANSYT plans for each time period. The plans are described in terms of the junction ID as given in Figure B.1, and the stages in order of appearance as defined by the stage IDs in Figures B.2–B.12. Each stage green time is described by its start and end time as they appear in each intersections common cycle length, and the duration of the stage. The common cycle lengths for the intersections as recommended by the TRANSYT cycle length optimisation process in the Selly Oak Model are:

- 110 s: junc0
- 120 s: junc10,junc9, junc1
- 170 s: junc3, junc12, junc7, junc8
- 180 s: junc4, junc5, junc6

Table D.3: TRANSYT signal timing plans for the off-peak flows.

Junction ID	Stage ID	Stage Start (s)	Stage End (s)	Stage Duration (s)
junc10	2	79	103	24
	1	111	74	80
junc11	1	18	89	71
	2	97	10	33
junc9	4	118	30	32
	1	37	61	24
	2	68	90	22
	3	97	111	14
junc1	1	96	46	60
	2	52	72	20
	3	78	90	12
junc0	1	129	49	60
	3	55	87	32
	4	93	105	12
	2	111	123	12
junc4	1	167	6	19
	2	13	83	70
	3	90	160	70
junc5	2	11	25	14
	1	32	96	64
	4	103	117	14
	3	124	4	60
junc6	1	105	175	70
	3	2	21	19
	2	28	98	70
junc3	2	13	81	68
	3	89	126	37
	4	134	150	16
	1	158	5	17
junc12	2	8	24	16
	3	32	75	43
	4	83	135	52
	1	143	0	27
junc7	3	141	41	70
	1	48	101	53
	2	108	134	26
junc8	3	42	74	32
	2	80	140	60
	1	146	36	60

Table D.4: TRANSYT signal timing plans for the inter-peak flows.

Junction ID	Stage ID	Stage Start (s)	Stage End (s)	Stage Duration (s)
junc10	2	47	102	55
	1	110	39	49
junc11	1	19	88	69
	2	96	11	35
junc9	4	119	30	31
	1	37	62	25
	2	69	91	22
	3	98	112	14
junc1	1	96	40	54
	2	46	72	26
	3	78	90	12
junc0	2	129	4	15
	1	10	70	60
	3	76	105	29
	4	111	123	12
junc4	1	48	68	20
	2	75	145	70
	3	152	41	69
junc5	2	72	86	14
	1	93	158	65
	4	165	179	14
	3	6	65	59
junc6	1	139	29	70
	3	36	55	19
	2	62	132	70
junc3	1	12	80	68
	2	88	125	37
	3	133	149	16
	4	157	4	17
junc12	2	6	24	18
	3	32	70	38
	4	78	134	56
	1	142	168	26
junc7	3	140	40	70
	1	47	100	53
	2	107	133	26
junc8	3	42	74	32
	2	80	140	60
	1	146	36	60

Table D.5: TRANSYT signal timing plans for the peak flows.

Junction ID	Stage ID	Stage Start (s)	Stage End (s)	Stage Duration (s)
junc10	2	81	106	25
	1	114	73	79
junc11	1	18	76	58
	2	84	10	46
junc9	4	0	30	30
	1	37	60	23
	2	67	92	25
	3	99	113	14
junc1	1	96	39	53
	2	45	72	27
	3	78	90	12
junc0	4	23	35	12
	2	41	53	12
	1	59	119	60
	3	125	17	32
junc4	1	48	68	20
	2	75	145	70
	3	152	41	69
junc5	2	72	86	14
	1	93	158	65
	4	165	179	14
	3	6	65	59
junc6	1	139	29	70
	3	36	55	19
	2	62	132	70
junc3	1	13	81	68
	2	89	126	37
	3	134	150	16
	4	158	5	17
junc12	2	8	24	16
	3	32	75	43
	4	83	135	52
	1	143	0	27
junc7	3	141	41	70
	1	48	101	53
	2	108	134	26
junc8	3	42	74	32
	2	80	140	60
	1	146	36	60

E MATS Algorithm Pseudocode

The pseudocode for the MATS algorithm is presented in Algorithm 2. The semantics for the pseudocode are based on a combination of the Python programming language (Rossum, 1995) and American Mathematical Society notation (Pakin, 2015), where '//' infers a comment rather than a command, and '**DO**' describes in plain English an action to be taken by an external part of the program.

Algorithm 2: MATS Algorithm Pseudocode

```
begin MATS
    DO: Gather CV data from the communications channel, collect flow data from inductive loops
    remainingTime ← stageDuration − elapsedTime
    if remainingTime ≤ checkThreshold then
        // Get loop extension time if loop data available
        if loopDataForControlledLanes then
            if ANY(lastDetectTime ≤ extensionThreshold) then
                loopExtendTime ← loopStageExtension
            else
                loopExtendTime ← 0
        else
            loopExtendTime ← NONE
        // Get CV extension time if CV data available
        if CVpenetration > CVPthreshold then
            if nearestVehicleSpeed ≥ 0.01 and nearestVehicleIsInRange then
                cvExtendTime ← nearestVehicleDistance / nearestVehicleSpeed
                if cvExtendTime > 2×loopStageExtension then
                    cvExtendTime ← 0
            else
                cvExtendTime ← 0
        else
            cvExtendTime ← NONE
        // Select extension from the available data, default to fixed-time plan
        if loopExtendTime ≠ NONE and cvExtendTime ≠ NONE then
            stageExtendTime ← max(loopExtendTime, cvExtendTime)
        else if loopExtendTime = NONE and cvExtendTime ≠ NONE then
            stageExtendTime ← cvExtendTime
        else if loopExtendTime ≠ NONE and cvExtendTime = NONE then
            stageExtendTime ← loopExtendTime
        else
            stageExtendTime ← max(0, fixedTimeDuration − elapsedTime)
        // Update stage time to fall within the upper and lower green time bounds
        stageDuration ← elapsedTime + max(stageExtendTime, remainingTime)
        stageDuration ← max(stageDuration, minGreenTime)
        stageDuration ← min(stageDuration, maxGreenTime)
    // If this is a new stage set a preliminary green time based on the queue length
    else if newStage and numberOfCVs > 0 then
        if lastVehicleDistance ≠ NULL then
            queueClearanceTime ← lastVehicleDistance × (maxGreenTime/maxQueueLength)
            stageDuration ← max(queueClearanceTime, minGreenTime)
            stageDuration ← min(queueExtendTime, maxGreenTime)
        else
            stageDuration ← minGreenTime
    // If no vehicles are moving due to blocking back then end stage
    else if elapsedTime > minGreenTime and remainingTime > checkThreshold and numberOfCVs > 0 and not
     queueIsMoving then
        DO: Set stage to end
    else
        DO: Continue
    // Continue stage if time remaining, else transition to next stage
    if elapsedTime < stageDuration then
        elapsedTime ← elapsedTime + timeStep
    else
        DO: Transition to next stage
        elapsedTime ← 0
        stageDuration ← 0
```

F User Attitudes to Sharing Data with Urban Traffic Management Services

In the literature review, the data sources present in the transport network were identified. In Chapter 3, the identified roadside and CV data were used to augment existing traffic signal infrastructure with CV data to reduce delays and stops. In Chapter 4, a method for determining the most useful CV data points to use for optimising a given PI was developed. Finally, Chapter 4 also described a method for adding deliberate coordination to a highly adaptive traffic signal controller using CV data.

The key difference between data gathered from roadside infrastructure and data gathered from CVs is that the data from roadside infrastructure belong to the authority who own the loops and the traffic signal control infrastructure. Conversely, the data produced by a CV belongs to the driver/occupant of the vehicle. Using CV data raises the issue that the owner of the data is no longer the operator of the traffic signals. As a result, the owner of the CV data must elect to share it with traffic management systems that wish to use it, and the traffic management service must use it securely, privately, and per the owners' wishes. If users do not see the benefit in sharing their CV data with a traffic management system, then algorithms that use data from connected vehicles will be challenging to deploy.

Previous surveys primarily deal with user perceptions of autonomous vehicle technology (Litman, 2019). Several surveys assess user attitudes towards connected vehicles in general terms. As the data that a CV can provide have been determined in previous chapters, this chapter aims to survey user attitudes towards sharing specific data with an urban traffic management system and provide more in-depth insights into what data will be shared with urban traffic management systems.

In this chapter, Section F.1 discusses the findings of previous surveys on user attitudes towards connected vehicles. Section F.2 describes the methods and questions used for the survey of user attitudes towards sharing data CV data with connect vehicle. Section F.3 discusses the results obtained from the survey data. Finally, the conclusions of the chapter a drawn in Section F.4.

F.1 Background

Many surveys seek to determine user perception on CAV driving technologies, but there is significantly more interest in gauging attitudes towards AV over CVs (Litman, 2019). In this section, the findings of surveys investigating user perceptions towards CVs are discussed.

Schoettle and Sivak (2014) surveyed participants in the US, UK, and Australia about their opinions on connected vehicles (questionnaire, $N = 1596$). Before the survey, 78% of participants had not heard of CVs, but 62% had a positive sentiment towards them. Participants were most confident about CVs being able to reduce crashes (86%), and least confident about CVs being able to reduce driver distraction (61%). Participants were most concerned about the security of the vehicle from hacking, the privacy of their data, and drivers coming to rely too much on CV technologies. Overall, the majority of respondents thought that safety was the most critical area for CVs to focus on, that a CV should integrate with their smartphone, and that they have a desire to have CV technology in their vehicles.

Shin et al. (2015) conducted a survey on user acceptance and willingness to pay for CV technologies (questionnaire, $N = 529$). Respondents reported price, collision avoidance, and travel assistance as the three most important considerations when considering the value of a CV. The survey found that the more educated participants were about CVs, the more willing to pay for a CV they were.

Owens et al. (2015) conducted a cross-generational study to assess user acceptance of CV technologies based on respondent age (questionnaire, $N = 1019$). The generations considered were Millenials (born 1983-2001), Generation X (born 1965-1982), Baby Boomers (born 1946-1964), and the Silent Generation (born 1929-1945). The study found that younger generations favoured the adoption of CV technologies compared with older generations, who were less interested in CV technologies, and less comfortable with advanced technology in general. Younger generations were also more likely to use smartphones to access music and navigation service in their cars. The priority of vehicle safety systems was high across the response distributions for all age groups. Respondents were also concerned about the privacy and security of their data regardless of age group.

Bird (2016) surveyed consumer uses of connected technologies and applications in their vehicles (questionnaire, $N = 1003$). The survey found that Millenials would be more willing on average to pay for connected services such as Wi-Fi and in-vehicle streaming than the average respondent. The study also highlighted that Millenials use smartphone navigation software more often than any other generation.

Sahebi and Nassiri (2017) studied user acceptance of CVs based on their impact in a Usage-Based Insurance (UBI) policy (questionnaire, $N = 244$). The study found that only 13% of the drivers' surveys would reject a UBI for CVs despite multiple levels of incentives being offered. Safer drivers were predominantly for a UBI policy for CV insurance, whereas younger, more reckless drivers were more reluctant to agree.

Foley and Lardner LLP (2017) conducted a survey of automotive and technology executives to determine their perceptions of CVs (questionnaire, $N = 83$). The respondents thought that the three most significant barriers to CV adoption were: cyber-security and privacy concerns, safety concerns, and uncertainty regarding CV capabilities. Respondents strongly believed that regulatory frameworks for CAV development and deployment should come from the government.

The Federation Internationale de L'Automobile (2017) surveyed respondents across 12 European countries to assess their perceptions of CVs (questionnaire, $N = 12000$). On average, 33% of participants were previously aware of CVs. France, Germany and Italy had the highest levels of respondents with prior knowledge, whereas the UK, Poland, and Denmark had the lowest levels. The respondents reported being most interested in buying a CV if it increased their safety and fuel efficiency, and reduced congestion in the traffic network. The survey is the first to assess user perception of sharing specific data points. The respondents were more comfortable sharing general information regarding their vehicle maintenance status, driving profile (speed, acceleration, braking), dashboard usage, and location. Respondents were less comfortable sharing information about their infotainment usage, use of connected features, information that would personally identify them, and their call/text information. 76% of the respondents felt that data should be shared with time-limited access, and over 95% felt that there should be legislation protecting their data privacy.

The Society of Motor Manufacturers and Traders (2017) conducted a survey to assess how CAVs will impact user mobility with an emphasis on users with disabilities (questionnaire, $N = 3641$ (total), $N = 1012$ (disabled)). The survey observed that 50% of respondents felt that current transport modes restrict their mobility. Disabled people were most excited (56%) by the increased mobility that the introduction of CAVs can offer. Generally, 95% of respondents felt that CAVs would provide more opportunities for them to socialise outside their homes. The survey identified that there is a clear need for CAVs and the current perception of CAVs is positive, but that much more needs to be done to improve awareness of CAVs in the UK and to improve the UK's connected infrastructure.

The Centre for Connected and Autonomous Vehicles (2019) conducted a focus group based survey in the UK to gauge user perceptions of CAV technologies through discussions with local communities (focus group, $N = 158$). The survey found that CAVs should:

1. Be proven to be safe and secure.
2. Be equally accessible to all citizens.
3. Provide societal benefits and promote job growth.
4. Be the opportunity for people to remain in control of their transport choices.
5. Be subject to clear guidance on who is accountable in the event of CAV accidents.
6. Be subject to independent oversight.

F.2 Survey Methodology

The literature on surveys about CV perceptions shows that the general trends in user perceptions of CVs are well understood. CV users would be reluctant to share personal information and are very concerned about the security and privacy of their data. Additionally, younger generations are more comfortable adopting advanced technologies and are the groups most likely to adopt CVs. The study by the Federation Internationale de L'Automobile (2017) was the most detailed investigation into how users feel about sharing different types of CV data, but there are no studies addressing user attitudes towards sharing their CV data for the specific purpose of enhancing traffic signal control. Therefore, the survey developed in this chapter specifically determines user attitudes towards sharing the data which have been identified in the literature review and traffic signal control chapters as being useful for traffic signal control.

Objectives, scales, and item generation are the three essential stages to questionnaire design (Rattray and Jones, 2007). In this section, the objectives for the survey are described, and the scales and item generation discussed in terms of the questionnaire design. Lastly, the tools used to perform the questionnaire and the respondent pool are discussed.

F.2.1 Survey Objectives

The literature review shows that there are several surveys on the general acceptance and concerns of users regarding CVs. It is not understood what data users would be most comfortable sharing with an urban traffic management service. Therefore, the objectives of this survey are to:

1. Assess road users' current travel preferences.
2. Compare road users' willingness to share their data with a social media platform versus an urban traffic management system.
3. Determine how willing road users are to share different data points from a CV.
4. Determine road users' preferred method of sharing their data.
5. Determine road users' willingness to prioritise certain vehicle types.

F.2.2 Questionnaire Design

The text of the questionnaire as presented to participants is given in Appendix G. The questions first assess the demographic information for the respondents. All questions were delivered as multiple-choice options, with the option to give a stated preference answer where relevant to discretise the responses. The demographic information covered: gender, age, education level, and social media usage. Race, income level, and sexuality were omitted as demographic question options as they are not relevant to the objectives of this survey.

The second section of the survey asks questions regarding the respondents' current transport usage to determine their current travel habits. Car ownership and usage, public transport usage, and typical travel modes are all determined. This section also determines what most frustrates users about traffic lights, to see if transport users have a preference over whether a traffic signal controller achieves reduced delays, reduced stops, or increased journey smoothness (no sudden need to stop at traffic lights). Finally, the respondents are asked about their use of satellite navigation services as a proxy to their current use of in-vehicle technology.

In the third section of the survey, the respondents are presented with the scenario in line with the objectives of the traffic controllers presented in this thesis. They are asked to imagine they own a CV, and that the CV sends its data to a traffic signal control system anonymously.

In exchange for their data, the traffic signal controller uses the data to improve traffic signal control. The survey then lists multiple data points that can be obtained from a CV as identifies in this research, and they are asked using a 5 point Likert scale, how willing they would be to share their data. The fourth section asks the respondents how comfortable each respondent would be with sharing their CV data with a traffic management service, and how they would prefer the data sharing to occur. Finally, section five asks if various types of vehicle should be given priority at traffic signals, to if priority measures should be included in a future iteration of the greedy stage optimisation algorithm.

The questions have been formulated to provide sufficient response variables to participants, to avoid introducing misleading language, and avoid introducing biases. The questionnaire was developed to be completed within 5 minutes ($\sim$1 minute per section) to increase response rates, and limit participant fatigue.

F.2.3 Survey Delivery

The survey was conducted using iSurvey (www.isurvey.soton.ac.uk), a web-based survey platform provided by the University of Southampton. A multi-part questionnaire was created to represent the target questions (see Appendix G), and the results gathered from respondents who completed the entire survey.

F.2.4 Respondents

The respondents to the survey were drawn from:

- Staff and students of the University of Southampton.
- ITS UK members.
- Members of the Universities' Transport Study Group (UTSG) mailing list.
- Staff at TRL.
- A call for respondents on Facebook.
- A call for respondents on Twitter.
- A call for respondents on Reddit (www.reddit.com/r/SampleSize/).

The only condition for participants was that they be over 18 years of age. Respondents were not compensated for their participation, so all the information gathered was provided voluntarily.

F.3 Survey Results and Findings

The responses of 396 individuals were recorded, of those, only $N = 113$ were complete responses. The following sections discuss the responses to the survey questions.

F.3.1 Demographic Information

Table F.6 shows the split in demographic information gathered from the respondents. The age group is predominantly 25–39 years old, followed by 40–59 years old. The dominance of these age groups is predominantly due to distributing the members of mailing lists of professional groups, and those groups providing most of the responses. The gender distribution is also unequal, with only 30% of the respondents being women. The gender imbalance is likely due to the known gender disparity in participation in technical and scientific subjects (Cheryan et al., 2017). The distribution of participant education levels also shows that the respondents are better educated than the national average (Department for Education, 2019). As with the age demographics, the education demographic is skewed higher due to the high numbers of respondents from the professional mailing lists.

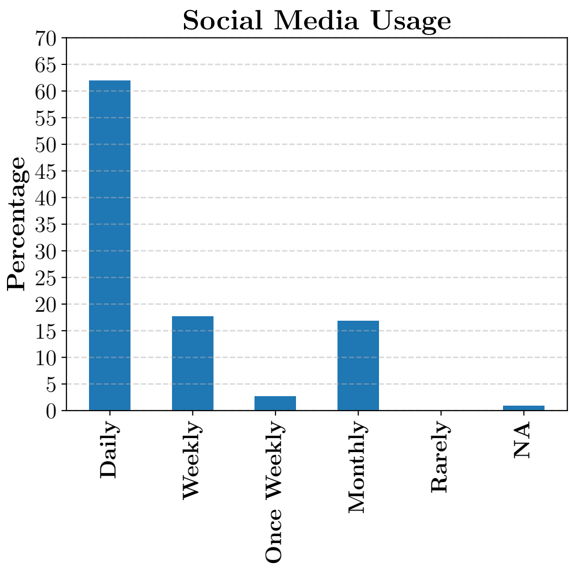
In order to have a reference for how willing respondents are willing to share their data with a traffic management service, the survey also asked how willing they were to share their data with a service many people commonly share their data with, social media. Social media platforms are those that allow the creation and exchange of user-generated content (Kaplan and Haenlein, 2010). Notable examples of social media platforms include: Facebook, Twitter, LinkedIn, Instagram, Reddit, and YouTube. Frequently, the host company uses users' data for analytics and marketing (Stieglitz et al., 2018) or sell users data to third parties to use (Raguseo, 2018). Figure F.15(a) illustrates how frequently survey respondents use social media platforms Figure F.15(b) shows the distribution of how willingly respondents share their data with social media platforms based on a 10-point Likert scale. The mean Likert value is 5.05, the median is 5, and the standard deviation is 2.43. The mean and median values correspond to a slight unwillingness to share data on the Likert range, showing a slightly negative opinion to sharing data with social media platforms. The Pearson mode skewness coefficient of the data is 0.061, which indicates the data is centred about the mean with minor left skew, confirming the tendency of respondents to be slightly unwilling to share data with social media platforms. It should be noted that none of the respondents were completely willing to share their data with social media services. The absence of respondents willing to completely trust in social media services is likely due to organisations misusing user data from social media services for corruption and misinformation (Allcott et al., 2019; Shah, 2018).

F.3.2 Current Transport Preferences

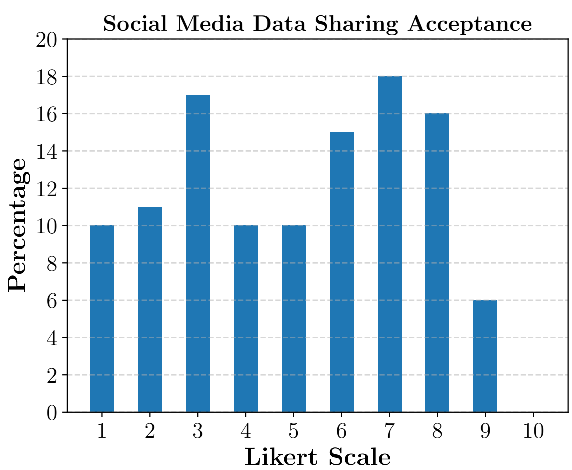
Table F.7 shows the splits between respondents current transportation access and preferences. The results show that the majority of respondents, 84.68%, held a full driving licence, but only 69.64% owned or had access to a car. When asked about how frequently they commuted via public transport or on foot/bike, over half of respondents used non-car options at least once per week (53.1%).

Table F.6: Demographic information for the survey respondents.

Demographic	Response	Percent
Age Group	18–24	6.19%
	25–39	61.95%
	40–59	21.24%
	60+	10.62%
	Prefer not to say	0.0%
Gender	Male	68.14%
	Female	31.86%
	Prefer not to say	0.00%
	Self-described	0.0%
Education Level	High school degree or less	2.65%
	Diploma/higher qualification	5.31%
	Bachelor's degree	23.90%
	Master's degree	41.60%
	Doctorate	25.66%
	Other/Prefer not to say	0.88%



(a) Frequency of social media usage



(b) Social media data sharing acceptance

Figure F.15: Plots of respondent frequency of social media usage (a), and distribution of 10 point Likert acceptance of data sharing in social media (b). For the Likert scale in (b) a 10-point scale was used, where 1=unwilling and 10=willing to share data with social media.

Figure F.16 shows how frequently respondents use a set of vehicular transport modes. It can be seen that cars are over half respondents most frequently used mode of transport (∼55%), with buses coming in second place (∼26%). Few respondents drive goods vehicles, indicating the survey does not necessarily represent the opinions of professional drivers.

Table F.8 compares which impact of signalised intersection control most frustrates vehicle users. Respondents were almost equally frustrated by frequent stops (39.8%) and large delays (37.2%) at signalised intersections. Respondents were less interested in the traffic signal suddenly changing red, putting them in the panic zone (13.3%). A small number of

Table F.7: Transport preferences for the survey respondents.

Data	Response	Percent
Has full driving license	Yes	84.68%
	No	15.32%
	N/A	0.0%
Has car access	Yes	69.64%
	No	30.36%
	N/A	0.0%
Public transport/ ride-share usage	Multiple times per week	38.95%
	About once per week	14.16%
	Several times per month	15.04%
	Once per month or less	30.97%
	N/A	0.88%
Pedestrian/cycle frequency	Multiple times per week	49.57%
	About once per week	7.96%
	Several times per month	6.19%
	Once per month or less	34.51%
	N/A	1.77%

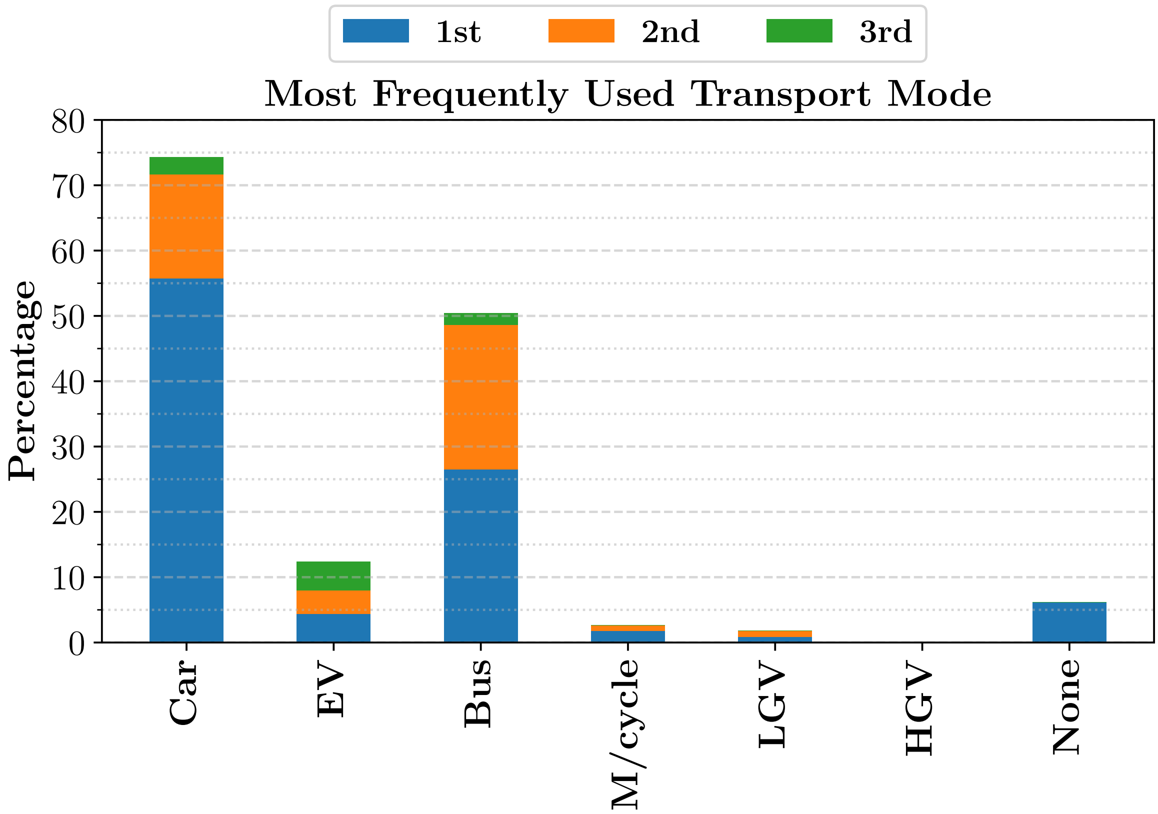


Figure F.16: Bar chart of respondents' top 3 most frequently used vehicle modes.

respondents (9.7%) had a frustration other than those listed or were not frustrated by traffic lights. The results confirm that the objective of reducing stops and delays, as the traffic signal control strategies in Chapters 3 and 4 have done, is both beneficial and serves to alleviate the concerns of the majority of surveyed road users.

Table F.9 shows the proportions of respondents that use satellite navigation, or a navigation app, and the proportion of those users whose main reason for using a navigation application are live traffic updates. Using maps to track location in real-time and receive traffic status information aggregated from other users is a connected service, so indicates the proportion of respondents who are already conduction their journey in a connected manner. The results show that 66.38% of respondents use navigation apps on a daily or weekly basis. Furthermore, over 75% of respondents reported that the ability to get live traffic information is their main use case. If the set of respondents who meet the following criteria are considered:

- Use navigation apps daily.
- Use navigation apps for live traffic information.
- Have a driving license and access to a car.
- Use cars or electric vehicles as their preferred mode of travel.

Then 19.47% of respondents fit these criteria, indicating that almost 20% of the respondents already drive in a connected way.

Table F.8: Most frustrating feature of traffic light control.

Frustration	Percent
Frequent stopping	39.83%
Long waiting times	37.17%
The traffic signal turning red when near the intersection	13.27%
None of the above	9.73%

Table F.9: Navigation app usage statistics.

Data	Response	Percent
Navigation app usage frequency	Daily	41.60%
	Weekly	24.78%
	Monthly	16.81%
	Rarely	16.81%
	N/A	0.0%
Live traffic updates are main use case	Yes	76.99%
	No	7.08%
	N/A	15.93%

F.3.3 Willingness to Share CV Data

In Table F.10, the results of users willingness to share specific data with an urban traffic management system are shown. A 5 point Likert scale was used to determine how willing or unwilling respondents were to share their data. The respondents were asked to imagine they own a CV, and that the CV sends its data to a traffic signal control system anonymously. In exchange for their data, the traffic signal controller uses the data to improve traffic signal control. The data points the respondents were asked if they would be willing to share were:

Vehicle position: The location of the vehicle in the road network.

Vehicle speed: The speed at which the vehicle is travelling.

Turn signal status: The status of the vehicles' turn signals, i.e. if the vehicle is indicating to turn left or right, or not indicating.

Number of passengers: How many passengers are in the vehicle.

Number of stops: How many times the vehicle has stopped this journey.

Time spent stopped: How long the vehicle has spent stopped this journey (waiting time).

Journey duration: How long the vehicle has been travelling for this journey.

Journey distance: How far the vehicle has travelled this journey.

Vehicle emissions class: How polluting the vehicle is.

Vehicle type: What type the vehicle is, e.g. car, bus, goods vehicle, motorcycle.

Speed factor: How fast the vehicle is going relative to the posted speed limit on that road, and how many times the speed limit has been exceeded.

The statistics in Table F.10 show that respondents were mostly willing to share each of the data points, as most had medians < 4, and a negative Pearson mode skewness coefficient, indicating a skew left which corresponds to higher willingness to share data. The exceptions to this trend are the data for passengers and speed factor. The willingness of respondents to share data about passenger numbers was more central, with a small positive skew, indicating respondents willingness to share this data point was more neutral with a small negative perception. It is possible that respondents felt passenger data is too personal to share with a traffic management service. The median value of the speed factor data suggested that respondents were somewhat unwilling to share this data point, and the strong positive skew indicates a tendency for respondents to be more unwilling to share this data point. The reason speed factor is treated negatively is likely to the fact that the information could be used to incriminate drivers who exceed the speed limit if the data could be linked to the driver. Figure F.17 supports Table F.10 with box plots of the Likert scale data, and the 90% prediction interval of the data. As with Table F.10, Figure F.17 illustrates that respondents were less willing to share passenger and speed factor information than the other data points.

Table F.10: Itemised Likert statistics on participant willingness to share their CV data with a traffic management service. A 5 point Likert scale was used, where 1=unwilling and 5=willing. The skewness is given by the Pearson mode skewness coefficient. (SD: standard deviation)

Data Point	Mean	Median	SD	Skewness
Vehicle position	3.61	4	1.49	-0.785
Vehicle speed	3.61	4	1.35	-0.867
Turn signal status	3.81	4	1.31	-0.435
Number of passengers	3.14	3	1.55	0.217
Number of stops	3.91	4	1.31	-0.206
Time spent stopped	3.93	5	1.35	-2.378
Journey duration	3.94	4	1.28	-0.141
Journey distance	3.89	5	1.38	-2.413
Vehicle emissions class	3.94	5	1.38	-2.304
Vehicle type	4.09	5	1.30	-2.1
Speed factor	2.60	2	1.47	1.224

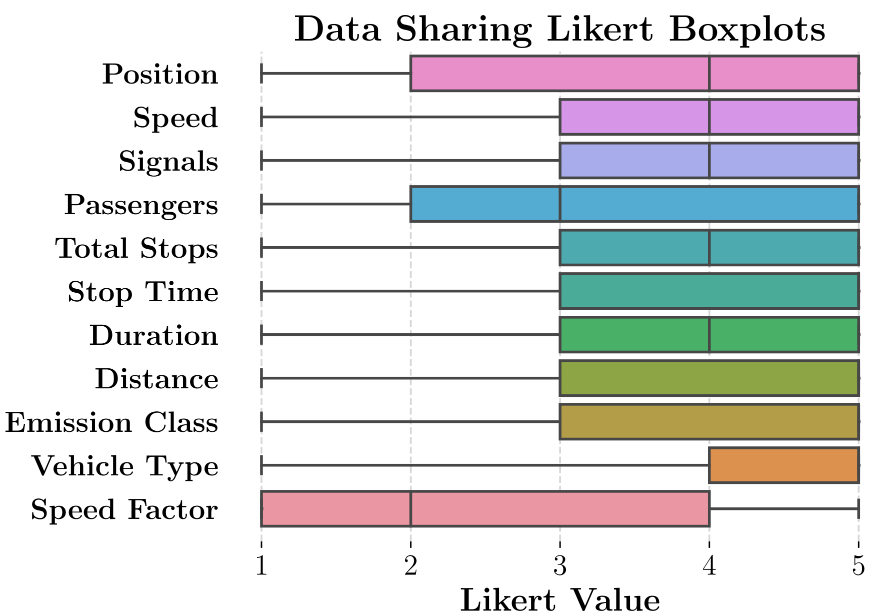


Figure F.17: Plots of the distribution of Likert responses on participant willingness to share specific CV data points. In the box plots, the central line corresponds to the median score, the box encompasses the 90% prediction interval, and the spines cover all other data points.

F.3.4 Data Delivery Preferences

In Part 4 of the survey, respondents were asked what their preferred method of sharing data is. Table F.11 shows the split in desired methods of sharing CV data with a traffic management service. The data shows that most users would like to share their CV data through a smartphone app, possibly integrating with a service they already use, or through a system that is built into their vehicles. A smaller proportion of respondents would add dedicated third-party hardware to their vehicles which would share their CV data. A small proportion would not share their data at all (11.5%). Three respondents elected to self-describe their preferred delivery method. Two of the respondents wanted the service to be delivered through roadside infrastructure, which would negate the need for a connected system. The third self-described solution suggested that hardware be built into a vehicle but with privacy settings being controlled by a smartphone app.

Table F.11: Respondents' preferred method of sharing data with a traffic management service. Manually entered responses are marked with a (*).

Data sharing option	Percent
Smartphone application	34.52%
Built-in vehicle hardware	31.86%
Third party/aftermarket hardware	19.47%
*Roadside sensors	0.88%
*Computer vision system	0.88%
*Built-in system with smartphone controlled privacy settings	0.88%
Would not share data	11.5%

Figure F.18 asks respondents to indicate how willing they are to share their data with a traffic management service on a 10 point Likert scale, similar to how they were asked to share their willingness to share their data with a social media platform in Figure F.15. From Figure F.18, it can be seen that respondents tend to be more willing to share their data with traffic management services than with social media services. Table F.12 compares the statistics on the Likert data for the two distributions. The results show that median respondent willingness to share data with a traffic management service is two points higher than for social media. Additionally, the Pearson mode skewness coefficient is negative for the traffic management Likert data, and positive for the social media Likert data. These results indicate that respondents were more willing to share their data with a traffic management service than with social media platforms.

The two Likert distributions were compared with a non-parametric Mann-Whitney U test, to determine if the social media acceptance Likert data and the traffic management Likert data were similarly distributed. The result of the Mann-Whitney U test rejected the null hypothesis (that the data are similarly distributed) significantly, with $p < 0.001$. The Pearson correlation coefficient between the two datasets is 0.559, indicating that respondents who were more willing to share their data with social media, were also more willing to share their data with a traffic management service. The results are consistent with those of Cruickshanks et al. (2013), who found that people are more willing to share their data with a transport service if there is a perceived personal or societal benefit.

Table F.12: Likert statistics on participant willingness to share their data with social media platforms versus a traffic management system. A 10 point Likert scale was used, where 1=unwilling and 10=willing. (SD: standard deviation)

Application	Mean	Median	SD	Skewness
Social Media	5.05	5	2.43	0.062
Traffic Management	6.66	7	2.74	-0.372

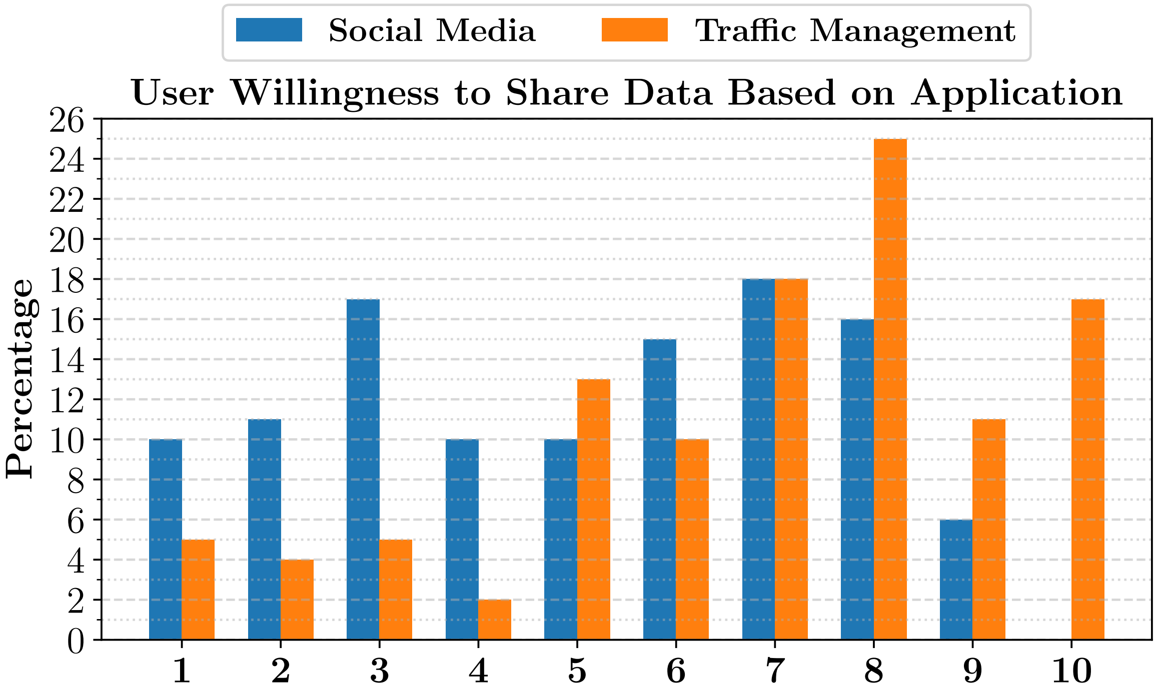


Figure F.18: Comparison of the Likert data for users willingness to share their data with social media platforms versus traffic management services. A 10 point Likert scale was used, where 1=unwilling and 10=willing.

F.3.5 Transit Priority Preferences

Figure F.19 shows respondents opinions on whether certain vehicle types should be given priority at traffic signals. The results show that respondents were in favour of giving buses and emergency service vehicles priority at traffic signals. In contrast, there was a clear lack of support for giving priority to electric vehicles, shared vehicles, and trade/professional vehicles. The results show that there is support for vehicles that serve public interests (buses and emergency service vehicles), and little support for rewarding shared transport, industrial vehicles, or road users with efficient vehicles that would benefit the environment.

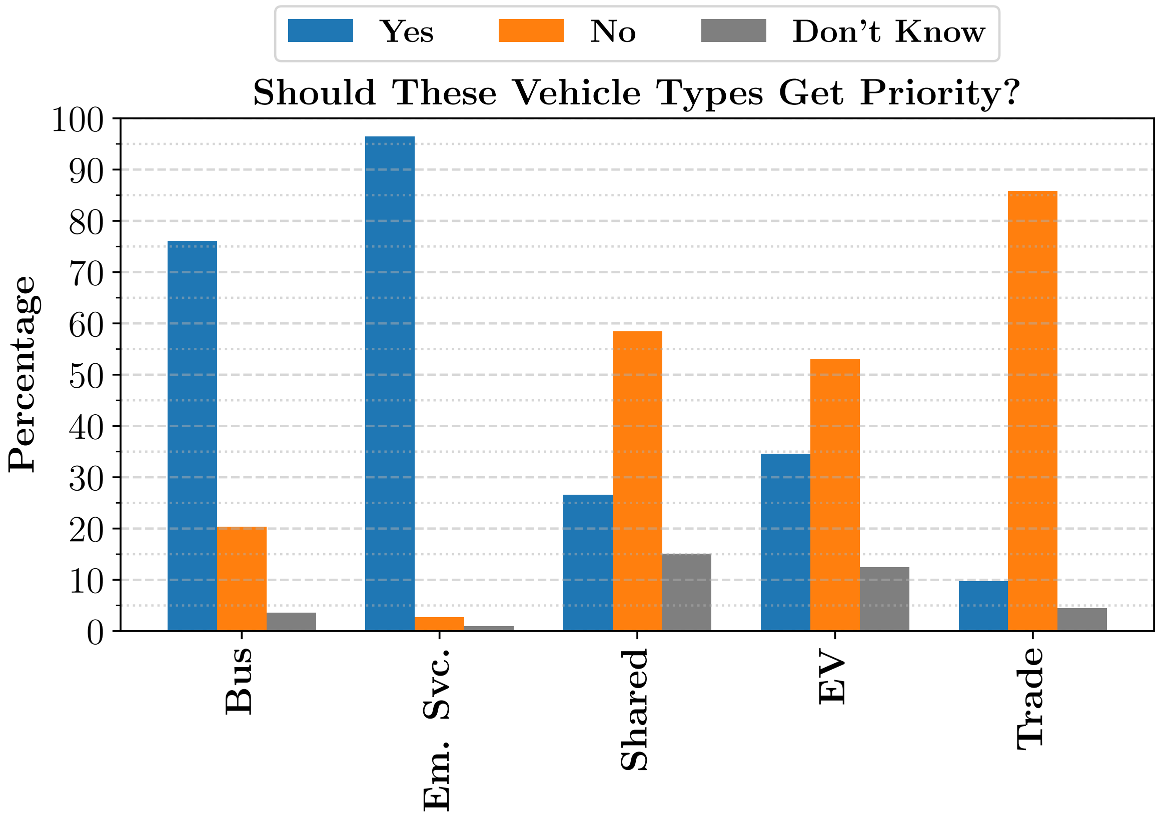


Figure F.19: Bar chart of respondents' opinions on offering transit priority to several vehicle types. (Em. Svc.: Emergency services, EV: Electric vehicles.))

F.4 Conclusion

In this chapter, a survey which determined participants willing to share data with a traffic management service if they owned a CV. The demographic data showed that the respondents were not a completely random sample. The sample is less representative of the general public but is a good representation of the opinions of transportation researchers and professionals. The survey respondents were predominantly car users, but over half regularly travelled using public transport or by foot/bike. The data showed that many of the respondents use navigation services to assist their journeys, and an estimated 19.47% of those users are travelling in a connected way.

The results for respondents willing to share specific data were positive. Respondents were mostly willing to share all of the data, except for passenger and speed factor data. The data needed for the CDOTS algorithm in Chapter 4 are position, speed, heading, and the number of stops, all of which were data points respondents were comfortable sharing. It is also relevant to the CDOTS algorithm that respondents were most frustrated by frequent stops and long delays, which are the quantities minimised by the algorithm. Overall, respondents were more willing to share their data with a traffic management service than with social media platforms, even though over 75% of respondents use social media regularly. In terms of how the respondents wanted to share their data, hardware built into the vehicles, or an app-based service were the most popular options.

The final part of the survey addressed if participants thought specific vehicle types should get priority at signals. The respondents strongly believed that buses and emergency vehicles should receive priority at signalised intersections. This information is useful, as it suggests that further research into the CDOTS algorithm should investigate adding priority measures.

This survey was developed to be short, and to focus on answering the main question 'How willing are road users to share different data points from a CV?' The survey was developed so that the average respondent would only require 5 minutes to complete it. In a future study on users' preferences for traffic signal control in a connected environment, a larger scale survey would be conducted involving a survey distributor to gather a more representative sample of the public in the UK and internationally. The scope of the survey would also be extended to gather broader data from respondents and assess their willingness to engage with a connected traffic signal control scheme. Other questions that would be useful to ask in an extended survey would be:

- If you own a vehicle, how old is the vehicle?
- Are you a professional driver? (e.g. taxi, goods, freight)
- Had you ever heard of connected vehicles before participating in this survey?
- How would you classify the location where you live? (City, Town, Village, Rural)
- How would you classify the location where you work? (City, Town, Village, Rural)
- If you drive, what services smartphone do use while you drive? (maps, audio, social media, hands-free phone calls)
- If you use your phone while driving, how often is it connected to mobile data (3G/4G/LTE/5G)?
- Better ranking of data sharing delivery choices (order of preference rather than single choice)
- Adding CVs and AVs as options to the question 'Should this vehicle type get priority?'

F.5 Summary of Chapter Findings

1. 19.47% of respondents already travel in a connected way through navigation services with live-traffic updates.

2. Respondents were more willing to share their data with a traffic management service than with social media platforms (median Likert score of 7 for traffic management services versus 5 for social media services, on a 10 point Likert scale where 1=unwilling and 10=willing).

3. Respondents were mostly willing to share their CV data with a traffic management service (median Likert score of 7 on a 10 point Likert scale where 1=unwilling and 10=willing). The two data points that were the exception to this trend were ‘number of passengers’ and ’speed factor’.

4. Respondents believe that buses ($> 75\%$) and emergency service vehicles ($> 95\%$) should receive transit priority at signalised intersections.

5. As the respondents were willing to share the data required by the MATS and CDOTS algorithms, the survey indicates that the algorithms proposed in this research would be acceptable to the public.

G User Attitudes to Sharing Data with Urban Traffic Management Services: Questionnaire

Welcome Statement

You are being invited to participate in a research study titled “Data sharing preferences for connected vehicle users”. This study is being done by Craig Rafter from the Transportation Research Group at the University of Southampton. Ethics Number: 50938

Purpose of this survey:

Connected vehicles are those that share their data wirelessly with other road users and roadside infrastructure (e.g. traffic lights) with the aim of improving the efficiency of the transport network. In this survey, you will answer questions about what data you would be willing to share if you were a driver or passenger in a connected vehicle. The data would be used by a traffic management service to improve traffic signals. Efficiently controlled traffic signals have the benefit of reducing travel delays, reducing the number of stops you make, and potentially improving safety and air quality.

Survey details:

This survey will take approximately 5 minutes to complete. Your participation in this survey is entirely voluntary and you may withdraw your submission at any time before the end of the survey by closing the survey window. You will not be identified in any reports of the research. We believe there are no known risks associated with this research study; however, as with any online activity the risk of a breach is always possible. To the best of our ability your participation in this study will remain confidential, and only anonymised data will be published. If you have any questions about the survey, please contact the investigator at c.b.rafter@soton.ac.uk. For full participant information please see (Participant Information Sheet).

Section 1: Background Information

Q1.1: What age bracket do you fall into? (pick one):

- ○ 18–24
- ○ 25–39
- ○ 40–59
- ○ 60+
- ○ Prefer not to say

Q1.2: What gender do you identify as? (pick one):

- ○ Male
- ○ Female
- ○ Prefer not to say
- Prefer to self-describe: ______

Q1.3: What is the highest level of education you have achieved to date? (pick one):

- ○ High school degree or less
- ○ Diploma or other higher qualification
- ○ Bachelor's degree
- ○ Master's degree
- ○ Doctorate
- ○ Other/Prefer not to say

Q1.4: How often do you use social media (e.g. Facebook, Instagram, Twitter)? (pick one):

- ○ Several times per day
- ○ Several times per week
- ○ About once a week
- ○ Several times per month
- ○ Once a month or less
- ○ Prefer not to say

Q1.5: Where 1 is not comfortable and 10 is very comfortable. How comfortable are you sharing your data with companies like Amazon/Google/Facebook?

Not Comfortable									Very Comfortable	Prefer not to answer
1	2	3	4	5	6	7	8	9	10	
○	○	○	○	○	○	○	○	○	○	○

Section 2: Transport Preferences

In this section, you will be asked questions about your current transport preferences.

Q2.1: Do you have a full drivers license?

- ○ Yes
- ○ No
- ○ Prefer not to say

Q2.2: Do you own or have access to a car?

- ○ Yes
- ○ No
- ○ Prefer not to say

Q2.3: How often do you use public-transport or ride-sharing services? (pick one):

- ○ Several times per week
- ○ About once per week
- ○ Several times per month
- ○ Once per month or less
- ○ Prefer not to say

Q2.4: How often do you commute by foot or bike? (pick one):

- ○ Several times per week
- ○ About once per week
- ○ Several times per month
- ○ Once per month or less
- ○ Prefer not to say

Q2.5: Typically, which vehicle types do you drive or are you a passenger in at least once per week? (rank in order of most frequently used, you may leave unused options blank)

- [#] Passenger car (Petrol/Diesel)
- [#] Passenger car (Electric/Hybrid)
- [#] Bus or coach
- [#] Motorbike/moped
- [#] Light-goods-vehicle (LGV e.g. van)
- [#] Heavy-goods-vehicle (HGV e.g. multiple axel truck or lorry)
- [#] None of the above

Q2.6: Which of these experiences do you find the most frustrating about traffic signals? (pick one):

- ○ Long waiting times
- ○ Having to start and stop between consecutive intersections
- ○ The traffic lights changing to red when you have nearly reached the intersection
- ○ None of these

Q2.7a: How often do you use services such as Google Maps, Waze, or a Sat Nav to plan your journeys? (pick one):

- ○ Several times per week
- ○ About once per week
- ○ Several times per month
- ○ Once per month or less
- ○ Prefer not to say

If the response to Q2.7a is not "Prefer not to say" then show this question:
Q2.7b: If you use services such as Google Maps, Waze, or a Sat Nav, do you find live traffic updates helpful?

- ○ Yes
- ○ No
- ○ No preference

Section 3: Data Sharing Preferences (1/3)

Q3.1: You will now be asked questions about what data you would be willing to share with a traffic management system if you owned a connected vehicle. For each data source listed, please indicate on the scale below if you would be willing to share the specified information with a traffic management service in exchange for improved traffic signal control. Here we consider a system where your data is shared but your identity is not linked to it. The scale ranges from 1 to 5, where 1 indicates that you would be unwilling to share the data, and 5 indicates you would be very willing to share the data

	Unwilling 1	2	3	4	Willing 5
The GPS position of your vehicle	○	○	○	○	○
The speed of your vehicle	○	○	○	○	○
The status of your vehicles' turn signals	○	○	○	○	○
The number of passengers in your vehicle	○	○	○	○	○
The number of times your vehicle has had to stop this journey	○	○	○	○	○
The amount of time your vehicle has spent stopped this journey	○	○	○	○	○
The current duration of your journey (travel time)	○	○	○	○	○
The current length of your journey (distance)	○	○	○	○	○
The emissions class of your vehicle	○	○	○	○	○
The type of your vehicle (car, van, motorbike, bus, etc.)	○	○	○	○	○
The number of times you've exceeded the speed limit by more than 10% on your current journey	○	○	○	○	○

Section 4: Data Sharing Preferences (2/3)

Q4.1: Where 1 is not comfortable, and 10 is very comfortable. How comfortable would you be sharing your data with a traffic management service?

Not Comfortable							Very Comfortable			Prefer not to answer
1	2	3	4	5	6	7	8	9	10	
O	O	O	O	O	O	O	O	O	O	O

Q4.2: Which of these would be your preferred method for sharing your vehicle data with a traffic management service? (pick one):

- O A smartphone app
- O A system built into your vehicle
- O A 3rd party device
  (e.g. one that plugs into a USB port or cigarette lighter port in your vehicle)
- O I would not share my data
- O Other: [ ]

Section 5: Data Sharing Preferences (3/3)

Q5.1: You will now be asked if you think that certain road users should be given priority over passenger cars at traffic lights. Please answer Yes/No if you think these road users should be given priority over passenger cars at traffic lights.

	Yes	No	Don't know
Buses/public transport	O	O	O
Emergency service vehicles	O	O	O
Car-pool/ride-share	O	O	O
Low-emission/electric vehicles	O	O	O
Professional/trade vehicles	O	O	O

*** END OF QUESTIONNAIRE ***

H Research Codes

The simulation code for this research may be found at:

https://github.com/cbrafter/SUMO_FRAMEWORK.

Please note, this code repository may be embargoed for up to 6 months after the submission of this thesis due to an intellectual property agreement with the research funding bodies.

Bibliography

3GPP (1997), Universal Mobile Telecommunications System; Requirements for the UMTS Terrestrial Radio Access system (UTRA) (UMTS 21.01 version 3.0.1), Technical report, 3GPP.

3GPP (2016), LTE; Evolved Universal Terrestrial Radio Access (E-UTRA) and Evolved Universal Terrestrial Radio Access Network (E-UTRAN); Overall Description; Stage 2 (3GPP TS 36.300 version 13.4.0 Release 13), Technical report, 3GPP.

3GPP (2019*a*), TR 21.915 V1.1.0: Technical Specification Group Services and System Aspects, Technical report, 3GPP.

3GPP (2019*b*), TS 22.261 V16.8.0: Service requirements for the 5G system, Technical report, 3GPP.

5G-PPP (2015), 5G Vision, Technical report, 5G-PPP.
URL: *https://5g-ppp.eu/wp-content/uploads/2015/02/5G-Vision-Brochure-v1.pdf*

Agbolosu-Amison, S. J., Sadek, A. W. and ElDessouki, W. (2004), 'Inclement Weather and Traffic Flow at Signalized Intersections: Case Study from Northern New England', *Transp. Res. Rec. J. Transp. Res. Board* **1867**(1).
URL: *http://journals.sagepub.com/doi/10.3141/1867-19*

Agiwal, M., Roy, A. and Saxena, N. (2016), 'Next Generation 5G Wireless Networks: A Comprehensive Survey', *IEEE Commun. Surv. Tutorials* **18**(3).
URL: *http://ieeexplore.ieee.org/document/7414384/*

Ahmane, M., Abbas-Turki, A., Perronnet, F., Wu, J., Moudni, A. E., Buisson, J. and Zeo, R. (2013), 'Modeling and controlling an isolated urban intersection based on cooperative vehicles', *Transp. Res. Part C Emerg. Technol.* **28**, 44–62.
URL: *https://linkinghub.elsevier.com/retrieve/pii/S0968090X12001374*

Alam, A. A., Gattami, A. and Johansson, K. H. (2010), An experimental study on the fuel reduction potential of heavy duty vehicle platooning, *in* '13th International IEEE Conference on Intelligent Transportation Systems', IEEE, pp. 306–311.
URL: *http://ieeexplore.ieee.org/document/5625054/*

Alexander Dennis (2019*a*), Enviro 200 (E200) Specification, Technical report, Alexander Dennis.
URL: *https://www.alexander-dennis.com/media/83813/enviro200-spec.pdf*

Alexander Dennis (2019*b*), Enviro 400 (E400) Specification, Technical report, Alexander Dennis.
URL: *https://www.alexander-dennis.com/media/83811/e400-e6-spec.pdf*

Allcott, H., Gentzkow, M. and Yu, C. (2019), 'Trends in the diffusion of misinformation on social media', *Res. Polit.* **6**(2).
URL: *http://journals.sagepub.com/doi/10.1177/2053168019848554*

Allsop, R. E. (1971), 'SIGSET: a computer program for calculating traffic signal settings', *Traffic Eng. Control* .

Andrews, J. G., Ghosh, A. and Muhamed, R. (2007), *Fundamentals of WiMAX: understanding broadband wireless networking*, Prentice Hall.
URL: *http://citeseerx.ist.psu.edu/viewdoc/download?doi=10.1.1.459.4347&rep=rep1&type=pdf*

Araniti, G., Campolo, C., Condoluci, M., Iera, A. and Molinaro, A. (2013), 'LTE for vehicular networking: a survey', *IEEE Commun. Mag.* **51**(5), 148–157.
URL: *http://ieeexplore.ieee.org/document/6515060/*

Archer, J. and Vogel, K. (2000), 'The traffic safety problem in urban areas', *Res. Rep.* .

Arsava, T., Xie, Y. and Gartner, N. H. (2016), 'Arterial Progression Optimization Using OD-BAND: Case Study and Extensions', *Transportation Research Record: Journal of the Transportation Research Board* **2558**(1), 1–10.
URL: *http://journals.sagepub.com/doi/10.3141/2558-01*

Au, T. C., Shahidi, N. and Stone, P. (2011), 'Enforcing Liveness in Autonomous Traffic Management.', *Proc. 25th AAAI Conf. Artif. Intell.* pp. 1317–1322.

Au, T. C., Zhang, S. and Stone, P. (2015), 'Autonomous Intersection Management for Semi-Autonomous Vehicles', *Handb. Transp.* .
URL: *http://www.cs.utexas.edu/users/pstone/Papers/bib2html-links/Routledge15-Au.pdf*

Aziz, H. M. A., Zhu, F. and Ukkusuri, S. V. (2018), 'Learning-based traffic signal control algorithms with neighborhood information sharing: An application for sustainable mobility', *J. Intell. Transp. Syst.* **22**(1), 40–52.
URL: *https://www.tandfonline.com/doi/full/10.1080/15472450.2017.1387546*

Bae, H. S., Ryu, J. and Gerdes, J. C. (2001), Road grade and vehicle parameter estimation for longitudinal control using GPS, *in* 'Proc. IEEE Conf. Intell. Transp. Syst.'.

Bani Younes, M. and Boukerche, A. (2016), 'Intelligent Traffic Light Controlling Algorithms Using Vehicular Networks', *IEEE Trans. Veh. Technol.* **65**(8), 5887–5899.
URL: *http://ieeexplore.ieee.org/document/7277098/*

Barceló, J. and Casas, J. (2005), Dynamic network simulation with AIMSUN, *in* 'Simul. approaches Transp. Anal.', Springer, pp. 57–98.

Barcelo, J., Montero, L., Marqués, L. and Carmona, C. (2010), 'Travel Time Forecasting and Dynamic Origin-Destination Estimation for Freeways Based on Bluetooth Traffic Monitoring', *Transp. Res. Rec. J. Transp. Res. Board* **2175**(1), 19–27.
URL: *http://journals.sagepub.com/doi/10.3141/2175-03*

Barkenbus, J. N. (2010), 'Eco-driving: An overlooked climate change initiative', *Energy Policy* **38**(2), 762–769.
URL: *https://linkinghub.elsevier.com/retrieve/pii/S0301421509007484*

Bastani, F., Huang, Y., Xie, X. and Powell, J. W. (2011), A Greener Transportation Mode: Flexible Routes Discovery from GPS Trajectory Data, *in* 'Proc. 19th ACM SIGSPATIAL Int. Conf. Adv. Geogr. Inf. Syst.', GIS '11, ACM, New York, NY, USA, pp. 405–408.
URL: *http://doi.acm.org/10.1145/2093973.2094034*

Bazzi, A., Masini, B. M., Zanella, A. and Thibault, I. (2017), 'On the Performance of IEEE 802.11p and LTE-V2V for the Cooperative Awareness of Connected Vehicles', *IEEE Trans. Veh. Technol.* **66**(11), 10419–10432.
URL: *http://ieeexplore.ieee.org/document/8031051/*

Beak, B., Head, K. L. and Feng, Y. (2017), 'Adaptive Coordination Based on Connected Vehicle Technology', *Transp. Res. Rec.* **2619**(1), 1–12.
URL: *https://doi.org/10.3141/2619-01*

Beak, B., Zamanipour, M., Head, K. L. and Leonard, B. (2018), 'Peer-to-Peer Priority Signal Control Strategy in a Connected Vehicle Environment', *Transp. Res. Rec. J. Transp. Res. Board* **2672**(18), 15–26.
URL: *http://journals.sagepub.com/doi/10.1177/0361198118773567*

Bell, M. C. and Bretherton, R. D. (1986), Ageing of fixed-time traffic signal plans, *in* 'Int. Conf. road traffic Control'.

Benekohal, R. F., Elzohairy, Y. M. and Saak, J. E. (2002), 'Comparison of Delays from Highway Capacity Software, Synchro, PASSER II and IV, and CORSIM for Urban Arterials', *Transportation Research Record: Journal of the Transportation Research Board* **1802**(1), 133–144.
URL: *http://journals.sagepub.com/doi/10.3141/1802-16*

Bengio, Y., Lamblin, P., Popovici, D. and Larochelle, H. (2006), Greedy Layer-wise Training of Deep Networks, *in* 'Proc. 19th Int. Conf. Neural Inf. Process. Syst.', NIPS'06, MIT Press, Cambridge, MA, USA, pp. 153–160.
URL: *http://dl.acm.org/citation.cfm?id=2976456.2976476*

Bergenhem, C., Shladover, S., Coelingh, E., Englund, C. and Tsugawa, S. (2012), Overview of platooning systems, *in* 'Proceedings of the 19th ITS World Congress, Oct 22-26, Vienna, Austria (2012)'.

Bertozzi, M., Broggi, A. and Fascioli, A. (2000), 'Vision-based intelligent vehicles: State of the art and perspectives', *Rob. Auton. Syst.* **32**(1), 1–16.

Bhaskar, A., Qu, M. and Chung, E. (2015), 'Bluetooth Vehicle Trajectory by Fusing Bluetooth and Loops: Motorway Travel Time Statistics', *IEEE Trans. Intell. Transp. Syst.* **16**(1), 113–122.
URL: *http://ieeexplore.ieee.org/lpdocs/epic03/wrapper.htm?arnumber=6841057*

Bielefeldt, C. (1994), MOTION - a new on-line traffic signal network control system motion, *in* 'Seventh Int. Conf. 'Road Traffic Monit. Control.', Vol. 1994, IEE, pp. 55–59.
URL: *https://digital-library.theiet.org/content/conferences/10.1049/cp_19940424*

Binning, J. C., Crabtree, M. and Burtenshaw, G. (2013), TRANSYT 15 User Guide, Technical report, TRL Software.

Bird, C. (2016), Consumer Survey - Connected Car US, Technical report, IHS Automotive.
URL: *https://cdn.ihs.com/www/pdf/TEST.pdf*

Birmingham City Council (2016), 'Birmingham and West Midlands real-time traffic data'.
URL: *https://data.birmingham.gov.uk/dataset/wm-utmc*

Bishop, R. (2005*a*), 'Intelligent vehicle R&D: A review and contrast of programs worldwide and emerging trends', *Ann. Des T{é}l{é}communications* **60**(3), 228–263.

Bishop, R. (2005*b*), *Intelligent vehicle technology and trends*, Artech House, Inc.

Bissessar, R., Cheung, L. and Le, H. (2015), TRAFFIC SIGNAL OPERATIONS POLICIES & STRATEGIES, Technical report, Traffic Management Centre Toronto.

Bluetooth Special Interest Group (2016), 'Bluetooth Core Specification, v5.0'.

Bonneson, J. A. and McCoy, P. T. (2005), *Manual of Traffic Detector Design*, Texas Transportation Institute, Texas A & M University System.
URL: *https://books.google.co.uk/books?id=Nz0QngEACAAJ*

Bonnet, C. and Fritz, H. (2000), Fuel consumption reduction in a platoon: Experimental results with two electronically coupled trucks at close spacing, *in* 'SAE Technical Papers'.
URL: *https://www.sae.org/content/2000-01-3056/*

Booz Allen Hamilton (2018), NCHRP 20-102(19): Update AASHTO's Connected Vehicle/Automated Vehicle Research Roadmap, Technical report, National Cooperative Highway Research Program (NCHRP).
URL: *http://onlinepubs.trb.org/onlinepubs/nchrp/docs/NCHRP20-102(19)_ResearchCatalog2018.pdf*

Box, S., Snell, I., Waterson, B. and Hamilton, A. (2012), A methodology for traffic state estimation and signal control utilizing high wireless device penetration., *in* 'EU-00524, 19th ITS World Congr. Vienna, Austria.'.

Box, S., Waterson, B. and Hounsell, N. (2010), A machine learning approach to signalised junction control., *in* '11th Annu. Paramics User Gr. Meet. Conf. Birmingham, GB, 15 Sep 2010.'.

Box, S. and Waterson, B. J. (2010), Signal control using vehicle localization probe data, *in* '42nd UTSG Conf.'.

Bradski, G. (2000), 'The OpenCV Library', *Dr. Dobb's J. Softw. Tools* .

Bretherton, D. (2003), PR/T/144/2003: Stage Skipping: Guidelines and Recommendations, Technical report, Transport Research Laboratory.

Bretherton, R. (1990), SCOOT URBAN TRAFFIC CONTROL SYSTEM - PHILOSOPHY AND EVALUATION, *in* 'Control. Comput. Commun. Transp.', Elsevier, pp. 237–239.
URL: *https://linkinghub.elsevier.com/retrieve/pii/B9780080370255500402*

Broadband Buyer (2019), 'Outdoor Antennas'.
URL: *https://www.broadbandbuyer.com/store/wifi-antennas/wifi-outdoor-antennas/*

Burghout, W., Koutsopoulos, H. and Andreasson, I. (2006), A discrete-event mesoscopic traffic simulation model for hybrid traffic simulation, *in* '2006 IEEE Intelligent Transportation Systems Conference', IEEE, pp. 1102–1107.
URL: *http://ieeexplore.ieee.org/document/1707369/*

Busch, F. and Kruse, G. (2001), MOTION for SITRAFFIC - a modern approach to urban traffic control, *in* 'ITSC 2001. 2001 IEEE Intell. Transp. Syst. Proc. (Cat. No.01TH8585)', IEEE, pp. 61–64.
URL: *http://ieeexplore.ieee.org/document/948630/*

Business Wire (2018), 'South Korea Connected Vehicle Market 2018-2023: Key Growth Factors and Threats'.
URL: *https://www.businesswire.com/news/home/20180815005583/en/South-Korea-Connected-Vehicle-Market-2018-2023-Key*

Cabezas, X., García, S. and Salas, S. D. (2019), 'A hybrid heuristic approach for traffic light synchronization based on the MAXBAND', *Soft Computing Letters* **1**, 100001.
URL: *https://linkinghub.elsevier.com/retrieve/pii/S2666222119300012*

Cai, C., Wang, Y. and Geers, G. (2013), 'Vehicle-to-infrastructure communication-based adaptive traffic signal control', *IET Intell. Transp. Syst.* **7**(3), 351–360.
URL: *https://digital-library.theiet.org/content/journals/10.1049/iet-its.2011.0150*

Cameron, G. D. B. and Duncan, G. I. D. (1996), 'PARAMICS: Parallel microscopic simulation of road traffic', *J. Supercomput.* **10**(1).
URL: *http://link.springer.com/10.1007/BF00128098*

CEBR (2014), The future economic and environmental costs of gridlock in 2030, Technical report, Centre for Economics and Business Research, London.

URL: *http://inrix.com/wp-content/uploads/2015/08/Whitepaper_Cebr-Cost-of-Congestion.pdf*

Cecchini, G., Bazzi, A., Masini, B. M. and Zanella, A. (2017), Performance comparison between IEEE 802.11p and LTE-V2V in-coverage and out-of-coverage for cooperative awareness, *in* '2017 IEEE Veh. Netw. Conf.', IEEE, pp. 109–114.
URL: *http://ieeexplore.ieee.org/document/8275637/*

Centre for Connected and Autonomous Vehicles (2019), CAV public acceptability dialogue engagement report, Technical report, UK Deptartment for Transport.
URL: *https://assets.publishing.service.gov.uk/government/uploads/system/uploads/attachment_-data/file/837958/cav-public-acceptability-dialogue-engagement-report.pdf*

Chandan, K., Seco, A. M. and Silva, A. B. (2017), 'Real-time Traffic Signal Control for Isolated Intersection, using Car-following Logic under Connected Vehicle Environment', *Transportation Research Procedia* **25**, 1610–1625.
URL: *https://linkinghub.elsevier.com/retrieve/pii/S2352146517305082*

Chang, F.-S., Wu, J.-S., Lee, C.-N. and Shen, H.-C. (2014), 'Greedy-search-based multi-objective genetic algorithm for emergency logistics scheduling', *Expert Syst. Appl.* **41**(6), 2947–2956.
URL: *https://linkinghub.elsevier.com/retrieve/pii/S0957417413008439*

Chang, H.-J. and Park, G.-T. (2013), 'A study on traffic signal control at signalized intersections in vehicular ad hoc networks', *Ad Hoc Networks* **11**(7), 2115–2124.
URL: *https://linkinghub.elsevier.com/retrieve/pii/S157087051200039X*

Chang, S.-L., Chen, L.-S., Chung, Y.-C. and Chen, S.-W. (2004), 'Automatic license plate recognition', *Intell. Transp. Syst. IEEE Trans.* **5**(1), 42–53.

Chaudhary, N. a., Kovvali, V. G. and Alam, S. M. M. (2002), 'Guidelines for Selecting Signal Timing Software', **7**(2).
URL: *http://citeseerx.ist.psu.edu/viewdoc/download?doi=10.1.1.536.6340&rep=rep1&type=pdf*

Chaudhary, N. A. and Messer, C. J. (1993), 'PASSER IV: a program for optimizing signal timing in grid networks', *Transportation research record* **1421**, 82–93.

Chen, J.-H., Lee, S.-C. and DeBra, D. B. (1994), 'Gyroscope free strapdown inertial measurement unit by six linear accelerometers', *J. Guid. Control. Dyn.* **17**(2).

Chen, L.-J., Sun, T. and Liang, N.-C. (2010), 'An Evaluation Study of Mobility Support in ZigBee Networks', *J. Signal Process. Syst.* **59**(1), 111–122.
URL: *http://link.springer.com/10.1007/s11265-008-0271-x*

Chen, Z., Samarabandu, J. and Rodrigo, R. (2007), 'Recent advances in simultaneous localization and map-building using computer vision', *Adv. Robot.* **21**, 233—-265(33).

Cheng, J., Wu, W., Cao, J. and Li, K. (2017), 'Fuzzy Group-Based Intersection Control via Vehicular Networks for Smart Transportations', *IEEE Trans. Ind. Informatics* **13**(2), 751–758.
URL: *http://ieeexplore.ieee.org/document/7508968/*

Cheryan, S., Ziegler, S. A., Montoya, A. K. and Jiang, L. (2017), 'Why are some STEM fields more gender balanced than others?', *Psychol. Bull.* **143**(1).
URL: *http://doi.apa.org/getdoi.cfm?doi=10.1037/bul0000052*

Cheung, S. Y., Coleri, S., Dundar, B., Ganesh, S., Tan, C.-W. and Varaiya, P. (2004), 'Traffic Measurement and Vehicle Classification with a Single Magnetic Sensor'.
URL: *http://www.escholarship.org/uc/item/2gv111tv*

Cho, H., Seo, Y.-W., Kumar, B. V. and Rajkumar, R. R. (2014), A multi-sensor fusion system for moving object detection and tracking in urban driving environments, *in* '2014 IEEE Int. Conf. Robot. Autom.', IEEE, pp. 1836–1843.
URL: *http://ieeexplore.ieee.org/document/6907100/*

Chou, L.-D., Deng, B.-T., Li, D. C. and Kuo, K.-W. (2012), A passenger-based adaptive traffic signal control mechanism in Intelligent Transportation Systems, *in* '2012 12th Int. Conf. ITS Telecommun.', IEEE, pp. 408–411.
URL: *http://ieeexplore.ieee.org/document/6425208/*

Churchill, W. and Newman, P. (2012*a*), Continually improving large scale long term visual navigation of a vehicle in dynamic urban environments, *in* '2012 15th Int. IEEE Conf. Intell. Transp. Syst.', IEEE.
URL: *http://ieeexplore.ieee.org/document/6338716/*

Churchill, W. and Newman, P. (2012*b*), 'Practice makes perfect? Managing and leveraging visual experiences for lifelong navigation', *Proc. - IEEE Int. Conf. Robot. Autom.* .

Coifman, B. and Li, L. (2017), 'A critical evaluation of the Next Generation Simulation (NGSIM) vehicle trajectory dataset', *Transportation Research Part B: Methodological* **105**, 362–377.
URL: *https://linkinghub.elsevier.com/retrieve/pii/S0191261517300838*

Cormen, T. H., Leiserson, C. E., Rivest, R. L. and Stein, C. (2009), *Introduction to algorithms*, MIT press.

Crabtree, M. (2017), Application Guide 44: MOVA Traffic Control Manual, Technical report, TRL.

Creative Commons (n.d.), 'Creative Commons Attribution-ShareAlike 2.0 Generic (CC BY-SA 2.0)'.
URL: *https://creativecommons.org/licenses/by-sa/2.0/*

Cruickshanks, S., Cherrett, T. J., Waterson, B., Norgate, S., Davies, N., Speed, C. and Dickinson, J. (2013), 'Will privacy concerns limit the ability of smart phone technologies to help foster collaborative school travel?', *TRB 92nd Annu. Meet.* .

Curtis, S. (2003), 'The classification of greedy algorithms', *Sci. Comput. Program.* **49**(1-3), 125–157.
URL: *https://linkinghub.elsevier.com/retrieve/pii/S0167642303000340*

D'Agostino, R. B. (1971), 'An Omnibus Test of Normality for Moderate and Large Size Samples', *Biometrika* **58**(2), 341.
URL: *https://www.jstor.org/stable/2334522?origin=crossref*

Dahlkamp, H., Kaehler, A., Stavens, D., Thrun, S. and Bradski, G. (2006), 'Self-supervised Monocular Road Detection in Desert Terrain', *Proc Robot. Sci. Syst. RSS* .
URL: *http://citeseerx.ist.psu.edu/viewdoc/download?doi=10.1.1.74.503&rep=rep1&type=pdf*

Darms, M., Rybski, P., Baker, C. and Urmson, C. (2009), 'Obstacle Detection and Tracking for the Urban Challenge', *IEEE Trans. Intell. Transp. Syst.* **10**(3).
URL: *http://ieeexplore.ieee.org/abstract/document/4840443/*

Datesh, J., Scherer, W. T. and Smith, B. L. (2011), Using k-means clustering to improve traffic signal efficacy in an IntelliDriveSM environment, *in* '2011 IEEE Forum Integr. Sustain. Transp. Syst.', IEEE, pp. 122–127.
URL: *http://ieeexplore.ieee.org/document/5973659/*

Davies, H. E. H. (1992), The PUFFIN pedestrian crossing: experience with the first experimental sites, Technical report, TRL.

De Coensel, B., Can, A., Degraeuwe, B., De Vlieger, I. and Botteldooren, D. (2012), 'Effects of traffic signal coordination on noise and air pollutant emissions', *Environ. Model. Softw.* **35**, 74–83.
URL: *https://linkinghub.elsevier.com/retrieve/pii/S1364815212000576*

De Dios Ortúzar, J. and Willumsen, L. G. (2011), *Modelling transport*, John Wiley & Sons.

Deelertpaiboon, C. and Parnichkun, M. (2008), 'Fusion of GPS, Compass, and Camera for Localization of an Intelligent Vehicle', *Adv. Robot. Syst. Int.* **5**(4), 315–326.

Department for Education (2019), Education and training statistics for the UK: 2019, Technical report, UK Department for Education.
URL: *https://www.gov.uk/government/statistics/education-and-training-statistics-for-the-uk-2019*

Department for Transport (2018), Intelligent Transport Systems in the UK: Progress Report, Technical report, Department for Transport.
URL: *https://ec.europa.eu/transport/sites/transport/files/2018_uk_its_progress_report_-2017.pdf*

Department for Transport (2019), Future of Mobility: Urban Strategy, Technical report, Department for Transport.
URL: *https://assets.publishing.service.gov.uk/government/uploads/system/uploads/attachment_data/file/846593/future-of-mobility-strategy.pdf*

Descant, S. (2020), 'Connected Car Data to Inform Ann Arbor's Transportation Plan'.
URL: *https://www.govtech.com/fs/infrastructure/Connected-Car-Data-to-Inform-Ann-Arbors-Transportation-Plan.html*

Dhilip Kumar, V., Chyne, P., Kandar, D. and Paul, B. S. (2016), 'Performance analysis of hybrid WiMAX/DSRC scenarios for vehicular communication environment', *Microsyst. Technol.* .
URL: *http://link.springer.com/10.1007/s00542-016-2927-y*

Diakaki, C. (1999), Integrated Control of Traffic Flow in Corridor Networks, PhD thesis, Technical University of Crete.

Diakaki, C., Papageorgiou, M. and Aboudolas, K. (2002), 'A multivariable regulator approach to traffic-responsive network-wide signal control', *Control Eng. Pract.* **10**(2).

Dickmann, J., Klappstein, J., Hahn, M., Appenrodt, N., Bloecher, H.-L., Werber, K. and Sailer, A. (2016), "Automotive radar the key technology for autonomous driving: From detection and ranging to environmental understanding", *in* '2016 IEEE Radar Conference (RadarConf)', IEEE, pp. 1–6.
URL: *http://ieeexplore.ieee.org/document/7485214/*

DiDi Chuxing (2020), 'GAIA Open Dataset'.
URL: *https://outreach.didichuxing.com/research/opendata/en/*

Dijkstra, E. W. (1959), 'A note on two problems in connexion with graphs', *Numer. Math.* **1**(1), 269–271.
URL: *http://link.springer.com/10.1007/BF01386390*

Dissanayake, G., Sukkarieh, S., Nebot, E. and Durrant-Whyte, H. (2001), 'The aiding of a low-cost strapdown inertial measurement unit using vehicle model constraints for land vehicle applications', *Robot. Autom. IEEE Trans.* **17**(5), 731–747.

DLR (2018), 'SUMO Vehicle Type Parameter Defaults'.
URL: *http://sumo.dlr.de/wiki/Vehicle_Type_Parameter_Defaults*

Dollar, P., Wojek, C., Schiele, B. and Perona, P. (2012), 'Pedestrian Detection: An Evaluation of the State of the Art', *IEEE Trans. Pattern Anal. Mach. Intell.* **34**(4).
URL: *http://ieeexplore.ieee.org/document/5975165/*

Dresner, K. and Stone, P. (2008), 'A Multiagent Approach to Autonomous Intersection Management', *Journal of Artificial Intelligence Research* **31**, 591–656.
URL: *https://jair.org/index.php/jair/article/view/10542*

Dreyer, N., Moller, A., Mir, Z. H., Filali, F. and Kurner, T. (2016), A Data Traffic Steering Algorithm for IEEE 802.11p/LTE Hybrid Vehicular Networks, *in* '2016 IEEE 84th Veh. Technol. Conf.', IEEE, pp. 1–6.
URL: *http://ieeexplore.ieee.org/document/7880850/*

Du, S., Ibrahim, M., Shehata, M. and Badawy, W. (2013), 'Automatic License Plate Recognition (ALPR): A State-of-the-Art Review', *IEEE Trans. Circuits Syst. Video Technol.* **23**(2).

Dunbar, W. B. and Caveney, D. S. (2012), 'Distributed Receding Horizon Control of Vehicle Platoons: Stability and String Stability', *IEEE Trans. Automat. Contr.* **57**(3).
URL: *http://ieeexplore.ieee.org/document/5876300/*

Eiben, A. E. and Smith, J. E. (2003), *Introduction to evolutionary computing*, Vol. 53, Springer.

Elefteriadou, L. A. (2016), 'The Highway Capacity Manual, 6th edition: A guide for multimodal mobility analysis', *TR News* **86**, 14–18.

Eskandarian, A. (2012), *Handbook of Intelligent Vehicles*, Springer London, London.
URL: *http://link.springer.com/10.1007/978-0-85729-085-4*

ETSI (2009), Intelligent Transport Systems (ITS); Vehicular Communications; Basic Set of Applications; Definitions, Technical report, ETSI (European Telecommunications Standards Institute).

ETSI (2010*a*), ETSI EN 302 665 - Intelligent Transport Systems (ITS); Communications Architecture, Technical report, ETSI (European Telecommunications Standards Institute).

ETSI (2010*b*), TS 102 637-3 - V1.1.1 - Intelligent Transport Systems (ITS); Vehicular Communications; Basic Set of Applications; Part 3: Specifications of Decentralized Environmental Notification Basic Service, Technical Report 1, ETSI (European Telecommunications Standards Institute).

ETSI (2011), 'TS 102 637-2 Vehicular Communications Part 2: Specification of Cooperative Awareness Basic Service'.

ETSI (2012), ETSI TS 102 724 Intelligent Transport Systems (ITS); Harmonized Channel Specifications for Intelligent Transport Systems operating in the 5 GHz frequency band, Technical report, ETSI.

ETSI (2014*a*), ETSI EN 302 637-2 V1.3.2 Intelligent Transport Systems (ITS); Vehicular Communications; Basic Set of Applications; Part 2: Specification of Cooperative Awareness Basic Service, Technical report, ETSI.

ETSI (2014*b*), ETSI EN 302 637-3 Intelligent Transport Systems (ITS); Vehicular Communications; Basic Set of Applications; Part 3: Specifications of Decentralized Environmental Notification Basic Service cation Basic Service, Technical report, ETSI.

ETSI (2018*a*), Testing Cooperative Intelligent Transport Systems, Technical report, European Telecommunication Standards Institute.
URL: *https://www.etsi.org/images/files/ETSITechnologyLeaflets/CooperativeITS.pdf*

ETSI (2018*b*), TS 122 186 V15.3.0: 5G Service requirements for enhanced V2X scenarios, Technical report, ETSI.

ETSI (2019*a*), '5G'.

ETSI (2019*b*), ETSI TR 103 181-3 V2.1.1 - Short Range Devices (SRD) using Ultra Wide Band (UWB); Part 3: Worldwide UWB regulations between 3.1 and 10.6 GHz, Technical report, ETSI.
URL: *https://www.etsi.org/deliver/etsi_TR/103100_103199/10318103/02.01.01_60/tr_-10318103v020101p.pdf*

EU-US ITS Task Force Standards Harmonization Working Group (2012), Status of ITS Communication Standards: Document HTG3-1, Technical report, EU-US ITS Task Force.

European Commission (2006), 'Commision decision on harmonisation of the radio spectrum for use by short-range devices (2006/771/EC)', *Off. J. Eur. Union* **45**(108).
URL: *http://eur-lex.europa.eu/LexUriServ/LexUriServ.do?uri=OJ:L:2006:312:0066:0070:EN:PDF http://eur-lex.europa.eu/legal-content/en/ALL/?uri=OJ%3AL%3A2002%3A108%3ATOC*

European Commission (2016), A European strategy on Cooperative Intelligent Transport Systems, a milestone towards cooperative, connected and automated mobility, Technical report, European Commission.
URL: *https://eur-lex.europa.eu/legal-content/EN/TXT/?uri=COM%3A2016%3A766%3AFIN*

European Commission (2019), Transport in the European Union Current Trends and Issues, Technical report, European Comission.
URL: *https://ec.europa.eu/transport/sites/transport/files/2019-transport-in-the-eu-current-trends-and-issues.pdf*

Ezawa, H. and Mukai, N. (2010), Adaptive Traffic Signal Control Based on Vehicle Route Sharing by Wireless Communication, *in* R. Setchi, I. Jordanov, R. J. Howlett and L. C. Jain, eds, 'Knowledge-Based Intell. Inf. Eng. Syst.', Springer Berlin Heidelberg, Berlin, Heidelberg, pp. 280–289.

Fairfield, N. and Urmson, C. (2011), Traffic light mapping and detection, *in* '2011 IEEE Int. Conf. Robot. Autom.', IEEE, pp. 5421–5426.
URL: *http://ieeexplore.ieee.org/lpdocs/epic03/wrapper.htm?arnumber=5980164*

Fajardo, D., Au, T.-C., Waller, S. T., Stone, P. and Yang, D. (2011), 'Automated Intersection Control', *Transp. Res. Rec. J. Transp. Res. Board* **2259**(1).
URL: *http://journals.sagepub.com/doi/10.3141/2259-21*

FCC (1998), Intelligent Transportation Services Report and Order, R&O FCC 99-305, Technical report, U.S. Federal Communications Commission.

FCC (2003*a*), Dedicated Short Range Communications Report and Order, Technical report, U.S. FCC, R&O FCC 03-324.

FCC (2003*b*), Dedicated Short Range Communications Report and Order, Technical report, U.S. Federal Communications Commission.

FCC (2006), Amendment of the Commission's Rules Regarding Dedicated Short-Range Communication Services in the 5.850âĂŞ5.925 GHz band (5.9 GHz band), MO & O FCC 06-110, Technical report, U.S. Federal Communications Commission.

Fédérale, L. (1931), Convention sur l'unification de la signalisation routière 0.741.21, Technical report, L'Assemblée fédérale.
URL: *https://www.admin.ch/opc/fr/classified-compilation/19310019/193504190000/0.741.21.pdf*

Federation Internationale de L'Automobile (2017), WHAT EUROPEANS THINK ABOUT CONNECTED CARS, Technical report, Federation Internationale de L'Automobile.
URL: *https://www.fiaregion1.com/wp-content/uploads/2017/06/FIA-Survey-Brochure-2016-web.pdf*

Felicio, G. P., Grepo, L. C., Reyes, V. F. and Yupingkun, L. C. (2015), 'Traffic Light Displays and Driver Behaviors: A Case Study', *Procedia Manuf.* **3**, 3266–3273.
URL: *https://linkinghub.elsevier.com/retrieve/pii/S235197891500880X*

Fellendorf, M. (1994), VISSIM: A microscopic simulation tool to evaluate actuated signal control including bus priority, *in* '64th Inst. Transp. Eng. Annu. Meet.', Springer, pp. 1–9.

Fellendorf, M. and Vortisch, P. (2010), Microscopic Traffic Flow Simulator VISSIM, *in* J. Barceló, ed., 'Fundam. Traffic Simul.', Springer, New York, NY, pp. 63–93.
URL: *http://link.springer.com/10.1007/978-1-4419-6142-6_2*

Feng, Y. (2015), Intelligent Traffic Control in a Connected Vehicle Environment, PhD thesis, University of Arizona.

Feng, Y., Head, K. L., Khoshmagham, S. and Zamanipour, M. (2015), 'A real-time adaptive signal control in a connected vehicle environment', *Transp. Res. Part C Emerg. Technol.* **55**, 460–473.
URL: *https://linkinghub.elsevier.com/retrieve/pii/S0968090X15000091*

FHWA (2019), 'NGSIM'.
URL: *https://ops.fhwa.dot.gov/trafficanalysistools/ngsim.htm*

Foley and Lardner LLP (2017), 2017 Connected Cars & Autonomous Vehicles Survey, Technical report, Foley and Lardner LLP.
URL: *https://www.foley.com/files/uploads/2017-Connected-Cars-Survey-Report.pdf*

Friedrich, B. (2003), MODELS FOR ADAPTIVE URBAN TRAFFIC CONTROL, Technical report, TRANSVER Transport Research and Consultancy.

Friedrich, B. and Keller, H. (1994), 'An Integrated Method of Demand Responsive and Traffic Actuated Signal Control', *IFAC Proc. Vol.* **27**(12), 565–571.
URL: *https://linkinghub.elsevier.com/retrieve/pii/S1474667017475318*

Furness, K. P. (1965), 'Time function iteration', *Traffic Eng. Control* **7**(7), 458–460.

Furth, P. G. and Muller, T. H. J. (1999), TRAFCOD: A Method for Stream-Based Control of Actuated Traffic Signals, *in* '78th Annu. Meet. Transp. Res. board'.

Gajda, J., Sroka, R., Stencel, M., Wajda, A. and Zeglen, T. (2001), A vehicle classification based on inductive loop detectors, *in* 'IMTC 2001. Proc. 18th IEEE Instrum. Meas. Technol. Conf. Rediscovering Meas. Age Informatics (Cat. No.01CH 37188)', Vol. 1, IEEE, pp. 460–464.
URL: *http://ieeexplore.ieee.org/lpdocs/epic03/wrapper.htm?arnumber=928860*

Gao, Y., Meng, X., Hancock, C., Stephenson, S. and Zhang, Q. (2014), 'UWB/GNSS-based cooperative positioning method for V2X applications', *27th International Technical Meeting of The Satellite Division of the Institute of Navigation (ION GNSS+ 2014)* .

Garcia-Garrido, M. A., Sotelo, M. A. and Martm-Gorostiza, E. (2006), 'Fast traffic sign detection and recognition under changing lighting conditions', *Intell. Transp. Syst. Conf. 2006. ITSC '06. IEEE* pp. 811–816.

Gardner, K., D'Souza, C., Hounsell, N., Shrestha, B. and Bretherton, D. (2009), 'Review of bus priority at traffic signals around the world', *UITP Work. Gr. Tech. Rep.* .

Gartner, N. (1990), 'OPAC: Strategy for Demand-responsive Decentralized Traffic Signal Control', *IFAC Proc. Vol.* **23**(2), 241–244.
URL: *https://linkinghub.elsevier.com/retrieve/pii/S1474667017526774*

Gerrits, J. F., Kouwenhoven, M. H., van der Meer, P. R., Farserotu, J. R. and Long, J. R. (2005), 'Principles and Limitations of Ultra-Wideband FM Communications Systems', *EURASIP Journal on Advances in Signal Processing* **2005**(3), 189150.
URL: *https://asp-eurasipjournals.springeropen.com/articles/10.1155/ASP.2005.382*

Gheorghiu, R. A. and Iordache, V. (2017), 'Analysis of the Possibility to Implement ZigBee Communications in Road Junctions', *Procedia Eng.* **181**, 489–495.
URL: *http://linkinghub.elsevier.com/retrieve/pii/S1877705817310044*

Gheorghiu, R. A., Iordache, V., Minea, M. and Cormos, A. C. (2017), Bluetooth latency analysis for vehicular communications in a Wi-Fi noisy environment, *in* '2017 40th Int. Conf. Telecommun. Signal Process.', IEEE, pp. 148–151.
URL: *http://ieeexplore.ieee.org/document/8075956/*

Gipps, P. G. (1981), 'A behavioural car-following model for computer simulation', *Transp. Res. Part B* **15**(2), 105–111.
URL: *http://www.sciencedirect.com/science/article/pii/0191261581900370*

GIZ (2018), Defining the Future of Mobility: Intelligent and Connected Vehicles (ICVs) in China and Germany, Technical report, Deutsche Gesellschaft für Internationale Zusammenarbeit (GIZ) GmbH.
URL: *http://www.sustainabletransport.org/wp-content/uploads/2018/09/Defining-the-Future-of-Mobility-ICVs-in-China-and-Germany-1-1.pdf*

Godha, S. and Cannon, M. E. (2005), Integration of DGPS with a low cost MEMS-based inertial measurement unit (IMU) for land vehicle navigation application, *in* 'Proc. 18th Int. Tech. Meet. Satell. Div. Inst. Navig. (ION GNSS05)', Citeseer.

Goodall, N., Smith, B. and Park, B. (2013), 'Traffic Signal Control with Connected Vehicles', *Transp. Res. Rec.* **2381**(2), 65–72.
URL: *http://trb.metapress.com/index/U0V73J295T10116V.pdf$%5C$nhttp://people.virginia.edu/%7B %7Dnjg2q/g %7Ddissertation.pdf$%5C$nhttp://trb.metapress.com/index/U0V73J295T10116V.pdf*

Goyal, A., Lu, W. and Lakshmanan, L. V. (2011), CELF++: Optimizing the Greedy Algorithm for Influence Maximization in Social Networks, *in* 'Proc. 20th Int. Conf. companion World wide web - WWW '11', ACM Press, New York, New York, USA.
URL: *http://portal.acm.org/citation.cfm?doid=1963192.1963217*

Gozalvez, J., Sepulcre, M. and Bauza, R. (2012), 'IEEE 802.11p vehicle to infrastructure communications in urban environments', *IEEE Commun. Mag.* **50**(5), 176–183.
URL: *http://ieeexplore.ieee.org/document/6194400/*

Gradinescu, V., Gorgorin, C., Diaconescu, R., Cristea, V. and Iftode, L. (2007), Adaptive Traffic Lights Using Car-to-Car Communication, *in* '2007 IEEE 65th Veh. Technol. Conf. - VTC2007-Spring', IEEE, pp. 21–25.
URL: *http://ieeexplore.ieee.org/document/4212445/*

Greenough, J. C. and Kelman, W. L. (1997), Metro Toronto SCOOT: Traffic Adaptive Control Operation, Technical report, Metro Transportation.

Grewal, M. S., Weill, L. R. and Andrews, A. P. (2001), *Global Positioning Systems, Inertial Navigation and Integration*, John Wiley & Sons.

Haartsen, J., Naghshineh, M., Inouye, J., Joeressen, O. J. and Allen, W. (1998), 'Bluetooth: Vision, goals, and architecture', *ACM SIGMOBILE Mob. Comput. Commun. Rev.* **2**(4), 38–45.

Haklay, M. and Weber, P. (2008), 'Openstreetmap: User-generated street maps', *IEEE Pervasive Comput.* **7**(4), 12–18.

Hallmark, S., Veneziano, D. and Litteral, T. (2019), PREPARING LOCAL AGENCIES FOR THE FUTURE OF CONNECTED AND AUTONOMOUS VEHICLES, Technical report, Minnesota Department of Transportation.
URL: *http://www.dot.state.mn.us/research/reports/2019/201918.pdf*

Hameed Mir, Z. and Filali, F. (2014), 'LTE and IEEE 802.11p for vehicular networking: a performance evaluation', *EURASIP J. Wirel. Commun. Netw.* **2014**(1).
URL: *http://jwcn.eurasipjournals.springeropen.com/articles/10.1186/1687-1499-2014-89*

Hamilton, A. (2015), Improving traffic movement in an urban environment, PhD thesis, University of Southampton.
URL: *https://eprints.soton.ac.uk/377283/*

Han, E., Lee, H. P., Park, S., So, J. J. and Yun, I. (2019), 'Optimal Signal Control Algorithm for Signalized Intersections under a V2I Communication Environment', *J. Adv. Transp.* **2019**, 1–9.
URL: *https://www.hindawi.com/journals/jat/2019/6039741/*

Hata, A. Y. and Wolf, D. F. (2016), 'Feature Detection for Vehicle Localization in Urban Environments Using a Multilayer LIDAR', *IEEE Trans. Intell. Transp. Syst.* **17**(2).
URL: *http://ieeexplore.ieee.org/document/7279128/*

Hausberger, S., Rexeis, M., Zallinger, M. and Luz, R. (2009), Emission Factors from the Model PHEM for the HBEFA Version 3, Technical report, TU Graz.
URL: *https://www.hbefa.net/e/documents/HBEFA_31_Docu_hot_emissionfactors_PC_LCV_-HDV.pdf*

Hausknecht, M., Au, T. C. and Stone, P. (2011), 'Autonomous intersection management: Multi-intersection optimization', *IEEE Int. Conf. Intell. Robot. Syst.* pp. 4581–4586.

Hawkins, T. R., Gausen, O. M. and Strømman, A. H. (2012), 'Environmental impacts of hybrid and electric vehiclesâĂŤa review', *Int. J. Life Cycle Assess.* **17**(8), 997–1014.
URL: *http://link.springer.com/10.1007/s11367-012-0440-9*

Haynes, W. M. (2014), *CRC handbook of chemistry and physics*, CRC press.

Hayward, J. C. (1972), 'Near miss determination through use of a scale of danger', *51st Annual Meeting of the Highway Research Board* .
URL: *https://trid.trb.org/view/115323*

He, Q., Head, K. L. and Ding, J. (2011), 'Heuristic Algorithm for Priority Traffic Signal Control', *Transp. Res. Rec. J. Transp. Res. Board* **2259**(1).
URL: *http://journals.sagepub.com/doi/10.3141/2259-01*

He, Q., Head, K. L. and Ding, J. (2012), 'PAMSCOD: Platoon-based arterial multi-modal signal control with online data', *Transp. Res. Part C Emerg. Technol.* **20**(1).
URL: *http://linkinghub.elsevier.com/retrieve/pii/S0968090X11000775*

He, Q., Head, K. L. and Ding, J. (2014), 'Multi-modal traffic signal control with priority, signal actuation and coordination', *Transp. Res. Part C Emerg. Technol.* **46**, 65–82.
URL: *http://linkinghub.elsevier.com/retrieve/pii/S0968090X14001144*

Henry, J. and Farges, J. (1990), 'PRODYN', *IFAC Proc. Vol.* **23**(2), 253–255.
URL: *https://linkinghub.elsevier.com/retrieve/pii/S1474667017526798*

Henry, J.-J., Farges, J. L. and Tuffal, J. (1984), The PRODYN real time traffic algorithm, *in* 'IFACIFIPIFORS Conf. Control'.

Hensher, D. A. and Button, K. J. (2007), *Handbook of transport modelling*, Emerald Group Publishing Limited.

Hertfordshire County Council (2011), Intelligent Transport Systems Strategy Package Report, Technical report, Hertfordshire County Council.
URL: *https://www.hertfordshire.gov.uk/media-library/documents/highways/transport-planning/local-transport-plan-live/intelligent-transport-systems-its-vision.pdf https://www.hertfordshire.gov.uk/media-library/documents/highways/transport-planning/local-transport-plan-live/package-report.pdf*

Highways Agency and Driver and Vehicle Standards Agency (n.d.), 'Highways Agency warns tailgaters that 'only a fool breaks the 2-second rule''.

Highways England (2018), 'Signs of the future: new technology testbed on the A2 and M2 in Kent'.
URL: *https://www.gov.uk/government/news/signs-of-the-future-new-technology-testbed-on-the-a2-and-m2-in-kent*

Highways England (2019), Operational Metrics Manual, Technical report, Highways England.
URL: *https://www.gov.uk/government/publications/highways-england-operational-metrics-manual*

History.com (2009), 'Ford Motor Company unveils the Model T'.
URL: *https://www.history.com/this-day-in-history/ford-motor-company-unveils-the-model-t*

Hofmann-Wellenhof, B., Lichtenegger, H. and Collins, J. (2012), *Global positioning system: theory and practice*, Springer Science.

HomChaudhuri, B., Lin, R. and Pisu, P. (2016), 'Hierarchical control strategies for energy management of connected hybrid electric vehicles in urban roads', *Transp. Res. Part C* **62**.
URL: *http://linkinghub.elsevier.com/retrieve/pii/S0968090X15004131*

Horiba Mira (2020), 'UK Central CAV Testbed'.
URL: *https://www.horiba-mira.com/research/uk-central-cav-testbed/*

Hounsell, N. B. and McDonald, M. (2001), 'Urban network traffic control', *Proc. Inst. Mech. Eng. Part I J. Syst. Control Eng.* **215**(4), 325–334.
URL: *http://journals.sagepub.com/doi/10.1177/095965180121500405*

Hounsell, N. and Shrestha, B. (2012), 'A New Approach for Co-Operative Bus Priority at Traffic Signals', *IEEE Transactions on Intelligent Transportation Systems* **13**(1), 6–14.
URL: *http://ieeexplore.ieee.org/document/6075256/*

Howard, A. (2008), Real-time stereo visual odometry for autonomous ground vehicles, *in* '2008 IEEE/RSJ Int. Conf. Intell. Robot. Syst.', IEEE, pp. 3946–3952.
URL: *http://ieeexplore.ieee.org/document/4651147/*

Hsu, L.-T. (2018), 'Analysis and modeling GPS NLOS effect in highly urbanized area', *GPS Solutions* **22**(1), 7.
URL: *http://link.springer.com/10.1007/s10291-017-0667-9*

Hu, J., Park, B. B. and Lee, Y.-J. (2015), 'Coordinated transit signal priority supporting transit progression under Connected Vehicle Technology', *Transp. Res. Part C Emerg. Technol.* **55**, 393–408.
URL: *https://linkinghub.elsevier.com/retrieve/pii/S0968090X14003556*

Hunt, P., Robertson, D., Bretherton, R. and Winton, R. (1981), *SCOOT: A Traffic Responsive Method of Coordinating Signals*, TRRL.
URL: *https://books.google.co.uk/books?id=MuqySgAACAAJ*

Husch, D. and Albeck, J. (2003), *Intersection capacity utilization: Evaluation procedures for intersections and interchanges*, Trafficware.

IEEE (2010), 'IEEE Standard for Information technology – Local and metropolitan area networks – Specific requirements – Part 11: Wireless LAN Medium Access Control (MAC) and Physical Layer (PHY) Specifications Amendment 6: Wireless Access in Vehicular Environments', *IEEE Std 802.11p-2010* .

IEEE (2012), 'IEEE Standard for Information technology–Telecommunications and information exchange between systems Local and metropolitan area networks–Specific requirements Part 11: Wireless LAN Medium Access Control (MAC) and Physical Layer (PHY) Specifications', *IEEE Std 802.11-2012 (Revision IEEE Std 802.11-2007)* pp. 1–2793.

IEEE (2013), 'IEEE Standard for Information technology– Telecommunications and information exchange between systemsLocal and metropolitan area networks– Specific requirements–Part 11: Wireless LAN Medium Access Control (MAC) and Physical Layer (PHY) Specifications–', *IEEE Std 802.11ac-2013 (Amendment to IEEE Std 802.11-2012, as Amend. by IEEE Std 802.11ae-2012, IEEE Std 802.11aa-2012, IEEE Std 802.11ad-2012)* pp. 1–425.
URL: *http://ieeexplore.ieee.org/document/6687187/*

IEEE (2014), 'IEEE Guide for Wireless Access in Vehicular Environments (WAVE) - Architecture', *IEEE Std 1609.0-2013* pp. 1–78.

IEEE (2018), 802.16-2017 - IEEE Standard for Air Interface for Broadband Wireless Access Systems, Technical report, IEEE.

Ilgin Guler, S., Menendez, M. and Meier, L. (2014), 'Using connected vehicle technology to improve the efficiency of intersections', *Transp. Res. Part C Emerg. Technol.* **46**.
URL: *https://linkinghub.elsevier.com/retrieve/pii/S0968090X14001211*

INRIX (2017), Global Traffic Scorecard, Technical report, INRIX.
URL: *www2.inrix.com/e/171932/NRIX-2016-Traffic-Scorecard-EN/chpd6/93565729*

INRIX (2020), Global Traffic Scorecard, Technical report, INRIX.
URL: *https://inrix.com/scorecard/*

InterCor (2019), 'InterCor'.
URL: *https://intercor-project.eu/*

Intercor (2020), 'Intercor'.
URL: *https://intercor-project.eu/*

Iordache, V., Gheorghiu, R. A. and Minea, M. (2017), On the usability of Bluetooth in V2I based communications for extended infrastructure support, *in* '2017 13th Int. Conf. Adv. Technol. Syst. Serv. Telecommun.', IEEE, pp. 287–290.
URL: *http://ieeexplore.ieee.org/document/8246282/*

Islam, M. R., Hurwitz, D. S. and Macuga, K. L. (2016), 'Improved driver responses at intersections with red signal countdown timers', *Transp. Res. Part C Emerg. Technol.* **63**, 207–221.
URL: *http://linkinghub.elsevier.com/retrieve/pii/S0968090X15004246*

Islam, S. B. A. and Hajbabaie, A. (2017), 'Distributed coordinated signal timing optimization in connected transportation networks', *Transp. Res. Part C Emerg. Technol.* **80**, 272–285.
URL: *https://linkinghub.elsevier.com/retrieve/pii/S0968090X17301298*

ISO/IEC JTC 1 Information Technology (1994), ISO/IEC 7498-1:1994 Information technology âĂŤ Open Systems Interconnection âĂŤ Basic Reference Model: The Basic Model, Technical report, ISO.
URL: *https://www.iso.org/standard/20269.html*

Iwasaki, Y., Misumi, M. and Nakamiya, T. (2013), 'Robust Vehicle Detection under Various Environmental Conditions Using an Infrared Thermal Camera and Its Application to Road Traffic Flow Monitoring', *Sensors* **13**(6), 7756–7773.
URL: *http://www.mdpi.com/1424-8220/13/6/7756*

JCT Consultancy (2018), LinSig 3.2 User Guide, Technical report, JCT Consultancy, Nettleham.
URL: *http://www.jctconsultancy.co.uk/Support/Manuals/LinSig32 User Guide UK.pdf*

Jeong, E., Oh, C., Lee, G. and Cho, H. (2014), 'Safety Impacts of Intervehicle Warning Information Systems for Moving Hazards in Connected Vehicle Environments', *Transportation Research Record: Journal of the Transportation Research Board* **2424**(1), 11–19.
URL: *http://journals.sagepub.com/doi/10.3141/2424-02*

Jie, M. (2019), 'Japan will let driverless cars roam freely ahead of 2020 Olympics'.
URL: *https://www.autonews.com/mobility-report/japan-will-let-driverless-cars-roam-freely-ahead-2020-olympics*

Kamali, B. (2018), The IEEE 802.16 Standards and the WiMAX Technology, *in* 'AeroMACS', John Wiley & Sons, Inc., Hoboken, NJ, USA, pp. 189–258.
URL: *http://doi.wiley.com/10.1002/9781119281139.ch5*

Kanayama, K., Fujikawa, Y., Fujimoto, K. and Horino, M. (1991), Development of vehicle-license number recognition system using real-time image processing and its application to travel-time measurement, *in* '[1991 Proceedings] 41st IEEE Veh. Technol. Conf.', IEEE, pp. 798–804.
URL: *http://ieeexplore.ieee.org/document/140605/*

Kang, J.-S. and Downing, S. (2015), 'Keystone effect on entry into two-sided markets: An analysis of the market entry of WiMAX', *Technol. Forecast. Soc. Change* **94**, 170–186.
URL: *http://linkinghub.elsevier.com/retrieve/pii/S0040162514002789*

Kaplan, A. M. and Haenlein, M. (2010), 'Users of the world, unite! The challenges and opportunities of Social Media', *Bus. Horiz.* **53**(1), 59–68.
URL: *https://linkinghub.elsevier.com/retrieve/pii/S0007681309001232*

Kari, D., Wu, G. and Barth, M. J. (2014), Development of an agent-based online adaptive signal control strategy using connected vehicle technology, *in* '17th Int. IEEE Conf. Intell. Transp. Syst.', IEEE, pp. 1802–1807.
URL: *http://ieeexplore.ieee.org/document/6957954/*

Kato, S., Tsugawa, S., Tokuda, K., Matsui, T. and Fujii, H. (2002), 'Vehicle control algorithms for cooperative driving with automated vehicles and intervehicle communications', *IEEE Transactions on Intelligent Transportation Systems* **3**(3), 155–161.
URL: *http://ieeexplore.ieee.org/document/1033758/*

Katrakazas, C., Quddus, M. and Chen, W.-H. (2019), 'A new integrated collision risk assessment methodology for autonomous vehicles', *Accident Analysis & Prevention* **127**, 61–79.
URL: *https://linkinghub.elsevier.com/retrieve/pii/S0001457518306614*

Katsaros, K., Kernchen, R., Dianati, M. and Rieck, D. (2011), Performance study of a Green Light Optimized Speed Advisory (GLOSA) application using an integrated cooperative ITS simulation platform, *in* '2011 7th International Wireless Communications and Mobile Computing Conference', IEEE, pp. 918–923.
URL: *http://ieeexplore.ieee.org/document/5982524/*

Kennedy, J. and Sexton, B. (2009), PPR436: Literature review of road safety at traffic signals and signalised crossings, Technical report, Transportation Research Laboratory.
URL: *http://content.tfl.gov.uk/literature-review-of-road-safety-at-traffic-signals-and-signalised-crossings.pdf*

Kenney, J. B. (2011), 'Dedicated Short-Range Communications (DSRC) Standards in the United States', *Proc. IEEE* **99**(7).
URL: *http://ieeexplore.ieee.org/lpdocs/epic03/wrapper.htm?arnumber=5888501*

Khader, M. and Cherian, S. (2018), An Introduction to Automotive LIDAR, Technical report, Texas Instruments.
URL: *http://www.ti.com/lit/wp/slyy150/slyy150.pdf*

Khan, I. and Harri, J. (2017), Can IEEE 802.11p and Wi-Fi coexist in the 5.9GHz ITS band ?, *in* '2017 IEEE 18th Int. Symp. A World Wireless, Mob. Multimed. Networks', IEEE, pp. 1–6.
URL: *http://ieeexplore.ieee.org/document/7974358/*

Kim, M. and Kim, H. K. (2020), 'Investigation of environmental benefits of traffic signal countdown timers', *Transportation Research Part D: Transport and Environment* **85**, 102464.
URL: *https://linkinghub.elsevier.com/retrieve/pii/S1361920920306519*

Kinney, P. (2003), Zigbee technology: Wireless control that simply works, *in* 'Commun. Des. Conf.', Vol. 2, pp. 1–7.

KonSULT (2003), 'Urban traffic control systems'.

KonSULT (2009), 'Urban Traffic Control Systems'.
URL: *http://www.its.leeds.ac.uk/projects/konsult/private/level2/instruments/instrument014/l2_-014c.htm*

Koonce, P., Rodegerdts, L., Lee, K. and Quayle, S. (2008), *Traffic signal timing manual*, Federal Highway Administration.
URL: *http://trid.trb.org/view.aspx?id=875807*

Kosmatopoulos, E., Papageorgiou, M., Bielefeldt, C., Dinopoulou, V., Morris, R., Mueck, J., Richards, A. and Weichenmeier, F. (2006), 'International comparative field evaluation of a traffic-responsive signal control strategy in three cities', *Transp. Res. Part A Policy Pract.* **40**(5), 399–413.
URL: *https://linkinghub.elsevier.com/retrieve/pii/S0965856405001096*

Koza, J. R. (1997), 'Genetic programming'.

Krajzewicz, D., Bonert, M. and Wagner, P. (2006), 'The Open Source Traffic Simulation Package {SUMO}', *Rob. 2006* .

Krauß, S. (1997), 'Towards a unified view of microscopic traffic flow theories', *IFAC Transp. Syst.* **2**, 901–905.

Krauß, S. (1998), Microscopic modeling of traffic flow: Investigation of collision free vehicle dynamics, Technical Report 8, DLR.

Krzyzanowski, M., Kuna-Dibbert, B. and Schneider, J. (2005), *Health effects of transport-related air pollution*, WHO Regional Office Europe.

Kulchandani, J. S. and Dangarwala, K. J. (2015), Moving object detection: Review of recent research trends, *in* '2015 Int. Conf. Pervasive Comput.', IEEE, pp. 1–5.
URL: *http://ieeexplore.ieee.org/document/7087138/*

Kurtzer, G. M., Sochat, V. and Bauer, M. W. (2017), 'Singularity: Scientific containers for mobility of compute', *PLoS One* **12**(5).
URL: *https://dx.plos.org/10.1371/journal.pone.0177459*

Kyodo, J. (2019), 'Cabinet paves way for self-driving vehicles on Japan's roads next year with new rules'.
URL: *https://www.japantimes.co.jp/news/2019/09/20/national/japans-cabinet-autonomous-driving/*

Laboratory, T. R. (1996), Overseas road note 13: The use of traffic signals in developing cities, Technical report, TRL.

Lee, J. and Park, B. (2012), 'Development and Evaluation of a Cooperative Vehicle Intersection Control Algorithm Under the Connected Vehicles Environment', *IEEE Trans. Intell. Transp. Syst.* **13**(1), 81–90.
URL: *http://ieeexplore.ieee.org/document/6121907/*

Lee, J., Park, B. B. and Yun, I. (2013), 'Cumulative Travel-Time Responsive Real-Time Intersection Control Algorithm in the Connected Vehicle Environment', *J. Transp. Eng.* **139**(10), 1020–1029.
URL: *http://ascelibrary.org/doi/10.1061/%28ASCE%29TE.1943-5436.0000587*

Lees-Miller, J., Box, S. and Wilson, R. E. (2013), Hidden Markov Models for Vehicle Tracking with Bluetooth., *in* '13-3032 TRB Highw. Traffic Monit. Comm. (ABJ35).'.

Lertworawanich, P., Kuwahara, M. and Miska, M. (2011), 'A New Multiobjective Signal Optimization for Oversaturated Networks', *IEEE Trans. Intell. Transp. Syst.* **12**(4), 967–976.
URL: *http://ieeexplore.ieee.org/document/5744121/*

Li, Y. and Stüber, G. L., eds (2006), *Orthogonal Frequency Division Multiplexing for Wireless Communications*, Signals and Communication Technology, Kluwer Academic Publishers, Boston.
URL: *http://link.springer.com/10.1007/0-387-30235-2*

Liang, X. J., Guler, S. I. and Gayah, V. V. (2019), 'Joint Optimization of Signal Phasing and Timing and Vehicle Speed Guidance in a Connected and Autonomous Vehicle Environment', *Transp. Res. Rec. J. Transp. Res. Board* **2673**(4), 70–83.
URL: *http://journals.sagepub.com/doi/10.1177/0361198119841285*

Lin, A., Zhang, J., Lu, K. and Zhang, W. (2014), An efficient outdoor localization method for smartphones, *in* '2014 23rd Int. Conf. Comput. Commun. Networks', IEEE.
URL: *http://ieeexplore.ieee.org/document/6911788/*

Linegar, C., Churchill, W. and Newman, P. (2015), 'Work Smart , Not Hard : Recalling Relevant Experiences for Vast-Scale but Time-Constrained Localisation', *Int. Conf. Robot. Autom.* .

Litman, T. (2019), 'Autonomous Vehicle Implementation Predictions', *Victoria Transp. Policy Inst.* **28**.
URL: *http://www.vtpi.org/avip.pdf http://www.vtpi.org/AVIP_TTI_Jan2014.pdf*

Little, J. D. C., Kelson, M. D. and Gartner, N. H. (1981), 'MAXBAND: A versatile program for setting signals on arteries and triangular networks'.

Liu, G., Ma, Z., Du, Z. and Wen, C. (2011), The Calculation Method of Road Travel Time Based on License Plate Recognition Technology, *in* 'Adv. Inf. Technol. Educ.', Springer Berlin Heidelberg.
URL: *http://link.springer.com/10.1007/978-3-642-22418-8_54*

Liu, W., Qin, G., He, Y. and Jiang, F. (2017), 'Distributed Cooperative Reinforcement Learning-Based Traffic Signal Control That Integrates V2X Networks' Dynamic Clustering', *IEEE Trans. Veh. Technol.* **66**(10), 8667–8681.
URL: *http://ieeexplore.ieee.org/document/7922594/*

Lowrie, P. R. (1990), 'Scats, sydney co-ordinated adaptive traffic system: A traffic responsive method of controlling urban traffic'.

Luyanda, F., Gettman, D., Head, L., Shelby, S., Bullock, D. and Mirchandani, P. (2003), 'ACS-Lite Algorithmic Architecture: Applying Adaptive Control System Technology to Closed-Loop Traffic Signal Control Systems', *Transportation Research Record: Journal of the Transportation Research Board* **1856**(1), 175–184.
URL: *http://journals.sagepub.com/doi/10.3141/1856-19*

Lv, F., Zhu, H., Xue, H., Zhu, Y., Chang, S., Dong, M. and Li, M. (2016), An Empirical Study on Urban IEEE 802.11p Vehicle-to-Vehicle Communication, *in* '2016 13th Annu. IEEE Int. Conf. Sensing, Commun. Netw.', IEEE, pp. 1–9.
URL: *http://ieeexplore.ieee.org/document/7732969/*

Maciejewski, M. (2010), 'A comparison of microscopic traffic flow simulation systems for an urban area', *Transp. Probl.* **5**, 27–38.

Maddern, W., Pascoe, G. and Newman, P. (2015), Leveraging experience for large-scale LIDAR localisation in changing cities, *in* 'IEEE Int. Conf. Robot. Autom.', IEEE.
URL: *http://ieeexplore.ieee.org/document/7139414/*

Mamouei, M., Kaparias, I. and Halikias, G. (2018), 'A framework for user- and system-oriented optimisation of fuel efficiency and traffic flow in Adaptive Cruise Control', *Transportation Research Part C: Emerging Technologies* **92**, 27–41.
URL: *https://linkinghub.elsevier.com/retrieve/pii/S0968090X18301475*

Mann, H. B. and Whitney, D. R. (1947), 'On a Test of Whether one of Two Random Variables is Stochastically Larger than the Other', *The Annals of Mathematical Statistics* **18**(1), 50–60.
URL: *http://projecteuclid.org/euclid.aoms/1177730491*

Mannion, P., Duggan, J. and Howley, E. (2016), *An Experimental Review of Reinforcement Learning Algorithms for Adaptive Traffic Signal Control*, Springer International Publishing, chapter 4.
URL: *https://doi.org/10.1007/978-3-319-25808-9_4*

Manx Tech Group (2019), 'How much will a server cost? (UK)'.
URL: *https://www.manxtechgroup.com/how-much-will-a-server-cost-uk/*

Martchouk, M., Mannering, F. and Bullock, D. (2011), 'Analysis of Freeway Travel Time Variability Using Bluetooth Detection', *J. Transp. Eng.* **137**(10), 697–704.
URL: *http://ascelibrary.org/doi/full/10.1061/(ASCE)TE.1943-5436.0000253*

Maslekar, N., Mouzna, J., Boussedjra, M. and Labiod, H. (2013), 'CATS: An adaptive traffic signal system based on car-to-car communication', *J. Netw. Comput. Appl.* **36**(5), 1308–1315.
URL: *https://linkinghub.elsevier.com/retrieve/pii/S1084804512001415*

Mathew, T. and Ravishankar, K. (2011), 'Car-following behavior in traffic having mixed vehicle-types', *Transp. Lett.* **3**(2), 109–122.
URL: *http://www.tandfonline.com/doi/full/10.3328/TL.2011.03.02.109-122*

Mauro, V. and Di Taranto, C. (1990), 'UTOPIA', *IFAC Proc. Vol.* **23**(2), 245–252.
URL: *https://linkinghub.elsevier.com/retrieve/pii/S1474667017526786*

McGarry, C. (2019), 'What Is 5G? The Definitive Guide to the 5G Network Rollout'.
URL: *https://www.tomsguide.com/us/5g-release-date,review-5063.html*

McShane, C. (1999), 'The Origins and Globalization of Traffic Control Signals', *J. Urban Hist.* **25**(3), 379–404.
URL: *http://journals.sagepub.com/doi/10.1177/009614429902500304*

Mejri, M. N., Ben-Othman, J. and Hamdi, M. (2014), 'Survey on VANET security challenges and possible cryptographic solutions', *Veh. Commun.* **1**(2).
URL: *http://linkinghub.elsevier.com/retrieve/pii/S2214209614000187*

Merkel, D. (2014), 'Docker: lightweight linux containers for consistent development and deployment', *Linux J.* **2014**(239), 2.

Miah, S., Milonidis, E., Kaparias, I. and Karcanias, N. (2020), 'An Innovative Multi-Sensor Fusion Algorithm to Enhance Positioning Accuracy of an Instrumented Bicycle', *IEEE Transactions on Intelligent Transportation Systems* **21**(3), 1145–1153.
URL: *https://ieeexplore.ieee.org/document/8671458/*

Michelson, D. G., Leung, V. C. M. and Chow, G. (2016), The AURORA connected vehicle technology testbed, *in* '2016 IEEE Canadian Conference on Electrical and Computer Engineering (CCECE)', IEEE, pp. 1–4.
URL: *http://ieeexplore.ieee.org/document/7726747/*

Milanes, V., Shladover, S. E., Spring, J., Nowakowski, C., Kawazoe, H. and Nakamura, M. (2014), 'Cooperative Adaptive Cruise Control in Real Traffic Situations', *IEEE Trans. Intell. Transp. Syst.* **15**(1).
URL: *http://ieeexplore.ieee.org/document/6588305/*

Mileounis, G., Babadi, B., Kalouptsidis, N. and Tarokh, V. (2010), 'An Adaptive Greedy Algorithm With Application to Nonlinear Communications', *IEEE Trans. Signal Process.* **58**(6).
URL: *http://ieeexplore.ieee.org/document/5424024/*

Millbrook (2020), 'Connected and Autonomous Vehicle Testing'.
URL: *https://www.millbrook.co.uk/services/connected-and-autonomous-vehicle-testing/*

Miller, A. J. (1963), 'A computer control system for traffic networks', *Proc. Second Int. Symp. Theory Traffic Flow* pp. 200–220.

Minderhoud, M. M. and Bovy, P. H. (2001), 'Extended time-to-collision measures for road traffic safety assessment', *Accident Analysis & Prevention* **33**(1), 89–97.
URL: *https://linkinghub.elsevier.com/retrieve/pii/S0001457500000191*

Mirchandani, P. and Head, L. (2001), 'A real-time traffic signal control system: architecture, algorithms, and analysis', *Transp. Res. Part C Emerg. Technol.* **9**(6), 415–432.

Mladenovic, M. and Abbas, M. (2013), 'A survey of experiences with adaptive traffic control systems in North America', *J. Road Traffic Eng.* **59**(2).
URL: *http://milosm.info/Professor Milos Mladenovic publications/A Survey of Experiences with Adaptive Traffic Control Systems in North America.PDF*

Monteiro, L. S., Moore, T. and Hill, C. (2005), 'What is the accuracy of DGPS?', *J. Navig.* **58**(2).
URL: *https://www.cambridge.org/core/product/identifier/S037346330500322X/type/journal_-article*

Montemerlo, M., Becker, J., Bhat, S., Dahlkamp, H., Dolgov, D., Ettinger, S., Haehnel, D., Hilden, T., Hoffmann, G., Huhnke, B., Johnston, D., Klumpp, S., Langer, D., Levandowski, A., Levinson, J., Marcil, J., Orenstein, D., Paefgen, J., Penny, I., Petrovskaya, A., Pflueger, M., Stanek, G., Stavens, D., Vogt, A. and Thrun, S. (2008), 'Junior: The Stanford entry in the Urban Challenge', *J. F. Robot.* **25**(9), 569–597.
URL: *http://dx.doi.org/10.1002/rob.20258*

Moore, J. E., Mattingly, S. P., MacCarley, C. A. and McNally, M. G. (2005), 'Anaheim Advanced Traffic Control System Field Operations Test: A Technical Evaluation of SCOOT', *Transp. Plan. Technol.* **28**(6), 465–482.
URL: *http://www.tandfonline.com/doi/abs/10.1080/03081060500515622*

Morgan, F., Hurney, P., Glavin, M., Jones, E. and Waldron, P. (2015), 'Review of pedestrian detection techniques in automotive far-infrared video', *IET Intell. Transp. Syst.* **9**(8).
URL: *http://digital-library.theiet.org/content/journals/10.1049/iet-its.2014.0236*

Msadaa, I. C., Cataldi, P. and Filali, F. (2010), A Comparative Study between 802.11p and Mobile WiMAX-based V2I Communication Networks, *in* 'Conf. Next Gener. Mob. Appl. Serv. Technol.', IEEE.
URL: *http://ieeexplore.ieee.org/lpdocs/epic03/wrapper.htm?arnumber=5558216*

Mueller, E. (1970), 'Aspects of the history of traffic signals', *IEEE Trans. Veh. Technol.* **19**(1), 6–17.
URL: *http://ieeexplore.ieee.org/document/1621978/*

Mukhtar, A., Xia, L. and Tang, T. B. (2015), 'Vehicle Detection Techniques for Collision Avoidance Systems: A Review', *IEEE Trans. Intell. Transp. Syst.* **16**(5).
URL: *http://ieeexplore.ieee.org/document/7066891/*

Nafi, N. S. and Khan, J. Y. (2012), A VANET based Intelligent Road Traffic Signalling System, *in* 'Australas. Telecommun. Networks Appl. Conf. 2012', IEEE, pp. 1–6.
URL: *http://ieeexplore.ieee.org/document/6398066/*

Najm, W. G., Koopmann, J., Smith, J. D. and Brewer, J. (2010), Frequency of target crashes for intellidrive safety systems, Technical report, NHTSA.

Nam Bui, K.-H. and Jung, J. J. (2018), 'Cooperative game-theoretic approach to traffic flow optimization for multiple intersections', *Comput. Electr. Eng.* **71**, 1012–1024.
URL: *https://linkinghub.elsevier.com/retrieve/pii/S0045790617318050*

National Archives (n.d.), 'Open Government License (UK)'.
URL: *http://www.nationalarchives.gov.uk/doc/open-government-licence/version/3/*

Nelder, J. A. and Mead, R. (1965), 'A Simplex Method for Function Minimization', *Comput. J.* **7**(4).
URL: *https://academic.oup.com/comjnl/article-lookup/doi/10.1093/comjnl/7.4.308*

Nesheli, M. M., Puan, O. C. and Roshandeh, A. M. (2009), 'Optimization of traffic signal coordination system on congestion: a case study', *WSEAS Trans. Adv. Eng. Educ.* **6**(7), 203–212.

Ngoduy, D. (2012), 'Effect of driver behaviours on the formation and dissipation of traffic flow instabilities', *Nonlinear Dyn.* **69**(3).

Ngoduy, D. (2014), 'Effect of the car-following combinations on the instability of heterogeneous traffic flow', *Transp. B Transp. Dyn.* **0566**(February 2015).
URL: *http://www.tandfonline.com/doi/abs/10.1080/21680566.2014.960503*

Nie, J., Zhang, J., Ding, W., Wan, X., Chen, X. and Ran, B. (2016), 'Decentralized Cooperative Lane-Changing Decision-Making for Connected Autonomous Vehicles*', *IEEE Access* **4**, 9413–9420.
URL: *http://ieeexplore.ieee.org/document/7811295/*

Nistér, D., Naroditsky, O. and Bergen, J. (2006), 'Visual odometry for ground vehicle applications', *J. F. Robot.* **23**(1), 3–20.
URL: *http://doi.wiley.com/10.1002/rob.20103*

Nopiah, Z. M., Khairir, M. I., Abdullah, S., Baharin, M. N. and Arifin, A. (2010), Time complexity analysis of the genetic algorithm clustering method, *in* 'Proceedings of the 9th WSEAS International Conference on Signal Processing, Robotics and Automation, ISPRA', Vol. 10, pp. 171–176.

Nourani-Vatani, N., Roberts, J. and Srinivasan, M. V. (2009), Practical visual odometry for car-like vehicles, *in* 'Robot. Autom. 2009. ICRA'09. IEEE Int. Conf.', IEEE.

ODHIAMBO, E. O. (2019), 'Evaluation of Signal Optimization Software: Comparison of Optimal Signal Pans from TRANSYT and LinSig–A Case Study'.
URL: *https://www.diva-portal.org/smash/get/diva2:1351990/FULLTEXT01.pdf*

of Transport, D. (1984), MCE 0141: Microprocessor based traffic signal controller for isolated linked and urban traffic control installations, Technical report, Department of Transport.

Open Data Commons (n.d.), 'Open Database License (ODbL)'.
URL: *https://www.openstreetmap.org/copyright*

OpenStreetMap Foundation (n.d.*a*), 'Open Street Maps'.
URL: *https://www.openstreetmap.org*

OpenStreetMap Foundation (n.d.*b*), 'Osmosis'.
URL: *https://wiki.openstreetmap.org/wiki/Osmosis*

Oshin, O. and Atayero, A. A. (2015), '3GPP LTE: An Overview'.

Oshin, T. O., Poslad, S. and Ma, A. (2012), Improving the Energy-Efficiency of GPS Based Location Sensing Smartphone Applications, *in* '2012 IEEE 11th Int. Conf. Trust. Secur. Priv. Comput. Commun.', IEEE, pp. 1698–1705.
URL: *http://ieeexplore.ieee.org/document/6296188/*

Outay, F., Kammoun, F., Kaisser, F. and Atiquzzaman, M. (2017), Towards Safer Roads through Cooperative Hazard Awareness and Avoidance in Connected Vehicles, *in* '2017 31st International Conference on Advanced Information Networking and Applications Workshops (WAINA)', IEEE, pp. 208–215.
URL: *http://ieeexplore.ieee.org/document/7929679/*

Owens, J. M., Antin, J. F., Doerzaph, Z. and Willis, S. (2015), 'Cross-generational acceptance of and interest in advanced vehicle technologies: A nationwide survey', *Transp. Res. Part F Traffic Psychol. Behav.* **35**, 139–151.
URL: *https://linkinghub.elsevier.com/retrieve/pii/S1369847815001710*

Pakin, S. (2015), 'The Comprehensive LATEX Symbol List'.

Palattella, M. R., Dohler, M., Grieco, A., Rizzo, G., Torsner, J., Engel, T. and Ladid, L. (2016), 'Internet of Things in the 5G Era: Enablers, Architecture, and Business Models', *IEEE J. Sel. Areas Commun.* **34**(3).
URL: *http://ieeexplore.ieee.org/document/7397856/*

Pandit, K., Ghosal, D., Zhang, H. M. and Chuah, C.-N. (2013), 'Adaptive Traffic Signal Control With Vehicular Ad hoc Networks', *IEEE Trans. Veh. Technol.* **62**(4), 1459–1471.
URL: *http://ieeexplore.ieee.org/document/6415344/*

Papageorgiou, M., Diakaki, C., Dinopoulou, V., Kotsialos, A. and Wang, Y. (2003), 'Review of road traffic control strategies', *Proc. IEEE* **91**(12), 2043–2067.
URL: *http://ieeexplore.ieee.org/document/1246386/*

Pascoe, G., Maddern, W. and Newman, P. (2015), 'Direct Visual Localisation and Calibration for Road Vehicles in Changing City Environments', *Iccv* .

Peng, H. (2019), Mcity Annual Report, Technical report, University of Michigan, Michigan.
URL: *https://mcity.umich.edu/wp-content/uploads/2020/02/Mcity-2019-annual-report.pdf*

Peng, J., Hao, H. and Chen, L. (2017), 'An Adaptive Traffic Signal Control in a Connected Vehicle Environment: A Systematic Review', *Information* **8**(3), 101.
URL: *http://www.mdpi.com/2078-2489/8/3/101*

Piniarski, K., Pawłowski, P. and Dąbrowski, A. (2015), 'Video Processing Algorithms for Detection of Pedestrians', *Comput. Methods Sci. Technol.* **21**(03), 141–150.
URL: *http://cmst.eu/articles/video-processing-algorithms-for-detection-of-pedestrians/*

Porche, I. and Lafortune, S. (1997), Dynamic traffic control: decentralized and coordinated methods, *in* 'Proc. Conf. Intell. Transp. Syst.', IEEE.
URL: *http://ieeexplore.ieee.org/document/660598/*

Posner, I., Schroeter, D. and Newman, P. (2008), 'Online generation of scene descriptions in urban environments', *Rob. Auton. Syst.* **56**(11), 901–914.

Powell, M. J. D. (1964), 'An efficient method for finding the minimum of a function of several variables without calculating derivatives', *Comput. J.* **7**(2).
URL: *https://academic.oup.com/comjnl/article-lookup/doi/10.1093/comjnl/7.2.155*

PPSC (2019), AUTOMATED AND CONNECTED VEHICLES POLICY FRAMEWORK FOR CANADA, Technical report, Policy and Planning Support Committee (PPSC) Working group on Automated and Connected Vehicles.
URL: *https://comt.ca/Reports/AVCV Policy Framework 2019.pdf*

Priemer, C. and Friedrich, B. (2009), A decentralized adaptive traffic signal control using V2I communication data, *in* '12th Int. IEEE Conf. Intell. Transp. Syst.'.
URL: *http://ieeexplore.ieee.org/document/5309870/*

Public Health England (2019), Review of interventions to improve outdoor air quality and public health, Technical report, Public Health England.

Quddus, M. A., Ochieng, W. Y. and Noland, R. B. (2007), 'Current map-matching algorithms for transport applications: State-of-the art and future research directions', *Transp. Res. Part C Emerg. Technol.* **15**(5).
URL: *http://linkinghub.elsevier.com/retrieve/pii/S0968090X07000265 https://linkinghub.elsevier.com/retrieve/pii/S0968090X07000265*

RACE (2020), 'Connected Autonomous Vehicle Testbed'.
URL: *http://race.ukaea.uk/test-facilities/cav/*

Radford, A. and Rafter, C. B. (n.d.), 'UTMCTools (GitHub)'.
URL: *https://github.com/cbrafter/UTMCTools/blob/markdown-edits/description.md*

Rafter, C. B., Anvari, B. and Box, S. (2017*a*), A hybrid traffic responsive intersection control algorithm using global positioning system and inductive loop data, *in* 'Proc. Transp. Res. Board 97th Annu. Meet.'.
URL: *https://eprints.soton.ac.uk/415632/*

Rafter, C. B., Anvari, B. and Box, S. (2017*b*), Traffic Responsive Intersection Control Algorithm Using GPS Data, *in* '20th Int. IEEE Conf. Intell. Transp. Syst.'.

Rafter, C. B., Anvari, B., Cherrett, T. and Box, S. (2019*a*), '(submitted) A greedy stage sequence optimisation algorithm with implicit coordination from arbitrary connected vehicle data', *Transp. Res. Part C Emerg. Technol.* .

Rafter, C. B., Anvari, B., Cherrett, T. and Box, S. (2019*b*), '(under review) Augmenting Traffic Signal Control Systems for Urban Road Networks with Connected Vehicles', *IEEE Trans. Intell. Transp. Syst.* .

Raguseo, E. (2018), 'Big data technologies: An empirical investigation on their adoption, benefits and risks for companies', *Int. J. Inf. Manage.* **38**(1), 187–195.
URL: *https://linkinghub.elsevier.com/retrieve/pii/S0268401217300063*

Rattray, J. and Jones, M. C. (2007), 'Essential elements of questionnaire design and development', *J. Clin. Nurs.* **16**(2), 234–243.
URL: *http://doi.wiley.com/10.1111/j.1365-2702.2006.01573.x*

Rhythm Engineering (2019), 'InSync: The Traffic Bot'.
URL: *https://rhythmtraffic.com/*

Robertson, D. and Bretherton, R. (1991), 'Optimizing networks of traffic signals in real time-the SCOOT method', *IEEE Trans. Veh. Technol.* **40**(1), 11–15.
URL: *http://ieeexplore.ieee.org/document/69966/*

Robertson, D. I. (1969), 'TRANSYT: a traffic network study tool', *Minist. Transp. Road Res. Lab. Rep.* **LR 253**.

Robertson, D. I. (1986), 'Research on the TRANSYT and SCOOT Methods of Signal Coordination', *ITE J.* **56**(1), 36–40.

Robillard, P. (1975), 'Estimating the O-D matrix from observed link volumes', *Transp. Res.* **9**(2-3), 123–128.
URL: *http://linkinghub.elsevier.com/retrieve/pii/0041164775900490*

Rode, P., Heeckt, C. and da Cruz, N. (2019), National Transport Policy and Cities: Key policy interventions to drive compact and connected urban growth, Technical report, Coalition for Urban Transitions.
URL: *https://lsecities.net/wp-content/uploads/2019/04/CUT2019_transport_final.pdf*

Rodrigue, J.-P., Comtois, C. and Slack, B. (2016), *The geography of transport systems*, 4 edn, Routledge.
URL: *https://transportgeography.org/?page_id=6279*

Rossum, G. (1995), Python Reference Manual, Technical report, Python Software Foundation, Amsterdam, The Netherlands.

SAE (2016), Dedicated Short Range Communications (DSRC) Message Set Dictionary, SAE Std. J2735, Technical report, SAE Int.
URL: *http://standards.sae.org/j2735_201603/*

Sahebi, S. and Nassiri, H. (2017), 'Assessing Public Acceptance of Connected Vehicle Systems in a New Scheme of Usage-Based Insurance', *Transp. Res. Rec. J. Transp. Res. Board* **2625**(1), 62–69.
URL: *http://journals.sagepub.com/doi/10.3141/2625-07*

Saidallah, M., El Fergougui, A. and Elalaoui, A. E. (2016), A Comparative Study of Urban Road Traffic Simulators, *in* 'MATEC Web Conf.', Vol. 81, EDP Sciences, p. 5002.

Santa, J., Pereniguez, F., Moragon, A. and Skarmeta, A. F. (2013), Vehicle-to-infrastructure messaging proposal based on CAM/DENM specifications, *in* '2013 IFIP Wirel. Days', IEEE, pp. 1–7.
URL: *http://ieeexplore.ieee.org/document/6686514/*

Santos, G. and Shaffer, B. (2004), 'Preliminary Results of the London Congestion Charging Scheme', *Public Work. Manag. Policy* **9**(2), 164–181.
URL: *http://journals.sagepub.com/doi/10.1177/1087724X04268569*

Sarjoghian, S., Alfadhl, Y. and Chen, X. (2016), On the limitation of ultra-wideband technique for medical scanning systems, *in* '2016 Loughborough Antennas & Propagation Conference (LAPC)', IEEE, pp. 1–4.
URL: *http://ieeexplore.ieee.org/document/7807562/*

Schmitt, R. (2002), Electromagnetics Explained, *in* R. Schmitt, ed., 'Electromagn. Explain.', EDN Series for Design Engineers, Newnes, Burlington.
URL: *http://www.sciencedirect.com/science/article/pii/B9780750674034500057*

Schneider, M. (2005), Automotive radar–status and trends, *in* 'Ger. Microw. Conf.'.

Schoettle, B. and Sivak, M. (2014), A SURVEY OF PUBLIC OPINION ABOUT CONNECTED VEHICLES IN THE U.S., THE U.K., AND AUSTRALIA, Technical report, University Of Michigan.

Schuster, F., Worner, M., Keller, C., Haueis, M. and Curio, C. (2016), Robust localization based on radar signal clustering, *in* '2016 IEEE Intell. Veh. Symp.', IEEE, pp. 839–844.
URL: *http://ieeexplore.ieee.org/document/7535485/*

Seo, H., Lee, K.-D., Yasukawa, S., Peng, Y. and Sartori, P. (2016), 'LTE evolution for vehicle-to-everything services', *IEEE Commun. Mag.* **54**(6), 22–28.
URL: *http://ieeexplore.ieee.org/document/7497762/*

Sessions, G. M. (1971), *Traffic Devices: Historical Aspects Thereof*, Institute of Traffic Engineers.
URL: *https://books.google.co.uk/books?id=yj9PAAAAMAAJ*

Shagdar, O., Nashashibi, F. and Tohme, S. (2017), Performance study of CAM over IEEE 802.11p for cooperative adaptive cruise control, *in* '2017 Wirel. Days', IEEE, pp. 70–76.
URL: *http://ieeexplore.ieee.org/document/7918118/*

Shaghaghi, E., Jabbarpour, M. R., Md Noor, R., Yeo, H. and Jung, J. J. (2017), 'Adaptive green traffic signal controlling using vehicular communication', *Front. Inf. Technol. Electron. Eng.* **18**(3), 373–393.
URL: *http://link.springer.com/10.1631/FITEE.1500355*

Shah, H. (2018), 'Use our personal data for the common good', *Nature* **556**(7699).
URL: *http://www.nature.com/doifinder/10.1038/d41586-018-03912-z*

Shapiro, S. S. and Wilk, M. B. (1965), 'An Analysis of Variance Test for Normality (Complete Samples)', *Biometrika* **52**(3/4), 591.
URL: *https://www.jstor.org/stable/2333709?origin=crossref*

Shelby, S. G., Sabra, Z. A. and Soyke, N. (2008), An overview and performance evaluation of ACS Lite–a low cost adaptive signal control system, *in* '87th TRB Annual Meeting'.

Shepherd, S. P. (1992), A REVIEW OF TRAFFIC SIGNAL CONTROL, Technical report, Institute of Transport Studies University of Leeds.

Shin, H.-S., Callow, M., Dadvar, S., Lee, Y.-J. and Farkas, Z. A. (2015), 'User Acceptance and Willingness to Pay for Connected Vehicle Technologies: Adaptive Choice-Based Conjoint Analysis', *Transp. Res. Rec. J. Transp. Res. Board* **2531**(1), 54–62.
URL: *http://journals.sagepub.com/doi/10.3141/2531-07*

Shladover, S. (2017), Connected and Automated Vehicle Policy Development for California, Technical report, University of California Institute of TransportationStudies.
URL: *https://escholarship.org/uc/item/2567n1bc*

Shladover, S. E. (2018), 'Connected and automated vehicle systems: Introduction and overview', *Journal of Intelligent Transportation Systems* **22**(3), 190–200.
URL: *https://www.tandfonline.com/doi/full/10.1080/15472450.2017.1336053*

Shladover, S. E., Nowakowski, C., Lu, X.-Y. and Ferlis, R. (2015), 'Cooperative Adaptive Cruise Control', *Transp. Res. Rec. J. Transp. Res. Board* **2489**.
URL: *http://trrjournalonline.trb.org/doi/10.3141/2489-17*

Siddall, T. (2015), Low Cost MOVA âĂŞ Retrofitting MOVA to Existing SCOOT Controlled Signals for Increased Performance and at Reduced Installation Costs, Technical report, Atkins.
URL: *http://www.jctconsultancy.co.uk/Symposium/Symposium2015/PapersForDownload/Low Cost MOVA - Retrofitting MOVA to Existing SCOOT Controlled Signals for Increased Performance and Reduced Installation Costs.pdf*

Siegel, J. E., Erb, D. C. and Sarma, S. E. (2018), 'A Survey of the Connected Vehicle LandscapeâĂŤArchitectures, Enabling Technologies, Applications, and Development Areas', *IEEE Transactions on Intelligent Transportation Systems* **19**(8), 2391–2406.
URL: *https://ieeexplore.ieee.org/document/8058008/*

Silvestri, S., Goss, K., Guo, Z. and Bhuiyan, A. (2017), 'Algorithms CS2500'.

Simmonite, B. F. (1985), 'LINSIG: A computer program to aid traffic signal design and assessment', *Traffic engineering & control* **26**(HS-039 139).

Simmonite, H. (2008), Fixed Time v Single Stream MOVA Control on a signalled roundabout, Technical report, JCT Consultancy.

Skabardonis, A. (2001), ITS benefits: the case of traffic signal control systems, *in* 'Transp. Res. Board 80th Annu. Meet.'.

Skolnik, M. I. (1962), 'Introduction to radar', *Radar Handb.* **2**.

Skolnik, M. I. (1970), *Radar handbook*, 1 edn, McGraw-Hill.

Skolnik, M. I. (1990), *Radar Handbook*, 2 edn, McGraw-Hill.
URL: *http://www.geo.uzh.ch/microsite/rsl-documents/research/SARlab/GMTILiterature/PDF/Skolnik90.*

Smart Mobility Living Lab (2020), 'Smart Mobililty Living Lab'.
URL: *https://smartmobility.london/*

Smith, B. L., Venkatanarayana, R., Park, H., Goodall, N., Datesh, J. and Skerrit, C. (2011), 'IntelliDriveSM Traffic Signal Control Algorithms'.
URL: *http://www.cts.virginia.edu/wp-content/uploads/2014/04/PFS_SIG99_Final.pdf*

Smith, M. (2015), 'Traffic signal control and route choice: A new assignment and control model which designs signal timings', *Transp. Res. Part C Emerg. Technol.* **58**, 451–473.
URL: *https://linkinghub.elsevier.com/retrieve/pii/S0968090X1500042X*

SMMT (2019), CONNECTED AND AUTONOMOUS VEHICLES, Technical report, SMMT.
URL: *https://www.smmt.co.uk/wp-content/uploads/sites/2/SMMT-CONNECTED-REPORT-2019.pdf*

Sochor, J. and Nikitas, A. (2016), 'Vulnerable users' perceptions of transport technologies', *Proc. Inst. Civ. Eng. - Urban Des. Plan.* **169**(3), 154–162.
URL: *http://www.icevirtuallibrary.com/doi/10.1680/jurdp.14.00054*

Society of Motor Manufacturers and Traders (2017), Connected and Autonomous Vehicles: Revolutionising Mobility in Society, Technical report, Society of Motor Manufacturers and Traders.
URL: *https://www.smmt.co.uk/wp-content/uploads/sites/2/Connected-and-Autonomous-Vehicles-Revolutionising-Mobility-in-Society.pdf*

Solwise (2019), 'Outdoor antenna'.
URL: *https://www.solwise.co.uk/wireless-outdoorantenna-24.htm*

Sommer, C., German, R. and Dressler, F. (2011), 'Bidirectionally Coupled Network and Road Traffic Simulation for Improved IVC Analysis', *IEEE Transactions on Mobile Computing* **10**(1), 3–15.
URL: *http://ieeexplore.ieee.org/document/5510240/*

South China Morning Post (2020), 'China's Baidu finishes building âĂŸworld's largest' test ground for autonomous vehicle, smart driving systems'.
URL: *https://kr-asia.com/chinas-baidu-finishes-building-worlds-largest-test-ground-for-autonomous-vehicle-smart-driving-systems*

Stantec (n.d.), 'ACTIVE-AURORA CV Test Bed Network'.
URL: *https://www.stantec.com/en/projects/canada-projects/a/active-aurora-cv-testbed-network*

Stevanovic, A. (2010), Adaptive Traffic Control Systems: Domestic and Foreign State of Practice A Synthesis of Highway Practice, Technical report, NCHRP.

Stevanovic, A., Dakic, I. and Zlatkovic, M. (2017), 'Comparison of adaptive traffic control benefits for recurring and non-recurring traffic conditions', *IET Intell. Transp. Syst.* **11**(3), 142–151.
URL: *https://digital-library.theiet.org/content/journals/10.1049/iet-its.2016.0032*

Stevanovic, A., Kergaye, C. and Martin, P. (2009), SCOOT and SCATS: A Closer Look into Their Operations, *in* '88th TRB Annu. Meet.'.

Stevanovic, A., Stevanovic, J. and Kergaye, C. (2013), 'Green light optimized speed advisory systems', *Transportation Research Record* **2390**(2390), 53–59.
URL: *http://journals.sagepub.com/doi/10.3141/2390-06*

Stieglitz, S., Mirbabaie, M., Ross, B. and Neuberger, C. (2018), 'Social media analytics - Challenges in topic discovery, data collection, and data preparation', *Int. J. Inf. Manage.*

39, 156–168.
URL: *https://linkinghub.elsevier.com/retrieve/pii/S0268401217308526*

Sun, R., Yang, Y., Chiang, K.-W., Duong, T.-T., Lin, K.-Y. and Tsai, G.-J. (2020), 'Robust IMU/GPS/VO integration for vehicle navigation in GNSS degraded urban areas', *IEEE Sensors Journal* pp. 1–1.
URL: *https://ieeexplore.ieee.org/document/9075286/*

Sun, Z., Li, W., Ban, X. J. and Huang, T. (2018), An Adaptive Traffic Signal Control System (ACS-Lite) in Heavily Congested Arterial Traffic: Experiences and Lessons Learned, *in* 'CICTP 2018', American Society of Civil Engineers, Reston, VA, pp. 1377–1385.
URL: *http://ascelibrary.org/doi/10.1061/9780784481523.138*

Sutton, R. S. and Barto, A. G. (2011), *Reinforcement learning: An introduction*, Cambridge, MA: MIT Press.
URL: *https://s3.amazonaws.com/academia.edu.documents/38529120/9780262257053_-index.pdf*

Svensson, A. (1998), *A method for analysing the traffic process in a safety perspective*, Lund Institute of Technology Sweden.

Swaroop, D. and Hedrick, J. (1996), 'String stability of interconnected systems', *IEEE Trans. Automat. Contr.* **41**(3).
URL: *http://ieeexplore.ieee.org/document/486636/*

Tajalli, M. and Hajbabaie, A. (2018), 'Distributed optimization and coordination algorithms for dynamic speed optimization of connected and autonomous vehicles in urban street networks', *Transp. Res. Part C Emerg. Technol.* **95**, 497–515.
URL: *https://linkinghub.elsevier.com/retrieve/pii/S0968090X18306429*

Tao, S., Manolopoulos, V., Rodriguez, S. and Rusu, A. (2012), 'Real-Time Urban Traffic State Estimation with A-GPS Mobile Phones as Probes', *J. Transp. Technol.* **02**(01), 22–31.
URL: *http://www.scirp.org/journal/doi.aspx?DOI=10.4236/jtts.2012.21003*

The 5G Public Private Partnership (2014), 'DEVELOPMENT OF THE 5G INFRASTRUCTURE PPP IN HORIZON 2020'.

The Engineer (1868), Street Signals, Bridge Street, Westminster, Technical report, The Engineer.
URL: *http://www.ukroads.org/ukroadsignals/articlespapers/18681211_theengineer.pdf*

Thrun, S., Montemerlo, M., Dahlkamp, H. and Others (2006), 'Stanley: The robot that won the DARPA Grand Challenge', *J. F. Robot.* **23**(9), 661–692.
URL: *http://isl.ecst.csuchico.edu/DOCS/darpa2005/DARPA 2005 Stanley.pdf*

Tiaprasert, K., Zhang, Y., Wang, X. B. and Zeng, X. (2015), 'Queue Length Estimation Using Connected Vehicle Technology for Adaptive Signal Control', *IEEE Trans. Intell. Transp. Syst.*

16(4), 2129–2140.
URL: *http://ieeexplore.ieee.org/document/7053921/*

Tonguz, O. K. and Zhang, R. (2019), 'Harnessing Vehicular Broadcast Communications: DSRC-Actuated Traffic Control', *IEEE Trans. Intell. Transp. Syst.* pp. 1–12.
URL: *https://ieeexplore.ieee.org/document/8693532/*

Torvalds, L. and Hamano, J. (2010), 'Git: Fast version control system', *URL http//git-scm.com* .

Trafficware (2019), 'Synchro Studio'.
URL: *https://www.trafficware.com/synchro.html*

Transport for London (2010), Traffic Modelling Guidelines TfL Traffic Manager and Network Performance Best Practice Version 3.0, Technical report, Transport for London, London.
URL: *http://content.tfl.gov.uk/traffic-modelling-guidelines.pdf*

Transport for London (2018), 'TfL marks the 150th anniversary of the traffic light'.
URL: *https://tfl.gov.uk/info-for/media/press-releases/2018/december/tfl-marks-the-150th-anniversary-of-the-traffic-light*

Treiber, M., Hennecke, A. and Helbing, D. (2000), 'Congested traffic states in empirical observations and microscopic simulations', *Phys. Rev. E* **62**(2), 1805–1824.
URL: *http://link.aps.org/doi/10.1103/PhysRevE.62.1805*

Treiber, M., Kesting, A. and Helbing, D. (2006), 'Delays, inaccuracies and anticipation in microscopic traffic models', *Phys. A Stat. Mech. its Appl.* **360**(1).
URL: *http://www.sciencedirect.com/science/article/pii/S0378437105004395*

TRL (n.d.), 'SCOOT'.

TRL Software (2019), 'MOVA'.
URL: *https://trlsoftware.com/products/traffic-control/mova/*

Turri, V., Besselink, B. and Johansson, K. H. (2017), 'Cooperative Look-Ahead Control for Fuel-Efficient and Safe Heavy-Duty Vehicle Platooning', *IEEE Transactions on Control Systems Technology* **25**(1), 12–28.
URL: *http://ieeexplore.ieee.org/document/7445860/*

Udomsilp, K., Arayakarnkul, T., Watarakitpaisarn, S., Komolkiti, P., Rudjanakanoknad, J. and Aswakul, C. (2017), 'Traffic Data Analysis on Sathorn Road with Synchro Optimization and Traffic Simulation', *Engineering Journal* **21**(6), 57–67.
URL: *http://engj.org/index.php/ej/article/view/2180/658*

Uhlemann, E. (2015), 'Active Safety Vehicles Evolving Toward Automated Driving [Connected Vehicles]', *IEEE Vehicular Technology Magazine* **10**(4), 20–23.
URL: *http://ieeexplore.ieee.org/document/7317855/*

UK Government (2019), 'Driving licence categories'.
URL: *https://www.gov.uk/driving-licence-categories*

UK Govt. Dept. Transport (1995), The SCOOT Urban Traffic Control System, Technical report, Department for Transport, UK.

UK Govt. Dept. Transport (2006), Traffic Advisory Leaflet 1/06 - General Principles of Traffic Control by Light Signals, Technical report, Department for Transport, UK.

UK Govt. Dept. Transport (2017), 'VEH0104: Licensed vehicles by body type, by region and per head of population: Great Britain and United Kingdom'.
URL: *https://www.gov.uk/government/statistical-data-sets/all-vehicles-veh01*

UK Govt. Dept. Transport (2019*a*), NTS0905: Car occupancy, England: since 2002, Technical report, Department for Transport, UK.
URL: *https://www.gov.uk/government/statistical-data-sets/nts09-vehicle-mileage-and-occupancy*

UK Govt. Dept. Transport (2019*b*), 'Table RAS30003: Reported road casualties, by severity'.

UK Govt. Dept. Transport (2019*c*), 'Table RAS50001: Contributory factors in reported accidents by severity'.

UK Govt. Dept. Transport (2019*d*), 'Table VEH0126: Licensed vehicles by year of manufacture, United Kingdom'.
URL: *https://www.gov.uk/government/statistical-data-sets/all-vehicles-veh01*

UMTRI (2020), 'UMTRI: Ann Arbour Connected Vehicle test Environment'.
URL: *http://www.aacvte.org/*

United States Department of Transportation (2015), 'Table 1-26 - Average Age of Automobiles and Trucks in Operation in the United States'.

United States Department of Transportation (2016), Vehicle-to-Infrastructure (V2I) Resources For Transportation Planners, Technical report, Department of Transportation, USA.
URL: *http://www.its.dot.gov/v2i/*

Upcroft, B., McManus, C., Churchill, W., Maddern, W. and Newman, P. (2014), Lighting invariant urban street classification, *in* '2014 IEEE Int. Conf. Robot. Autom.', IEEE, pp. 1712–1718.
URL: *http://ieeexplore.ieee.org/document/6907082/*

Urmson, C., Anhalt, J., Bagnell, D. and Others (2008), 'Autonomous driving in urban environments: Boss and the Urban Challenge', *J. F. Robot.* **25**(8), 425–466.
URL: *https://onlinelibrary.wiley.com/doi/pdf/10.1002/rob.20255*

Urmson, C., Baker, C., Dolan, J., Rybski, P., Salesky, B., Whittaker, W., Ferguson, D. and Darms, M. (2009), 'Autonomous Driving in Traffic: Boss and the Urban Challenge', *Al Mag.*

30(2).
URL: *http://citeseerx.ist.psu.edu/viewdoc/summary?doi=10.1.1.182.3644*

US DoT (2015), 'Safety Pilot Programme'.

US DoT (2020*a*), 'Best Practices for Deploying Devices Integrated with Secure Credential Management Systems (SCMS)'.
URL: *https://www.its.dot.gov/pilots/scms_devices.htm*

US DoT (2020*b*), 'CV Pilot Deployment Program'.
URL: *https://www.its.dot.gov/pilots/index.htm*

Uvarov, A. V., Gerasimov, M. Y. and Uvarov, A. V. (2019), 'On the Fundamental Limitations of Ultra-Wideband Antennas', *Journal of Communications Technology and Electronics* **64**(3), 229–233.
URL: *http://link.springer.com/10.1134/S1064226919030185*

Van Arem, B., Van Driel, C. J. G. and Visser, R. (2006), 'The impact of cooperative adaptive cruise control on traffic-flow characteristics', *Intell. Transp. Syst. IEEE Trans.* **7**(4), 429–436.

Van Der Horst, R. (1988), 'Driver decision making at traffic signals', *Transp. Res. Rec.* **1172**, 93–97.

Van Zoonen, L. (2016), 'Privacy concerns in smart cities', *Gov. Inf. Q.* **33**(3), 472–480.
URL: *https://linkinghub.elsevier.com/retrieve/pii/S0740624X16300818*

Varga, A. (2010), OMNeT++, *in* 'Modeling and Tools for Network Simulation', Springer Berlin Heidelberg, Berlin, Heidelberg, pp. 35–59.
URL: *http://link.springer.com/10.1007/978-3-642-12331-3_3*

Vince, A. (2002), 'A framework for the greedy algorithm', *Discret. Appl. Math.* **121**(1-3).
URL: *https://linkinghub.elsevier.com/retrieve/pii/S0166218X01003626*

Vincent, G. R. and Peirce, J. R. (1988), 'MOVA: Traffic responsive, self-optimising signal control for isolated intersections', *TRRL Res. Rep.* **RR170**.

Vinel, A. (2012), '3GPP LTE Versus IEEE 802.11p/WAVE: Which Technology is Able to Support Cooperative Vehicular Safety Applications?', *IEEE Wirel. Commun. Lett.* **1**(2).
URL: *http://ieeexplore.ieee.org/lpdocs/epic03/wrapper.htm?arnumber=6155707*

Vogel, K. (2003), 'A comparison of headway and time to collision as safety indicators', *Accident Analysis & Prevention* **35**(3), 427–433.
URL: *https://linkinghub.elsevier.com/retrieve/pii/S0001457502000222*

Walker, R., Winnett, M., Martin, A. and Kennedy, J. (2005), Puffin crossing operation and behaviour study, Technical Report PPR239, TRL Limited.

Wandinger, U. (2005), *Introduction to lidar*, Springer.
URL: *https://pdfs.semanticscholar.org/3d7f/a175b8ecb80d8bf9ab35535ebe8db83a34fd.pdf*

Ward, E. and Folkesson, J. (2016), Vehicle localization with low cost radar sensors, *in* '2016 IEEE Intell. Veh. Symp.', IEEE, pp. 864–870.
URL: *http://ieeexplore.ieee.org/document/7535489/*

Waterson, B. and Box, S. (2012), 'Quantifying the impact of probe vehicle localisation data errors on signalised junction control', *IET Intell. Transp. Syst.* **6**(2).
URL: *https://digital-library.theiet.org/content/journals/10.1049/iet-its.2010.0113*

Waterson, B. J., Cherrett, T. J. and McDonald, M. (2005), 'The use of simulation in the design of a road transport incident detection algorithm', *J. Oper. Res. Soc.* **56**(11), 1250–1257.
URL: *https://www.tandfonline.com/doi/full/10.1057/palgrave.jors.2601973*

Watkins, J. (2019), *An Introduction to the Science of Statistics: From Theory to Implementation*, 1 edn, University of Arizona, Arizona.
URL: *https://www.math.arizona.edu/ jwatkins/statbook.pdf*

Webster, F. V. (1958), Traffic signal settings, Technical report, London : H.M.S.O.

Webster, N. (2011), Operation of Traffic Signals during Low Demand Periods, Technical report, Department for Transport.

Wei, H., Zheng, G., Yao, H. and Li, Z. (2018), IntelliLight, *in* 'Proceedings of the 24th ACM SIGKDD International Conference on Knowledge Discovery & Data Mining', ACM, New York, NY, USA, pp. 2496–2505.
URL: *https://dl.acm.org/doi/10.1145/3219819.3220096*

Weichenmeier, F., Hildebrandt, R. and Szarata, A. (2015), The Tristar and Kraków systems a PTV Balance and PTV Epics case study, *in* 'The JCT Traffic Signal Symposium'.

Wiedemann, R. and Reiter, U. (1992), 'Microscopic traffic simulation: the simulation system MISSION, background and actual state', *Proj. ICARUS Final Rep.* **2**.

Wilcoxon, F. (1945), 'Individual Comparisons by Ranking Methods', *Biometrics Bulletin* **1**(6), 80.
URL: *https://www.jstor.org/stable/10.2307/3001968?origin=crossref*

Wirtz, S. and Jakobs, E.-M. (2013), 'Improving User Experience for Passenger Information Systems. Prototypes and Reference Objects', *IEEE Trans. Prof. Commun.* **56**(2).
URL: *http://ieeexplore.ieee.org/document/6524067/*

Wongpiromsarn, T., Uthaicharoenpong, T., Wang, Y., Frazzoli, E. and Wang, D. (2012), Distributed traffic signal control for maximum network throughput, *in* '2012 15th Int. IEEE Conf. Intell. Transp. Syst.', IEEE.
URL: *http://ieeexplore.ieee.org/document/6338817/*

Wood, K. (1993), PR41: Urban Traffic Control, Systems Review, Technical report, TRL.

Wood, K., Bielefeldt, C., Biora, F. and Kruse, G. (1998), COSMOS - CONGESTION MANAGEMENT STRATEGIES AND METHODS IN URBAN SITES, Technical report, Transportation Research Laboratory.
URL: *https://www.napier.ac.uk/ /media/worktribe/output-281171/cosmoscongestionmanagementstrategiesandmethodsinurbansitespdf.pdf*

Wood, K., Crabtree, M., Kirkham, A., Maxwell, A. and Robbins, R. (2007), PPR252: Survey of MOVA and SCOOT Operation at M42 Junction 6, Technical report, TRL.

Wu, J. and Hounsell, N. (1998), 'Bus Priority Using pre-signals', *Transportation Research Part A: Policy and Practice* **32**(8), 563–583.
URL: *https://linkinghub.elsevier.com/retrieve/pii/S0965856498000081*

Wünsch, G. (2008), *Coordination of Traffic Signals in Networks and Related Graph Theoretical Problems on Spanning Trees*, Cuvillier Verlag.

Xiang, J. and Chen, Z. (2016), 'An adaptive traffic signal coordination optimization method based on vehicle-to-infrastructure communication', *Cluster Comput.* **19**(3), 1503–1514.
URL: *http://link.springer.com/10.1007/s10586-016-0620-7*

Xiaoxu Ma and Grimson, W. (2005), Edge-based rich representation for vehicle classification, *in* 'Tenth IEEE Int. Conf. Comput. Vis. Vol. 1'.
URL: *http://ieeexplore.ieee.org/lpdocs/epic03/wrapper.htm?arnumber=1544855*

Xu, B., Ban, X. J., Bian, Y., Li, W., Wang, J., Li, S. E. and Li, K. (2019), 'Cooperative Method of Traffic Signal Optimization and Speed Control of Connected Vehicles at Isolated Intersections', *IEEE Trans. Intell. Transp. Syst.* **20**(4), 1390–1403.
URL: *https://ieeexplore.ieee.org/document/8408521/*

Yang, K., Guler, S. I. and Menendez, M. (2016), 'Isolated intersection control for various levels of vehicle technology: Conventional, connected, and automated vehicles', *Transp. Res. Part C Emerg. Technol.* **72**.
URL: *http://www.sciencedirect.com/science/article/pii/S0968090X16301437*

Yang, S., Kalpakis, K. and Biem, A. (2014), 'Detecting Road Traffic Events by Coupling Multiple Timeseries With a Nonparametric Bayesian Method', *IEEE Trans. Intell. Transp. Syst.* **15**(5), 1936–1946.
URL: *http://ieeexplore.ieee.org/document/6763098/*

Yang, X. K. (2001), 'Comparison among Computer Packages in Providing Timing Plans for Iowa Arterial in Lawrence, Kansas', *Journal of Transportation Engineering* **127**(4), 311–318.
URL: *http://ascelibrary.org/doi/10.1061/%28ASCE%290733-947X%282001%29127%3A4%28311%29*

Yang, X. T., Chang, G.-L., Zhang, Z. and Li, P. T. (2019), 'Smart Signal Control System for Accident Prevention and Arterial Speed Harmonization under Connected Vehicle Environment', *Transp. Res. Rec. J. Transp. Res. Board* **2673**(5), 61–71.
URL: *http://journals.sagepub.com/doi/10.1177/0361198119837242*

Yao, Z., Jiang, Y., Zhao, B., Luo, X. and Peng, B. (2019), 'A Dynamic Optimization Method for Adaptive Signal Control in a Connected Vehicle Environment', *J. Intell. Transp. Syst.* pp. 1–17.
URL: *https://www.tandfonline.com/doi/full/10.1080/15472450.2019.1643723*

Yulianto, B. (2018), Detector technology for demand responsive traffic signal control under mixed traffic conditions, *in* 'AIP Conference Proceedings 1977, 040021'.
URL: *http://aip.scitation.org/doi/abs/10.1063/1.5042991*

Zhang, C., Xie, Y., Gartner, N. H., Stamatiadis, C. and Arsava, T. (2015), 'AM-Band: An Asymmetrical Multi-Band model for arterial traffic signal coordination', *Transportation Research Part C: Emerging Technologies* **58**, 515–531.
URL: *https://linkinghub.elsevier.com/retrieve/pii/S0968090X15001552*

Zhang, K. and Batterman, S. (2013), 'Air pollution and health risks due to vehicle traffic', *Sci. Total Environ.* **450-451**.
URL: *https://linkinghub.elsevier.com/retrieve/pii/S0048969713001290*

Zhang, R., Song, L., Jaiprakash, A., Talty, T., Alanazi, A., Alghafis, A., Biyabani, A. A. and Ozan Tonguz, A. (2019), Using Ultra-Wideband Technology in Vehicles for Infrastructure-free Localization, *in* '2019 IEEE 5th World Forum on Internet of Things (WF-IoT)', IEEE, pp. 122–127.
URL: *https://ieeexplore.ieee.org/document/8767347/*

Zhang, Z., Schwartz, S., Wagner, L. and Miller, W. (2000), 'A Greedy Algorithm for Aligning DNA Sequences', *J. Comput. Biol.* **7**(1-2).
URL: *http://www.liebertpub.com/doi/10.1089/10665270050081478*

Zhao, B. (2019), Connected Cars in China: Technology, Data Protection and Regulatory Responses, *in* A. Rossnagel and G. Hornung, eds, 'Grundrechtsschutz im Smart Car', 1 edn, Springer Vieweg, Wiesbaden.
URL: *http://link.springer.com/10.1007/978-3-658-26945-6_24*

Zhao, Y. and Tian, Z. (2012), 'An Overview of the Usage of Adaptive Signal Control System in the United States of America', *Appl. Mech. Mater.* **178-181**, 2591–2598.
URL: *https://www.scientific.net/AMM.178-181.2591*

Zheng, F. and Van Zuylen, H. (2013), 'Urban link travel time estimation based on sparse probe vehicle data', *Transportation Research Part C: Emerging Technologies* **31**, 145–157.
URL: *https://linkinghub.elsevier.com/retrieve/pii/S0968090X12000575*

Zhou, H., Hawkins, H. G. and Zhang, Y. (2017), 'Arterial signal coordination with uneven double cycling', *Transp. Res. Part A Policy Pract.* **103**.
URL: *https://linkinghub.elsevier.com/retrieve/pii/S0965856416305146*

ZigBee Alliance (2012), 'Zigbee specification'.

Zirari, S., Canalda, P. and Spies, F. (2010), WiFi GPS based combined positioning algorithm, *in* '2010 IEEE Int. Conf. Wirel. Commun. Netw. Inf. Secur.', IEEE.
URL: *http://ieeexplore.ieee.org/document/5544653/*

Zou, B., Li, W. and Wang, D. (2019), 'Analysis on current situation of China's intelligent connected vehicle road test regulations', *MATEC Web of Conferences* **259**, 02003.
URL: *https://www.matec-conferences.org/10.1051/matecconf/201925902003*