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Exploring Person-based Signal Control Paradigms

in Urban Road Networks

by

Zongyuan Wu

Thesis for the degree of Doctor of Philosophy

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Abstract

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Connected vehicle technology can provide traffic signal controllers with abundant types of data resources, e.g., vehicle occupancy data, etc. The provided data can be used to improve the performance of signal control methods and enable conversion from vehicle-based controls to person-based controls, which focus on optimizing person-related objective values, such as minimising average person delay. However, so far research in relevant fields has not fully exploited potential paradigms and benefits of person-based controls. In respect of such, this study has provided a better understanding about the impacts of occupancy information collected from connected vehicles (CVs) on urban signal controls and potential benefits to person-related performance that those information can bring.

The contributions of this study include: 1) development of a three-layered DP person-based signal control mechanism (PerSiCon-Junction) in a fully CV environment at an isolated junction with a signal phase transition exploration mechanism and car-following updating theories; 2) development of a person-based control mechanism (PerSiCon-Bus) with completely flexible signal plans to apply the PerSiCon-Junction to more complex vehicle mixtures of cars and buses in a generalized 8-phases options junction; 3) proposal of a coordinated paradigm PerSiCon-Network to better understand how PerSiCon-Bus with flexible phase combinations and stage sequences should be implemented in multiple junctions; 4) realistic case and scenarios studies that assess the performance of the proposed method against benchmarking models involving vehicle-based controls using CV data; and 5) proposal of a EUVO algorithm to estimate status of unequipped vehicles with occupancy so as to improve the behaviour of PerSiCon-Network under imperfect CV penetration rate environments.

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Research Thesis: Declaration of Authorship

Print name: Zongyuan Wu

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I, Zongyuan Wu, declare that this thesis 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;
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7. Parts of this work have been published as: see Appendix A for more information

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Zongyuan Wu

Date: 05/01/2022

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Definitions and Abbreviations

AASHTO	American Association of State Highway and Transportation Officials
APC	Automated Passenger Counting
AV	Autonomous Vehicle
AVL	Automatic Vehicle Location
BSM	Basic Safety Message
CAM	Cooperative Awareness Message
CAV	Connected and Autonomous Vehicle
CEBR	Centre for Economics and Business Research
CTR	Cumulative Travel-Time Responsive
CTT	Cumulative Travel Time
CV	Connected Vehicle
DC	Distributed-Coordinated
DENM	Decentralized Environmental Notification Message
DfT	Department for Transport
DP	Dynamic Programming
DSRC	Dedicated Short Range Communication
EUVO	Estimation status of Unequipped Vehicle with Occupancy
EVLS	Estimation of Location and Speed
FCC	Federal Communications Commission
FIFO	First-In-First-Out
FSM	Four-Step Model
GPS	Global Positioning System
HGV	Heavy Goods Vehicle
HOV	High Occupancy Vehicle
ILACA	Inductive Loop Actuated Control Algorithm
ILACA-Network	Inductive Loop Actuated Control Algorithm in Road Network
IMA	Junction Management Agent
ITS	Intelligent Transportation Systems
JRC	Joint Research Centre
KPI	Key Performance Indicator
LGV	Light Goods Vehicle
MOVA	Microprocessor Optimised Vehicle Actuation
MC	Motorcycle
NMEA	National Marine Electronics Association

NP	Non-deterministic Polynomial
OBU	On-board Units
OGV	Other Goods Vehicle
OPAC	Optimisation Policies for Adaptive Control
PerSiCon-Bus	Person-based Adaptive Control Algorithm with Buses
PerSiCon-Junction	Person-based Adaptive Control Algorithm in Isolated Junction
PerSiCon-Network	Coordinated Person-based Signal Control in Road Network
PMSA	Predictive Microscopic Simulation Algorithm
PSV	Public Service Vehicle
PRODYN	PROgramme DYNamique
RHODES	Real-time Hierarchical Optimised Distributed Effective System
RSU	Road-Side Unit
SAE	Society of Automotive Engineers
SCAT	Sydney Coordinated Adaptive Traffic Signals
SCOOT	Split Cycle and Offset Optimisation Technique
SPaT	Signal phases and timing
STM	Signal Timing Manual
SUMO	Simulator of Urban Mobility
SVD	Selective Vehicle Detectors
TRANSYT	Traffic Network Study Tool
TRANSYT-Network	Traffic Network Study Tool in Road Network
TSP	Transit Signal Priority
UTC	Urban Traffic Control
UV	Unequipped Vehicle
VA	Vehicle Agents
VANET	Vehicular Ad-Hoc Networks
VehSiCon	Vehicle Based signal control using data from CVs
VehSiCon-Network	Vehicle Based signal control using data from CVs in Road Network
V2I	Vehicle-to-Infrastructure
V2S	Vehicle-to- on-board Sensors
V2V	Vehicle-to-Vehicle
WAVE	Wireless Access in Vehicular Environments

Chapter 1 Introduction

1.1 Problems and challenges in urban roads

Due to rapid growth of urban population, car ownerships and passenger vehicle miles travelled, traffic delay and congestion has been increasing in urban areas. In the UK in 2019, motor vehicle and passenger miles travelled have reached record high of 357 billion vehicle miles and 873 billion passenger-kilometres, respectively, or 186% and 117% increment over the past 50 years, respectively (UK Govt. Dept. Transport, 2019a). In 2020, vehicle and passenger miles travelled decreased by 21% and 33% from one year ago, respectively, owing to the COVID-19 pandemic starting in March 2020 (UK Govt. Dept. Transport, 2020). However, it is unclear whether such decrease will remain for long time. As a matter of fact, congestions at UK city centres in 2021 have shown signs of recovery back to 2019 levels along with ease of lockdown policies (INRIX, 2021).

Traffic delays and congestions often lead to excessive waste of time for vehicle users and passengers and costs of economic activities. According to statistics from INRIX, each British driver and passenger lost 73 hours in traffic on average in 2021, which is lower than the 115 hours in 2019 pre-COVID but significantly higher than the 37 hours in 2020 (INRIX, 2021). For each Brits, the average time spent by sat in traffic in 2021 equals to £595 of traffic cost or £8 billion nationwide (INRIX, 2021). Table 1.1 lists the 10 most congested urban areas in the UK in 2021. It indicates that congestion circumstances in London are most serious. London is also one of the most congested cities in the world in 2021. Drivers in Paris and New York lost an average of 140 and 102 hours due to traffic congestion in 2021, respectively (INRIX, 2021).

Urban delay and congestion is expected to worsen in the future. There is no forecast on congestion cost in recent years, but it can still be roughly calculated from the forecast of vehicle miles and fuel prices. The world's population is predicted to increase by 147% from 2019 to 2050 (United Nations, 2019). Traffic volume levels and congestion in England and Wales are also expected to increase by 17% to 51% and 8% to 16% from 2015 to 2050, respectively (UK Govt. Dept. Transport, 2018a). In addition, the petrol and dispel fuel prices in the UK in November 2021 has reached 150 pence per litre, the highest level over the past five years (Department for Business, Energy and Industrial Strategy, 2021). Therefore, urban congestion will result in increasing transportation-related costs for people living in big cities. Conventional approaches, such as constructing new roads and lanes, are not feasible solutions in most urban cities due to political and environmental concerns along with limited lane resources and infrastructure construction restrictions (Baskar et al., 2011). Instead, efficient traffic management on existing infrastructures has become increasingly essential to reduce traffic congestion, travel time loss and related costs. For example, the UK Department for Transport (DfT) has recently highlighted the challenges for future urban person mobility and proposed to utilise data sensing technology (UK Govt. Dept. Transport, 2019b). If person-based signal controls can improve person mobility significantly over vehicle-based signal controls, lots of benefits such as people travel time loss saving, congestion cost reduction and traffic demand reduction can be achieved.

Table 1. 1 10 most congested urban areas in the U.K. (INRIX, 2021)

2021 UK Rank	Urban Area	Average Delay 2021 (hours)	2021 Driver Cost	2021 City Cost
1	London	148	£1,211	£5.1B
2	Cambridge	75	£618	£11M
3	Bristol	66	£542	£28M
4	Exeter	71	£578	£36M
5	Cheltenham	71	£576	£140M
6	Manchester	62	£502	£35M
7	Belfast	60	£487	£32M
8	Birmingham	53	£434	£123M
9	Nottingham	58	£469	£65M
10	Hull	56	£459	£226M

1.2 Existing urban traffic control system and limitations

Traffic signal junctions are essential components of urban road network. Traffic signal control system is one of major traffic management approaches to control vehicle flows by scheduling traffic light schemes for competing flows and allowing vehicles to share the junction spaces without collision (Gordon and Tighe, 2005). Urban Traffic Control (UTC) systems has developed rapidly with improved hardware and control strategies. Current UTC systems formulate signal timing plans based on either historic data (fixed-time signals) or real-time data collected by sensors (inductive loops, radar, infrared) at fixed locations. The below are three major UTC strategies (Feng et al., 2015):

1. **Fixed-time control strategies** do not change phase durations and cycle lengths. The phase sequence and phase durations of fixed-time control are pre-determined by local historical traffic data for different times of a day (Jing et al., 2017). Therefore, fixed-time control methods do not require any further infrastructures to measure traffic demand. The infrastructure construction and maintenance costs can be saved. Nevertheless, fixed-time strategies have poor flexibility and are insensitive to traffic flow fluctuations during the day

(Maslekar et al., 2013), leading to frequent traffic congestion and disturbance to high-priority vehicles such as emergency vehicles.

2. **Actuated signal control strategies** collect real-time traffic data using sensors, such as loop detectors, radar and video detectors. They adjust signal cycle lengths, phase durations and signal sequences by applying simple logic-like extending unit green time (Feng et al, 2015). Actuated signal controls have a better response to real-time traffic flows than fixed-time control. Apart from that, simple signal logics can also save computational expenses. However, the availability of real-time detection is limited at traffic flows on green phase roads, despite those lanes on red phase with vehicle information. Moreover, actuated traffic signals rely on a set of pre-defined static parameters, such as unit extension time, minimum and maximum green time to transform collected data into traffic control strategies (Jing et al., 2017). Furthermore, the coverage of infrastructure-based detectors is low due to high installation and maintenance costs.
3. **Adaptive signal controls strategies** use similar information resources as actuated control to acquire data (e.g., speed and acceleration) from the upstream urban road. They are advantageous in respect of estimating short period incoming traffic flows and able to reach maximum or minimum objective functions by optimizing timing strategies. Current well-known adaptive control strategies include SCATS (Besley et al., 1998), OPAC (Gartner, 1983), SCOOT (Bing and Carter, 1995), RHODES (Mirchandani and Head, 2001), PRODYN (Henry et al., 1984) and MOTION (Brilon and Wietholt, 2013).

Traditional actuated and adaptive signal strategies currently can only partially adjust their decisions to variable demand (Guler et al., 2014). With rapid technological developments, the performance of UTC systems can be improved. However, there are still two major limitations preventing UTC systems from tackling urban congestion and cost issues:

The first limitation of UTC systems is inadequate traffic data collected from inductive loop detectors and other existing sensors. Traffic data collection sensors (e.g. inductive loops embedded under roads) in most commonly used UTC systems are point detectors, which can only provide a brief snapshot of vehicles (Box and Waterson, 2010). It is thus challenging for UTC systems to understand accurately the state of vehicular environments and accordingly make signal timing decisions. This issue can be addressed by the advancement in wireless communication technologies. With the developments of Vehicle-to-Infrastructure (V2I) and Vehicle-to-Vehicle (V2V) communication systems (Qu et al, 2010), new data sources are available for signal control optimization by accessing to road and vehicle states. New data stream that is continuously that is continuously provided by Connected Vehicles (CVs) can deliver information such as vehicle locations, speeds and accelerations to traffic signal controllers. This area has become the focus of current research where great improvements have been achieved.

The second limitation of existing UTC systems is they are all vehicle-based but not person-oriented. In other words, the optimization objectives of these signal controls are to reduce total vehicle delays, vehicle travel time, and number of stops or increase vehicle throughput. Thus the importance of personal mobility in urban networks has been ignored (Vilarinho et al., 2017). But most of the cost caused by urban road congestions are measured by how much time a person has spent rather than a vehicle. Those vehicle-based signal control optimizations tend to cause unfair treatment of vehicles with high occupancy level. Therefore, development of person-based controls is more useful with respects to reducing delays, congestion and related costs. The person-based controls optimize signal timing plans using CV data and occupancy data of CV. However, fixed point detectors used by UTC systems can only count the number of arrival vehicles at a certain time. It is difficult for them to obtain vehicle occupancy data. This issue has been addressed by application of advanced CV communication technology, detailed in Sections 1.3.3 and 2.4.

1.3 Motivations of this research

As mentioned above in Section 1.2, existing UTC systems have some limitations which can be addressed by CV technology and sufficient data resources. The connected vehicle technologies can potentially reduce congestion on the entire road network by providing real-time vehicle trajectory data to signal control systems. Moreover, they collect the occupancy information of every vehicle connected as a prerequisite of proposing person-based control. The state-of-the-art researches only focus on improving the first limitations at present.

This section investigates the importance of implementing person-based signal control systems, the introduction of CV technology for technical realization, what progress has been achieved by researchers in this field and the potential benefits of developing person-based signal control systems.

1.3.1 Time loss savings and cost reduction

The major motivation for researching person-based signal control systems is the potential benefits of time loss savings and cost reductions for passengers. INRIX (2018) research estimated that the total congestion cost across US, UK and Germany almost reaches 461 billion dollars. The direct cost accounts for a great proportion of the total costs of congestion, which is mainly a result of the needlessly time wasted by drivers and passengers in congestion. The calculation of direct costs of congestion is associated with time loss of average drivers, different values of time and different vehicle occupancy rates among three countries (INRIX, 2018). In other words, the direct costs of congestion largely depend on the time loss and related costs of all people in one vehicle rather than the vehicle itself. The situation of a high occupancy vehicle (e.g. 4 people in a vehicle) suffering from heavy congestion is worse than a low occupancy vehicle (e.g. 1 person in a vehicle) under that case as the time losses of all people in high occupancy vehicle will increase. On the contrary, reducing delay of the vehicles with more people can significantly save the time loss and cost reduction.

However, notably that improving urban mobility and reducing total passenger delay in the current level of congestion is not a straightforward task. The global average time loss of every person in urban areas due to congestion is predicted to be 106 hours per year in 2050, three times higher than the value in 2018 (Lerner, 2018). The costs of urban mobility are estimated to be 829 billion euros, which are four times greater than those costs in 1990 worldwide.

A study for vehicle-based adaptive signal control based on wireless communication (Wang et al., 2018) suggested great flexibility than the existing UTC system as more detailed data sources were provided for the signal decision-making process. The utilisation of cheaper detectors in V2V and V2I communication systems, such as On-board Units (OBU), Dedicated Short-Range Communication (DSRC), and satellite navigation systems, also significantly reduces costs. However, additional spaces can be further explored to reduce total people time losses and costs by transferring adaptive vehicle-based signal controls to adaptive person-based controls. This is because the objectives and metrics of vehicle-based systems are measured by vehicles and do not consistent with the costs of congestion measured by people. Although there is no exact statistics for vehicle occupancy level distributions, the reasonable estimates for different ratios of vehicle occupancy based on average occupancy statistics in Section 2.3 indicate that vehicle occupancy is not a constant. While vehicle-based control systems regard all vehicles on the road as the same occupancy level.

Some policies in transport have realized the importance of reducing person delay or providing more delay reduction chances to those vehicles with high occupancies. Bus priority schemes are critical strategies to protect bus services with a great level of priority and to improve the reliability of buses, thus enhancing the levels of services to bus passengers (Ahmed, 2014). Bus priority plays an important role in public transport and is advocated by most cities and towns worldwide due to its large passenger capacity and applicability in limited urban road spaces (Cheney, 1992). Supposing that the delay of bus significantly reduces through bus priority strategy, travel time of the mass amount of passengers would also be reduced so that it contributes greater to savings of people time losses and related costs than passenger vehicles. This priority idea has expanded to high occupancy private cars through implementing High Occupancy Vehicle (HOV) lanes (Stamos et al., 2012) in some cities to ensure faster, more reliable travel of those vehicles with high occupancies.

Owing to this, one of the principles proposed by DfT for improving urban people's mobility is to reduce urban congestion through more efficient use of limited road space and innovative approaches, such as increasing vehicle occupancy rates or car consolidating. However, implementing HOV lanes is a conventional method to respond to this principle like constructing new roads, which do not fit with efficient utilisation of limited land resources. The person-based signal control systems have potential benefits to reduce personal costs and improve urban mobility, which is worthy to research.

1.3.2 Pressures on increasing traffic demand

The values of average occupancy for cars and vans in England fluctuated between 1.55 and 1.6 from 2002 to 2019 (seen in Figure 1.1). In 2020, the average car occupancy in England decreases to 1.49 affected by the COVID-19 pandemic, as a result of trip restrictions imposed by authorities and fear of infection by individuals. Based on this level, the UK Department of Transport (DfT) forecasted traffic growth of approximately 35% over the 2015 and 2050 period due to increasing car ownership and vehicle miles travelled with the assumption of a 1.5 average car occupancy rate. DfT also carried out sensitivity tests to observe the influences of changing car occupancy to traffic demand. The average car occupancy rate is assumed to be 1.3 and 1.7 in 2050 in the private travel test and ride-sharing test respectively to represent changes in average car occupancy in different modes. As a result, road traffic is estimated to grow 55% between 2015 and 2050 in case of average vehicle occupancy rate decreases from 1.5 to 1.3 (UK Govt. Dept. Transport, 2019b). Contrarily, if the average vehicle occupancy value rises from 1.5 to 1.7, the increment of traffic demand during the same period will only be 5%. The results indicate big differences in traffic demand increment even if there are only slight changes in average car occupancy. The increasing rate of low occupancy vehicles possibly caused by private travel will deteriorate the increasing traffic level demand in future. However, a bit higher average car occupancy rate could dramatically relieve pressures on future traffic demand. Ride-sharing is one way to potentially increase the average car occupancy level. The person-based signal controls may also contribute to increasing the vehicle occupancy levels from the perspective of urban signal control if it can assign higher priority to high occupancy vehicles, enabling them to suffer less delay and congestion on urban roads.

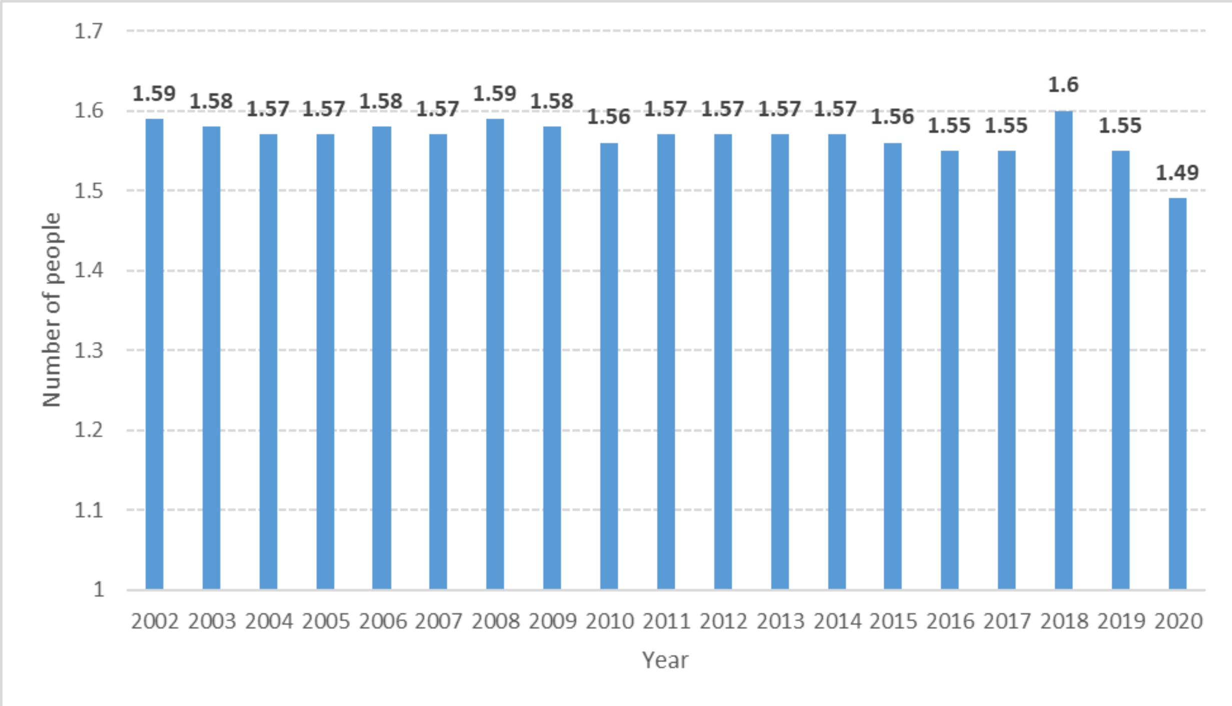


Figure 1. 1 Average car and van occupancy in England from 2002 to 2020 (UK Govt. Dept. Transport, 2021a)

1.3.3 Connected vehicle technology

Connected Vehicle (CV) technology (see details in Chapter 2) emerges promptly in to response the urgent requirement of improving traffic congestion and delays. Intelligent Transportation Systems (ITS) have demonstrated the potential of absorbing technologies from multiple disciplines to improve current transport conditions for CVs (Qu et al., 2010). Meanwhile, CVs are expected to deliver enormous mobile data demand flow in transport-related applications (Lu et al., 2014). CVs equipped with on-board devices and sensors enable the acquisition of self-vehicular data. By means of powerful, interoperable networked wireless communications, connected vehicles create a communication environment with other road elements.

Within a definite network communication scope, CVs achieve information exchange to other connected vehicles (V2V), roadside infrastructure (V2I), as well as on-board sensors (V2S). Those interactions combine several developing network technologies such as cellular, Wi-Fi, satellite radio, or DSRC into wireless communications to provide an enriched information platform. For instance, advanced vehicle sensors are used for collecting real-time vehicle and driver status. On-board computer processing system copes with data streamed from V2I and V2I communications in coordination with mobile smart devices (Olia et al., 2016). GPS navigations also provide more accurate vehicle positions and other vehicular parameters (Faezipour et al., 2012). Hence, the connected vehicle system makes multiple levels of data sensing, gathering, sharing, computing and releasing to be possible through two-way connectivity (shown in Figure 1.2). Thus complicated information broadcast and multiple events can be realized simultaneously (Qu et al., 2010).

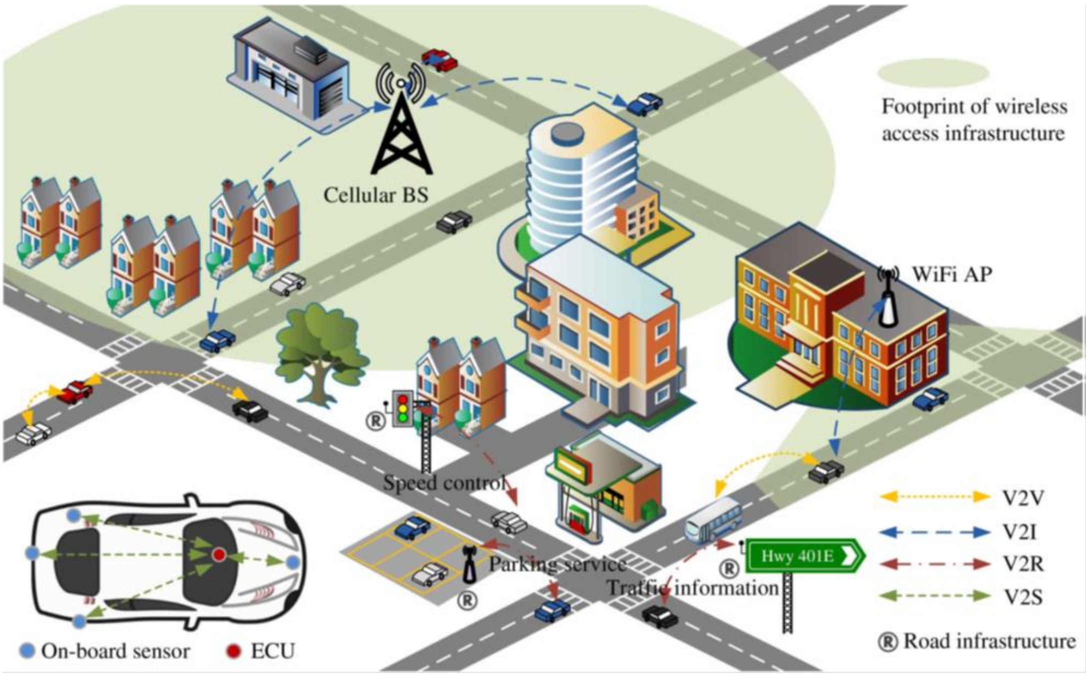


Figure 1. 2 Overview sketch map of connected vehicle (Faezipour et al., 2012)

Due to the powerful data handing capacity and wide applicability, CV has been developed and deployed in many transport areas (Chang et al., 2015). The main aspects include driver safety, infotainment, dealer services, location-based services, quality & reliability and customer experience (SAS Institute GmbH, 2016). Not like the traditional methods adopted to alleviate the damages and destroy when accidents occur, such as airbags or sudden deceleration manoeuvres, safety applications aim to avoid vehicle crashes. Safety applications are designed to process high hazard awareness towards surrounding environments (Uhlemann, 2015). The collision avoidance system warns when it is too near to surrounding vehicles and adjust the vehicle speed automatically (Qu et al., 2010). While mobile applications enhance the travel ability of vehicles by warning drivers of the upcoming flow and recommending the corresponding speed (UK Govt. Dept. Transport, 2019b). As for environment applications, they provide more information about signal timings and phases to help drivers adjust the speed to pass through the junction when the lights are green (Zlotchenko, 2017), and thus reaching the targets of reducing stops or decelerations frequency in a more eco-friend way.

Connected cars also have extremely promising prospects for development. The numbers of new produced connected vehicles meet a booming surge in a future short period. The size of the globally connected car fleet on the road in 2021 is estimated to be 237 million units. European Union accounts for almost 30% of the globally connected car fleet with 76 million units (Martin

Placek, 2021). In 2035, the size of the connected car fleet in the European Union is predicted to be 261 million units. In terms of the UK, 71% of all newly registered vehicles on road in 2019 are estimated to be connected vehicles (Statista Research Department, 2022). From the statistics forecasted by Statista Research Department, all of the new vehicles registered on road in the UK would be connected starting from 2026.

The significantly demands for CVs in the future result in great development and profits in the CV devices market. According to the statistics in 2020, the total value of the global connected cars market was USD 55.56 billion, while it would be expected to account for USD 191.83 billion by 2028 (Fortune Business Insights, 2022). Moreover, the generated revenue of the globally connected car market in 2025 will reach USD 198 billion, which is almost triple that of value in 2019 (USD 72 billion) (P&S Intelligence, 2020). As for Europe and UK, Europe's connected car market is expected to reach USD 37.15 billion in 2026, with a 7% compound annual growth rate (Market Data Forecast, 2022). The market for Connected and Autonomous Vehicles (CAVs) in the UK is forecasted to be worth £41.7 billion in 2035, accounting for 6.4% of the global market (Connected Places Catapult, 2020). These statistics indicate that the CVs, in terms of passenger cars, will be mainstream in the future road network. However, they still need a process to transit from a low CV penetration rate in the current stage. These statistics highlight the rapidly growing tendency of CVs on roads with a mass amount of available real-time data. Understanding how to utilise this connected information on improving urban mobility and reducing congestion and costs is very important.

1.3.4 Proposed urban signal controls in connected vehicle environment

There is a great number of researches being carried out to explore the future possibilities of new urban signal control paradigms with more powerful effectiveness over UTC systems due to restrictions of constructing new roads and principles of efficiently making use of limited land resources. The decision-making processes of existing UTC systems completely do not incorporate available new data from rising numbers of CVs. The development of connected vehicle technologies brings unique opportunities for the improvement of urban signal controls as they can help junction control realize the state of road environments by delivering vehicular detailed information (e.g. positions, speeds, accelerations). A study made by Olia et al. (2016) has suggested that CVs have the potential of reducing 37% of corridor travel time by providing more route information to drivers. A High Bid control algorithm was also proposed on the basis of position and speed additional data and outperformed the MOVA control system as a baseline, in terms of 25% delay reduction achieved (He et al., 2012). These researches highlight the potential benefits of utilising CV information in traffic signal controls, hence why the state-of-the-art researches and this project concentrates on developing new urban signal control systems by incorporating connected data sources as inputs.

A series of urban signal control algorithms have been developed to solve road congestion problems under connected vehicle environments. As discussed in Section 1.3.3, the number of CVs is dramatically rising and a great amount of data can be collected from CVs to provide a better realization of road networks. Therefore, the state-of-the-art urban signal control systems are reviewed in this project (see details in Chapter 2) to understand what has been achieved in this field, also which kind of connected data could be useful, how to use connected information in the urban signal control paradigm and what are benefits of using such information.

Adaptive urban signal controls using CV data can be mainly divided into three roughly directions. (1) paying attention to fully connected and autonomous vehicles' trajectory and incorporating them into signal control schemes (Li and Wang, 2006); (2) central signal controllers optimize the signal timing phases according to positions and speeds information of connected vehicles (He et al., 2012); (3) considering different discharge sequences for each individual vehicle; providing prepared reservations for them at junctions in advance, or optimizing vehicle platoon sequence of departures (Guler et al., 2016). They took into account connected vehicle information, such as current speeds, positions, and headings used for describing trajectories and movements of CVs as inputs of the proposed signal control algorithm. A variety of vehicle-based objective functions were established as aims of developing control methods, for instance, reducing vehicle delays, number of vehicle stops, queuing lengths, maximum vehicle throughputs and junction capacities.

The analysing results of a number of signal control researches indicated that the connected vehicle signal control method significantly improves the performance of vehicle-based objectives against benchmarking existing control strategies. For instance, a study found a proposed junction signal control algorithm minimising vehicle delay using information from CVs can decrease average delay per vehicle by up to 60% compared to fixed time control (Guler et al., 2016). However, in the latest years, researchers focused on testing the connected vehicle model in more realistic scenarios and attempted to identify the possibilities of implementing these models in real-world road networks. There are parts of researches that applied proposed models in more authentic road environments, like different traffic demand levels and various connected vehicle penetration rates. However, only a small group of researchers attempted to consider vehicle priorities at different levels given different vehicle occupancies.

1.3.5 Potential benefits of adaptive person-based urban signal controls

In recent years, few studies introduced the concept of person-based signal controls. Person-based signal controls change the objective function for optimization from vehicle-related metrics in vehicle-based controls to person-related metrics and assign corresponding weights to CVs according to their individual occupancy data. Optimal signal plans in person-based controls are expected to reduce travel times, delays and the number of stops of all people in vehicular environments (drivers and passengers) and perform more powerful than vehicle-based controls in this subject area. If this target could be achieved, the outlined problems above, such as enhancing time loss savings of people, cost reduction, and improving person mobility are possible to be improved. The pressures of increasing traffic demands in future can also be significantly relieved by assigning more priorities to those high-occupancy vehicles to encourage car-sharing behaviours.

It is important to recognize the potential benefits that could be achieved if person-based urban signal controls are developed so as to determine whether the study of exploring person-based signal controls is worthy. Although there are no completely ready-made person-based urban controls, the performance and effects of bus priority strategies can be taken as references due to their similar principles of providing different priority levels to different occupancy vehicles (buses and passenger cars) accordingly.

Daniel et al. (2004) conducted a survey of the impacts and benefits of signal priority for buses through accessing a number of bus priority schemes in USA cities. The bus priority plans in Los Angeles decreased 20-27% of overall bus travel time over no priority strategy. Similarly, a 34% of average bus delay reduction was found in Seattle when a bus was eligible for priority treatment. These statistics highlight that the travel time and delay of buses could be reduced with higher priority treatments. In this case, a relatively large number of passengers on buses can save their travel time; total time losses and congestion cost savings will be higher than those of low occupancy vehicles. Therefore, exploring person-based signal controls has the potential of reducing travel time losses and related costs for urban people, responding to urban mobility strategy in future.

The connected vehicle technology is also considered to be applied to Transit Signal Priority (TSP) as real passenger numbers in buses are not incorporated in traditional bus priority schemes. Various public transport priority systems give priority to public transport (e.g. buses) in case of priorities request (more details can be found in Section 2.1.2) by signal timing adjustments (e.g., green extension, recall, stage skipping) (Diakaki et al., 2013). With the introduction of Connected Vehicles (CVs), TSP researches assumed that detailed occupancy information, which is a necessary data input in person-based controls, can be collected from both connected passenger cars and connected buses in the system. This makes the transit priority system better react to the arrival statuses of public transits and it can be used to improve the performance of traditional TSP strategies. Based on this, the research problems of person-based control become: if relevant connected vehicle data is available in signal controls, what the decision algorithm would look like to be, what are roles of these connected data and what kinds of benefits could be achieved by person-based signal controls over vehicle-based controls. This research will be carried out to answer these problems.

1.4 Unanswered questions for urban signal controls under CV environment

A number of connected vehicle-based urban junction control managements have been developed to identify the improvements brought by real-time data from connected vehicles. However, the majority of current research about urban signal control methods under the CV environment only exploited a small part of available connected information. Meanwhile, they regarded all of the vehicles on the road as are same and focused on vehicle delay rather than person delay. While the connected TSP approaches, which provide higher priority to public transport vehicles, inspire the urban signal control strategies that connected vehicles on road should be treated differently. Besides, they attempted to insert or remove specific stages and breaking the fixed stage sequences in order to make give the highest priority to transits. There are some TSP-related papers that considered the occupancy levels in passenger cars and developed person-based delay signal control methods. Few person-based approaches also attempted to achieve person-related objectives by incorporating occupancy data into their methods, but only changed the objective function value to optimize the signal plans.

However, there is no research that attempts to thoroughly investigate how person-based traffic signal timing schemes and traffic vehicular systems would be if only considering the passenger cars but different occupancy levels in urban junctions. The vehicular environments are complicated in different areas and person-based controls should be well-embedded in both vehicle situations with/without buses. There is also no research exploring the traffic signal control paradigms by predicting the person-based performance of different signal timing choices without the constraints of fixed stage sequences and non-conflicting phase combinations at every decision inspired by public transport approaches. Besides, current researches do not account for how the junction control method will work if considering more realistic scenarios, such as coordinated junction control managements, imperfect CV penetration rates and different traffic demand levels, and also, supporting the control algorithms for better performance and stabilities in various situations.

1.5 Aims and objectives

The state-of-the-art urban signal control systems were developed using connected vehicle information (e.g. instantaneous positions and speeds) while the person-based controls require additional vehicle occupancy data. In CV environments, the occupancy data of each CV can be obtained by cameras installed in vehicles or on roadsides. Vehicle occupancy detection technology using cameras has been developed in most recent years and some researches are proposed (see details in Section 2.3). TSP researches inspire the transformation from adaptive vehicle-based signal control to person-based signal control. The objective of reducing person delay or travel time is possible to be accomplished by fairly assigning priority levels to all vehicles for the purpose of reducing more person delay, congestion and related costs over vehicle-based signal controls. However, there is no research to understand how exactly the person-based signal control paradigm would be, how to use CV data in more complicated situations such as large road networks, and imperfect CV penetration rates and what are their benefits of them in a real-world case study. Three key research questions are outlined:

1. How exactly the person-based signal control paradigm would be?

2. Which kinds of data can be used and how to use them in person-based signal controls?

3. Are there any benefits to use the data in person-based signal controls?

Aims: to better understand the impacts of occupancy information from connected vehicles (CVs) on urban signal controls and the potential benefits of adopting them, in terms of person-related performance.

Objectives: 1) Investigating the relationships between vehicle-based and person-based signal controls; understanding the current state-of-the-art signal controls using connected vehicle data;

2) Proposing an Adaptive Person-based Signal Control Algorithm (PerSiCon-Junction) to reduce person average delay in isolated urban junction under 100% CV penetration rate;

3) Developing an Adaptive Person-based Signal Control Algorithm with Buses (PerSiCon-Bus) which integrates bus mode into vehicular environments of person-based control; constructing real-world case study to validate the performance of the proposed control method in isolated junction;

4) Developing Coordinated Person-based Control (PerSiCon-Network) to extend algorithm from isolated junction to multiple road networks and evaluating its performances in road network case study;

5) Proposing an Estimation status of Unequipped Vehicle with Occupancy (EUVO) algorithm to improve the behaviours of PerSiCon-Network under imperfect CV penetration rate environments.

1.6 Thesis structure

This section provides a descriptive summary of seven chapters in this thesis below:

Chapter 1: Introduction

Chapter 1 presents the background and motivation if this research, points out the main limitations of current urban signal controls and outlines the research aims and objectives, and the structure of this thesis.

Chapter 2: General background

Chapter 2 reviews traditional vehicle-based controls and signal priority strategies to identify their relationships and differences of them. The review of connected vehicle technology and data types provides opportunities to improve the performance and transitions of signal controls. The chapter also reviews state-of-the-art vehicle-based junction control strategies. The chapter points out that most of the urban signal controls in CV environments are vehicle-based controls and it is important to develop person-based controls.

Chapter 3: Person-based adaptive signal control background and concept

This chapter reviews the state-of-the-art researches in person-based junction control strategies and signal controls with flexible signal plans. The discussion of the reviews indicates where the present challenges in person-based controls are, and what the critical gaps in the knowledge are. The chapter firstly introduces the solutions of this research to fulfil the objectives, and to make contributions to the study area. The harmonised evaluation and validation frameworks for proposed person-based control algorithms are also clarified in this chapter.

Chapter 4: The detailed methodologies of proposed person-based control algorithms

Chapter 4 proposes an innovative person-based adaptive control algorithm (PerSiCon-Junction) in all passenger cars environments in isolated junction. PerSiCon-Junction is developed with a three-layered dynamic programming system to minimise total passenger delay over specific prediction periods. The approach is novel, as flexible phase combinations and stage sequences signal schemes are adopted to explore optimal solutions for reducing passenger delay of passenger cars from all feasible signal plan possibilities in a certain period.

This chapter then modifies the paradigm of PerSiCon-Junction to be a Person-Based Adaptive Control Algorithm with Buses (PerSiCon-Bus) and extends its scope of application into more complicated vehicular environments containing both buses and passenger cars. PerSiCon-Bus is a scalable framework which can join different vehicle modes into the algorithm as it calculates and estimates the possible discharging time of each vehicle with their respective parameters during the optimization process.

This chapter also proposes a Coordinated Person-based signal Control algorithm (PerSiCon-Network) to extend PerSiCon-Bus to coordinated paradigms with flexible phase combinations and stage sequences that would be implemented in multiple junctions. The CV information from both surrounding CVs and adjacent junctions can be acquired to enable junction controllers to know vehicular situations within further range. To incorporate further information properly for controllers to make adaptive signal timing decisions to all surrounding vehicles with different occupancies, the data from the adjacent junction will be utilised as a supplement form of predictive vehicle arrival time list according to vehicle trajectory data and signal strategy.

Chapter 5: Experiments and evaluations of person-based controls in isolated junction and road networks

Chapter 5 reproduces an isolated junction and a road network real-world case study in Birmingham, UK in SUMO simulation to validate the performance of PerSiCon-Bus and PerSiCon-Network in more realistic situations respectively. Section 5.1 lists the assumptions and limitations of evaluation frameworks in simulation. Section 5.2 introduces the location and geometry of the case study area. Section 5.3 describes the traffic flow data sources for the case study area obtained from manual traffic surveys and an online data portal. Section 5.4 elaborates on the traffic flow data treatment process from the online portal collected by inductive loops to the O-D matrix to generate traffic flows from different zones. Sections 5.5 and 5.6 describe the model calibration and validation process, junction settings and vehicle parameters for simulation experiments. Section 5.7 provides passenger count estimation for passenger cars and buses to determine their occupancy ratios. Section 5.8 clarifies the general simulation operations. Sections 5.9 and 5.10 discuss the results of PerSiCon-Bus/PerSiCon-Network operation and performance changes to CV penetration rates, accumulation time weighted factors, predictive horizons and bus occupancy levels.

Chapter 6 Improving the performance of person-based control under imperfect connected vehicle penetration rate

Chapter 6 develops an Estimation status of Unequipped Vehicle with Occupancy (EUVO) algorithm to estimate the vehicle statuses of those unequipped vehicles based on several data types collected from CVs, inductive loops and cameras. EUVO algorithm is proposed to improve the behaviours of PerSiCon-Network under imperfect CV penetration rate environments. To validate the effectiveness of the EUVO algorithm, the enhanced PerSiCon- Network augmented by the EUVO algorithm is evaluated in the case study and its person-based performance are compared to those of PerSiCon-Network illustrated in Chapter 5.

Chapter 7 Conclusions and future works

Chapter 7 summarises how the research works to achieve the objectives of the research, the implementation procedure of proposed person-based control and discusses the opportunities for future work.

Chapter 2 General background

2.1 Introduction

The growing traffic demands caused by increasing automobile fleets bring severe congestion and mobility problems to urban road networks. Developing efficient urban signal controls is a major way to mitigate the delay conditions on urban roads and manage growing traffic volumes. Therefore, this chapter provides a general background about the urban signal controls, CV technology and their combinations. This chapter reviews a number of existing urban signal control systems that have been implemented throughout the world; summarises key characteristics of every control system before highlighting their limitations resulting from inaccurate real-time data collection infrastructures. In addition, existing urban signal controls focus on vehicle-based optimization objectives rather than person-based metrics. The chapter thus justifies the practical meanings of setting person-based policy goals for urban signal controls and gets inspiration from the reviews of existing transit priority strategies. These two limitations need to be solved in follow-up researches.

More adaptive and person-based urban signal controls need the support of greater detail levels of real-time vehicle information as data inputs. Connected vehicle technology brings unique opportunities for the improvements of urban signal controls. The chapter then reviews the technical principles of connected vehicle communication technology, involving which kind of data they can provide and how they transmit real-time messages to corroborate that how to potentially improve the limitations of existing control methods.

After that, the chapter provides a comprehensive review of state-of-the-art vehicle-based new adaptive urban signal control paradigms designed for the near future, in which connected vehicle data are incorporated. The chapter points out at which levels the urban signal controls have been improved, and what are the remaining problems of the majority of state-of-the-art vehicle-based signal controls in CV environments.

The state-of-the-art transit signal priority strategies combined with connected vehicle information are also reviewed. The review highlights that the research problems from adaptive person-based urban signal controls are still not solved. Therefore, the chapter justifies the gap in knowledge of current researches for adaptive urban signal controls, aim, objectives and the contributions of this project in terms of person-based controls and realistic situations.

The structure of this chapter is as follows: Section 2.2 provides a review of current prevailing signal control strategies. Section 2.3 justifies the importance of person-based control and a review of bus priority strategies. It points out the potential paradigms of person-based controls inspired by the review of bus priority strategies. Section 2.4.1 provides an overview of those advanced technologies which have been integrated into CV and ITS applications. The roadside infrastructure data and on-board vehicular data determine the degree of junction control performance and which data types are available to be adopted in signal control strategies. Sections 2.4.2 and 2.4.3 introduce the wireless communication channel and massage sending formats to realize how the various data sources can be transferred between junction infrastructures and CVs. Section 2.5 then looks into the state-of-the-art adaptive signal controls and reviews how connected vehicle technologies optimize and broaden the control algorithm with diverse forms of input data, control objectives, Key Performance Indicators (KPIs) and control decision styles. Section 2.6 makes a summary of general literature and highlights their main limitations.

2. 2 Existing urban signal control systems

The development of signal control strategies can be traced back to 1868, when the prototype coloured traffic light was utilised in Westminster, England (Webster and Cobbe, 1966). After that signal traffic lights experienced numerous changes including their hardware and design strategies. The traffic control managements can be classed into three stages: fixed-time, actuated, and traditional adaptive. Fixed-time controls decide signal timings based on historically recorded data and cannot react to fluctuating flow demands. Actuated methods and traditional adaptive control strategies are developed to make responsive to traffic flow demands by real-time data collected from loop detectors. This section reviews the existing urban signal control strategies in the world in four categories: Fixed-time isolated control, fixed-time coordinated control, traffic-response isolated control and traffic-response coordinated control.

As the main junction control means in urban roads, signal control systems with traffic signals in different directions guarantee insurance for all road users (e.g., drivers, passengers, cyclists, pedestrians) from conflicting traffic streams. However, it was also found later that the occurrence of traffic signals led to severe delays and lower efficiency in the road network because of rule restrictions on red traffic lights. Hence, the optimal traffic signal control strategies have been developed to seek the best solutions with the targets of reducing the total time vehicle remaining in the junction.

Regardless of the design instructions and theories, the modelling junction layouts of urban traffic signal strategies are quite similar: 1) one junction or road network which are comprised of a series of successive junctions; 2) a number of approaches which are represented different road directions and a certain range of crossing area; 3) one or several lanes in each approach with vehicle queues and traffic flows (Papageorgiou et al, 2003). Under such circumstances, the basic parameters and factors of traffic lights that may affect the performance of control strategies are listed as follows:

- Cycle length: The total time required by operating a complete specific sequence of stages, expressed by seconds. The cycle length is added by the durations of each stage and a certain total loss time (Younes and Boukerche, 2016). The longer cycle length will cause a higher traffic flow capacity in the junction due to the lower proportion of losses time (Papageorgiou et al, 2003). While the total delay of vehicles will ascend as the long waiting time for vehicles without green times.
- Phase: Set of conditions that fix the pattern of movement and schedule for one or more traffic streams during the signalling cycle (UK Govt. Dept. Transport, 2006). In general, green light represents the acquisition of right-of-way priority and red light means stop.
- Stage: Indication by traffic signals during a period of the signalling cycle that gives the right of way to one or more particular traffic movements at the same time (UK Govt. Dept. Transport, 2006). The reasonable design of optimal numbers and specified order of stages is the core of signal schemes, which can greatly improve the transport efficiency of the junction.
- Split: The green time proportion is proposed by the signal control system for individual stage (Younes and Boukerche, 2016). Those stages with right-of-way for larger traffic flow demand should be rendered more duration.
- Offset: The time difference between a defined point and a reference point in the cycles for two successive junctions (Younes and Boukerche, 2016). Offset is an important factor to result in ‘green waves’ when deciding plans for multiple junctions, which make the traffic lights turn green along serval junctions in the same direction.

Before reviewing the urban signal control methods, objective functions for signal controls and KPIs need to be first introduced as they are essential components to decide the signal control optimization targets and evaluation standards. The most commonly used objective functions and KPIs for vehicle-based signal controls are introduced in Sections 2.2.1 and 2.2.2 respectively.

2.2.1 Objective functions for vehicle-based urban adaptive signal controls

As the main purpose of the adaptive signal control strategies, the different objective functions will result in different behaviours of signal timing decisions. The objective function attributes under the CV environment could be improving junction efficiency (minimising vehicle delay, minimising queue length, minimising number of stops, minimising travel time), increasing junction capacity (maximum junction throughput) or environmental economy (minimising fuel consumption and emission rate). In each proposed method the objective function adopted could be either one or multiple (e.g. minimising vehicle delay and number of stops with different weighted ratios (Goodall et al, 2013), minimising the weighted sum of total fuel consumption and travel time of the vehicle in (Li and Ban, 2017). The common used objective functions and requisite data inputs will be listed.

2.2.1.1 Minimising vehicle delay

Minimising vehicle delay in junction is one point to guarantee junction efficiency through eliminating the travel time expense of waiting for avoiding collision as much as possible. The total delay of a sequence of vehicles in set N can be calculated by supposing every possible departure time D_C for each vehicle c in this set minus the virtual departure time V_C (cross time without other vehicles and traffic signal) and then finding the distinctive control state to reach minimum vehicle delay value taking vehicle sequences in all phases in junction into account (Yang et al., 2016), shown as:

$$min \sum_{c \in N} (D_C - V_C) \tag{2-1}$$

Alternatively, the total delays of vehicles are counted by the summation of queue lengths of all phases during one optimizing horizon (one or two cycle lengths) (Feng et al., 2015). The proper state variables and control variables are allocated to form the minimum delay. Therefore, the calculation of total delay needs previous testing free flow travel time for each route and possible departure time of single vehicle, or queue length at various time steps, which can be measured by CVs mentioned in Section 2.4.1.

2.2.1.2 Minimising vehicle queue length

The optimal control methods based on minimising queue length objective are developed by either using current situations of queue length or future situations as references. The current situation queue length method calculates the queue length for all phases in the junction at the moment and selects the phase with the max combined queue length as the next phase (Kari et al., 2014; Tiaprasert et al., 2015). The future method compares the vehicle queue length conditions over different optimization strategies, and then implements the one with the minimum metric (Feng et al., 2015; Islam and Hajbabaie, 2017).

2.2.1.3 Minimising vehicle number of stops

Minimising vehicle stops, as a kind of channel to improve steady steam and save fuel consumption, is reckoned by reducing the sum of all vehicles in a phase combination that switch speed to 0 and then accelerate to pass through the junction (Guler et al, 2014). The number of stops SW_C for individual vehicle c in set N equals the number of green light time that switch to the current lane between its arrival time and departure time due to every vehicle suffering from one stop if failure to cross the junction (Guler et al, 2014). Thus the minimising total number of stops of each combination is simplified to the sum of all cars considered, shown as (Guler et al, 2014):

$$min \sum_{c \in N} (SW_C - SW_{C''}) \tag{2-2}$$

Where C'' is the smallest index of car departing after the arrival of car c.

2.2.1.4 Minimising vehicle travel time

As the travel time can be detected and recorded by inductive loops located at different positions or CVs, the cumulative total travel time for vehicles in each lane is calculated. The vehicle movement lanes with the highest combined travel time for possible combination phases (i.e., NEMA phases 2 & 6 or 4 & 8 in (Lee et al., 2013)) were then selected for the next decision stage. Or models based on travel time consider total summation of vehicle n_p travel time $T_{np,t}(s_p, x_p)$ as a function in terms of state variables s_p and decision variables x_p at time t within range of time step $s_{p-1}$to s_p (Li and Ban, 2017), minimise it as:

$$min \sum_{n_p}^{N_p} \sum_{s_{p-1}}^{s_p} T_{np,t}(s_p, x_p) \tag{2-3}$$

2.2.1.5 Maximum vehicle junction throughput

The capacity maximum models intend to improve the average number of vehicles left the road network per unit time, which is also called throughput. In Islam and Hajbabaie (2017) this target is calculated by the number of vehicles n_i^t leaving the approach lane i in all movements lanes M in one phase at time step t ∈ T, filtering the phase with the highest value as the next control variable, which is represented by:

$$\max \sum_{t \in T} \sum_{i \in M} n_i^t \tag{2-4}$$

Sun et al. also improve the junction throughput by selecting maximum flow demand in combined lanes divided by corresponding lane numbers as evaluation criteria (Sun et al., 2018).

The objective of traditional signal control methods concentrates on maximising the throughput or reducing vehicle delay limited by original data sources. The connected vehicle technology brings diverse objective functions, being able to optimize the junction from multiple standards. Meanwhile, high precision connected vehicle delay estimation and vehicle number identification make adaptive signal control better performance.

2.2.2 Key performance indicators for vehicle-based urban adaptive signal controls

KPIs are measurable, calculable values to demonstrate how effectively models achieve their key objectives. KPIs in adaptive signal control under connected vehicle technology are defined to weigh the effectiveness of junction control strategies, moreover, comparing against the benchmarking models, for instance, fixed time control and actuated control. KPIs also supply researchers with ways to validate and calibrate the validity and reliability of their models and to what degree they achieve the cost functions. Table 2.1 outlines a description of the most common KPIs adopted in adaptive signal controls and procedures of how to collect those data. Besides, Table 2.1 lists those KPIs selected by researchers to measure the effectiveness of their algorithm.

Table 2. 1 Descriptions and measurements of common KPIs in vehicle-based signal controls

KPI	Description	Measurement
Average vehicle travel time	The time a vehicle spends to move from the original point to the destination point	The time step end at destination minus the time start from origin
Average vehicle delay	The excess time one vehicle spends to complete its journey than free flow travel time	Travel time of individual vehicle – free flow time on the same route
Queue length	The number of vehicle stopped behind the cross line waiting for discharging	Count the number of vehicles with speed 0 in each lane at special time step
Throughput	The number of vehicle clear from the junction or road network per unit time	Count the number of vehicles disappear from the simulation per unit time

Flow	The number of vehicle enter the junction or travel along the specific road point per unit time	Count the number of vehicles enter the simulation per unit time
Fuel consumption	The volume of fuel consumption (e.g. gasoline) vehicle cost per kilometer	The fuel consumption model adopted for each vehicle and add up
Emissions	The volume of emission (e.g. FC, CO_2, CO, HC, NOx) produced by vehicles per kilometer	Use instantaneous emission model to calculate the emissions each vehicle and add up
Average vehicle number of stop	The number of travelling vehicle switch its speed to 0 and acceleration	Count the number of stop by tracking each vehicle and judging stop by speed variation
Robustness to errors	The observation of how robust the model algorithm are effected to different errors(arrival patterns, demand ratio, information level and others)	Measure the coefficient of variation between the performance of any above and designated error type

The KPIs mentioned in Table 2.1 are representative factors in the road traffic environment due to validation of algorithm effectiveness towards the objectives of the model and are widely acknowledged in signal control papers. The required data collection for calculating KPIs are automated processes, for instance, GPS, speedometers, and accelerometers mentioned in Section 2.4. Those data are gathered in a specified way at the regular transmission interval within an acceptable well-defined error margin. In contrast to manual data collection, electronic data collection pattern by connected vehicle eliminates the affection of human error. Therefore, KPI data in this research can be regarded as both more accurate and reliable than the traditional method. Remarkably, the improvements of KPI for one algorithm model are not only restricted to its objective. In other words, even though there is only one objective function in control strategies the benefits could be various aspects. For instance, the CTT algorithm proposed by Lee et al (2013) also found enhancement to average speed, throughput, emission and fuel consumption.

2.2.3 Review of existing urban signal controls

Current urban signal control methods are generally classified into four categories according to two parallel elements: 1) isolated or coordinated control decided by the scales of planning objects; and 2) fixed-time or traffic-response control due to different attitudes toward arterial traffic flow (Papageorgiou et al, 2003).

- Isolated control: Each junction is considered as an independent individual for signal control systems, which is applicable for sparsely distributed junctions.
- Coordinated control: The signal control regards a large zone road network involving multiple junctions as a whole. The usual method is to achieve 'green waves' phenomena, which let one or more streams in lanes in the same direction pass through several junctions smoothly without stop-and-go to reach maximum vehicle throughput.
- Fixed-time control: The patterns, sequences and splits of each stage in the cycle are determined by offline historical constant demands data beforehand. The values of stage timings are variable, depending on a different given time of day (e.g. peak hour).
- Traffic-response control: Traffic response strategies decide the stage settings and signal timings online by acquiring real-time traffic demand data (usually measured by one or two inductive loops in each lane).

Thus, four types of signal controls combined with these features are formed: fixed-time isolated control, fixed-time coordination control, traffic-response isolated control and traffic-response coordination control will be introduced in the following sub-sections.

2.2.3.1 Fixed-time isolated control

Pre-timed control assigns the right of way at a junction according to a predetermined schedule. The length of the time interval for each signal indication in the cycle is fixed, based on historic traffic patterns. The timing is repeated over and over regardless of the presence or absence of traffic demand. As a result, it is critical to determine the values of a cycle and split in fixed time control.

There are different ways to determine the cycle length. Webster (1958) developed a relatively simple expression to determine the optimal cycle length C_0, based on total lost time L and the sum of q_i/s_i ratios Y at all junction phases. The optimal cycle length C_0 is calculated as:

$$C_0 = \frac{1.5L + 5}{1 - Y} \tag{2-5}$$

The sum of q_i/s_i ratios Y is calculated as:

$$Y = \sum_{i=1}^{p} (q_i/s_i\,) \tag{2-6}$$

Recall that q_i/s_i is the maximum ratio of the arrival flow rate q_i to the saturation flow rate s_i at all approaches at phase i). After the calculation of the optimal cycle length, the splits of all phases can be determined. For instance, the green time split G_i at phase i can be determined by:

$$G_i = (C_0 - L)\frac{q_i/s_i}{Y} \tag{2-7}$$

Besides the general description of fixed-time control provided above, there are also some advanced fixed-time controls developed to optimize some specific objective values in two groups: stage-based strategies and phase-based strategies:

a) One type of fixed-time isolated strategy reaches the maximum traffic flow capacity or minimum total vehicle delay through optimizing the cycle and split timings, which are called stage-based strategies. SIGSET (Allsop, 1971a) and SIGCAP (Allsop, 1976) are two well-known methods in this category. The former aims to reduce the stream delay while SIGCAP attempts to maximise the capacity for an isolated junction. Assuming that both of the strategies predetermine p phases for one cycle and they divide the splits for each stage, known as $\lambda_1, \dots, \lambda_p$. Then have

$$\lambda_0 + \lambda_1 + \cdots + \lambda_p = 1 \tag{2-8}$$

where $\lambda_0 = L/c$, L is the total lost time in the cycle and c is the cycle length. To avoid vehicle queue generation in each approach, the average arrival rate or demand q_j of stream j should be constrained by the following inequality:

$$s_j \sum_{i=1}^{p} \alpha_{ij}\lambda_i \geq q_j \tag{2-9}$$

note that s_j is the saturation flow of stream j, which means the average flow rate crossing the stop line during the effective green time. α_{ij} is a binary value and equals to 1 if stream j has right of way in phase i, otherwise the value is 0. This formula reflects that the flow demand should be no more than the maximum possible saturation flow to prevent congestion according to the split assigned for this approach. Other constraints such as minimum green time and maximum cycle length are introduced in (Allsop, 1971b). The Webster average delay estimation method (Webster, 1958) under saturated conditions is adopted by SIGSET as an objective function, which is shown as:

$$d_j = \frac{9}{10}\left\{\frac{c\left(1 - g_j/c\right)^2}{2\left(1 - q_j s_j\right)} + \frac{{x_j}^2}{2q_j\left(1 - x_j\right)}\right\} \tag{2-10}$$

where d_j is the average delay for each vehicle in stream j, $g_j$represents the effective green duration for approach j and $x_j = q_j c/s_j\, g_j$. Therefore, SIGSET treats the objective as a linearly constrained nonlinear programming problem by combining constraints with vehicle average delay. As for SIGCAP, it replaced q_j by μq_j ($\mu \geq 1$) so that the maximum value μ will contribute to maximum flow capacity. Thus SIGCAP would find solutions by solving a linear programming problem. It should be noticed that both SIGSET and SIGCAP are only suitable for under-saturated situations because of the capacity constraint.

b) Another class, phase-based strategies, considers optimal cycles and splits, as well as the compatibility of stages. The phase-based method (Improta and Cantarella, 1984) adopted a binary mixed-integer linear programming methodology to test the stage specifications. In this way, different combinations of stages are calculated by adding variety of binary variables. The flexibility and result of phase-based strategies are inarguable better than stage-based strategies. While the computation and difficulty degree of phase-based strategies step up to another level. However, the off-line predetermined characteristic of isolated signal control makes it non-significant.

2.2.3.2 Fixed-time coordinated control

Similar to the principles of fixed-time isolated junction schemes, fixed-time coordinated strategies also predetermine the settings of phase and stage based on historical data but apply them to larger scale road networks with several successive junctions. The main design concepts of fixed-time coordinated control seek a solution for the maximum number of crossing vehicles in streams without stopping. Therefore, the coordination of traffic lights is required to satisfy that the bands formed by all vehicles in one stream are covered by green time on two opposite arterials. The illustration is shown in Figure 2.1.

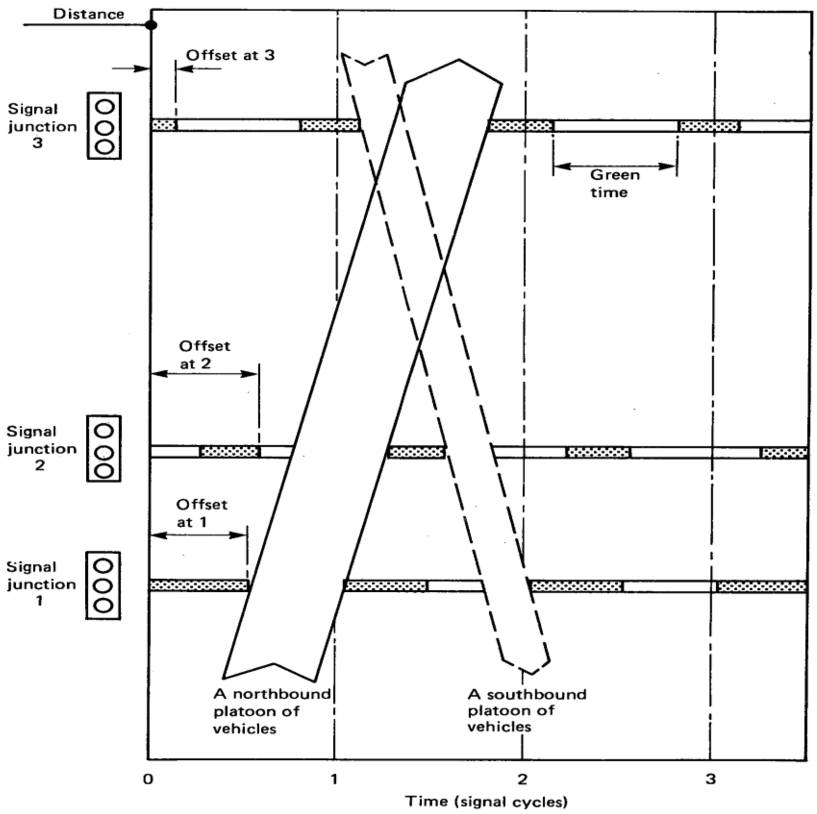


Figure 2. 1 Time-distance diagram for traffic signal coordination on a fixed time plan (Hunt et al., 1981)

As a representative of bandwidth-based fixed time coordinated control, MAXBAND was first formulated by Little on a two-way arterial for the sake of maximum total progression bandwidths (Little, 1966). A Mixed Integer Linear Programming (MILP) formulation is adopted by MAXBAND to specify the corresponding offsets of signals for their separate junctions so that several decision variables are integer. Little et al. (1981) then extended the original MAXBAND model to a new vision for a triangle network with three arterials and a closed loop, which was also based on MILP formulation. Corresponding to a more rigorous mathematical problem, MAXBAND is designed for an offline computer program so that it can automatically calculate the appropriate offset, cycle length, split and left-turn phase sequence values for arterials. The MAXBAND determines the weighted combinations of bandwidths as a globally optimal solution.

Later, MAXBAND applies to grid networks with multiple arterials and closed loops to maximise the progression bandwidths, which is called MAXBAND 86 (Chaudhary et al., 1991). MAXBAND 86 is the first attempt of fixed-time coordinated control at multi-arterials networks. However, MAXBAND 86 is regarded as an extremely simple assumption model without considering green split optimization (Chaudhary et al., 1991). The tremendous computations of MAXBAND 86 also cause the system inefficient. PASSER II is another bandwidth optimization program by using a heuristic optimization procedure to decide the best combination of offsets with the widest bands (Messer et al., 1973). While PASSER II cannot be implemented in multiple arterials compared to

MAXBAND 86. Due to the insensitive variations toward actual traffic flow limitations that existed in these bandwidth-based models, the MULTIBAND model is created by incorporating a traffic-dependent criterion into progression calculated procedures (Gartner et al., 1991). The MULTIBAND figures out the individual bandwidth for each special link, as well as maintains the platoon of the vehicle stream. The flexible individual bandwidths along with varying traffic flow make MULTIBAND perform better, specifically reflecting on the significant decrease in vehicle delays, number of stops, and fuel consumption over traditional models. Referring to the sensitive traffic pattern matching characteristic of MULTIBAND, The MULTIBAND-96 is then generated by absorbing this advantage and optimizing crossing arterial signal control variables simultaneously (Stamatiadis and Gartner, 1996). Therefore, MULTIBAND acquires better measurements than MAXBAND 86 when operating models into multi-arterials road networks. PASSER IV is also a good attempt to optimize signal timings for closed grid multi-arterial networks by combining multiband and green splits (Chaudhary and Messer, 1993).

Different to the above bandwidth-based models, the delay-based fixed time coordinated control method Traffic Network Study Tool (TRANSYT) minimises the delay of the whole road network. The TRANSYT model is contribute to selecting suitable offsets to allow the interactions of traffic flows and continuous road sections (Robertson, 1969). The TRANSYT included a heuristic optimization algorithm that leads to a simple but efficient method to find the minimum vehicle delays as a representative of platoon dispersion and flow control. As an improvement of TRANSYT, TRANSYT-7F calculates the performance index of variables in the road network to achieve delay minimisation, given quantities of traffic parameters, such as splits, offsets and cycle time (Li and Gan, 1999).

TRANSYT-7F models have been commonly adopted in North America. However, the delay-based fixed time coordinated controls reveal poorer ability to optimize phasing sequence than bandwidth-based controls (Gartner et al., 1991).

LinSig is another widely used fixed-time coordinated control which can be operated in either an isolated junction or road network comprising successive junctions (Moore and Cheng, 2010). It optimizes the signal timing plans to reduce delay or maximum reserve capacity. Different from TRANSYT which is predominantly useful for modelling large networks, LinSig is more suitable to be adopted in detailed modelling of junctions. Cyclic flow profiles are used in LinSig to represent the patterns of traffic and queues for each cycle period and model the signal timing plans. The stage lengths and offset can also be adjusted in LinSig to minimise delay for the whole network. As a result, the LinSig outputs are deterministic and relatively stable.

2.2.3.3 Traffic-response isolated control

Traffic-response strategies can detect whether a vehicle passes through the specified point at a certain time utilising the flag change function of buried inductive loops. The flag signal will transfer if lanes are occupied by vehicles and the short-time cruise speed of vehicles can also be measured. Thus the real-time vehicle flow will be a key parameter to arrange signal controls. Microprocessor Optimised Vehicle Actuation (MOVA) is a real-time self-optimization isolated junction control system with the target of reducing vehicle stops and delays, or maximum capacity throughput during oversaturate periods (Peirce and Webb, 1990). Two loop detectors are placed 40m and 100m upstream from the stop line respectively in the design of MOVA, which are estimated to leave about 3.5 and 8.0 times vehicle cruise time from loops to cross lines (Vincent and Peirce, 1988). More sophisticated vehicle actuation logic were then applied in MOVA. The minimum green durations are assigned for every phase so that each lane has sufficient time to discharge the remaining queue in front of 40m upstream detectors (Lu et al., 2014). If there is no vehicle detected from the related detectors, the control system will proceed to the next determined stage. Otherwise, a critical interval of several seconds will be created to extend the green durations of the current stage, clearing the vehicle at the full saturation rate. The detection and additional interval step will be repeated until the green duration reaches the maximum green time or no vehicle is detected. Miller (1963) proposed a more complicated vision of MOVA, considering the opportunity to switch to the next stage (takes place at once or postpone). The optimizing process solution balances the benefits of extending the green phase against the losses of a vehicle stopped in red lanes.

System D vehicle actuation is another traffic responsive control in the isolated junction (UK Govt. Dept. Transport, 2006). As illustrated in Figure 2.2, three inductive loops are used in System D vehicle actuation to replace pneumatic detectors. The furthest inductive loop is normally distributed at 39 meters from the stop line. A green extension can be scheduled for the current approach if a vehicle passes through the buried inductive loop or Above Ground Detectors (AGDs). Otherwise, the traffic signal will be switched from green to red light if no vehicle is detected in a gap duration. The next two inductive loops are used for extending green duration.

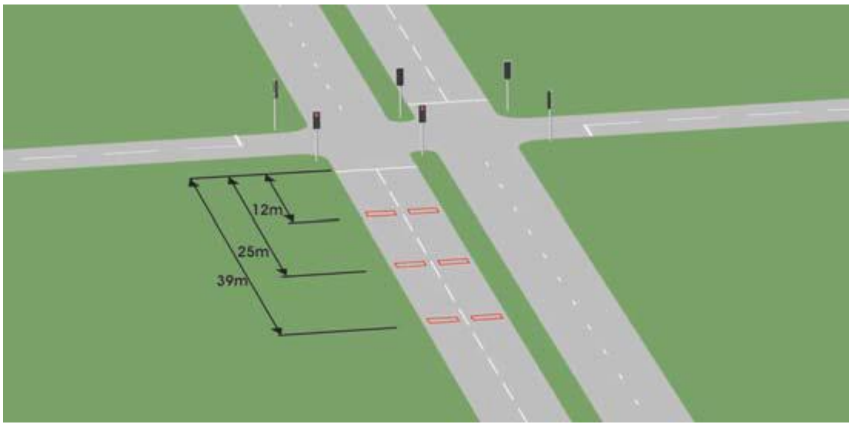


Figure 2. 2 Illustration of System D vehicle actuation (UK Govt. Dept. Transport, 2006)

2.2.3.4 Traffic-response coordinated control

Traffic response coordinated strategies developed the isolated controls into network-wide applications, which provide more practical significance than the latter. The characteristics of widely used strategies in this category are summarized in Table 2.2. Split Cycle and Offset Optimisation Technique (SCOOT) (Hunt et al., 1981) and Sydney Coordinated Adaptive Traffic Signals (SCAT) (Lowrie, 1990) are two first famous traffic response versions which can be applied in urban network scale coordinated junctions. SCOOT can be regarded as an improvement of TRANSYT with similar principles. While the vehicle flow and occupancy measured and stored by loop detectors are adopted to replace the historical data used in TRANSYT (Hunt et al., 1981). A central online network model is selected in SCOOT to predict the traffic queues, delays and stops repeatedly by every few seconds with the updated latest real-time measurements as input. The consecutive alternations would be approved and implemented by local signal controls once they are estimated to bring positive effects to the junction operation, particularly the prescribed performance index. The structure of SCAT is a two-level approach. The upper level predetermines the network-wide signal plan for centre control and the decentralised level adjusts the signal control strategies so that they can fit with major traffic situations (Lowrie, 1990). However, in the initial trials towards more than one junction, the limited effects of subtle alternations in answer to changeable adjacent upstream flow against the fixed time plan cannot satisfy the rapid flow changes.

After that, a series of model-based traffic response methods are proposed to better visualize urban control challenges as combinative optimizations without demonstrably splits, cycles and offsets. Optimisation Policies for Adaptive Control (OPAC) (Gartner, 1983) provided a feasible and promising complete enumeration method for considering all possible integer switching times. While PROgramme DYNamique (PRODYN) (Henry et al., 1984) adopted a bi-level signal setting approach which places decomposition coordination at the upper level and dynamic programming hierarchical algorithm at the lower level. Dynamic programming is also applied in Real-time Hierarchical Optimised Distributed Effective System (RHODES) (Mirchandani and Head, 2001), responding to predicted real-time vehicle arrivals, platoon arrivals, traffic flow rates and queues in each junction. Current road capacities, vehicle travel times and network disruptions can be measured from loop detectors and videos as inputs of a hierarchical architecture in RHODES to activate traffic signal behaviours. REALBAND (Dell'Olmo and Mirchandani, 1995) also followed similar hierarchical control architecture to identify the variety of vehicle platoons and predict their movements.

An approximate traffic model developed from the theory of MAXBAND boosted the throughputs of the detected platoons in networks, as well as balanced the benefits of two conflicting movements to decide which one is awarded priority. ALLONS-D (Porche and Lafortune, 1997) is a traffic response decentralized method combining dynamic programming and rolling horizon, carrying out the signal timing results in a short roll period decided by a larger horizon plan. The plan decision is updated every few seconds based on real-time measurements. MOTION (Brilon and Wietholt, 2013) also executed separated local junction network signal controls second by second in a three-level optimization system to promote operational efficiency than SCOOT and SCAT.

However, all of the above model-based methods solved the urban coordinated signal control in a perspective of global network minimum, resulting in exponential complexity of algorithms so that they are barely applicable to more than one junction in actual operation. On the contrary, CRONOS (Boillot et al, 2006) built a polynomial complexity algorithm heuristic achieving local minimum so that the optimization solutions would be founded faster. Video sensors are used in CRONOS to seize vehicle spatial position, density and queue length on the road for simultaneous working out strategies under several junctions. One common challenge of those model-based approaches is that they do not consider the downstream vehicles for each junction, hence they are not suitable in saturated flow conditions (Papageorgiou et al., 2003).

The store-and-forward models are designed for various urban road traffic controls to provide a more efficient and feasible approach than model-based strategies (Diakaki et al., 2002). By abandoning discrete variables as parameters inside traffic flow demand descriptive mathematical models, store-and-forward methods opened a new era for coordinated dynamic strategies. A crowd of high-efficiency optimization programming methods are frequent occurrences. The examples include linear programming, multivariable regulators, nonlinear programming and quadratic programming. Bi-level programming (Yang and Yagar, 1995) and mixed integer linear programming (Lo et al., 2001) approaches have also been explored to be available in over-saturated traffic flows.

2.2.3.5 Discussion and conclusion for existing urban signal control

The main drawbacks of fixed-time strategies are highlighted in several aspects. The most obvious feature of fixed time controls is the predefined off-line signal timing schemes according to local historical observed data. This data collection mode makes them cannot respond to the temporal and spatial variations of traffic flows. In actual circumstances, traffic demands are inconstant both at a time of day and on different days because of special events, festivals, and week attributes. The long-term traffic demands and turning movements are also unfixed. The unpredictable disturbances will cause heavy interference in traffic conditions. All of those situations indicate that the effects of fixed time controls will be poor, which becomes a major problem to provide junction efficiency. Moreover, the optimizations of fixed-time signal controls are only developed under saturated flow conditions, which fail to consider the oversaturated situations.

Isolated response signal controls (e.g. MOVA) change the operation way from fixed time controls. However, they still fail to exploit the full characteristics and potentials of urban signal junctions, for the reason that they ignore the correlations among modelling junctions and surrounding junctions. The signal control managements need to be coordinated within a region of related junctions, guaranteeing the delay reduction in the urban transport network rather than a particular space.

Coordinated response urban signal controls have evolved from fixed time and isolated signal controls with better operationally treatment of traffic volumes and network scales. Therefore, they are the most powerful signal control method among these four categories due to their practicability in larger-scale road networks. In addition, they make responses to dynamic flow demands to a certain degree. Table 2.2 summarises the prevailing traditional adaptive coordinated control strategies and their key characteristics.

Coordinated response urban signal controls provide additional sensors for signalized operators, enabling them to sense the state of the road network and approaching vehicles. The data they collected is processed by control algorithms and made real-time signal decisions corresponding to dynamic traffic volumes. However, from Table 2.2 most of the data collection sensors used by coordinated traffic response control strategies are inductive loops or camera/video sensors. From the perspective of cost and stability, the loop detectors' expense of installation and maintenance is considerable. Thus the loop detectors were only installed upstream and downstream of the road links (Hunt et al., 1981) and cannot cover the whole network. Moreover, once robustness errors occur to loop detectors, the data collection and control behaviour of coordinated traffic response would heavily degrade (Feng et al., 2015).

On top of that, all of those sensors collect data at fixed points, which can detect the numbers of vehicles when they pass through the places where inductive loops are embedded (Younes and Boukerche, 2016). These census data only provide a snapshot of the state of the road network, being less capable of describing detailed information. More concretely, the SCATS and SCOOT models can only provide slightly alternations against the fixed cycle plans with limited effects. Although OPAC and PRODYN introduce queue length as new data resources in their models, advanced knowledge of queue length and vehicle arrivals are challenging to be obtained in the circumstances (Gartner, 1983). The predictions of vehicle movements (e.g. arrival time, vehicle size and vehicle speeds (Dell'Olmo and Mirchandani, 1995)) by loop detectors implemented in RHODES and REALBAND are also not so accurate because of the stochastic nature of vehicular movements (Lee et al., 2013). To improve these limitations, new detection and communication technology is required to support urban signal controls to have a better understanding of vehicular and road network states. Connected vehicle technology is such a choice to provide abundant data resources for the signalized controller, which is presented in Section 2.4.

Another limitation of traditional urban signal control can be observed from Table 2.2 that all of the policies adopted are vehicle-based signalized optimization (e.g. minimising total vehicle delay). In other words, these strategies regard all of the vehicles on road at the same priority level. Such vehicle-based objectives result in unfairness to those vehicles with high occupancy vehicles and passengers inside vehicles, which is also not consistent with the future city development target of enhancing person mobility projected by UK DfT and European Commission. It is more valuable and realistic to apply person-based optimization approaches. Concerning this, Section 2.3 justifies person-based policies and performance indicators for urban signal controls.

Table 2. 2 Key features of current coordinated traffic response control strategies

Control strategy	Objectives	Means of collecting data	Types of Data collected	System	Case Study	Benefits compared to fix-time plan
SCATS	Improving vehicular throughput, reducing congestion	Loop detectors	Vehicle flow, Road occupancy	3-level hierarchical architecture	Sydney, Australia	Travel time, accident, fuel consumption, air pollution reduction
OPAC	Minimise total vehicle delay	Loop detectors	Queue length (assumed), vehicle flow	Dynamic programming	———	Delay reduction, speed improvement

SCOOT	Minimise average vehicle delay	Loop detectors	Vehicle flow, Occupancy	On-line computer	Glasgow, UK	Delay, fuel, pollutant accident reduction
RHODES	Minimise average vehicle delay	Loop detectors	Traffic flow	3-level hierarchical architecture	Arizona, USA	Delay reduction, throughput improvement
PRODYN	Minimise total vehicle delay	Loop detectors	Vehicle presence time, queue length (assumed)	Dynamic programming	______	Delay reduction
MOTION	Improve traffic flow performance	GPS	Traffic volumes	Adaptive Signal Control Technique	Muenster, Germany	Traffic flow performance improvement
ALLONS-D	Minimise average vehicle delay	Loop detectors	Vehicle arrivals	Branch and Bound algorithm	______	Delay reduction
REALBAND	Minimise total vehicle delay	Loop detectors	Traffic flow	3-level hierarchical architecture	______	Delay reduction
CRONOS	Minimise total vehicle delay	Video sensors	Queue length, number of stopped vehicles	CRONOS algorithm	Paris, French	Delay and number of stops reduction

2. 3 Transform urban signal controls to person-based paradigm: reasons and inspirations

The review of existing urban signal controls in Section 2.2 concludes that all of the systems operating throughout the world are vehicle-based optimization policies and take into account that all vehicles on road are the same. This section elaborates on the motivations of selecting person-based objectives and performance measurements. However, the transition from vehicle-based signal controls to person-based approaches is a challenging task. Both new kinds of data sources and new signal control algorithm paradigms are required. The urban signal-control-based priority methods, which are most commonly incorporated in urban junction managements, award high priority levels to public transport so that they can pass through the road sections and junctions as quickly. By reviewing these strategies, the different treatments of public transport vehicles and passenger cars\vans may provide inspiration to the ways how urban person-based signal controls should be and related potential challenging problems.

2.3.1 The meanings of person-based urban signal controls

Over the past 50 years, personal transport, which was dominated by private vehicles, has been rapidly developed to provide users with a high degree of freedom by enabling them to arrive to any location they want. However, the massive adoption of private vehicles in urban areas also leads to heavy congestion and related negative economic and environmental impacts (European Commission, 2020). Therefore, addressing future person mobility challenges in cities has been a critical subject area in Science for Policy report by the Joint Research Centre (JRC) to support the

European policymaking process ((European Commission, 2020). With the signal control system widely deployed in urban networks, one of the most efficient ways to enhance person mobility is developing person-based signal controls to provide preferential treatment to those vehicles with high occupancy (Christofa et al, 2013a). Several people in one vehicle with high priority have chances to greatly enhance the people mobility compared to one person in the same vehicle as the former one achieves multiple travelling with one vehicle.

The report “Future of Mobility: Urban Strategy” was published by Department for Transport (DfT) of the UK government in 2019, discussing the challenges and opportunities of urban transport in future and strategies that may improve transport mobility (UK Govt. Dept. Transport, 2019b). Reducing congestion and better utilisation of limited urban road spaces is one of the important targets for future transport innovation in this report. The traffic volumes in England and Wales are forecasted to increase by 55% between 2015 and 2050 if the vehicle occupancy level decreases from 1.5 to 1.3 (UK Govt. Dept. Transport, 2019b). This prediction value is far beyond a 5% increment of traffic volumes if average vehicle occupancy increase to a level of 1.7. It is worth mentioning that the forecasts are made before the COVID-19 pandemic and could not have foreseen the influence of the extraordinary circumstances on the traffic volumes and vehicle occupancy on road. In 2020, the average car occupancy in the UK decreased to 1.49 and total vehicle miles decreased 21% compared to that in 2019 (UK Govt. Dept. Transport, 2021a). Travel demand and mode preferences (from public transport to private vehicles) have shifted during COVID-19 pandemic situations compared to normal situations due to trip restrictions imposed by authorities and fear of infection by individuals (Abdullah et al., 2020). However, as discussed in Section 1.1, this unusual trend will not last for long period. Overall, the occupancy levels of vehicles in the network still seriously affect the urban road traffic conditions. Therefore, one of the urban strategy innovation principles which are expected to be underpinned by the government is described as follows:

> *“Mobility innovation must help to reduce congestion through more efficient use of limited road space, for example through sharing rides, increasing occupancy or consolidating freight.*
>
> *There is finite road and pavement space in our towns and cities, many of which were laid out long before the advent of motorised transport. The lower running costs enabled by new technologies and business models could worsen congestion if vehicle occupancy and load factors remain low.”*

Person-based urban signal control is such a conceptual framework that intends to offer higher priority levels to high occupancy vehicles in the urban road network. Person-based signal controls are designed to put more emphasis on person-related values and provide better strategies to improve average person delay. Besides, the promotion and implementation of these strategies are advantageous for car-sharing policy realization. Those people who are willing to share cars with others would be more likely to cross the urban junctions quicker. Therefore, the researches for person-based urban signal controls are consistent with the future strategic target of urban transport mobility.

Public transport priority system is operated in such circumstances where bus occupancy is higher than passenger cars in most cases. The measures for qualities and capabilities of public transport modes and tools are determined based on passengers' load capacities in the same situation, not merely departure frequency. For public transport modes, the higher vehicle carrying capacities are transited by seat numbers multiplying respective load factors, considering carriage sizes, seats and well as standees (MacKechnie, 2017). So that the capacities of bus transit, light rail and subway can be regarded as 90, 90 and 100 passengers per vehicle per grade separately (MacKechnie, 2017). Passenger capacity is one of the most important factors to measure the performance of public transit modes (MacKechnie, 2017), which refers to how many passengers can be carried by one mode per hour. This index is calculated by passenger number of one mode and operation frequency, indicating the importance of considering people in the vehicle. In addition, high occupancy vehicle (HOV) lanes are designed to provide a dedicated passageway for those vehicles with high occupancy (minimum occupants of 2 or 3) and prohibit low occupancy vehicle (Institute for Transport Studies, 2018). HOV lanes are a road strategy to award higher priority to portion vehicles based on numbers of people and have been applied in Leeds, South Gloucestershire and other cities (Institute for Transport Studies, 2018).

Most of the current signal control researchers set their goals as minimising vehicular delays and attempting to offer more vehicles to pass through the junction at the same time in the absence of passenger information consideration. In some ways, reducing vehicle delays is equivalent to reducing person delays if identical number of people in each car. However, the average value of car occupancy is 1.6 according to statistics from UK DfT (UK Govt. Dept. Transport, 2019a). Although there are no specific distribution proportions of different car occupancies released from UK DfT, the distribution of car occupancies (excluding drivers so that the value can start from 0) can be estimated in this project with proper assumptions. Poisson distribution is a proper model that helps to describe the discrete probability distribution of the number of events occurring in a given period/space interval and having a known constant mean value. In this case, a thing that happens in a period/space interval is replaced by a passenger sitting in a vehicle. The Poisson can be used once all of the criteria are satisfied:

- The number of independent trials is large: in this project, the number of vehicles on road in the UK is a large value;
- The probability of occurrence in one experiment is very small: for individual passenger, the person can only be inside one of the vehicles and the probability of a person in a specific vehicle is very small;
- The events are independent: for any two passengers, a passenger in a vehicle is independent of another person in a vehicle. The relationships between two passengers, (e.g. family members, friends) are not considered for simplification.

From the analysis above, the probability of car occupancy (excluding drivers) in a vehicle can be assumed to follow the Poisson distribution. Thus the distributions of different car occupancies are calculated in Table 2.3. As a typical passenger vehicle can load at most 3 passengers, the probability of 3 car occupancy in a vehicle in Table 2.3 is the summation of the probabilities of 3 and more passengers in a vehicle.

Table 2. 3 Different probabilities of cars occupancies from 1 to 4 in a vehicle assumed Poisson distribution with a mean of 1.6

Car occupancy	0	1	2	3
Probability	54%	33%	10%	3%

In Table 2.3 it can be found that the probability of a car with high occupants (2 or more occupants in a car) is around 46% of the total amount with a mean occupancy value of 1.6. The person-based control could be properly proposed to reduce delays of those HOVs to achieve person-related objectives. In addition, the statistics of average car occupancies sorted by different time of days and vehicle types are also released by UK DfT, which can be seen in Tables 2.4 and 2.5 respectively.

Table 2. 4 Average car occupancies sorted by time of days and journey purposes in UK in 2010 (UK Govt. Dept. Transport, 2021b)

Journey Purpose	Weekday 7am – 10am	Weekday 10am – 4pm	Weekday 4pm – 7pm	Weekday 7pm – 7am	Weekday Average Weekday	Weekend Average	All Week Average
	Occupancy per Vehicle Kilometre travelled						
Work	1.13	1.16	1.15	1.17	1.15	1.31	1.16
Commuting	1.13	1.15	1.14	1.15	1.14	1.21	1.15
Other	1.71	1.82	1.79	1.79	1.79	2.12	1.91
Average Car	1.35	1.63	1.43	1.45	1.48	2.01	1.61
	Occupancy per Trip						
Work	1.20	1.19	1.17	1.18	1.19	1.26	1.20
Commuting	1.17	1.15	1.16	1.18	1.17	1.24	1.18
Other	1.68	1.65	1.71	1.66	1.67	1.90	1.73
Average Car	1.43	1.55	1.48	1.48	1.49	1.81	1.57

Table 2. 5 Average vehicle occupancies sorted by vehicle types and journey purposes in UK in 2000 (UK Govt. Dept. Transport, 2021b)

Vehicle Type	Journey Purpose	Weekday Average	Weekend Average	All Week Average
		Occupancy per Vehicle Kilometre travelled		
LGV	Work (freight)	1.20	1.26	1.20
	Non Work	1.46	2.03	1.59
	Average LGV	1.23	1.35	1.25
OGV1	Work only	1.00	1.00	1.00
OGV2	Work only	1.00	1.00	1.00
PSV	Driver	1.00	1.00	1.00
	Passenger	12.20	12.20	12.20

From Table 2.4, the average car occupancy values during the weekday are lower than those during the weekend. The average numbers of passengers travelling with the purpose of work and commuting are compared to be less than the numbers of passengers with other purposes. Comparing the values in different time-of-day periods, the average car occupancies at morning peak hours are slightly lower while the car occupancies at inter-peak periods are relatively higher than those in other periods. From Table 2.5, the average occupancies of Light Goods Vehicles (LGV) and Other Goods Vehicles (OGV) during weekdays are also less than those values during weekends. The occupancies of Public Service Vehicles (PSV), for instance, buses, are considerable. In summary, UK car occupancies fluctuated between 1.1 and 2.2, depending on the various variables of travelling purposes, vehicle types and different periods of the day. Moreover, supposing that car occupancy is a constant value, the car occupancy sequences arriving from different lanes and approaches to the junction in a short time also have large quantities of combinations. The vehicular situations and potential varying traffic demands for person-based controls are much more complicated than vehicle-based controls and TSP approaches. The person-based control paradigms therefore should be designed to be more adaptive to different vehicular situations, and flexible to consider different possibilities of signal timing plans and their function values. Even if the HOVs on road are extremely low proportion and almost all vehicles are under the same priority levels, the optimal strategy adopted by vehicle-based control is one of the potential solutions which should be considered in the person-based control design to ensure its performance.

2.3.2 Traditional transit signal priority

Public transport priority strategies and other forms of priority methods are dominant to be implemented in many cities in several decades, proceeding from better making use of limited road space with the larger capacity tool. All forms of bus lanes and HOV lanes are designed to segregate those priority needed vehicles and normal cars. Compared to those dedicated priority methods resorted to facilities, giving priority to traffic signal situations is more universal due to unavailable facility-based systems and most cases existing traffic lights (Diakaki et al., 2015). Under urban traffic lights network circumstances, approaching vehicle priority (e.g. bus) is quite realistic and achieved by adjusting signal timing settings.

A series of traffic response control strategies mentioned in Section 2.2 alter their signal timings to give priority to public transport without severe disadvantages to other traffic, such as bus priority in SCOOT (Hunt et al., 1981). Many priority methods at urban traffic lights are flexibly utilised. The green time extension is applied for those approaches which detect the public transport upon lanes and request to clear beyond the normal green time. The recall method shortens green time of the phases without detecting public transport and move them to the phases with bus routes. The stage skipping method directly cancels one or more stages against the prior setup sequence to provide service for priority vehicles. Stage re-ordering also disturbs the signal timing ranks and selects the activate stage as well as later stages according to bus information. Green wave strategies are frequently served for emergency vehicles to allow them to pass through several junctions with all green signals to reach high-level priority. All green for bus method helps bus arrive at the lane stop line with green lights anytime. Compensation methods will recover the normal signal control operation once the priority vehicle is detected disappearing from the lane. Current signal control-based priority methods select several options from the above skills to achieve their method, which can be classified into passive priority and active priority methods.

2.3.2.1 Passive priority method

The passive priority method acquires the public transport vehicle information and timetable to consider which flow streams will contain more priority vehicles. Higher green times towards those flows are weighted and allocated in advance. TRANSYT method also formulates a fixed-time plan for the whole network corresponding to public transport (Robertson, 1969). This coordinated plan makes use of rough buses and tram lines' arrival information and their frequencies without detecting approaching priority vehicles. VISGAOST is another program determining appropriate signal light parameters including cycle, offsets and stage sequences with an off-line genetic algorithm (Stevanovic et al., 2008). Green extension or stage recall signal priority optimization limited by maximum green will be operated in case of priority request, and then signal settings beforehand will be recovered. However, passive priority methods appeared to be inefficient, which attributes to the high accuracy degree of priority vehicle streams forecasting and information acquisition. The inappropriate signal timing arrangement for actual missing or unpredictable priority vehicles brings even more negative effects than normal signal controls.

2.3.2.2 Active priority method

Owing to bus loops, public transport receivers or other detectors, active priority methods attempt to overcome the shortcoming of passive methods by sensing each public priority vehicle arriving on the road. Higher priority schemes are only assigned for buses once they are detected. Therefore, the minimum requirements of active methods are Selective Vehicle Detectors (SVD) to gather real-time public transport approaching data. The SCOOT system installed a variety of facilities to provide priority to public transport vehicles (Hunt et al., 1981). Besides this, the system also implemented active strategies such as preventing red light stopping, stage recall and stage skipping for individual heavy delay buses, which are widely applied in London, Glasgow, Southampton, York and many other UK cities (Oliveira-Neto et al., 2009).

SCATS system, which is mainly appeared in Australia, Canada, and Brazil around the globe, also adopted green extension, stage recall, stage skipping, special stage, and stage reordering as means of serving late priority vehicles (TCRP, 1998). While it treated different kinds of vehicles as three layers: highest priority for trams, medium layer for buses forbidden stage skipping, and low priority for other vehicles. Different levels of priority framework from no priority to absolute priority also performed in the lower layer of the two-layer BALANCE system, making it responsive to the lateness degree of public transport and traffic demand (Fox et al., 1998). BCC-RAPID made decisions on whether the buses are out of the green schedule and worthy to provide priority via green extension or stage recall (Fox et al., 1998). Upon separation of buses from other vehicles by SDVs, MOVA gave general priority means to a bus (Fox et al., 1998). Similarly, SPRINT also sought the earliest possible chances to clear the buses selective from the junction when individual buses were detected (Fox et al., 1998). Different from the above strategies, PRIBUSS developed flexible priority programming based on First-In-First-Out (FIFO) theory which enabled engineers to select the traffic situations, procedures, limitations and other parameters (Wahlstedt, 2011). This system can be available in isolated junction or coordinated signal control, becoming the main public transport priority method in Sweden.

Another sort of active method relies on optimization techniques rather than explicitly consideration of signal timings. The vehicle priority part of PRODYN took into account public transport equivalent to a single vehicle platoon comprised of several normal vehicles to reach minimum delay in the junction (TCRP, 1998). Quite similar to PRODYN by leaving off traditional cycle length and green splits, SPPORT considered whether to terminate the current stage or not and which phase could be awarded the next green duration at every decision point (Dion and Hellinga, 2001). BUSBAND priority system can either transfer buses into ordinary cars with weighted values or add a constraint to the network control logic thus providing bus priority (TCRP, 1998). As an updated version of BUSBAND system, CAPRI operated quite similar logic to the former one via additional predicted public transport, at-grade rails and trains arrivals (Mirchandani and Lucas, 2004). DARVIN also predicted vehicle movement conditions and identified network quality upon integration of buses and other vehicles to perform instantaneous signal control settings adaptively (Duerr, 2000). The bi-level priority optimization systems, SPOT (TCRP, 1998) and MOTION (Gardner et al., 2009), decided on the central component signal setting optimization at the upper level and provided local parameter adjustments calculated by the cost function at the lower level.

Urban junction priority systems were then improved by more advanced detections which are capable of accessing more detailed and accurate public transport-related data than SDVs. The instances include Automatic Vehicle Location (AVL) and Global Positioning Systems (GPS), which make multiple detections points feasible. iBus system in London is such a representative (Wong and Hounsell, 2010). Instead of costly physical hardware detections installed on urban road fixed places, AVL and GPS improve the flexibility of iBus system with locations and other information. The system is also cost-saving by replacing the installation and maintaining cost of those numerous bus detections on street.

2.3.3 Discussions and conclusions

The priority schemes for public transport vehicles are applied to respond to the government policies of promoting public transport operation. The detectors and sensors such as SVD or AVL are capable of detecting the locations of public transport vehicles approaching the junctions, delivering the information to the decision-making algorithm and adjusting signal schemes to be biased towards buses with higher occupancies. Through the review in this section, traditional TSP strategies are challenging to be considered intelligent and adaptive since the special detectors dedicated to public transport vehicles can only provide location information and not be adequate to predict accurate arrival times for buses. Those schemes also only take into account whether the public transport vehicles are approaching, neglecting the real occupancies in them and passenger cars. Most importantly, public transport priority systems are designed merely for providing priority to limited buses and are hard to be implemented in person-based urban signal controls where different occupancy levels of all vehicles should be fairly modified.

However, there are still two inspirations from the review of existing urban signal control-based priority schemes for person-based urban signal controls. The priority methods treat differently public transport vehicles and passenger cars, as public transport vehicles can load a great number of passengers far beyond those in cars. The occupancy level differences make the signal control system provide different priority levels to them. Servings for public transport vehicles first are accessible to support more travellers less suffering from junction delay and congestion to achieve people mobility target. Some studies investigated the travel time and delay benefits of TSP. An early field experiment of TSP in Louisville, Kentucky reported 9% - 17% time savings for buses compared to those without TSP (Capelle et al., 1976). Another trial in Virginia found 2.3% - 2.5% travel time savings for express buses, 4.8% time savings for local buses and an 18% increase in average travel time for all traffic when unconditional TSP is executed. Hounsell et al. (1996) reported a 20% - 30% bus delay reduction with TSP in SCOOT. Wahlstedt (2011) reported an overall 6% travel time improvement for buses from two directions but up to 13% and 6% travel time increment of other vehicles on the cross street and main street respectively. From these researches, traditional TSP methods were found to improve the travel time and delay of buses compared to the cases without bus priority. However, they also made impacts on other vehicles on road and even negative impacts like the results reported by Wahlstedt (2011). One of the challenges of the person-based control paradigm is how to achieve the objectives of reducing the person delay of all vehicles with and without the presence of buses.

Another inspiration is that the stage sequences of person-based urban signal controls may not be as fixed as a vehicle-based system. The fixed stage sequences applied in existing signal controls make them only decide the duration of the separate stage for the convenience of implementation. This will not significantly disrupt the performance of signal controls when all vehicles are assumed to be the same. Since high priorities are occupied by public transport vehicles and their common arrivals conflict with current green active stages, priority signal systems take a series of measures, such as stage recall, stage skipping, and stage reordering to avoid these circumstances. The measures break the stage sequences, allowing public transport vehicles to pass as fast as possible. The person-based signal controls can also adopt complete flexible stage sequences to make sure of passages of those high occupancy vehicles.

Notably, the realizations of person-based urban signal controls need not only detailed information on the state of vehicles and road networks, but the occupancy information from all vehicles as well for a better understanding of priority levels. The fixed point detections for existing urban systems discussed in Section 2.2 are not capable of collecting such an abundant level of data. New connected vehicle technology offers opportunities to shift existing urban signal controls to be more adaptive and correspond to variable traffic situations. In Section 2.4 connected vehicle technology will be introduced to reveal the opportunities it brings to widen the affordability, availability and accessibility of urban signal controls.

2.4 Review of connected vehicle technology

High levels of detailed and accurate real-time information are the prerequisites for the innovation of urban signal controls. Connected vehicle technology enables all of the vehicles and junction controllers in a certain range to be connectivity. It absorbs the variety of current mature data collection and wireless communication technologies, fundamentally changing the ways how traditional sensors monitor the state of roads. This section provides a detailed survey for connected vehicle technology, including the data collection technologies it adopts, data type available, wireless communication standards dedicated used for transport mobility and related standardized message sets designed for information delivering efficiency.

2.4.1 Main data types and sources for connected vehicle communication

Collecting traffic environment-related data is positively the first step to constructing a new adaptive signal control paradigm. ITS technologies are combinations of advanced vehicle sensors, smart infrastructure, GPS navigation and other advanced modules to provide an information-rich platform for junction management. Available data information participants and devices include pedestrians, vehicles, road infrastructures, sensors, as well as management centres (Qu et al., 2010). In general, the data source collection system is comprised of vehicle on-board units and roadside infrastructures (Olia et al., 2016). On-board units utilise different components (as shown in Figure 2.3) installed on the body of CV to acquire individual vehicular parameters. While road infrastructures gather the road conditions and vehicle flow or tracking information. This chapter summarizes common acquisition devices and data sources respectively for on-board units and roadside infrastructures, which are relevant to this project. Comprehensive descriptions of available technologies in connected vehicle communication systems for both vehicular and roadside data are outlined in Table 2.5 and Table 2.6.

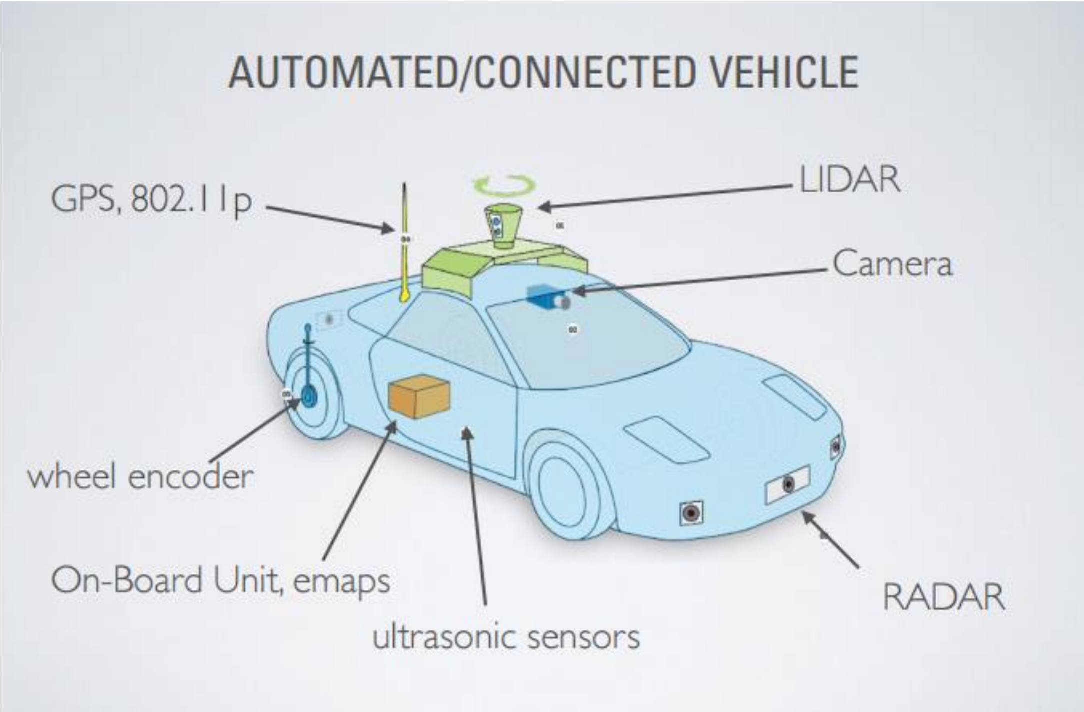


Figure 2. 3 On-board units on connected vehicle (Diakaki et al., 2015)

On-board unit data sources

The on-board unit equipment can be roughly divided into five classifications: GPS device, vehicular camera and video, various vehicle sensors and seat pressure system. The data contributions they can provide are concluded in Table 2.6.

- Global position system (GPS) is a U.S.-owned technology to provide positioning, navigation and timing functions to the user by 24 operating satellites (Hofmann-Wellenhof et al., 2012). The main compositions of GPS are space, control and user segment. If the user segment is equipped with connected vehicles, the GPS generic receiver will receive the signals from satellites and then calculate three-dimensional position and time by antenna (Hofmann-Wellenhof et al., 2012). The final navigation outputs contain position, velocity, heading and time fault information (Grewal et al., 2001). To ensure the signal is accurate, 35-55 dB of gain and 20MHz nominal bandwidth are provided for radio frequency amplification and two GPS signals (Grewal et al., 2001). One or two antennae on GPS can also use for detecting road grades by obtaining the ratio of vertical to horizontal vehicle velocity (Hofmann-Wellenhof et al., 2012).

- Numerous on-board sensors distribute in different locations of internal vehicle spaces to perceive vehicle status and parameters in multivariate travelling phases. Collecting single-vehicle data is relatively easy if integrating observation values from different sensors (SAE, 2012). Wheel encoder can obtain vehicle speed, while steering and brake sensors collect vehicle heading and state (SAE, 2012). Similarly, vehicle acceleration and deceleration from the accelerometer can be measured, even turning intention from the turn signal on the vehicle.
- Seat pressure system is a kind of on-board sensor installed under car seats to obtain car occupancy data. Electronic, pneumatic and electro-pneumatic are three main types of sensors used for measuring seat-buttock interface pressure (Gyi et al, 1998). In the first type, a deformable component consists of Electronic transducers to connect sensors which can electorally measure variations in resistance caused by applied force (Cooper et al, 1986). The pneumatic sensor is connected to an air reservoir. The volume of air in the sensor will increase suddenly when an inflation pressure rises, resulting in an abrupt drop in a pressure increase rate. The value changed is recorded as interface pressure (Eckrich and Patterson, 1991). Electro-pneumatic sensors have electronic components on the inner surface of a flexible sac, which balances the internal and external pressure when air is pumped into it. The pressure value at this moment is recorded as interface pressure for occupancy detection (Robertson et al, 1980).
- Different from the seat pressure system or camera used for measuring car occupancy, bus occupancy is acquired from the Automated Passenger Counting (APC) system. APC is an electronic counting device which can counts and record the number of passengers boarding and disembarking at every bus stop (Sojol et al, 2018). The APC system consists of two sensors, which are typically installed at the same height level of the front and rear doors of a bus. When passengers get on or get off a bus, they break the infrared beam between the corresponding sensor and the value is recorded. The computer then calculates the passenger information according to the order in which the beam was broken.
- Camera and video installed inside the CVs (Figure 2.4 provides a location of the installed infrared camera) can also capture the figures of passengers so that car occupancy can be distinguished by recent technology of occupancy detection system (details provided in sub section below).

Table 2. 6 On-board unit connected vehicle data type relevant to the research

Available technology and equipment	Data contribution for connected vehicle
GPS	Position, velocity, heading

On-board sensors (steering, speed, brake)	State, velocity, acceleration, heading, route, type
Seat pressure system	Car occupancy
Automatic passenger counting system	Bus occupancy
Camera/video	Car occupancy

Figure 2. 4 Thermal camera and its location for data capture (Nowruzi et al. 2019)

Roadside infrastructures data sources

Roadside infrastructures data is generally collected by inductive loops, junction infrastructures and infrared cameras placed on road surfaces or roadside in advance. Their common feature is stationary rather than moving with the vehicles; hence data sources they produced are fixed regions, which can be seen in Table 2.7.

• Inductive loops are installed on the entire road surface, each of them supervising the lanes they are located. When vehicles surpass the loop detectors, the weights of vehicles and durations will transfer to special electrical signals in the management section. The detection flags will form to judge the number and types of vehicles that pass through this place in a certain period (Cheung et al., 2004). Based on this information, inductive loops can conduct vehicle flow and occupancy data, which are also used for vehicle classification at the measurement zone (Gajda et al., 2001).

• Junction management system is a special existing to represent signal control operation strategies and junction geographical information. Signal phases and timing (SPaT) and Map data elements describes those junction situations and are remained to delivery and communicate with connected vehicles. Dataset includes four fundamental sections: 1) SPaT (describes the signal state and duration of the junction); 2) Map data (describes physical geometry of one or more junctions); 3) Signal Request Message (current signal pre-emption and priority status); 4) Signal Status Messages (California PATH Program, 2011). The final part contains the information of lane set or movements, current signal state and rest time to switch the signal.

• As illustrated in Figure 2.5, the cameras installed at the roadside can also capture images of vehicles when they cross the photo-shoot locations to detect the car occupancy information.

Table 2. 7 Roadside infrastructure connected vehicle data type

Available technology and equipment	Data contribution for connected vehicle
Inductive loops	Vehicle classification, vehicle flow, road occupancy, number of turns
Junction system	Signal phases and timing (SPaT), the geometry of the junction,
Roadside cameras	Car occupancy

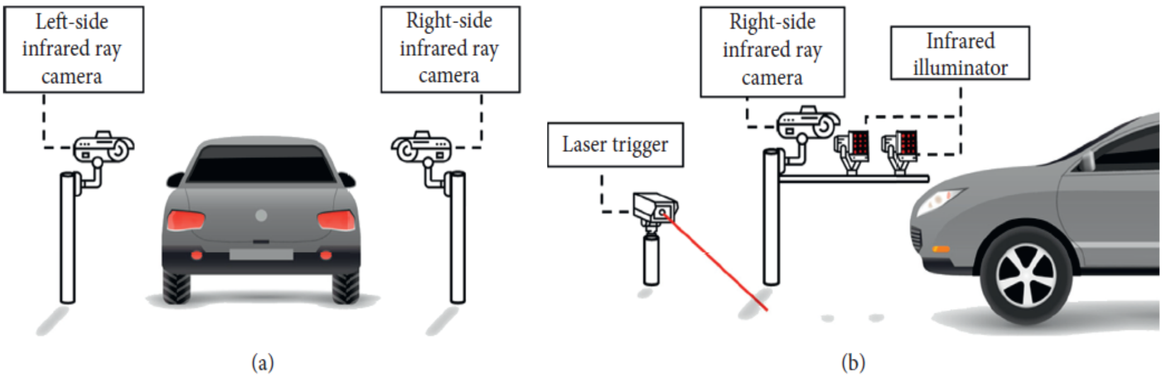


Figure 2. 5 Overview of the image acquisition system for vehicle occupancy detection. (a) Rear view. (b) Side view (Lee et al, 2020)

The variety of vehicular data and roadside infrastructure data that can be supplied by connected vehicles are reviewed in this section. The scale of vehicular data providing multiple dimensions is proportional to the number of CVs presented in the road network, with a high rate of information conversion among moving vehicle agents and junction agents. The potential enormous data size supplies the opportunity and possibility for more intelligent adaptive signal control towards dynamic traffic. Moreover, although the data size of roadside technologies is inferior to vehicular information, they indeed provide additional helpful data for signal control such as vehicle flows and SPaT information from the whole road situation. All of the available data collected by those technologies are possible to be utilised in designing signal control algorithms.

Vehicle occupancy detection technology

The technical systems that can be used to get vehicle occupancy data from CV environments have been summarized in Figure 2.6. The sensors in the seat pressure system and APC system are connected to a computer and therefore the passenger occupancy can be displayed on board. However, the CV-equipped cameras and roadside cameras can only take images and there is still a need for a process to transfer the image information to car occupancy data.

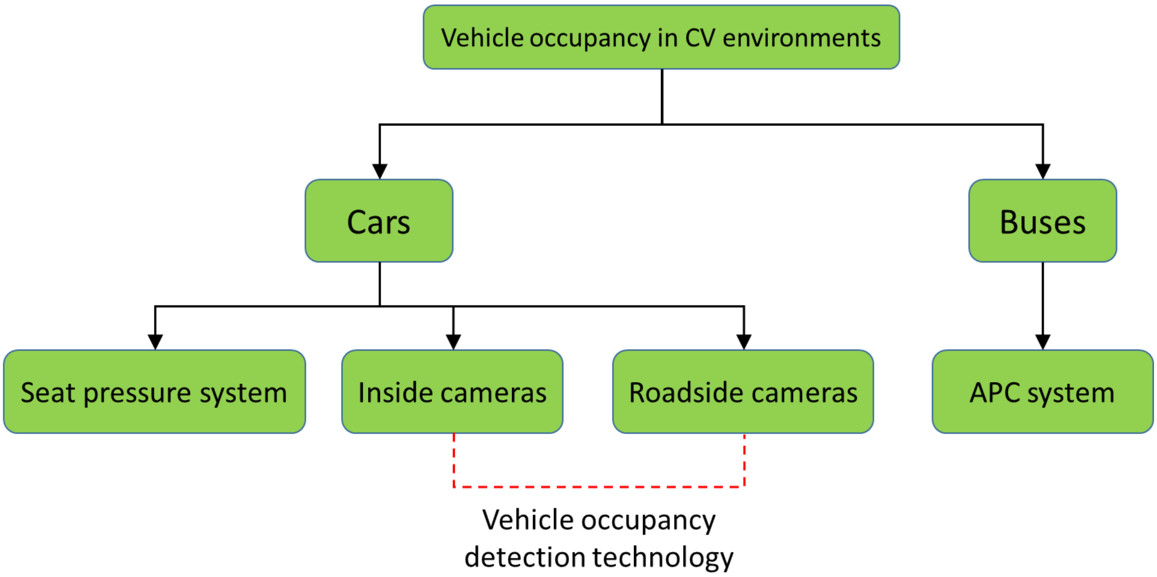


Figure 2. 6 The technical mechanisms for capturing vehicle occupancy data in CV environments

The most recent researches attempted to develop vehicle occupancy detection technology to solve this problem. The initial purpose of proposing vehicle occupancy detection system is to enforce HOV lane monitoring policies, which encourage carpooling and the use of public transport. The traditional manual method to count for vehicle occupancy is labour-intensive, has low operational efficiency, and increases labour costs (Schijns and Mathews, 2005). The various studies were conducted to fast and automatically achieve the vehicle occupancy estimation process in two groups: using in-vehicle sensors and using roadside cameras. The detection accuracy of occupancy estimation from in-vehicle cameras is generally high (Owechko et al, 2003). Infrared cameras are also used in some studies to replace general cameras to protect the privacy of passengers (Nowruzi et al, 2019). However, cameras or sensors are required to be equipped inside vehicles. The occupancy detection system using roadside cameras had limited scopes for detecting occupancy and some of them can only detect the passengers in the front seat (Hao et al, 2006; Artan et al, 2014). A new study in recent two years improved the limitations of previous research and it reached a 99% detection accuracy for two-sided roadside cameras and 87%

detection accuracy for one-sided roadside cameras. In this project, the car occupancy data from CVs are assumed to be obtained from in-vehicle cameras as the literature on detecting car occupancy from in-vehicle cameras indicated high levels of detection accuracy. The occupancy detection system for one-side roadside cameras will be used in an unequipped vehicle status estimation algorithm to capture the occupancy of all crossing vehicles (see details in Section 6).

This subsection lists the available data sources that can be collected by on-board units from CVs, which are related to this project. Notably, not all of the CVs are equipped with the full data collection devices mentioned at present. However, this is not a critical thing as the aim of this subsection is to realize which kinds of data can be collected and how can they be collected from CVs so that the assumptions and methodologies adopted in this project can be made. The sensitivity tests for different sorts of CV penetration rates are also carried out in the following sections to explore the performance of proposed signal controls in different situations.

2.4.2 Dedicated Short-Range Communication (DSRC)

In Section 2.4.1 it has been shown that a quantity amount of data resources collected electronically are available via connected vehicle enabling technologies. IEEE 802.11p is found the most suitable standard for data transmission among CV environments (Qiao et al., 2011). On the basis of IEEE 802.11p, dedicated short-range communication (DSRC) is specially designed to support vehicular ITS applications under V2V and V2I connectivity. Federal Communications Commission (FCC) specially allocated 75MHz bandwidth at 5.9 GHz licensed spectrum for DSRC (Lee et al., 2013). The dedicated 5.9 GHz spectrum is divided into seven 10MHz bands used to exchange information among vehicles and infrastructures (Lee et al., 2013). IEEE Wireless Access in Vehicular Environments (WAVE) defines the specifications and version of DSRC (Kenney, 2011). IEEE 802.11p decides the PHY and MAC layers of DSRC while IEEE 1609 family determine the upper layer (Kenney, 2011). The DSRC/WAVE system consists of on-board unit (OBU) and Road-Side Unit (RSU), which are equivalent to serving as mobile stations and base stations in cellular networks (Kenney, 2011). IEEE 802.11p-based DSRC enables wireless communication in CV environments, and can potentially meet various requirements for road messaging and control.

2.4.3 SAE_J2735 message sets

From section 2.4.1 it has been found that a variety of data collected by enabling current ITS equipment are available. From section 2.4.2 the wireless standard for connected vehicles has also been identified. However, how to use an established format to send the message can be quickly recognized by connected vehicle elements and identifying which kinds of data are more useful and crucial to ensure efficient and sustainable communication. In general, there are two most common message sets designed for connected vehicle environments by the US and the EU. The Society of Automotive Engineers (SAE) in the US defines the message sets in the SAE J2735 standard. While European Telecommunications Standards Institute (ETSI) in the EU defines two kinds of message types Cooperative Awareness Message (CAM) and the Decentralized Environmental Notification Message (DENM).

SAE standard attempts to support the collaborations among those connected vehicle segments in a means of DSRC applications, in terms of the standardized message set aspects. Therefore, SAE specifically designed a special message set focused on the 5.9 GHz DSRC/WAVE communication system, named SAE J2735 standard (SAE, 2016). SAE J2735 message set has its data frames and data elements covering a quantity of useful connected vehicle data in different types (shown in Table 2.8). The purpose and all contained data of each kind of message type are described in Table 2.8. SAE J2735 message set belongs to both awareness-based messages and event-based messages. The awareness-based message implies SAE J2735 can timely send pieces of messages describing the status information of a vehicle in a short interval (SAE, 2016). Each piece of the SAE J2735 message includes DSRC message ID corresponding to a separate message framework and other information, which make it easy to be recognized (SAE, 2016). Meanwhile, event flags contained in SAE J2735 represent different vehicle failures (e.g. hard braking, disabled).

Table 2. 8 Summary of the SAE J2735 Message Sets

DSRC message ID	Message set type	Typical use	Descriptions
	Message Frame	V2X	Fixed form to send flexible contexts
2	Basic Safety Message	V2V	Exchange vehicle state information data for V2X applications
3	Common Safety Request	I2V, V2V	Request vehicle state information data from another vehicle
4	Emergency Vehicle Alert Message	I2V, V2V	Broadcast emergency vehicle warning messages to surrounding vehicles
5	Junction Collision Avoidance	V2X	Broadcast potential collision warning messages to other devices
6	Map Data	I2V	Convey geographic road information
7	NMEA Corrections	I2V	NMEA 183 style differential corrections
8	Personal Safety Message		Broadcast safety data regarding vulnerable road users
9	Probe Data Management	I2V	Sent by RSU to control the type of vehicle probe data collected
10	Probe Vehicle Data	V2I	Exchange vehicle status along road segments
11	Roadside Alert	I2V, V2V	Send alerts for nearby hazards to passing vehicles
12	RTCM Corrections	I2V	RTCM differential corrections for GPS
13	Signal Phase and	I2V	Convey the current status of one or more

	Timing Message		signalized junctions
14	Signal Request Message	V2I	Request a priority signal or a preemption signal by vehicle
15	Signal Status Message	I2V	Sent by the RSU to convey the status of signal requests
16	Traveler Information Message	I2V	Send various types of advisory information
240-255	Test Message		Support the development new message for local and regional deployment use

Basic safety message (BSM) is an important and most widely used component in SAE J2735 Message Sets. BSM can broadcast at most 10 times per second and is comprised of two parts. The first part contains core elements connected to vehicle data, including vehicle size, position, speed, heading acceleration, and brake system status (Cronin, 2012). While part 2 can choose optional data to supply part 1 of BSM according to the needs, such as weather data, and vehicle data (Cronin, 2012). The details of all possible data type in BSM and those not including vehicle status are summarized in Table 2.9. Other frequencies used message sets in signal control applications are Signal Phase and Timing Message, Map Data and Probe Vehicle Data.

Table 2. 9 Data contexts in Basic Safety Message set (Cronin, 2012)

BSM part	High priority	Medium priority	Data not in BSM
BSM part 1 data elements	Timestamp; Position; Speed and heading; Acceleration; Brake system status; Vehicle size	Steering Wheel Angle; Positional Accuracy	Fuel type; Fuel consumption; Emissions; Fuel level; Road grade; Engine drive cycle; Operating mode; Engine temperature
BSM part 1 data elements 2	Recent braking; Path prediction; Throttle position; Vehicle mass; Trailer weight; Vehicle type; Vehicle description	ABS, Traction status; Stability control; Differential GPS; Lights status; Wiper status; Brake level; Coefficient of friction; Rain type; Air temperature; Air pressure; Vehicle identification Cargo weight GPS status	

Cooperative Awareness Message and Decentralized Environmental Notification Message

CAMs are broadcasted periodically by each vehicle to its neighbours to communicate information. Both sending and receiving devices are specific ITS agents, which need to be compliant with the ETSI standard (Santa et al., 2013). The context of CAM contains the presence, position, temperature, and basic status of the vehicle. CAM is an awareness-based message and needs to receive more than one message if tracking needs. The CAM will be produced only need to meet one of the requirements as follows (ETSI, 2011):

• Maximum CAM generated interval is less than 1s.
• Minimum CAM generated interval is greater than 0.1s.
• Vehicle heading angle value is larger than 4° compared to last CAM.
• Vehicle positon distance is larger than 5m compared to last CAM.
• Vehicle speed changes more than 1m/s compared to last CAM.

DENMs belong to event-based messages. Therefore, they are generated once hazardous events happen to alert road users (Santa et al., 2013). The message structure of DENM is more complex than those of CAM. The body of the DENM structure contains more details. The decentralized situation management in the DENM body includes general information about the event. While the second part claims the detailed context about what the event wants to be reported. The final situation group gives location data about the event (Santa et al., 2013).

There are significant differences exist in data definition formats and application cases by comparing SAE J2735, CAM and DENM. However, all of them have similar data types so they can be matched mutually. Apart from that, the message broadcasting intervals and type of messages of BSM and CAM are not similar. The BSM prefer to be generated more periodically fixed, but CAM will be generated when one of the requirements meet. The corresponding message types of CAM will be several options. That means the contexts and sending frequency of BSM are more stable. Another difference is SAE J2735 can provide Signal Phase and Timing and map data information with DSRC message IDs 13 and 6, while CAM/DENM cannot. In most cases of adaptive control models, for instance, in Feng et al. (2015), BSM in J2735 DSRC Message Set Dictionary based on IEEE 802.11p is used.

The introduction of connected vehicle communication proves that connected vehicles can broadcast Basic Safety Message (BSM) to both other connected vehicles and infrastructures. Society of Automotive Engineers (SAE) J2735 Dedicated Short Range Communications (DSRC) Message Set Dictionary regulates a variety of specialized transmission data types for V2V and V2I communication, also called BSM (Goodall et al., 2013). Each piece of BSM can provide vehicle ID location, speed, heading, acceleration, size, and infrastructure system information (Feng et al., 2015). Moreover, the broadcasting frequency of BSM can reach to 10Hz along the DSRC radio (Feng et al., 2015). In other words, the BSM can be received by Junction Management Agent (IMA) and Vehicle Agents (VA) connected in Vehicular Ad-Hoc Networks (VANET) every 0.1 seconds. The optimization decision algorithm for signal control is typically discretized into 1s intervals (Li and Ban, 2017). Therefore, for every decision point, the signal centre infrastructure is capable of obtaining affluent real-time connected vehicle data.

The message sets currently contain the most useful information to be transmitted for modelling new adaptive urban signal controls. The message sets are designed to be concise enough to be launched and received efficiently and minimise the occupation of channel use. From Table 2.9 some essential data sources for monitoring the road state, such as locations, and speeds of connected vehicles have been incorporated. Also, there is no standardization for the collection of vehicle occupancy data at present, the APC system has been implemented to count for the passenger numbers in transit. The bearing loading sensors installed on vehicles and videos/cameras on road sections offer potential ways to check out the occupancy in the passenger car. It is not difficult to combine the occupancy level information of vehicles into message sets if they are found to have the potential to improve the development of person-based urban signal controls.

2.4.4 Connected vehicle data sources and processions for new urban adaptive signal controls

Given available data sources can be collected in Section 2.4.1, the connected vehicle data selection as inputs of respective state-of-the-art urban signal control strategies are listed in this section. The instantaneous speeds and positions of each connected vehicle in VANET ranges are commonplace and entire in most models, due to they are the most possible information to describe the traffic situations surrounding the junction. Thus, a number of vehicle and traffic parameters with regard to model objective functions have access to be precisely predicted or calculated, for instance, vehicle arrival time, vehicle trajectories, queue length, vehicle stopping times, arrival rates and so on.

a. Vehicle arrival time

Given the locations and speeds of those vehicles detected by the communication system, the vehicle arrival time from the current space to the possible spaces towards the stop line (consider queue exist) can be predicted. Arrival time information is used commonly in situations of multi-agent interaction. After obtaining arrival time information, the junction contributes to planning the vehicle motion, holding a future place for the vehicle to pass through the junction with the maximum speed, as well as smoothing vehicle trajectories (Jin et al., 2012). The time-of-arrival information can be calculated by considering all the possible conditions according to the distance from the vehicle to the stop line, current speed and maximum speed of the vehicle (Jin et al., 2012). More directly, the vehicle agents predict their own arrival time based on the proposed model and inform infrastructure (Kari et al., 2014). In the traditional method, arrival time information is unavailable because the loop detectors cannot detect the speed of vehicles crossing them.

b. Arrival flow/ Departure flow

As an important parameter to represent the vehicle flow demand coming to the junction or measure the vehicle queue length, arrival flow can be acquired directly from connected vehicle technology (Feng et al., 2015). In some cases the vehicle flow is set to follow the Poisson distribution (Chang and Park, 2013), therefore (Chandan et al., 2017) use the Poisson distribution to estimate the number of arrival vehicles entering in a certain period to represent the arrival flows. The departure flow is relatively counted by the number of vehicles leaving the cross line during the period. The queue calculation at the decisive moment and ratio flow estimation cannot be separated from the departure flow value. Cumulative departure flow numbers are obtained by estimating the vehicle departure time from the car-following model and then checking the numbers of vehicle passing through (Chandan et al., 2017). Similarly but not the same, loop detectors have limited effects to measure the number of vehicles passing through a certain point in a given period. Compared to this, the connected vehicle can provide arrival or departure rates at any point within the network transmission range.

c. Departure time

Departure time describes the duration spent for vehicles from the waiting status to the moment they cross the stop line under traffic light states. This value is a key factor to estimate the delay vehicle may suffer corresponding to different traffic light operations to decide the most suitable case to assign green light for each lane as a whole (Guler et al., 2014). The departure time of vehicle D_C is influenced by many factors depending on whether it exists in a queue or not, which is calculated as follows (Box and Waterson, 2010; Yang et al., 2016):

$$D_C = max\left\{V_C;\ D_{C'} + \frac{1}{S_m} + P_C\right\} \tag{2-11}$$

Where V_C represents the duration of vehicle travel to the downstream end of the junction under the situation that there is no queue exists. $D_{C'}$ means the departure time of the previous vehicle and S_m is the value of the saturation flow in this lane. P_C is the delay penalty of this vehicle related to its initial speed and acceleration. For the situation when a queue exists, the vehicle departure time can also be simplified in (Younes and Boukerche, 2014; Younes and Boukerche, 2016) like this:

$$D_C = \alpha + \frac{F_d}{S_{tf}} \tag{2-12}$$

Where α refers to the start-up lost time of the first vehicle when the green light is awarded. F_d is the distance from the furthest vehicle in this queue to the stop line and S_{tf} is the vehicle speed of traffic flow. In traditional real-time signal control strategies departure time of the vehicle still cannot be measured for the reason that the vehicle location and how many vehicles are ahead of it are unknown to the loop detectors.

d. Vehicle queue length

Vehicle queue length is a critical factor to measure the traffic congestion conditions in a specific lane. Part of the proposed strategies adopted minimum vehicle queue length as their objective function. In most cases, the queue length taking a vehicle as a unit is represented by the number of vehicles idling behind the cross line and waiting for discharge at one time. Considering those vehicles approaching the existing vehicle queue with deceleration, the method to capture such a constant under a dynamic vehicle stream environment is not unique. A method which is similar to regarding the arrival flow and departure flow as intake and discharge was mentioned in (Feng et al., 2015) with available arrival flow and departure flow data collected by connected vehicles. This queue measurement method is shown as:

$$l(n) = l(n-1) + q_a(n) - q_d(n) \tag{2-13}$$

Where $l(n)$ and $l(n-1)$ mean the queue length for the specific lane at time n and time n-1 respectively. $q_a(n)$ is the arrival flow and $q_d(n)$ represents the departure flow at time n. Another proposed method in (Tiaprasert et al., 2015) discriminated the three kinds of queue length situations in terms of connected vehicle speeds and positions. The vehicle would be determined to be stopped if its speed was lower than the pre-defined stopped speed. Thus 1) the vehicle queue is estimated to 0 if no stopped vehicle is detected at all; 2) if stopped vehicles are found but no moving connected vehicle detected, the queue length equals the furthest stopped vehicle distance to the cross line divided by effective vehicle length; 3) if both stopped vehicle and moving vehicle detected, the vehicle length is decided between the rank number of the furthest stopped vehicle and the nearest moving vehicle. The alternative format by using meters as a unit to present queue length is also acceptable in Yang et al. (2016), which also account for the number of stopped vehicles N in formula (2-7):

$$l(n) = \sum_{i=0}^{N} VL_i + ADBV * (N-1) \tag{2-14}$$

Where VL_i is the individual vehicle length for vehicle i in stopped sequence and $ADBV$ represents the average gap between vehicles. All of the above cases to calculate queue length require instant speeds and positions of vehicles to judge vehicle stopped or moving status, which are impossible to achieve in traditional methods without that information.

e. Travel time

The Cumulative Travel Time (CTT) for individual vehicles still not passed the junction could be also a major aim for the designed model (Lee et al., 2013; Kari et al., 2014) or as part of process variables to determine vehicle delay (Yang et al., 2016). One of the feasible methods for calculating travel time is to count the elapsed time from when the vehicle enters the communication range of the approach link to the current position (Lee et al., 2013). While aggregating the separate vehicle position and speed information with the traffic light, the queue message provides an alternative solution for predicting vehicle travel time in four cases (Li and Ban, 2017): directly pass through; arrivals during green and queue exists; arrivals during red; arrival during red and queue exists.

f. Vehicle trajectories management

Besides gathering vehicle information for junction centres by V2I communication, the connected vehicle technology enables the guidance from the signal controller for every connected vehicle with better trajectories by I2V communication, definitely beyond traditional methods. Vehicle efficiency-based models expect to plan the trajectories for identified vehicle platoons recognized by mutual distances to let the vehicle pass through the junction at the maximum possible speed at a certain time and avoid stopping at all possible ((Yang et al., 2016; Feng et al, 2018; Pourmehrab et al., 2017). The future trajectories of the leader vehicle in the platoon and the behaviours of following vehicles will be predicted by optimal control using the car-following model (Feng et al, 2018; Pourmehrab et al., 2017). Thus the departure time of the leader vehicle controlled by the optimal trajectories model will cater to the green light switch for reducing vehicle travel delay. Eco-driving models also optimize the target velocity for connected vehicles and suggest advisory velocity for drivers or automatic operation systems based on model predictive control (Du et al., 2017) for the sake of improving fuel economy and reducing emissions. Therefore, those connected vehicles followed by the trajectories information from the optimal model would be more smooth and energy economy.

g. Vehicle occupancy

The vehicle occupancy level is a unique data type required in person-based control. For each vehicle, the vehicle occupancy is a constant value at a certain time. In most person-based control researches, perfect occupancy data are assumed to be available without claiming access to them (Christofa et al, 2013b; Yu et al., 2017; Yang et al, 2018). Vehicle occupancy can be used for calculating person-related objective values. For instance, the person delay can be calculated by vehicle delay scaled by occupancy data of this vehicle. The passenger travel time equals vehicle travel time multiples occupancy data.

2.5 The state-of-the-art vehicle-based urban signal controls in connected vehicle environments

In Section 2.4 connected vehicle communication technology is introduced to enable junction infrastructure to acquire more detailed connected vehicle information, providing a good prospect for adaptive signal control. The new data sources from connected vehicle technology are preparing for the innovation of urban transport mobility and potentially remedy the limitations of existing urban signal controls with better knowledge of the road environment. However, whether formations or quantities of connected data are fundamentally different from the data inputs collected from point detectors (e.g. inductive loops). Therefore it is very important to develop new urban signal control systems, exploring how will these sorts of connected vehicle data will be boosted and incorporated into the urban signal control paradigm.

This section reviews the state-of-the-art vehicle-based urban adaptive signal controls in connected vehicle environments, investigating the progress they have made and the limitations for future researches. A comprehensive review has been made in survey papers by Wu and Waterson (2021) and Wang et al (2021a). Given the inputs of connected vehicle real-time information and objective functions, the decision algorithms are introduced in this section, as well as their pros, cons, applicable conditions and case studies. The generic frameworks of adaptive signal control and the detailed aspects which are worthy to be noticed are also explained in this section. It is a critical step to justify what is the main limitation of vehicle-based urban signal controls in connected vehicle environments and then focus on more specific researches to enhance this limitation in the next chapter.

The core of the adaptive signal control systems, known as the road traffic information from the CV dataset (Section 2.4.1), is how to take action to optimize the strategies so that more responsive to objective functions (Section 2.2.1). The actions implemented by the junction could be either signal timing parameters adjustments (phase sequences, durations and cycle length), or optimum connected vehicle trajectories (speed, acceleration, headway suggestions). Hence, the adaptive signal control process can be viewed as incorporating the current state (vehicle delay, queue length, travel time and other situations) and decision variables (different signal timing control strategies) to decide the best solution (max or min objective functions) which make vehicles perform better (validate and calibrate by KPIs in section 2.2.2 with benchmarking models). This section will review the state-of-the-art decision algorithms to see how the junction works under connected vehicle technology, including comments and discussions, which are summarized in Table 2.10.

2.5.1 Integer programming and solution algorithms

Mathematical programming model is the most commonly used method to solve junction control optimization, which is dedicated to the optimization problems. Objective function z, constraints like Equation (2-15) and decision variables x are three fundamental components of mathematical programming, the canonical form of which can be presented as:

$$\min(\text{or max})\, \mathrm{z} = \mathrm{f}(x_i),\ \ x_i = [x_1, \dots, x_n]^T \tag{2-15}$$

$$s.t. \qquad G_{min} \leq x_i \leq G_{max} \tag{2-16}$$

As part or all of the decision variables are only possible integers (e.g. number of vehicles in lane cells (Islam and Hajbabaie, 2017), green time duration for one phase (Feng et al., 2017)), the mathematical programming models for signal control methods are classified as integer programming. The range of the decision variables is limited by traffic control constraints, such as the restrictions of minimum and maximum green time (Feng et al., 2017), and red or green signal state (Islam and Hajbabaie, 2017). In other words, the possible optional decision schemes which are feasible for the junctions are finite in a given operating time horizon. Different decision variables will cause a variety of vehicle delays, queue lengths and others for different lanes concerning which phase is prioritized with green and how long duration it lasts. Countable decision variables will result in the exclusive optimum solution, which is predicted or calculated as the best objective value performance after junction control management executes this decision, which can be found by integer programming. For instance, a Mixed Integer Linear Program (MILP) was adopted by Islam and Hajbabaie (2017) to maximise the junction throughput while also minimising the queue length within 2 junctions with 14 two-lane links and 9 junctions with 48 two-lane links. A mixed-integer non-linear programming with multi-objectives of maximising the capacity and minimising number of vehicles crossing the centreline of the road are also tested in numerical examples with different demand compositions (Sun et al., 2018).

The most basic approach to solving the integer programming problem is enumeration, which lists all the possible decisions made by junction controllers and yields respective function value results. The solution leading to the max or min value will be optimum. The enumeration method using CV was initially proposed to find the longest queue length and minimum delay by considering 5 optional phase transition decisions in a real road network in Hannover, Germany, consisting of 9 signalized junctions (Cai et al., 2013). Afterwards, the algorithms explore the highest cumulative vehicle travel time for the next green phase (Lee et al., 2013), the next vehicle departure sequence to minimise delay and number of stops (one junction) (Younes and Boukerche, 2014), and largest vehicle density from defined phase combinations (a 4-legs simulated junction) (Younes and Boukerche, 2016), the current longest queue length (isolated junction) (Tiaprasert et al., 2015) were all successfully enumerated and performed better than calibrated models. In order to absorb more updated recent connected vehicle data to prevent unforeseen changes in dynamic traffic (Feng et al., 2017) and decrease the complexity of integer programming, the proposed models collect data at the current time step, predicting future traffic states in certain time horizon to find optimal solutions, then execute in next several time steps (Islam and Hajbabaie, 2017), which is called as rolling horizon approach. The rolling horizon circle will be continued once the last horizon has been run out with a variety of cycle lengths in their methods (15s in (Goodall et al., 2013), 80s in (Feng et al., 2017) and 2s in (Feng et al., 2018)).

The enumeration algorithm for integer programming visits all the possibilities but has operational efficiency difficulties due to exponentially increasing complexity when a number of cars increase in the algorithm (Yang et al., 2016). A branch and bound algorithm were therefore adopted by (Yang et al., 2016) to directly cut down those unnecessary nodes in a tree search problem. A total of 1896 cases were tested in contrast to the enumeration method, and the computational efficiency of branch and bound algorithm was found significantly improved (Yang et al., 2016). Moreover, dynamic programming algorithm divides the whole optimization problem into sub-problems, attempting to seek optimum solutions for each sub-problem by recursion (Feng et al., 2015). The sub-optimum solutions will finally form together to the whole and avoid repetition when going through the specified parts. A dynamic programming algorithm has been completed to test in an isolated junction in Gavilan Peak and Daisy Mountain in Arizona Connected Vehicle Test Bed (Feng et al., 2015) and coordination signals (Li and Ban, 2017) toward large dimension and no-linear problem. Approximate dynamic programming was then developed to overcome the complete set of connected vehicle information required in dynamic programming by function approximation techniques in numerical experiments of one and two junctions (Cai et al., 2013).

In most recent years, signal-trajectory joint control is designed for vehicle environments transferring from CVs to mixtures of Connected and Autonomous Vehicles (CAVs) and conventional vehicles. Signal-trajectory joint control receives vehicular information from CVs and Autonomous Vehicles (AVs) to optimize the signal timing plans by integer programming to reduce vehicle delay. AVs are regarded as leaders of vehicle platoons, with the signal controller adjusting the trajectories of whole vehicle platoons by sending commands to AVs (the trajectories of following vehicles can be predicted based on car-following models) to enable the platoons to enter the junction with the desired speed at the beginning of the green light.

Xu et al. (2018) propose a two-level method, in which the upper level optimizes the signals and vehicle arrival time, and the lower level optimizes engine power and brake force. Yu et al. (2018) proposed a comprehensive framework for the cooperative driving problem, which considered detailed signal parameters and vehicle trajectories with lane-changing behaviour at an isolated junction. Feng et al (2018) proposed a two-stage optimization problem is formulated, in which traffic signal is optimized with dynamic programming, and vehicle trajectory is controlled based on the optimal control theory. Yu et al., (2019) then extended the integrated control to a corridor level to coordinate control of the CAV trajectories in a centralized formulation. An integrated optimization in mixed traffic conditions is proposed by Guo et al. (2019) considered the mixed traffic of CAVs and RVs and develop a two-step control framework, in which the first layer optimized the signal timing plan accounting for vehicle trajectories, and the second layer designed optimal trajectories for CAVs. The study by Liu et al. (2019) prioritized CACC platoons at junctions to maximise the throughput of the junction. Information on conventional vehicles was estimated by the location and speed of CACC vehicles. A coordinated work proposed by Wang et al. (2020) tried to optimize both signal timing plans and vehicle trajectories at an arterial level. Yang et al. (2021) developed a hierarchical and implementation-ready cooperative driving framework with a mixed traffic composition of CAVs in a coordinated distributed way in corridors.

Integer programming is a well-performed method to work out the optimum solution gaining max benefits or min expense with multivariate constraint conditions (limited green light resources). Integer programming has a unified algorithm to deal with junction control problems, which is another advantage. While integer programming sometimes cannot be solved analytically and needs great computational requirement (Li and Ban, 2017) because of exponential order to the large dimensions size of state and complexity of the non-linear model (Cai et al., 2013), which leads to integer programming model too complicated to implement in a real network. Extremely accurate road traffic input data and predicted vehicle performance are also required in integer programming so that controller can ensure their optimum solution will bring the greatest objective value in case study testing. At this point, the CV-based methods will prominently perform better than the traditional method due to their more detailed and accurate information.

2.5.2 Traditional theory based method

The optimal cycle length C of traditional fixed time models is formulated by modifying Webster's model for isolated signalized critical junction, which is derived from computer simulation and field observation under Federal Highways Administration Signal Timing Manual (STM) (Koonce et al., 2008), shown in Equation (2-17):

$$C = \frac{1.5Lt + 5}{1 - \sum_{i=1}^{M} z_i} \tag{2-17}$$

Where Lt is the total lost time per cycle (usually the sum of inter-green periods), z_i is the flow ratio (observed flow/adjusted saturated flow) of lane index i for each lane with a number of M in junction, which also represents the ratio of density to length in the cluster in (Maslekar et al., 2013; Shaghaghi et al., 2017). Then the green time GT_i for each lane i is described in Equation (2-18):

$$GT_i = \frac{z_i}{\sum_{i=1}^{M} z_i} (C - Lt) \tag{2-18}$$

The traditional theory-based method of using CV was initially researched by Gradinescu et al. (2007) on the basis of Webster's model in a junction in Iuliu Maniu / Vasile Milea streets in downtown Bucharest. Then it was tested in one simulated junction for 2000 cycles and repeated 10 times (Chang and Park, 2013). Tomescu et al developed this method in consecutive junctions by including new parameters (weather, vehicle type, minor events) to decide offset coefficients adopting fuzzy logic function (Tomescu et al., 2012). The ratio of density and length (replacing the flow ratio) formatted by density information from CVs gathered by clustering algorithm was also successfully implemented in 7 junctions (Maslekar et al., 2013) and 36 junctions in a central urban area from Open-Street Map (Shaghaghi et al., 2017). Similarly, the traditional theory proposed method followed junction green time flow ratio profile regular and defined the lanes with the highest flow ratio as the next stage were simulated in one isolated junction along Castle Downs Road and 97 Street, Edmonton, Canada (Chandan et al., 2017) and a bidirectional crossroads (Nafi and Khan, 2012) respectively.

Webster's model cannot be directly adopted in the traditional proposed method due to the flow ratio for each lane in each cycle is various. Hence, the traditional fixed-time method computed flow ratio parameters based on historic recorded data, which failed to be adapted to varying flow demand (Maslekar et al., 2013). The green durations decided by the traditional method were thus viewed as inaccurate and unreliable. Whilst traditional theory-based methods are capable of gathering the real-time flow demand or density information every time step by means of CVs, making the signal control more efficient. The most outstanding benefit of traditional theory-based methods is they are easy to be implemented and have almost no computation (Chandan et al., 2017). Nevertheless, this kind of method is hard to reach the optimum solution because of stochastic nature of vehicular movements still existed during the green time. The control schemes are not flexible enough, such as without stage skipping in integer programming. Unclear objective functions and lack of future vehicle performance prediction also cause this method more inefficiency than the integer programming method.

2.5.3 Reinforcement learning method

As a kind of machine learning paradigm, reinforcement learning has been widely adopted in various fields as artificial intelligence technology, such as Alpha Go broad games (Silver et al., 2016), computer games (Mnih et al., 2015) and helicopter control (Ng et al., 2006), letting systems themselves optimize their policies through trial-and-error interactions react to dynamic environments. Adaptive signal control strategies are such a general process: make a series of decisions to optimize the junction signal timing reacting to dynamic traffic demands, which is extremely following the pattern of reinforcement learning. A schematic operation process of reinforcement learning is illustrated in Figure 2.7.

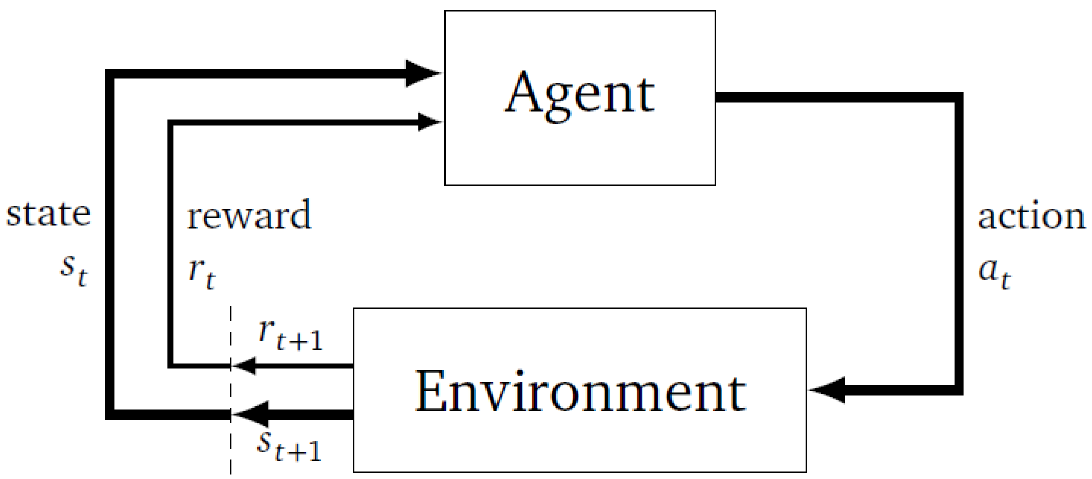


Figure 2. 7 Schematic figure for reinforcement learning

The working principle of reinforcement learning adopted in adaptive signal control is like this: the junction signal controller is considered as an agent, who needs to adjust the management aiming to the environment (dynamic road traffic circumstances). The algorithm starts with an initialisation randomly (Yang, 2017) or on the basis of historical data and experience (Xiang and Chen, 2016) of the action value function (mapping from correlations of state-action pair to the expected value) and improves it iteratively in discrete time steps. The algorithm, at every time step t, captures the proper information from CVs as representative as the state s_t(e.g. queue length and queue waiting time (Liu et al., 2017), positions and speeds of vehicles at a junction (Xiang et al., 2018)) of the environment. The controller then decides its action (determines green and red light state for each lane in the next period (Yang, 2017; Xiang and Chen, 2016), selects a pair of non-conflicting phases (Liu et al., 2017), and durations of every phase (Xiang et al., 2018)) from a set of finite actions according to its policy, which represent the probabilities of taking different actions for a particular state. The controller at the current stage prefers to select those state-action pairs mapping to the higher expected return value (objectives, e.g. min queue length, min average waiting time) developed by the reward accumulations up to the current reward R_t (the change of the cumulative waiting time between two cycles (Xiang et al., 2018), the negative sum of the squared delays of all vehicles (Yang, 2017), the sum of vehicle queue length and waiting time of queue (Liu et al., 2017)) given by the environment. Then the action selected at the current state will result in a transition to the new state s_{t+1} and new reward R_{t+1}, which contribute to correcting the parameters of mapping state-action pair with a more accurate objective value for reproducing updated policy (Yang, 2017). The positive rewards will reinforce the algorithm selection of this action while negative rewards are on the contrary. The optimal policy is pursued by the algorithm with an ultimate aim to reach the highest excepted objective value through continuous iterations.

The reinforcement learning method using CVs for adaptive signal control was primarily developed in a bi-directional junction with only two phases (Yang, 2017), but met with difficulties due to the exponentially increasing complexity of the neural network (input states, actions and export rewards) as vehicle number increases. A dynamic clustering algorithm (Liu et al., 2017) and deep learning algorithm (Xiang et al., 2018) were then associated with reinforcement learning by researchers for the sake of achieving a relatively stable connected vehicle data structure from mass communication loads and reliving exponential complexity of traditional reinforcement learning. Their algorithms have been implemented in 78 road segments with 96 junctions in Changsha, China (Liu et al., 2017) and simply isolated junction separately. In addition, a neuro-fuzzy network was adopted to evaluate both fairness and average waiting time of grouping vehicles, considering the benefit levels of each grouping vehicle by gathering group size, the difference in size and average waiting for time information as inputs (Cheng et al., 2017). Preliminary processing of connected data by a neuro-fuzzy network declined the complexity of reinforcement learning violently, tested in a junction (Cheng et al., 2017). The co-learning algorithm was also combined with reinforcement learning for providing the recommended shortest time paths for vehicles beyond signal timing control in 22 junctions in Xiaogan, China (Xiang and Chen, 2016). Wang et al. (2021b) then proposed a deep reinforcement learning method for the effective rewarding mechanism that takes into account the impact of the detouring on the network traffic to improve efficiency.

As a model-free algorithm, reinforcement learning is unnecessary to establish complicated traffic flow models like integer programming method (Xiang and Chen, 2016)and prior information to the road network as well (Liu et al., 2017). In contrast to integer programming, reinforcement learning methods incrementally optimize their management policies by experiencing trial and error interactions with the environment, without the constraint of being computationally expensive (Xiang et al., 2018) and sensitive to noisy errors (Yang, 2017; Xiang and Chen, 2016).

However, in addition to the great complexity of the action-value function, explicit rules about signal control principles are not expected to be perceived from reinforcement learning (Brooks and Dahlke, 2017). Reinforcement learning will not choose explicit actions even if meets the same states inspired by the mechanism of exploiting new actions (Brooks and Dahlke, 2017). Large capacity input data are required to form proper rewards and give feedback to the current mechanism (Brooks and Dahlke, 2017), meanwhile, the updating process for reproducing more perfect policies and parameters will cause delay when new actions are ready to be selected (Xiang et al., 2018).

2.5.4 Multi-agent junction management

Autonomous vehicles (AV), which process the functions of connected vehicles and intelligent autopilot without drivers at the same time, are expected to dominate road traffic in future and significantly reduce the accident number mainly ascribed to human error (Jin et al., 2012). Dresner and Stone firstly proposed a reservation-based cooperative junction management system for completely all autonomous vehicles in the isolated no-turn junction (Dresner and Stone, 2005). They regarded the junction controller and each autonomous vehicle as an individual agent, which opened a new era for multi-agent (system comprised of Junction Management Agent (IMA) and Vehicle Agents (VA) (Li and Ban, 2017)) junction control management.

The multi-agent management method needs communications and collaboration among agents (infrastructure to vehicle, vehicle to vehicle, vehicle to infrastructure). Autonomous vehicles send their parameters (e.g. time of arrival predicted (Kari et al., 2014)) to other vehicles and junctions, who also receive the connection information to adjust their driving behaviours. The multi-agent method was then developed into two categories: reservation-based method and trajectory-based algorithm. In reservation-based method, IMA allocates the finite temporal and spatial junction right-of-way to certain VAs permitted in fixed-time slot according to pre-defined policies (e.g. request ever cancelled priority, with lane-based policy, first come first serve (Jin et al., 2012), no conflicts policy (Webster, 1958)) by IMA. If VA attempts to cross the junction, they need to send a request for junction and “booking” a junction space possession at one point in the future (Jin et al., 2012). The junctions balance their policies and then grant the permissions for those eligible vehicles; requests for other vehicles will be rejected to wait until proper opportunities. Reservation-based method has been tested in the isolated junction (Jin et al., 2012) and a grid of 4 junctions with 9000 veh/h flow demand (Hausknecht et al., 2011). Trajectories-based method coordinates vehicle trajectories by an invisible junction management unit, which attempts to seek optimal sufficient safe gaps for those vehicles approaching from conflicting directions (Lee and Park, 2012). Hence vehicles are capable of searching for a safe gap between the opposite vehicle flow and going through the junction without stopping in a suitable case (like situation (a) in Figure 2.8), as well as collision avoidance. A unique feature of trajectories-based methods is that they removed traffic lights in the junction because of inessential when tested in an isolated junction (Kamal et al., 2015; Budan et al., 2018).

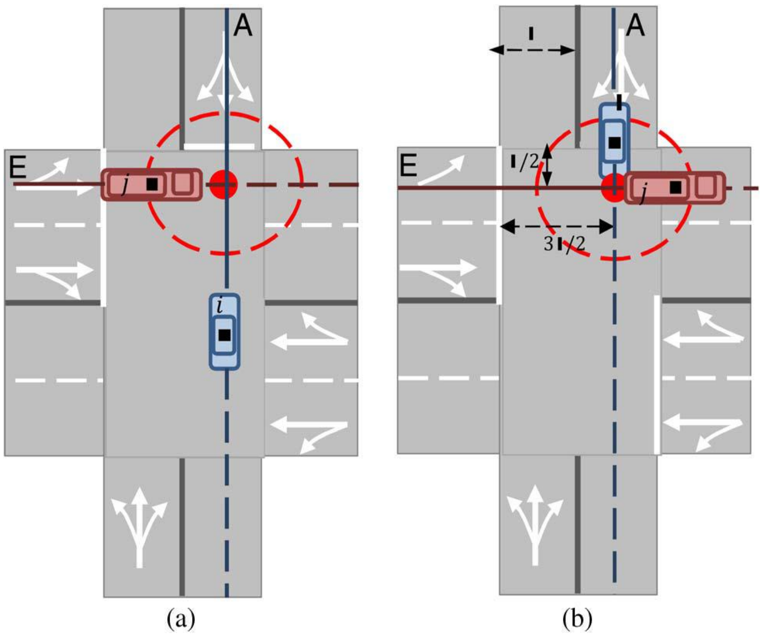


Figure 2. 8 Illustration of the collision avoidance concept around a cross collision point: (a) safe situation and (b) unsafe situation (Kamal et al., 2015)

Multi-agent control methods break through traditional cognitions of signal timing control, such as vehicles participating in junction management as subjects rather than merely confined to report information for infrastructure, signal control at the non-signalized junction (Budan et al., 2018), vehicles travelling from conflicting phases without collision (Kamal et al., 2015). Multi-agent methods also provide new ideas for autonomous vehicles managements in the future. However, the over-idealized assumptions of multi-agent methods restrict their applicable range. All of the multi-agent methods require 100% well-equipped connected vehicles or autonomous vehicles (Li and Ban, 2017), which is impossible to achieve in the current stage, as well as assuming the best manoeuvres for all vehicles (Lee and Park, 2012). Communication and connected data performance of junction centres are also required to be perfect (e.g. no packet drops and transmission delays (Lee and Park, 2012)). High-precision vehicle speed and position data have to be gathered, which is far beyond the accuracy connected vehicle data needed; otherwise frequently accidents due to vulnerability in no traffic light junctions.

2.5.5 Analogy method

Besides the aforementioned adaptive control method, a subclass of models draws lessons from the knowledge and architectures of other areas. An artificial immune network (Darmoul et al., 2017; Louati et al., 2017) was implemented for controlling signalized junctions. The current traffic situations such as queue length and average queue delay (Louati et al., 2018) obtained by CVs were treated as antigens and control decisions like phase sequences with separate durations were considered to be antibodies. By detecting affinity between an antibody and a pathogen by rewards and penalties the mechanism found the control strategies corresponding to variable traffic states (Louati et al., 2018). The artificial immune network model was tested in an isolated junction (Louati et al., 2017) and six junctions ((Darmoul et al., 2017) with several scenarios and compared with fixed-time, actuated time and longest queue selection algorithms (Louati et al., 2017). The job schedule model recognized each vehicle group as a job, operating the junction control by the oldest job first (OJF) algorithm (Pandit et al., 2013). The first arrival vehicle platoons would be served at the first chance. The method is distributed in an isolated junction with four typical approaches. The ideas of applying the Petri Nets model (Ahmane et al., 2013) and weighted backpressure model (Wu et al., 2018) to manage traffic networks were also presented.

The novelty solutions to address traffic signal control represent innovative strategies for connected vehicle signal methods. Whilst the alignments of mechanisms they proposed towards traffic road characteristics and effects are required to calibrate rigorously. The models established by small group researchers merely refer to their comprehensions of adaptive junction control, which still lacks widely acknowledgment.

Table 2. 10 Summary of vehicle-based adaptive signal controls using connected vehicle technology

Main author and year	Model name	Case study Scale	Objectives of the model	Decision making algorithm	Data Resources	Key Performance Indicator	Simulation Platform	Benchmarking model
Lee and Park (2012)	Cooperative Vehicle Junction Control System	Isolated Junction	Minimising total length of overlapped trajectories	Multi-agent junction management	Vehicle speeds and positions	Total stopped delay; Total travel time; Throughput; Fuel consumption; CO2 emissions	VISSIM-COM	Actuated Control System
Goodall et al. (2013)	Predictive microscopic simulation algorithm (PMSA)	4 Junctions	Minimising total delay	Integer programming	Vehicle speeds and positions	Average Velocity; Average delay; Number of stops; Stopped delay	VISSIM-COM	Coordinated-actuated timing plan
Islam et al. (2020)	A network-level traffic signal control with partial CV information	3 junctions	Maximising the total number of completed trips	Integer programming	Vehicle speeds, accelerations and positions	Number of completed trips, total travel time	VISSIM	Fixed time optimized by VISTRO
Jin et al. (2012)	Multi-agent advanced traffic management system	Isolated Junction	Increase junction throughput, reduce energy consumption and pollutant emissions	Multi-agent junction management	Vehicle speed, acceleration, turning angle, position, road map	Average travel time; Fuel consumption; CO2 emissions	SUMO	——

Liang et al. (2020)	A flexible, real-time traffic signal control algorithm	Isolated Junction	Minimising total vehicle delay	Integer programming	Vehicle speeds and positions	Average vehicle delay; computational effort	micro-simulation program written in Java	Complete enumeration
Feng et al. (2015)	Real-time adaptive traffic control algorithm	Isolated Junction	Minimising total vehicle delay, total queue length	Integer programming	Vehicle speeds and positions	Average vehicle delay	VISSIM-COM	Fully actuated control
Wang et al. (2020)	A joint control model for CV platoon and arterial signal coordination	5 junctions	Minimising the travel time and improve passing speed	Integer programming	Vehicle speeds and positions	Average vehicle delay; average stop time; average number of stops	VISSIM	MAXBAND
Lee et al. (2013)	Cumulative travel-time responsive(CTR) real-time control algorithm	Isolated junction	Minimising total delay time, average speed	Integer programming	Cumulative travel-time	Average delay; Average velocity; CTT; Mean queuing time; Throughput; Fuel consumption; CO2 emissions	VISSIM-COM	Actuated control
Guler et al. (2014)	Junction traffic control algorithm	Isolated junction	Minimising total delay, the total number of stop	Integer programming	Vehicle speeds and positions	Average vehicle delay	MATLAB	FIFO strategy, fixed-time traffic signal, actuated signal
Wang et al. (2021b)	Joint traffic signal and connected vehicle control	Isolated junction	Maximise the cumulative reward of travel time and waiting time	Reinforcement learning method	Vehicle speeds and positions	Average vehicle travel time; accumulated waiting time	SUMO	Greedy method, fixed time and conventional DRL method
Yang et al. (2016)	A bi-level optimization model	Isolated junction	Minimising the total delay	Integer programming	Vehicle speeds and positions	Average delay; Number of stops; Stopped delay	micro-simulation platform Java	Actuated signal control
Guo et al. (2019)	An efficient dynamic programming with shooting heuristic algorithm	Isolated junction	Minimising total vehicle delay	Integer programming	Vehicle speeds, accelerations and positions	Average vehicle delay; Fuel consumption	VISSIM	Adaptive signal control
Pandit et al. (2013)	Oldest arrival first algorithm	Isolated junction	Minimising average delay per vehicle	Analogy method	Vehicle speeds and positions	Average vehicle delay	SUMO OMNET++ Venis	Vehicle-actuated traffic signal control, Webster's algorithm, fixed-time control
Kamal et al. (2015)	Vehicle-junction coordination scheme (VICS)	Isolated junction	Maximising capacity, fuel consumption, and minimising travel time	Multi-agent junction management	Vehicle speeds, positions and destination	Average travel time; Average idling time; Average fuel consumption	Matlab	Actuated signalized junction scheme
Younes and Boukerche (2014)	Intelligent Traffic Light Controlling algorithm	Isolated junction	Minimising average delay waiting time, maximising throughput	Integer programming	Vehicle speeds and positions	Average vehicle delay; Throughput	SUMO, NS-2	Adaptive traffic signal control mechanism (OAF)
Chandan et al. (2017)	Connected vehicle signal control (CVSC)	Isolated junction	Minimising travel time delay, average number of stops per vehicle	Traditional theory based method	Vehicle speeds and positions	Travel time delay; Average number of stops	VISSIM COM	EPICS's adaptive signal control, Webster's fixed-time signal control
Pourmehrab et al. (2017)	Trajectory-based optimization algorithm	Isolated junction	Minimising average travel time and average delay	Multi-agent junction management	Vehicle positions	Average vehicle delay; Average travel time; Throughput	Matlab	Fully actuated control strategy
Liu et al. (2019)	A cooperative signal control algorithm by leveraging the CACC capabilities	Isolated junction	Minimising of the total queue length	Integer programming	Vehicle speeds, accelerations and positions	Average fuel economy; Average speed; Average queue length	——	0% CACC cass
Xiang and Chen (2016)	Multi-agent based control method	22 junctions	Minimising total travel time	Reinforcement learning method	Vehicle positions	Average travel time; Average vehicle delay; Throughput; Number of stops	VISSIM	Fixed-time control and actuated controlmethod
Yao et al. (2020)	A dynamic optimization method for adaptive signal control	Isolated junction	Minimising average vehicle delay	Traditional theory based method	Vehicle speeds and positions	Average vehicle delay; Queue length	VISSIM	COP algorithm

Tiaprasert et al. (2015)	Queue-based adaptive signal control	Isolated junction	Minimising the queue length	Integer programming	Vehicle speeds and positions	Queue length	VISSIM	Actuated Signal
Yang et al. (2017)	Reinforcement learning based methods	Isolated junction	Minimising the vehicle delay	Reinforcement learning method	Vehicle speeds and positions	Average vehicle delay	SUMO	Fixed time control
Islam et al. (2017)	Distributed-Coordinated (DC) approach	2 and 9 junctions	Maximising throughput, minimising queue length	Integer programming	Vehicle speeds and positions	Average travel time; Average delay; Number of stops; Average speed	VISSIM	Fixed-time Coordinated, Actuated Coordinated
Darmoul et al. (2017)	distributed, intelligent and adaptive traffic signal control system	3 and 6 junctions	Minimising of vehicle delays, and vehicle queue lengths	Analogy method	Queue length, average queue delay	Average vehicle delay; Average queue length	VISSIM	MAS-LQF-MWM, fixed-time control
Kamal et al. (2019)	A novel adaptive traffic signal in a mixed manual-automated traffic	Isolated junction	Minimising total crossing times of all vehicles	Integer programming	Vehicle speeds and positions	Average speed; Average passing time; Fuel efficiency; CO_2 emission	MATLAB	Fixed-time and actuated control
Liu et al. (2017)	Cooperative RL-based signal control algorithm	3 junctions	Improving traffic throughput and reducing average waiting time	Reinforcement learning method	Vehicle speeds and positions	Average vehicle delay; Average waiting time; Total waiting queue length	SUMO NS-3	——
Rafter et al. (2020)	Multi-mode adaptive traffic signals	12 junctions	Reduce vehicle delay	Traditional theory based method	Position from CVs and inductive loops	Average vehicle delay; Number of stops;	SUMO	Fixed time control
Ahmane et al. (2013)	Timed Petri Nets with Multipliers based signal control	Isolated junction	Minimising queue length	Analogy method	Vehicle positions	Average waiting time; Average queue length	Video 2	ML-FCFS, Traffic lights
Maslekar et al. (2013)	car-to-car communication based adaptive traffic signal system	7 junctions	Reducing the average waiting time, the queue length	Traditional theory based method	Vehicle directions and positions	Average waiting time; Queue length	NCTUns	C-DRIVE
Yang et al. (2021)	cooperative driving framework for arterial corridors in a mixed traffic condition	6 junctions	Optimizing traffic flow and improving mobility	Integer programming	Vehicle trajectory data from BSM and detector	Total vehicle delay; number of stops; CO_2 emissions	VISSIM	Fixed time optimized by VISTRO
Cheng et al. (2017)	fuzzy group-based junction control	Isolated junction	Reducing the average waiting time	Reinforcement learning method	Vehicle speeds and positions	Average waiting time	NS-3	Adaptive light, no group, fuzzy group
Chang and Park (2013)	queue length estimation model control	Isolated junction	Minimising average junction waiting time, the total queue length	Traditional theory based method	Vehicle speeds and positions	Total waiting queue length	GLD	random control, best-first control
Cai et al. (2013)	approximate dynamic programming (ADP) control algorithm	Isolated junction	Reducing travel time	Integer programming	Vehicle speeds and positions	Mean travel time; Number of stops	Commuter	benchmark methods
Younes and Boukerche (2016)	an intelligent traffic light controlling algorithm and an arterial traffic light controlling algorithm	Isolated junction	Reducing the expected queuing delay, increasing the throughput	Integer programming	Vehicle speeds and positions	Total delay; Average vehicle delay; Throughput	SUMO NS-2	OAF mechanism
Gradinescu et al. (2007)	Modified Webster's formula	Isolated Junction	Minimising the average delay	Traditional theory based method	Vehicle speeds and positions	Average vehicle delay; Fuel consumption; Emissions	Ns-2, Jist/SWANS VISSIM	Fix timed
Kari et al. (2014)	An agent-based online adaptive signal control (ASC) strategy	Isolated Junction	Reducing the travel delay and the fuel consumption	Multi-agent junction management	Vehicle speeds and positions	Average travel time; Fuel consumption	SUMO	QEM/HCM based strategy
Nafi and Khan (2012)	Intelligent Road Traffic Signaling System	Isolated junction	Reducing the average waiting time	Traditional theory based method	Vehicle speeds and positions	Average waiting time; Throughput	OPNET Modeler	Fixed time
Shaghaghi et al. (2017)	Adaptive green traffic signal controlling using vehicular communications (AGTSC-VC)	36 junctions	Decreasing the vehicle waiting time and pollutant emission	Traditional theory based method	Vehicle directions and positions	Average waiting time; Throughput	Veins	VANET-based adaptive TSCSs (MC-DRIVE), Traditional ATSCS
Yu et al. (2019)	A MILP model to cooperatively optimize CAV trajectories	4 junctions	Minimising total vehicle delay	Integer programming	Vehicle speeds,	Average vehicle delay; Throughput	SUMO	Coordinated fixed-time control

					accelerations and positions			
Priemer and Friedrich (2009)	Decentralized adaptive traffic signal control	Signalized and unsignalized junctions	Reducing the total queue length	Integer programming	Vehicle speeds and positions	Average vehicle delay; Average vehicle speed	AIMSUN NG	DP&CE without ql-estimation
Yu et al. (2018)	An MILP model to optimize traffic signals and vehicle trajectories	Isolated junction	Minimise fuel consumption and emission	Integer programming	Vehicle speeds, accelerations and positions	Average vehicle delay; Throughput; CO_2 emission	——	Actuated control
Wu et al. (2018)	Delay-based backpressure traffic signal control	Isolated junction	Reduce queue Lengths, throughput optimal	Analogy method	Vehicle speeds and positions	Average queue length	——	Queue-based Back-Pressure Control, Delay-based Back Pressure
Liang et al. (2018)	Deep reinforcement learning model	Isolated junction	Minimising delay, reducing average waiting time	Reinforcement learning method	Vehicle speeds and positions	Average waiting time; Cumulative vehicle delay	SUMO	Fixed time
Feng et al. (2018)	An integrated framework for joint control	Isolated junction	Minimise vehicle travel time delay	Integer programming	Vehicle speeds, accelerations and positions	Vehicle delay; CO_2 emission; Execution time	——	Fixed time control
Sun et al. (2018)	Maximum capacity junction operation scheme for CAVs	Isolated junction	Maximum capacity ;Minimise vehicle numbers crossing centreline	Integer programming	Vehicle positions	Capacity	——	Conventional signal operation scheme

2.5.6 Discussions and conclusions

The state-of-the-art adaptive signal control models in connected vehicle environments are summarized in Table 2.10. The diversity of model objective selections, data sources and KPIs are all originally derived from connected vehicle technology, which is far beyond those of traditional proposed methods. The adaptive connected vehicle methods also presented significant improvements in various aspects compared to the benchmarking models they selected (generally fixed time and actuated control method), for instance, 48% average travel time reduction against benchmarking models in Islam and Hajbabaie (2017) in coordinated junctions under saturated flows, 34% total travel time reduction, 36% average speed and 4% throughput increase in Lee et al. (2013) in isolated junction under saturated flows. The results shown by researchers prove that connected vehicle data have great potential to support the development of new adaptive urban signal controls in future by offering detailed information about the state of junctions. From the perspective of flow conditions, most researches improved the performance of urban signal controls under saturated flow situations (Feng et al., 2018; Guler et al., 2016; Yang et al., 2016). Few papers attempted to improve the effectiveness of their control methods in oversaturated flows (He et al., 2012; Rafter et al., 2020). The majority of researches selected an isolated junction as a research object (Feng et al., 2015, Lee et al., 2013; Yang et al.). Part of the studies achieved the optimized goal of coordinated control in an arterial or a network with the coordination considerations of all controllers (Xiang and Chen, 2016; Wang et al., 2020)

However, several limitations are found in the most advanced researches. From Table 2.10 and reviews in Sections 2.2.1 and 2.2.2, the signal schemes determined by connected vehicle urban signal controls are all optimized by vehicle-based objectives (e.g. minimising average vehicle delays, minimising vehicle number of stops, minimising vehicle queue lengths). Besides, the measures of their proposed signal decision algorithms are vehicle performance indicators. These policies and measurement methods mean that they treat all of the vehicles on road are same and prevent them from exploring the person-based signal control styles. However, Section 2.3 justify that the development of person-based urban signal controls is essential in future and more meaningful than vehicle-based models to accelerate the progress of urban mobility. The vehicle-based models can result in unfair treatment of those vehicles with high occupancy levels.

Another limitation in current researches is unrealistic experiment assumptions used to test the effectiveness of proposed models. The existing urban control systems have been successfully implemented in complex real-world scenes. The testing factors include large road network scales consisting of coordinated junctions, and different levels of traffic volumes during peak and off-peak periods in the local area. Further, the transitions from conventional vehicles with neither connectivity nor autonomy in current situations to the deployments of 95% or higher connected vehicles on road are estimated to be long-term (Feng et al., 2015). Therefore, it is very essential to understand the new paradigms of urban junction managements under the presence of connected vehicles, notably, the different adoption levels of connected vehicles and conventional vehicles.

Up to now, the whole publications on urban junction controls with CAVs use simulation to approach their researches. Examples of simulation platforms include VISSIM (PTV Group, 2011), SUMO (Krajzewicz et al., 2006), Veins (Sommer et al., 2010), NCTUns (Wang and Lin, 2008), NS-2, etc. This on its own is not a problem, because the practical approach requires quantities of high-expense connected vehicles and great network scales for trials, which is quite difficult to prepare in the current stage. Contrarily, mathematical analytical approaches are also infeasible to be applied as the complexity of combinations of junction controls, increasing number of vehicles, and various incoming lanes. However, it is notably that simulations for junction operation are necessary to be as realistic as real-world traffic situations so that these junction controls will make sense when they are implemented in the field. Only mathematical programming and part of other optimization-based methods are aware to evaluate their models in realistic scenarios but not adequate. The rest of the methods make ideal or even unpractical assumptions for their proposed algorithms. As for person-based urban signal controls, things would be more complex as the information absence of occupancy levels of vehicles at different rates also need to be considered. Therefore, another research gap here is how to develop coordinated paradigms for person-based signal control in multiple junctions, test and ensure the performance of person-based models in realistic situations, including dynamic traffic volumes, mixture vehicular environments with/without buses imperfect connected information from under 100% connected vehicle environments.

2.6 Summary

This section summarizes literature on vehicle-based signal controls, discusses their relationships and points out research gaps in this area. The overview summary is graphed in Figure 2.9. Traditional UTCs have evolved significantly from fixed time control to infrastructure-based traffic responsive control to better respond to dynamic road traffic so that reducing urban road congestion and delay, which have been reviewed in Section 2.2. However, the performance of current UTC coordinated signal controls are still limited by the availability of data sources from fixed point detectors such as inductive loops, which cannot describe the detailed state of the road network. There are still promoting spaces for UTC systems if they are provided with abundant road information enabling accurate vehicular predictions. The UTC systems are vehicle-based signal controls, not fitting with encouraged policies of urban people congestion reduction and mobility improvement.

The review of bus priority schemes in Section 2.3.2 indicates that the development of person-based signal controls is more realistic and meaningful than vehicle-based controls from the perspectives of urban mobility improvement, direct travel time costs reduction and social management. However, the review also finds that the transition from vehicle-based controls to person-based controls is not a straightforward task. The person-based controls require occupancy information from every vehicle and more complicated signal control paradigms assigning different priority levels to vehicles according to their occupancy levels and resulting in flexible phase combinations and stage sequences, which is difficult to implement by UTC systems due to detection technology.

The review of state-of-the-art detection and communication technology in Section 2.4 presents that new communication technology collected road information from various most advanced equipment (e.g. GPS, on-board sensors, infrared camera) are available to support urban signal control systems. They create a communication network among junction controllers and connected vehicles (V2V, V2I) through wirelessly communication technology (e.g. IEEE 802.11p, DSRC). Abundant and detailed real-time information (e.g. speeds, positions, accelerations) become available for the next generation of urban signal controls. As an essential data source for implementing person-based approaches, vehicle occupancy can also be collected from several sensors, such as in-vehicle cameras, roadside cameras, and AVL. Therefore, the signal control paradigms need to be changed to accommodate those new data sources to conduct new decision optimization processes.

The state-of-the-art vehicle-based adaptive signal control systems in connected vehicle environments are then reviewed in Section 2.5. A number of new signal control decision algorithms are developed and great improvements are found against benchmarking models (e.g. reducing vehicle travel time, reducing vehicle delay, reducing vehicle number of stops), which highlights the potential benefits and opportunities of adopting connected information into urban signal controls as data sources. The utilisation of CV technology improves the performance of vehicle-based signal controls compared to existing urban signal controls. However, the majority of adaptive signal controls in Section 2.5 still do not take into account occupancy levels of information and they are still vehicle-based signal controls by assuming all vehicles on road are the same except for their IDs. Meanwhile, simulations are found to be the most common method to reproduce the proposed adaptive signal controls and evaluate their performance. And part of vehicle-based signal controls considers realistic environments (e.g. coordinated junctions, not perfect penetration rates, and varying traffic flow demands) to extend their models and simulation experiments to make them realistic in real-world implementations.

From Section 2.4, the connected vehicle information supports the improvements of transit signal priority by realizing real occupancy levels of buses. The available occupancy data from CV also enables the transition from vehicle-based to person-based control to be realizable. Up to now, there are few researches developed person-based controls by incorporating vehicle occupancy data. In next chapter, few researches focus more on person-based control and flexible signal timing plans are reviewed. The chapter discusses their limitations and points out the research gaps, aim and objectives of this project. The challenging and requirements of the new methodology that need to be adopted to fill in the research gaps are also elaborated in next chapter as well as a general harmonised evaluation framework to validate the performance of the proposed algorithm.

Chapter 3 Person-based adaptive signal control background and concept

Chapter 2 reviews the general literature related to vehicle-based signal controls in CV environments, pointing out the main limitation of the majority of state-of-the-art research in Section 2.6. The connected vehicle also supports vehicle occupancy data, which makes the transmission from vehicle-based controls to person-based controls to be possible. This chapter is divided into three parts. The first part reviews the state-of-the-art person-based controls in CV environments and signal controls with flexible signal timing plans and highlights their limitations and the critical research gaps in urban signal control areas in Sections 3.1 and 3.2.

The second part of this chapter claims research gaps based on the literature and tries to make contributions to the study area by achieving objectives in Section 3.3. To fulfil the objectives of the research area. Section 3.4 discusses and decides the general methodology for this project by analysing the potential challenges and requirements of developing new person-based algorithms.

The rest of this chapter in Section 3.5 structures the evaluation framework to validate the performance of proposed person-based algorithms. The selections of evaluation tools, car-following model, benchmarking signal control algorithms, experiment scenarios and KPIs are elaborated to ensure that all of the algorithms are tested in a fair and consistent evaluation framework.

3.1 The state-of-the-art person-based urban signal controls in connected vehicle environments

Most junction management papers proposed vehicle-based signal control models with small parts of all kinds of connected vehicle data mentioned in Section 2.4 such as vehicle speeds and positions, signal phase and timing information, which are shown in Table 2.10. These researches are out of consideration the occupancy level diverges of vehicles on road.

However, some researchers have noticed the importance of considering passenger delay by incorporating passenger occupancies of transits and cars into their optimization algorithms and frameworks. Different from vehicle-based controls, person-based signal controls are optimized and evaluated by unique person-related objective functions (minimising person delay and minimising person number of stop) and KPIs (average person delay and average person number of stop), which are described below:

- Minimising person delay is the most commonly used objective indicator to measure the effectiveness of person-based controls (Christofa et al, 2013b; Yu et al., 2017; Yang et al., 2018). All of the passengers and drivers inside a vehicle suffer the same vehicle delay. Therefore, the calculation of objective value is extended from the calculation of vehicle delay, which is represented by:

$$min \sum_{c \in N} V_O(D_C - V_C) \tag{3-1}$$

Where V_O is the occupancy value of a specific vehicle.

- Minimising person stop is an indicator used in part of person-based controls to measure the travelling experiences of all people in vehicles (Christofa et al, 2013a). Similar to minimising vehicle delay, minimising person number of stop is calculated by vehicle number of stop scaled by occupancy data of this vehicle, which is shown as:

$$min \sum_{c \in N} V_O(SW_C - SW_{C''}) \tag{3-2}$$

- Average person delay is the excess times of all people in one vehicle spend to complete its journey than free flow travel time, its value equals to average vehicle delay multiples its occupancy data.

- Average person number of stop is the number of people in a vehicle who switch their speed to 0 and acceleration, which can be calculated by average vehicle number of stop multiples its occupancy data.

Some studies developed TSP strategies in CV environments to assign high priority to buses with more passengers to reduce passenger delay with more attention on buses than on passenger cars (Christofa et al, 2011; Wu et al, 2017). The extension works include investigating the implementation locations of TSP strategies at arterial levels (Guler et al, 2018; Bagherian et al, 2015; Bayrak and Guler, 2020), considering the bus stops (Yang et al, 2018), bus dwell time (Lin et al, 2019; Kim et al 2019), bus requests from conflicting directions (Xu et al, 2018) and bus arrival numbers (Lian et al, 2020). These papers put more emphasis on improving the prediction time of arrival buses or considering more details of bus routes and bus facilities.

Other studies focused more on reducing person-based metrics in car and bus mixture environments and have been summarized in Table 3.1. The person-based controls assumed that occupancy data of buses and cars were known information. A person-based signal control system proposed by Christofa et al. (2013a) attempted to minimise total passenger delay by accounting for cars and buses number in an isolated junction. The arrival times of vehicle platoon were predicted using auto delay estimation theory.

However, this paper adopted fixed cycle length, phase sequence and stage combinations. The simulations indicated the best result of 4.5% person delay reduction achieved in cross streets compared to vehicle-based optimization during evening peak duration. The system was then extended to be implemented in successive junctions along signalized arterial corridors, which found up to 7.9% person delay reduction in Main Arterial Southbound compared to TRANSYT-7F (Christofa et al, 2016).

Yu et al., (2019) broke through the assumption of fixed cycle lengths in previous works by accommodating flexible cycle lengths. The approach also improved the system to better deal with the uncertain arrival time of buses, but it was implemented in a fixed three-stages isolated junction. The algorithm extended green time using available green time from the next cycle to serve arriving buses. The study found a 25% delay reduction for all passengers compared to person-based strategy with fixed cycle length.

Vilarinho et al. (2017) developed a bid-based total passenger delay reduction approach beyond public transport priority, aiming for assigning different priorities to passenger vehicles with different occupancy levels under 100% car environments, but it only used a traditional experience formula to estimate the number of pedestrians. The data sources used in this study were vehicle arrival flows rather than explicit vehicle trajectory information. The optimized signal plans were also constrained in a three-stage junction with fixed phase combinations.

A user-based signal optimization algorithm was then designed to maximise user throughput rather than minimising passenger delay in a four-leg isolated junction using fixed phase sequence and stage combination settings (Mohammadi et al, 2019). This paper assumed a vehicular environment without the presence of buses and used a similar vehicle trajectories theory adopted in Christofa et al (2013b) to estimate the arrival times of vehicles in a platoon under different statuses. Phase sequence settings are adopted according to National Marine Electronics Association (NEMA) Standard ring-and-barrier. Results showed a significant increase in user throughput compared to vehicle-based optimization with the same algorithm.

Hu et al. (2015) developed a person delay-based optimization method that enables bus/signal cooperation and coordination among a pair of junctions under connected vehicle technology. The proposed method is an extension work of transit signal priority (TSP) logic by using binary mixed integer linear programs. The advanced connected vehicle data are capable of providing more accurate bus locations and counting passenger numbers in each bus to decide the coordination strategies against conventional TSP. The numerical experiments of TSP combined with connected vehicles found great bus delay reduction than the traditional method.

He et al. (2012) proposed a platoon-based arteria signal control method considering multiple modes (buses, pedestrians, cars) in V2I communications. This actuated coordinated method identified the vehicle stream platoon by connected vehicle. The priority phase will be determined by the priority levels of each platoon and choose whether extend a green actuation time or switch to next phase. The case study tested in a pair of junctions with public transport facilities (bus routes and bus stops). The proposed method was strengthened later by He et al. (2014) to better performance in low levels of communications penetration.

Another research attempted to maximise the weighted passenger number through the junction for the disposal of both demands of private vehicles and buses (Polgar et al., 2013). The study divided the available green time among the signal stages of the junction in order to maximise the number of passengers crossing the stop line with fixed cycle time and stage order in a two-stage junction. The scheme which can acquire a maximum number of weight passengers was adopted as the optimal strategy to assign green duration for two stages.

Table 3. 1 Summary of person-based adaptive signal controls using connected vehicle technology

Main author and year	Model name	Case study Scale	Objectives of the model	Signal phase settings	Data Resources	Key Performance Indicator	Simulation Platform	Benchmarking model
Christofa et al. (2013a)	A person-based traffic responsive signal control system	Isolated junction	Minimising total person delay	Fixed phase sequence and cycle length	Demand, turning ratios, vehicle occupancies, bus speed and location	Total passenger delay; Number of stops and emissions of buses	AIMSUN	TRANSYT-7F
Christofa et al. (2013b)	A person-based traffic responsive signal control system	Isolated junction	Minimising total person delay	Fixed phase sequence and cycle length	Demand, travel times, and turning ratios, vehicle occupancies, bus speed and location	Total passenger delay	AIMSUN	Vehicle-based optimization with same algorithm
He et al. (2012)	Unified platoon-based mathematical formulation	8 junctions	Minimising the total weighted delay	Fixed phase sequence, offset and cycle length	Travel mode, Vehicle speeds and positions, vehicle occupancies	Average vehicle delay; Average bus delay; Throughput	VISSIM-COM	Coordinated-actuated control optimized by SYNCHRO, PAMSCOD
He et al. (2014)	Multi-modal traffic signal control	2 junctions	Minimising the total weighted delay	Fixed phase sequence, offset and cycle length	Travel mode, Vehicle speeds and positions, vehicle occupancies	Average vehicle delay; Average bus delay	VISSIM-COM	Coordinated-actuated traffic signal control
Christofa et al. (2016)	A person-based traffic signal control system on arterials	4 junctions	Minimising total person delay	Fixed phase sequence and cycle length	Demand, travel times, and turning ratios, vehicle occupancies, bus speed and location	Total passenger delay	AIMSUN	TRANSYT-7F
Hu et al. (2015)	A person-delay-based optimization method for TSP	2 consecutive junctions	Minimising total person delay	Fixed phase sequence and cycle length	Vehicle speeds, locations and occupancies	Bus delay; Total person delay	VISSIM-COM	TSPCV, Conventional TSP, No TSP

Polgar et al. (2013)	Passenger number dependent traffic control	Isolated junction	Maximising number of weighted passenger	Fixed cycle length in a two-stage junction	Vehicle positions and occupancies	Number of weighted passenger	VISSIM	Fixed-time control
Yu et al. (2019)	A f person-based frameworks for traffic signal timing optimization	Isolated junction	Minimising total person delay	Fixed phase sequence and cycle length	Vehicle positions and occupancies	Bus delay; Total person delay	——	No uncertainty, deterministic, robust optimization, and blended strategy
Vilarinho et al. (2017)	A person-based traffic signal control strategy	Isolated junction	Minimising total person delay	Flexible phase sequence and cycle length, fixed phase combination in a three-stage junction	Vehicle occupancies, queue length and traffic arrivals	Average person delay	AIMSUN	Fixed-time control
Mohammadi et al. (2019)	A user-based signal timing strategy	Isolated junction	Maximising user throughput	Fixed phase sequence and combinations, flexible cycle length	Vehicle speeds, locations and occupancies	Average junction throughput	VISSIM	Vehicle-based optimization with same algorithm

3.2 Flexible signal plans in connected vehicle environments

The majority of vehicle-based control (reviewed in Section 2.5) and person-based control (reviewed in Section 3.1) optimized their signal plans in several limited criteria (e.g. fixed cycle length, phase sequence, phase combinations). Table 3.2 provides a summary review of signal controls using CV data with at least flexible cycle length and flexible phase durations. The flexibility degrees (whether phase sequence, phase combinations and cycle length are flexible or not) and the number of phase options of traffic signals they assumed to adopt their methods are also summarized in Table 3.2.

Table 3. 2 Summary of signal controls with flexible signal plans in connected vehicle environments

Main author and year	Methodology	Phase sequence flexible?	Cycle length flexible?	Flexible phase combinations?	No. of phase options	Vehicle-based/ Person-based
Vilarinho et al. (2017)	Two-stage bid mechanism	Yes	Yes	No	3	Person-based
Mohammadi et al. (2019)	Mixed-integer nonlinear program	Limited by NEMA dual-ring	Yes	No	8	Person-based
Liang et al. (2018)	Complete enumeration	Yes	Yes	No	4	Vehicle-based
Beak et al. (2017)	Dynamic Programming	Limited by NEMA dual-ring	Yes	No	8	Vehicle-based
He et al. (2012)	Mixed-integer nlinear program	Limited by NEMA dual-ring	Yes	No	8	Vehicle-based
Lee et al. (2013)	Complete enumeration	Yes	Yes	No	8	Vehicle-based
Priemer and Friedrich (2009)	Complete enumeration and DP	Yes	Yes	No	3	Vehicle-based
Feng et al. (2015)	Dynamic programming	Limited by NEMA dual-ring	Yes	No	8	Vehicle-based
Guo et al. (2019)	Dynamic programming with shooting heuristic	Yes	Yes	No	4	Vehicle-based

Liang et al. (2020)	Heuristic method	Yes	Yes	Yes	8	Vehicle-based

Only a few existing papers adopted flexible phase sequence and cycle length in their proposed approaches (Vilarinho et al., 2017; Liang et al., 2018, Priemer and Friedrich, 2009; Guo et al., 2019). However, the algorithms employed in these studies either consider a simplified junction with two one-way streets or only three or four-phase options for a three/four approach junction. The simplified assumptions of junction layouts limit their methods to be applied in real-world case studies or scenarios with unbalanced and fluctuating traffic demands, which cannot be regarded as completely flexible.

Some other studies offered limited phase sequencing options by using the NEMA dual-ring signal phase structure, which does not allow flexible signal strategies, such as phase skipping, between two barrier groups (Feng et al, 2015; Beak et al., 2017; He et al, 2012; Mohammadi et al, 2019). The signal plans in these studies operated with a fixed phase sequence order and a phase to have zero duration due to minimum green times are also not allowed. This simplification reduces the number of phase sequence options but limits the flexibility degree of signal plans adapting to varying traffic flows.

Lee et al. (2013) determined the next optimal signal phase by minimising the CTT of vehicles with flexible phase sequences in an 8-phases junction. However, the algorithm used fixed phase combinations and it only optimized the first phase without consideration for the impacts on future phases. This caused the decision-making process only get a sub-optimal solution rather than an optimal signal plan for the whole period.

To the best knowledge of the author, there is only one vehicle-based control study that developed a complete flexible signal plan approach in the generalized 8-phases junction (Liang et al., 2020). However, the flexible signal plans in this paper were operated to serve the departure sequence of the first platoon to reduce vehicle delay. Completely flexible signal plans are more valuable and sensible in person-based controls than those in vehicle-based controls due to various priority levels of car and bus sequences. As different signal plan decisions will result in different statuses of vehicles, the prediction departure time of vehicles will also need to be changed. Therefore, there is a critical research gap that more flexible signal plans should be optimized for person-based signal controls to better react to passenger cars and buses with various occupancy levels from different directions and arrival lanes. The new vehicle trajectory and car-following updating theories need to be developed to predict the departure time of cars and buses under different potential signal timing plans as well.

3.3 Research gaps and contributions

3.3.1 Research gaps

There are a few papers summarized in Table 3.1 that developed person-based controls focusing on passenger delays including public transport, some of which extended the person-based objectives towards a regular junction environment with/without the interpretation of public vehicles. This enables signal control transitions from vehicle-based systems to person-based systems utilising CV data. From the experiences of TSP strategies, flexible signal timing approaches were adopted for buses with more passengers than cars to award higher priorities, e.g., stage skipping, green extension, and stage recall (Anderson et al, 2020). However, the vehicular environments of different occupancy passenger vehicles with/without buses are even further complicated for controllers to reach the total passenger delay objective as it is hard to predict the arriving distributions of passenger vehicles, which lane they will arrive and related occupancy sequences. Inspired by TSP strategies, complete flexible signal plans should be adopted for person-based controls with flexible stage sequences, specific phase combinations and phase durations. However, from Table 3.2 the state-of-the-art researches do not adopt completely flexible signal plans in person-based approaches. They also do not understand how different possible signal plans will impact the vehicle trajectories, departure times of vehicles in different occupancies and the decision-making process of person-based approaches. Those researches lay particular emphasis on adjusting signal schemes to provide priorities to transits rather than vehicles and still do not answer how to react to different priority levels of passenger cars on normal urban roads.

On the other side, small groups of the signal control plans adopted in person-based controls in Section 3.1 are not completely flexible and they do not explore the impacts of different possible signal strategies on vehicle trajectories and departure times.

While no research understands how person-based signal control paradigms would be and what are their potential benefits for urban mobility and person congestion reduction over adaptive signal controls. More specifically, how would person-based control be in realistic scenarios? As can be seen in Figure 3.1, the research gaps are found in the literature:

- There is no research developing person-based signal controls with completely flexible signal plans in CV environments in a generalized 8-phases options isolated junction. It is unknown how the trajectories and predictive departure times of vehicles from different lanes with different occupancies will be changed with possible signal plans, and how these changes impact the person-based will signal control paradigms. More concisely, what person-based control paradigm would exactly be, which sort of data could be used in person-based control and how to use them.

- There is no research developing coordinated paradigms for person-based controls with completely flexible signal plans implemented in multiple junctions. How to utilise the information from adjacent junctions and how to achieve coordination for person-based control are unknown.
- It also needs to figure out how to develop person-based signal controls with completely flexible signal plans in vehicle mixtures of cars and buses, and how to implement person-based controls in real word case studies with more realistic scenarios including varying traffic flow demands, CV penetration rates, planning durations and other variables and what are benefits in these different scenarios.
- There is no research answering how to develop person-based signal controls with mixtures of CVs and conventional vehicles in the case that not all of the vehicles are connected. How to improve the performance of person-based controls when part of vehicle trajectory and occupancy data cannot be acquired.

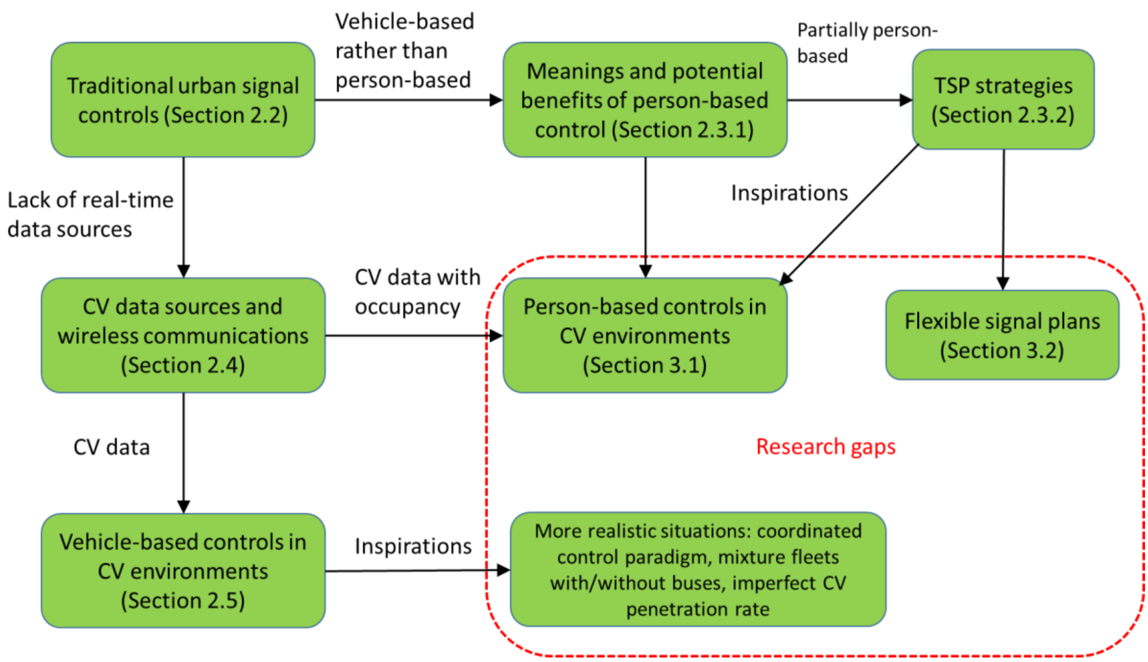


Figure 3. 1 Overview of literature review and research gaps

3.3.2 Contributions of this research

Aim and objectives in Section 1.5 try to fill in the research gaps. The contributions of this project are:

- A three-layered DP person-based signal control mechanism PerSicon-Junction is developed in isolated junction and CV environments. This signal control system searches for the most suitable signal timing plans to reach the minimum person delay in the defined planning horizon. The possible signal plans and corresponding delay reduction benefits are considered here. Inside PerSicon-Junction, a signal phase transition exploration mechanism is developed to efficiently explore all possible signal timing plans for every next planning step according to non-conflicting phase rules. The vehicle trajectory and car-following updating theories are proposed and used for predicting discharging time of all vehicles from incoming lanes under different cases.
- A person-based control PerSicon-Bus with completely flexible signal plans is developed to apply PerSicon-Junction in more complex vehicle mixtures of cars and buses in generalized 8-phases options isolated junction. Buses are considered to be a special vehicle mode which can be incorporated into the algorithm of PerSicon-Junction. A realistic isolated junction and a number of scenarios are constructed to investigate the performance of the proposed method against benchmarking models involving vehicle-based controls using CV data. The performance are evaluated under car and bus mixtures under varying flow demands, as well as other sensitivity analysis factors such as CV penetration rates and bus occupancies.
- The proposed PerSicon-Network extends PerSicon-Bus to coordinated paradigms to better understand how person-based signal control with flexible phase combinations and stage sequences would be implemented in multiple junctions. The CV information from both surrounding CVs and adjacent junctions can be acquired to enable junction controllers to have knowledge of vehicular situations within further range. In order to incorporate further information properly for controllers to make adaptive signal timing decisions to all surrounding vehicles with different occupancies, the data from the adjacent junction will be utilised as a supplement form of predictive vehicle arrival time list according to vehicle trajectory data and signal strategy. A real-world road network is built to evaluate the performance of PerSicon-Network.
- Estimation status of Unequipped Vehicle with Occupancy (EUVO) algorithm is proposed to improve the behaviours of PerSicon-Network under imperfect CV penetration rate environments. The EUVO algorithm collects vehicle data from roadside cameras and inductive loops to support the data inputs and performance of PerSicon-Network.

It is worth noting the relationships between different proposed person-based algorithms. PerSicon-Junction is the initial version which only considers passenger cars in isolated junction. PerSicon-Bus is an evolution of PerSicon-Junction, which incorporates bus mode with higher occupancy levels against passenger cars in isolated junction. PerSicon-Network is an upgraded version of PerSicon-Bus, extending the junction scales from isolated junction to road networks. The EUVO algorithm enhances the data inputs of PerSicon-Bus to improve its performance in imperfect CV penetration rates.

3.4 Challenges for modelling adaptive person-based signal controls in urban isolated junction

In contrast to the vehicle-based approach, there should be an additional vehicle occupancy level state variable to be considered in the person-based signal control paradigm due to occupancy levels in passenger cars are different. The signal control design and signal timing strategies, in person-based control, may make different choices to guarantee the right-of-ways of all passengers in junction surrounding vehicles with real-time information from CVs. The design of person-based signal control algorithm is not an easy task as constant vehicle flow demands, irregular vehicle and inside passenger arrival distributions, varying traffic state parameters and the influence of signal plan decisions on vehicular environments cause the traffic situations more complex than the vehicle-based approach. In order to develop a fair passenger occupancy priority assigning system that specifically reacts to the real-time road network environment, several challenges need to be considered:

Special person-based signal optimization mechanism: The most common adaptive vehicle-based signal controls follow fixed, or dual ring (Feng et al., 2015) phase sequences, and provide green durations to specific stages according to vehicle queues or vehicle trajectories. It is suitable when vehicle numbers are only determinable for signal planning decisions as all vehicles account for the same proportions of weights with a slight impact on vehicle delay. While the public transport priority-based strategies apply different signal timing priorities to detecting public transport vehicles, such as stage skipping, green extension, and stage recall (Diakaki et al., 2013), which breaks the current stage ordering sequence for the aim of assigning higher priority to those vehicles with a mass amount of passengers. This is because public transport vehicles with more passengers are more susceptible to be suffered from delays than passenger vehicles from the perspective of reducing person delays. The flexible stage schemes could also be implemented in person-based signal control in urban junctions for all passenger vehicles. However, this leads to a more complicated signal optimization mechanism for a person-based approach since flexible stage schemes would be extra determination factors for signal timing design.

The person-based approach controller should select the priority green stage rather than the pre-defined stage sequence for next stage to better reduce person delay. While various patterns of unpredicted passenger occupancy levels in queuing or arriving make signal controller challenging to identify which lane and how many vehicles should be awarded junction crossing priority. In the public transport priority-based approach the green time priority will be given for detecting public transport vehicles and related lanes it belongs. In vehicle-based approaches, if flexible stages adopt, those lanes with higher queuing vehicles might be promised priority as more vehicles will be discharged before stage switches. However, neither of them can apply to the person-based urban signal control approach. A basic example illustrated in Figure 3.2 can describe this situation. Without the consideration of passenger number, the queuing platoon with four vehicles in a vertical lane in Figure 3.2 is more efficient to be provided with priority than two queuing vehicles in conflicting lanes, taking into account the average vehicle discharging rate and start-up time loss caused by stage switching. However, if comprehensively considering the influence of passenger numbers in each of the vehicles in Figure 3.2, the horizontal lane will acquire green pre-emption first due to higher occupancy rates in two vehicles in the horizontal lane. This situation will become more complex if more combinations of different passenger occupancy levels occur. The circumstances in Figure 3.2 or more complex traffic situations indicate that the person-based signal controller cannot assign priority to those lanes with the highest occupancy level vehicle, or decide the priority according to vehicle number in a separate lane. The person-based signal control should develop a special innovation signal optimization mechanism to manage the global maximum benefits and travelling experience through properly deciding the priority of vehicles from different lanes.

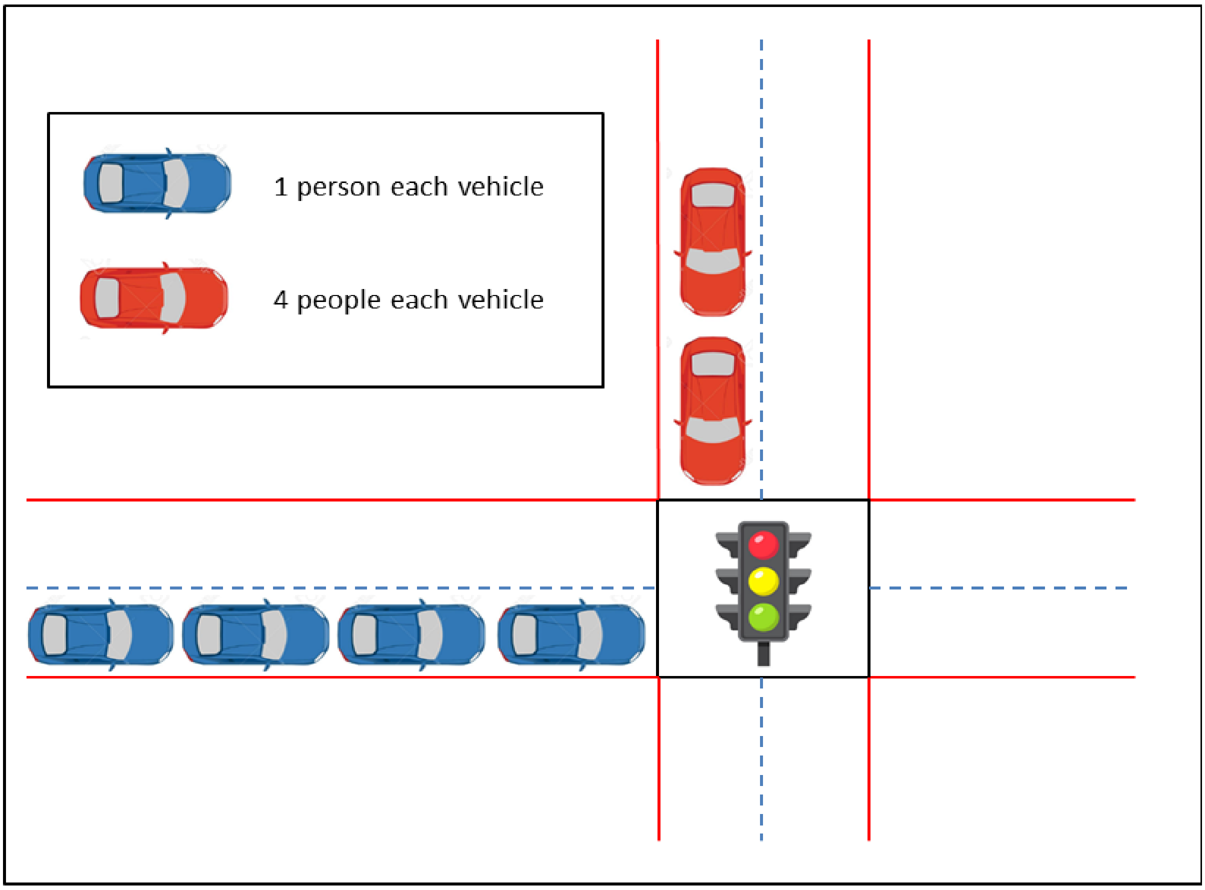


Figure 3. 2 A basic example: priority should be provided for which lane in person-based approach?

Stochastic passenger level distributions among different lanes: There is typically more than one lane per incoming approach serving all vehicle movements (left turn, straight, right turn) in one junction. Two or three of those non-conflicting phases could be operated with green lights at the same time to share the limited junction spaces more efficiently. The non-conflicting phase combinations in the vehicle-based approach are fixed; loop executing one stage after another. The signal timing plan for bus priority also follows this trend, only switching to the specific stage when it involves a high priority arriving bus at the current time. However, notably, the proportion of buses in the total vehicle number coming towards the junction is rather low and buses are moving along relatively regular routes. As for passenger vehicles in the situations of the person-based signal control approach, those high occupancy vehicles (typically 3 or 4 people in each vehicle) occupy a considerable part of the total amount of vehicles and their arrival patterns are stochastic. The distributions of vehicle occupancy are varying, unpredictable and irregular among all possible lanes approaching the junction. The vehicle groups with high occupancy level combinations may appear in non-conflicting phases out of pre-defined stage settings and situations may be changeable in the following stages. The present vehicle-based signal control algorithms are hard to satisfy the requirements of reacting to such dynamic network situations and reducing passenger delay. The flexibility of the person-based signal design paradigm needs to be significantly extended to explore the most appropriate signal timing possibility to react to various occupancy level distributions and improve passenger mobility on the premise of ensuring junction user safety.

Constant vehicle flow demand towards junction: The person-based signal control optimization is a dynamic planning process. The constant vehicle flow demands travel towards the junction from different directions at every time step, with varying passenger occupancy levels. The incoming vehicles continuously bring variables to junction environments and vehicular status and thus influence the priority strategy judgement made by the person-based signal controller. Vehicles with a high number of passengers may arrive in the following time and step out of the detection region of the current junction; join the lane regarded as a low priority to reform junction priority situations. The adaptive signal control system using connected vehicle data can merely capture a snapshot of current localization traffic conditions, based on which predicts the short-term future traffic state and optimize signal timing parameters (Islam and Hajbabaie, 2017). Signal controllers need to figure out real-time signal timing plans that yield the highest person-based objective functions over the prediction horizon period in isolated urban junction, eliminating the unforeseen changes in constant traffic demand as possible toward global optimal solutions.

Influence of signal decision to next state: The principle of reinforcement learning approach of stochastic approaches introduced in Chapter 2 indicates that controller decision in the next state is a consequence of vehicle states, junction actions and rewards in the current step. Vehicle-based controls assign green time for each stage according to queuing vehicle numbers or real-time vehicle flows in the current lane and it does not need to explicitly consider the influence of the controller decision. This is because the general objective of the vehicle-based approach is to discharge more vehicles with the same priority weights at the same time. Ensuring green time assignments for saturated flows is rather effective. However, the person-based approach needs to take into account passenger vehicles at different priority levels and it is more likely to switch active traffic lights to other stages with higher priority vehicle groups. In this case, the role of the current signal timing decision is critical to affecting the signal timing optimization process over prediction duration. The signal decision of the junction controller made in the current time step (extending green stage time or switching to any possible next stage) have effects to unblock or obstruct all vehicles and passengers inside them in all approaching lanes.

The value of predicted crossing times of those high occupancy level vehicles and lane state in the next time step partial depend on immediate signal stage arrangements. The estimated high-priority vehicle group crossing time will be postponed if the current lane is inactive with the red traffic light. This may lead to different person-based objective function values in the next time step as the priority centre probably shifts to other lanes or postponed prediction crossing time. Therefore, formulating the environmental state every time step to explore all the possibilities for person-based function values is important.

3. 5 Requirements for modelling adaptive person-based signal controls in urban isolated junction

Person-based signal controls in urban isolated junction is a rarely implemented design concept, which makes it challenging to determine the format of the signal timing optimization paradigm. It is not the first time to propose the person-based signal control approach for an urban isolated junction. In Vilarinho et al. (2017) the proposed control system attempted to consider the occupation of any vehicle and fairly treat vehicles and their passengers. The system should bring up the benefits of stage designs and phase change as needed to replace the fixed paradigm. The paper also discusses how a person-based approach would look like to be to react to unexpected traffic events including varying occupancy levels. Combining with the challenges of the person-based approach against vehicle-based signal control need to be addressed mentioned above, the characteristics of expected paradigm formation of the person-based approach are:

Delay predictions for every vehicle in any junction approaching lane: The first challenge of the person-based approach claims that a new signal optimization mechanism should be developed to ensure the urban junction discharges people in passenger vehicles at the highest rates. The distributions of vehicle occupancy levels are varied in dynamic environment states so it is hard to calculate how many vehicles in which lane should be prioritized directly. For instance, the signal timing duration awarded based on queuing vehicles in person-based approaches or stage resetting for arriving buses and its prediction of crossing time in the bus priority approach are not suitable in these complex situations. The vehicles waiting for departure in incoming lanes are separable into different vehicle groups with different discharging opportunities. Providing more green active duration for one crowded lane means more queuing vehicles are expected to be discharged in the following time, but may not be the optimal discharging rate. In the proposed person-based approach, it is essential to predict explicit crossing time corresponding to every passenger vehicle in any incoming lane in an isolated junction. Only in this way junction controller is capable of figuring out which kind of signal timing strategy should be adopted, how many vehicles in which lane could be released as predicted, and whether it is the most efficient solution to reducing person delay, improving people's mobility and person-based performance.

Traffic states update for every stage: The crossing time prediction for every vehicle relies on the newest traffic states in the approach lane, more specifically, how many vehicles are in front of it, what are their statuses and whether the junction controller assigns lasting green time priority to this lane. The last challenge mentioned above presents that the current traffic state is affected by the traffic state and signal timing strategy last time. It also becomes recursive to be a critical factor to determine various junction states in the next stage with different controller actions. Any one of the feasible signal timing schemes is possible to achieve the underlying person-based objectives, part of which may significantly be different from signal strategy in vehicle-based controls and result in different traffic states. It is challenging to figure out which signal plan should be executed unless all of the possible schemes are judged by a new person-based mechanism at the end of the prediction period. The person-based signal optimization approach should be able to identify the relationships between traffic states in the current time step and last time step. Moreover, the traffic states in every time step need to be updated and recorded for the sake of exploring vehicle crossing opportunities and their benefits for passenger mobility.

Flexible stage sequences and phase combinations: The most common vehicle-based adaptive CV signal controls are constrained to follow a pre-determined stage order. Dual ring-and-barrier diagram (shown in Figure 3.3) is a standard formation of fixed stage sequence adapted in many vehicle-based approaches such as (Li and Ban, 2017). The traffic signal in an isolated junction successively executes two non-conflicting phases in their separate rings (for instance, phase 1 & 5 in the first stage, phase 2 and 6 in the second stage in Figure 3.3) and repeats the cycle. Given the fact that passenger vehicles with higher passenger occupancies may instantaneously arrive at the final place of fixed stage order to cause heavier person congestions, the proposed person-based approach provides the possibility of no pre-defined stage order. The next signal timing stage scheme can be assumed any phase combinations (e.g. phase 1 & 5 or phase 1 & 6 in Figure 3.3) or any flexible stage sequences (e.g. executing phases 4 & 8 as the first stage in Figure 3.3) within permitted ranges. Therefore, the person-based signal controller has capable of selecting any possible but permissible stage on the basis of the most beneficial stage plan for person-based objectives at any prediction period for solving the second challenge, considering all vehicle users present and expected in junction.

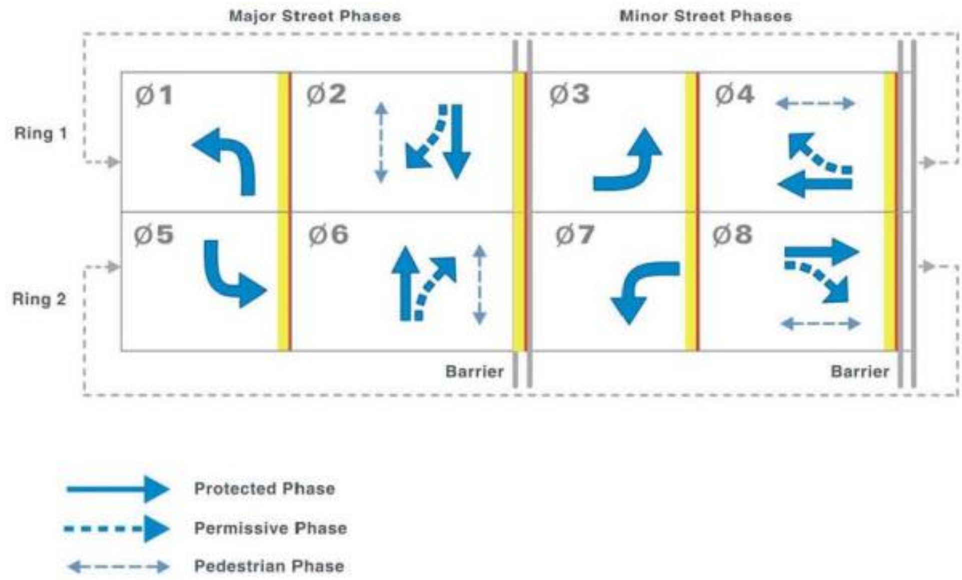


Figure 3. 3 Standard ring-and-barrier diagram (Koonce et al., 2008)

Different from sequential signal timing plans in vehicle-based signal controls, flexible signal planning in person-based control may result in uncertain stop-and-go behavioural adaptation in drivers as they cannot learn the dynamic decision-making mechanism of the controller rather than the repetitive structure. As a result, the expected performance of person-based controls may be reduced if drivers hesitate to cross the junction at the earliest chance. However, the CV technology allows two-way communication between junction controllers and CVs, which has the chance to solve this matter. After determining the signal plans for person-based controls, the junction controller can inform timing opportunity for each driver in CV to cross the junction by wireless communication to make them have mental preparation in advance.

No constraints of cycle length; minimum green time and maximum green time in another version: Minimum green time, maximum green time and cycle length are typical traffic signal parameters used in the vehicle-based approach. Minimum green time is adopted as the first portion of the green interval and is set for the consideration of satisfying driver expectancy and clearing storage of vehicles between the detectors and the stop line that cannot be detected in the presence of inductive loops (Koonce et al., 2008). The minimum green time setting has appeared in another version. This is because in the person-based approach, the signal transitions are more flexible (e.g. phase 1 & 5 or phase 1 & 6), and the vehicle clear time is calculated by the person-based signal optimization mechanism and traffic states obtained by CVs. This person-based mechanism can determine the signal timing assignments more precise according to the benefits to all passengers in vehicles while meeting the requirements of minimum green time by using CV communication systems.

The maximum green time and cycle length are produced to prevent one of the approaching lanes from operating overlong duration and excessive waiting time of vehicles in other lanes. In a person-based approach, the cycle length and maximum green time are hard to be defined due to flexible phase combinations and stage reorder. Therefore, the fixed cycle length is not adopted and maximum green time appears in another version. Instead, the person-based control agent evaluates whether it is worthy and favourable to continue the green time or turn into another stage with the highest benefits to people's mobility. The green duration can be assumed at any value without constraints of cycle length. To replicate the negative effects of serving one lane for a too long time, the person-based approach introduces the accumulated waiting time of passengers in any vehicle detected as a factor into person-based objective functions. Moreover, the green time for a specific lane will be terminated if it serves too long and the signal plans related to it are excluded in the next step from the list of all possible signal schemes.

Rolling horizon approach: As discussed in the third challenge, **CV** communication allows junction controllers a detailed snapshot of dynamic networks and a person-based approach need to figure out the optimal solutions for the future period. To avoid unforeseen changes in dynamic traffic demand, and occupancy level distributions and reduce the complexity of the problem formulation as possible, a rolling horizon solution technique is developed. The proposed approach collects data at the moment time step and predicts the traffic state for certain time steps up to the prediction period. The person-based approach then figures out optimal signal timing parameters that yield the highest objective function values at the isolated junction over the prediction period. The decisions for signal timing schemes will be implemented from the next time step until the prediction period ends. The optimization process is triggered again and repeats the same works.

3. 6 Methodology consideration for person-based signal control approach in isolated junction

The characteristics of the person-based signal control approach should have are presented in Section 3.5 to solve all of the challenges for the transformation from vehicle-based approaches. This project reviews the state-of-the-art vehicle-based adaptive CV signal control systems in Chapter 2. The review of vehicle-based signal control decision algorithms indicates that there are five alternative options for developing a new person-based paradigm: integer programming and solution algorithms, traditional theory-based methods, stochastic approaches, multi-agent junction managements and analogy methods.

Other methods except integer programming are not suitable for person-based control with completely flexible signal plans. The traditional theory-based methods determine the signal timing parameters such as green duration split, cycle length, and offset based on real-time flow demands or the number of vehicles in a certain section collected by CVs. It is not suitable to be adopted in person-based control as those flow demands which indicate regional vehicle counts cannot shift to explicit traffic states in every stage. Hence, the traditional theory-based methods also fail to predict the crossing time of every passenger vehicle and compute the different occupancy level priorities of any vehicle group. The stochastic approaches are effective in small traffic networks and they have good performance when traffic signal timing selections are limited such as in some cases in vehicle-based approaches (Hu et al., 2014). However, as discussed in Section 3.5, there have potentially plenty of traffic signal choices in person-based approaches to find out the most appropriate to reduce passenger delays. The number of traffic state patterns in a person-based approach is also greater than in vehicle-based approaches due to additional occupancy level distributions in different incoming lanes. The matching of state patterns and junction controller action patterns is much more difficult and complex for stochastic approaches such as reinforcement learning methods and neural networks, also resulting in severe time consumption for model structure construction. The performance of stochastic approaches are also very sensitive to changes in traffic state parameters and susceptible when traffic volumes and road network scales increase. Multi-agent junction managements are more appropriate for traffic vehicular environments in the presence of autonomous vehicles. This research only focuses on the person-based approach in connected vehicle environments. Besides, they emphasise the vehicle platoon trajectory planning negotiated by junction agents and vehicle agents, which may be hard to calculate the highest person-based objective function values in a person-based approach. Analogy methods are not prevailing vehicle-based approaches, and lack validation of signal control principles and performance.

Therefore, integer programming is chosen for modelling the person-based signal control approach due to its optimization capability to formulate person-based objective functions (e.g. minimising average person delay) mathematically and figure out the optimal signal timing parameters with the highest objective values under finite available signal scheme options over prediction period. The integer programming can increase the number of constraints for describing the vehicle's free-slow or queuing status, maximum vehicle discharging rates and lowest crossing time, and available signal strategies considering collision avoidance conditions and their respective passenger proceeds. Modelling constraints for integer programming contribute to finding out all eligible signal timing options and computers are sufficiently fast to model the person-based outcomes of different junction choices. Therefore, it is applicable to be formulated in complicated traffic situations and execute the optimization process in real-time signal approach implementation.

Integer programming solution algorithms have been reviewed in Chapter 2 and dynamic programming is selected as the methodology for the proposed person-based approach. The reason to choose dynamic programming is it is a powerful technique to solve a particular class of problems and able to characterize the optimal decision based on partial solved solutions, and thus, more efficient than other solution algorithms (e.g. enumeration approach, branch and bound approach) avoid duplication of same traffic situations. It is also more reasonable than part of solution algorithms such as greedy algorithms to calculate the optimal solutions for the whole prediction period rather than one stage, emphasizing the relationships between two consecutive time stages. Nevertheless, the usage of dynamic programming requires a recursive structure for solving problem and it is only applicable to those problems which have several properties:

- The given problem can be partitioned into smaller sub-problems.
- Each of the sub-problems can be solved independently.
- Optimal solutions to the sub-problems contribute to the optimal solution of the given problem.
- Sub-problems should have the same optimal substructure property.

The person-based approach in isolated urban junction follows all of the requirements for developing a dynamic programming method. As for a certain prediction period, the signal timing optimization problem for this duration can be broken up into sub-problem, for instance, figuring out signal timing optimal solutions in a shorter prediction term. The estimation process of junction traffic states can be regarded as a recursive structure, those of which in every step are results of traffic states and junction actions in the last step and can be part of references for the next step. All of the sub-problem that have been solved would not take effect in the junction states in the following step. In the first step, the person-based algorithm attempts to find optimal traffic signal plans for the current step as an outcome of the smallest sub-problem. The recorded sub-optimal solution can be directly quoted to calculate the benefits for passengers in the next step without over-lapping optimization from the very beginning. Moreover, the algorithm only remains and records the signal plan with the highest value results reacting to the same situation at the current step to avoid the unnecessary re-calculation of the rest of the possible signal plans to reduce time complexity; repeats the same optimization process until the final step.

The initial adoptions of dynamic programming methods in adaptive CV vehicle-based signal control systems, such as (Feng et al., 2015; Priemer and Friedrich, 2009), only consider the explicit green duration for a specific stage or limited stage selections available for junction controller. In the proposed signal control approach, the dynamic programming method is used to explore the optimal signal timing solutions for the greatest person-based objective values based on all possibilities of flexible stage sequences and phase combinations for every time step efficiently. Two ways of dynamic programming approaches are considered:

Forward recursion dynamic programming: the problem is solved by starting from the first step and proceeding toward the last step. The value function of the initial state is set to zero. The result obtained at a step is used as a consideration of the decision modifiers of the states in the next step. This recursive optimization process will continue until the last step. The optimal policy with minimum cost or maximum benefits will be adopted at the final step.

Backward recursion dynamic programming: in a backward recursion case, the optimal decision is computed starting from each state recursively, beginning at the last period. The value function for a state represents the cost of an optimal decision sequence beginning from the given state. In the last step, there are no decisions left to be made and therefore the value function for all states is set to zero. When the decision space left is adequate to execute a policy, its corresponding value will be recorded to find the optimal solution with the greatest value function until the first step.

The backward recursion dynamic programming needs to realize all of the passenger mobility benefits when the junction controller takes any signal timing plan in any step from the last state in the first step. As for the person-based approach, the benefit values to passengers in vehicles are not identified at the very beginning as the dynamic traffic state determined benefit value in the next step cannot be figured out until the junction state and action in the last step are obtained. Therefore, in this project, the forward recursion dynamic programming will be used to model the core part of the person-based signal control algorithm to find the highest objective value for passengers.

3.7 General evaluation framework for proposed person-based controls

Signal control evaluation is a critical part to validate the performance of proposed algorithms. In this section, the simulation tool and car-following model used for operating signal controls and imitating vehicle behaviours are discussed and selected. The benchmarking signal controls are also described to compare and validate the effectiveness of the proposed algorithm. It is important to ensure that the benchmarking models and proposed algorithm are operated in the same vehicular and traffic dynamic environments and evaluated under a consistent and fair evaluation framework. Therefore, the developed evaluation framework is consistently applied for all of the signal control algorithms and key points of the evaluation framework are summarized in summary.

3.7.1 Microsimulation tool selection for this research

The methodology to validate the performance of the proposed algorithm PerSiCon-Junction needs to be considered and selected. There are three frequently used methods in transport research: analytical computation (e.g. developing car-following models (Krauß, 1998), simulation and field trials. Considering large amounts of CV and wireless communication devices are required in this research to achieve PerSiCon-Junction, the field trial approach would be difficult to implement such researches logically due to the heavy cost of CVs and wireless communication devices and large scaled test sites for trials. Meanwhile, the performance indicators in real trials for the CV technology approach are complicated to be collected. The directly analytical computation approach also appears to be unrealistic for this research because the junction control system and performance involving large numbers of vehicles, communication systems and controller agents are too complex to be measured. Microscopic simulation is found the most suitable way to approach this research compared to other main research approaches due to the low cost and efficient KPI collection process with high-performance computation of computer.

There are three types of simulation which can be used to evaluate road network performance: microscopic, mesoscopic and macroscopic simulations. Microscopic simulations collect the behaviours of individual vehicles in the road network, such as speeds, and locations. Macroscopic simulations collect the performance of the road network or a zone as a whole area, for instance, vehicle flows and average speed for a road section. Mesoscopic simulations consider the small groups of traffic elements with similar traffic behaviours, such as flows and average speed of vehicles from one lane. Mesoscopic simulations are relatively less computationally intensive than microscopic simulations while providing more detail than macroscopic. In this project, the microscopic simulations allow large quantities of detailed vehicle information to be collected with different characteristics (e.g. vehicle occupancy levels) to be compared among models. Detailed information on the individual vehicle is also necessary for PB-AVA as data sources, which cannot be captured from mesoscopic and macroscopic simulations. Therefore, signal control models are applied in microscopic simulation to test the performance of the proposed algorithm with benchmarking models.

The microscopic simulations available for this project should satisfy several criteria:

- The simulation software should have accessible documentation.
- The simulation software should support CV as a user case.
- The simulation software should contain a scripting function though which the traffic models and traffic signals could be controlled.

Three microscopic simulations were found to meet the several criteria mentioned above: Aimsun (Barceló and Casas, 2005), SUMO (Krajzewicz et al., 2006), and VISSIM (Fellendorf, 1994). Some key features of the three microscopic simulations used to identify which one is most suitable for this project have been reviewed in Table 3.3.

Table 3. 3 Comparisons of microscopic simulations

	VISSIM	SUMO	Aimsun
License	Commercial	Open-source	Commercial
Visualization	2D/3D	2D	2D/3D
Vehicle types	Car, bus, truck	Any types	Car, bus, truck
Scope	City/Region	City/Region	Regional/Country
Parallel operation	4 instances	With multi-scripts	With extra cost
CPU usage	50 – 60%(2D), 60 – 70%(3D),	30 – 40%	30 – 40%
RAM usage	720MB(2D), 780 - 800MB(3D)	12-16MB	300 - 400MB(2D), 1GB(3D)

VISSIM is a commercial microsimulation package based on the Windows system which uses the Wiedemann car-following model (Wiedemann and Reiter, 1992). It only supports the simulations of cars, buses and trucks. VISSIM has a link to TRANSYT which can be reproduced as a benchmarking model. VISSIM also integrates travel demand modelling tools to assist road network buildings. Vissim has the best graphical representation which supports a two/three-dimensional preview of road networks and it provides more realistic vehicles, pedestrians and even static city buildings. However, the scripts can only interface with VISSIM after the simulations have been operated. The CPU and memory usage of VISSIM is the highest among the three microsimulation software.

Simulator of Urban Mobility (SUMO) is an open-source microsimulation package which supports Windows and Linux operating systems based on car-following models of Krauß (Krauß, 1998), IDM (Treiber et al., 2000), or Wiedemann (Wiedemann and Reiter, 1992). Unlike VISSIM and Aimsun, SUMO does not provide visualization details of vehicles and surrounding buildings. It also does not have links with other traffic signal controllers due to its open-source licence. SUMO supports parallel simulations with different scripts so that there is no extra cost. The CPU/memory usage of

SUMO is the lowest and the simulation in SUMO can be operated starting from its scripts, which ensures that SUMO simulation is more efficient than the other two simulations.

Aimsun is a commercial microsimulation package based on a Windows system with Gipps car-following model (Gipps, 1981). Aimsun has the largest simulation scope from the regional level to the country level. It also has built-in demand modelling tools to simplify road network modelling. Similar to VISSIM, the simulation in Aimsun needs to be running before the scripts can be used to interface with signal controls.

The overview of three microsimulation software find that the script operation property of SUMO is superior to VISSIM and Aimsun as it supports parallel simulation without extra cost and the scripts can be operated to interface with the simulation. These benefits can save simulation operation time in performance evaluations of proposed PerSiCon-Junction and benchmarking models with the number of experiments. Moreover, the algorithm mechanism of PerSiCon-Junction is rather complicated and it requires more computation complexity than traditional UTC systems. The last memory storage and CPU occupation in SUMO enable the proposed algorithm to be implemented smoother. SUMO also supports more vehicle types than VISSIM and Aimsun, which can make PerSiCon-Junction scalable to more complicated vehicular situations in future research. Therefore, SUMO is selected as the most appropriate software to simulate models in this research.

3.7.2 Car-following model consideration

Section 3.7.1 identifies that SUMO is the most appropriate software to simulate the proposed signal control algorithm. SUMO implements a few well-validated car-following models, namely Krauß, IDM, or Wiedemann. Pourabdollah et al. (2017) evaluated the performance of three car-following models using real-world vehicle data. The results indicated that IDM car-following model replicated better driving behaviours than the other two models in the case of high driver imperfection parameter. IDM car-following model is more suitable to be applied when driver reactions are almost perfect or in vehicular environments with AVs. The performance of Krauß improved significantly with optimized parameters and time delay. Another research found that Krauß car-following model performed better than the other two models in mixed traffic scenarios with passenger cars and buses (Mathew and Ravishankar, 2011).

This study develops the person-based signal controls with CVs and conventional vehicles. The proposed algorithm could be scalable to incorporate buses with higher passenger volume in Chapter 4 and other vehicle types (e.g. emergency vehicles) with different priority levels in future research. These vehicle types have different parameters including vehicle length, saturated flow and acceleration rates. In addition, Krauß can generate stable and collision-free traffic flow, which has been validated (Krauß, 1998). Therefore, Krauß car-following model is considered to be most appropriate for this research.

3.7.3 Benchmarking models for validation

3.7.3.1 TRANSYT fixed-time control

Fixed-time control uses historical traffic demand data as inputs and deploys an offline optimization process to generate predetermined signal plans. The junction controller operates through the stages sequentially and repeats the cycle. Figure 3.4 illustrates a flowchart for a fixed time control mechanism.

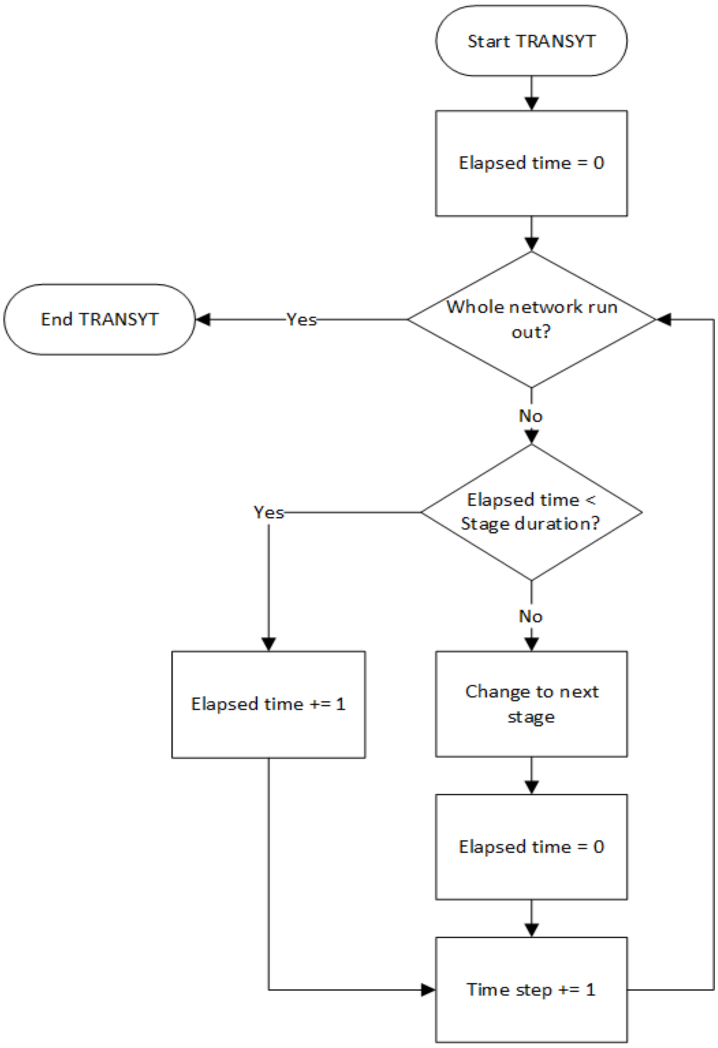


Figure 3. 4 Flowchart overview of TRANSYT

As introduced in Section 2.2, TRANSYT (Robertson, 1969) is one of the most widely adopted fixed-time control. TRANSYT can calculate the optimized fixed time signal plans using historical flow measurements for both isolated junction and coordinated junctions. Although open-source microsimulation software SUMO does not have a link to incorporate TRANSYT into simulation operation, the TRANSYT 16 software (Binning, 2019) license can be accessible from Transportation Research Laboratory (TRL). The signal timing optimization process can be conducted in TRANSYT and applied in SUMO with the flowchart in Figure 3.4. The details of TRANSYT parameters are introduced in Chapter 5.

Besides the fixed-time optimization function in isolated junction, TRANSYT also provides the coordination version to operate fixed-time controls in road networks by optimizing the offsets between one cycle start time and another cycle start time. In this project, the coordination version of TRANSYT is called TRANSYT-network to distinguish that it is a coordination signal plan for the road network.

3.7.3.2 Inductive loop based actuated signal control (ILACA)

Due to open-source license of SUMO, the MOVA traffic signal actuated control in isolated junction does not provide a link to be incorporated into SUMO simulation. In this research, an Inductive Loop Actuated Control Algorithm (ILACA) which can detect traffic situations and correspondingly adjust the flexible durations for each stage by means of loop detectors (Papageorgiou et al., 2003) is proposed. A fully-actuated junction control strategy is introduced here in Figure 3.5 as a benchmarking model from Federal Highways Administration Signal Timing Manual guidelines (Koonce et al., 2008). A maximum green time and minimum green time are pre-determined for ILACA, which are illustrated in Chapter 5 with their specific values. The junction will be operated following pre-defined stage sequences. When the junction control switches to the new stage, it will run out the minimum green time and judge whether the current flow exceeds the flow threshold at the end of the duration. The stage duration will be extended to an extension unit time in response to the vehicle flow approximated saturated flow of this lane (typically 80% of the saturated flow of this lane). This circle will last until the detected flow does not reach this threshold or the cumulated stage duration exceeds the limitation of maximum green time. The ILACA will then transfer to the next stage and experience the same process. The parameters of ILACA are described in Chapter 5.

In fully-actuated control, each junction controller makes signal timing decisions based on data received from all approaches to the junction. The junction controller operates without a common background cycle (Koonce et al., 2008). As a result, there is no coordination version for fully-actuated control ILACA. To maintain the consistency of the evaluation framework, ILACA-network is defined as the ILACA operation in the road network in this research. Each junction controller makes its signal timing decisions independently in ILACA-network with data from inductive loops installed surrounding it.

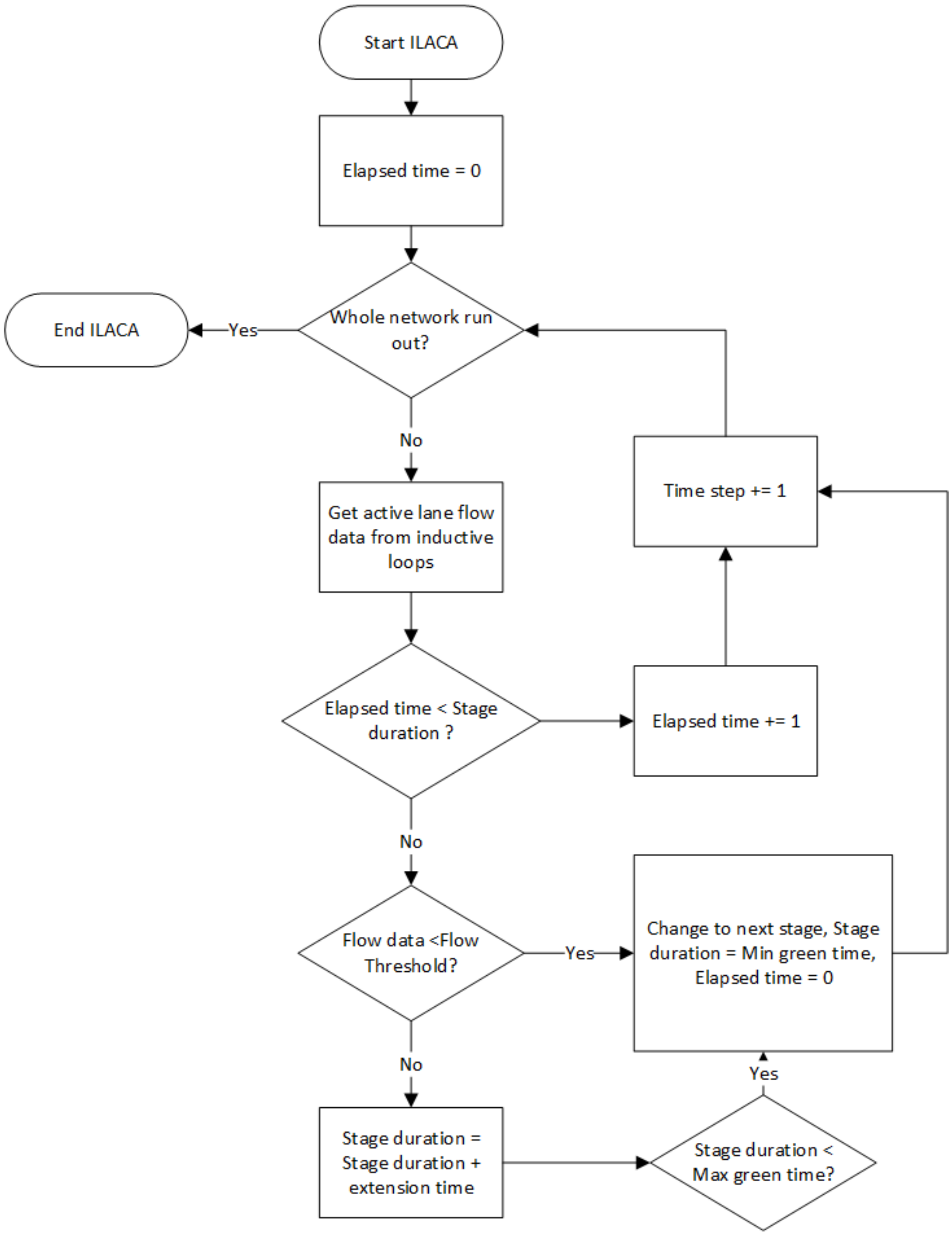


Figure 3. 5 Flowchart overview of ILACA

3.7.3.3 Vehicle-based signal control using data from CVs (VehSiCon)

The performance of proposed PerSiCon-Junction optimize signal timing plans with person-based objectives using CV data is meaningful to compare with the performance of algorithms with vehicle-based objectives using CV data. The state-of-the-art researches are difficult to be reproduced and compared in this project because of their complex algorithm paradigms and different modelling objects. This research proposes a vehicle-based signal control using CV data, namely VehSiCon, as a benchmarking model. The VehSiCon use the same initial vehicle departure time prediction theory to put more emphasis on investigating the impacts on complete flexible signal plans, vehicle trajectory update theory and person-based objective optimizations. Figure 3.6 provides an overview flowchart for VehSiCon.

The VehSiCon adopts fixed stage sequences and phase combinations to minimise vehicle delay in a certain planning horizon. When the vehicle-based control triggers, it collects speed and location information of CVs and predicts the departure time of every arriving vehicle from green light lanes using theories in Section 4.3.2. The core part of the optimization process is to determine how long the green time durations should be assigned for different stages, in other words, when the most appropriate cases switch the traffic light to the next stage. A possible switch point appears when a vehicle discharges from the lane in the last time step to avoid wasting the green light.

From the initial time step to the planning horizon, each vehicle's initial prediction discharging time step in the current stage forms a possible point to switch to the next stage. For instance, the vehicle's initial departure time list for the current stage (phase 1&5) is predicted to be [3s, 5s, 7s, 9s], and each element in this list is regarded as a case to switch the traffic light (green light for phase 1&5 will last for 3, 5, 7 and 9 seconds respectively for four different cases and switch to next phase 2&6 after an intergreen duration). The departure times of vehicles in the next stage are also predicted using the vehicle updating theories from Section 4.3.5 based on when it is activated. For instance, assuming intergreen duration is 3 seconds, 6, 8, 10, and 12 seconds red light durations are considered in vehicle updating predictions for phases 2&6 to calculate switch points according to the departure times of vehicles in this stage. This circle repeats in Figure 3.6 until the end of the horizon duration. After all of the stage switch points and their corresponding cases are founded, the optimal signal timing plan can be found within the time horizon to achieve the objective of minimising vehicle delay using Equation (4-2) without the presence of vehicle occupancy and be executed until the start of next horizon. The green duration for each stage in VehSiCon should also follow the constraints of minimum green time and maximum green time.

The coordination version of VehSiCon, namely VehSiCon-Network, has the same coordination optimization structure as PerSiCon-Network. As claimed in Section 4.5, the decentralized coordination structure predicts the arrival time of vehicles which are out of the communication range, to enhance the data inputs of the three-layered person-based optimization algorithm. VehSiCon-Network also adopts the enhancement of optimization algorithm data inputs to realize the further vehicle arriving information. The main differences between VehSiCon-Network and PerSiCon-Network are their optimization algorithm mechanisms and objective functions.

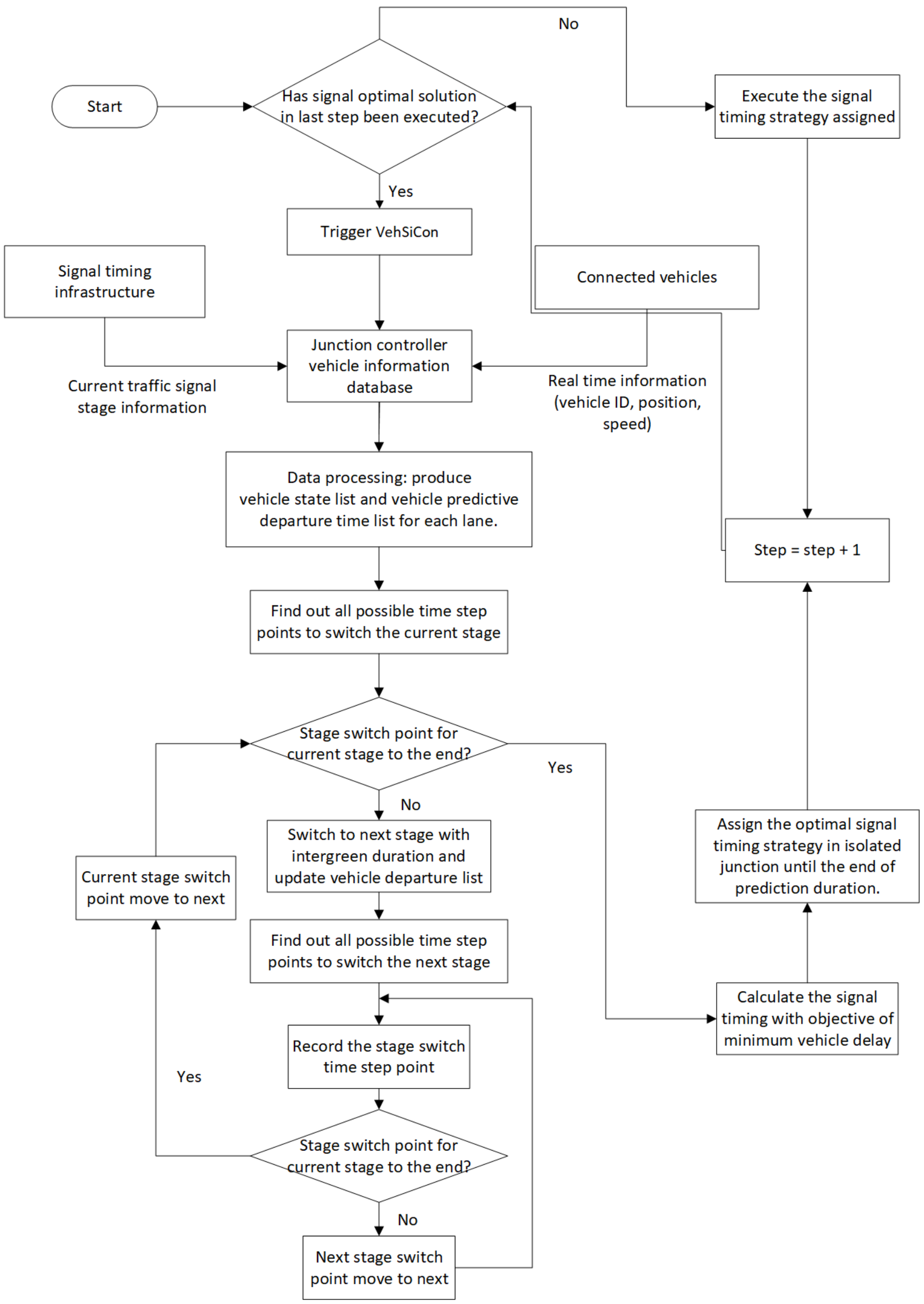


Figure 3. 6 Flowchart overview of VehSiCon

3.7.4 Simulation experiment scenarios and performance indicators (KPIs)

The evaluation framework needs to carry out a variety of simulation experiment scenarios for validating the performance of the proposed algorithm and benchmarking models with different sensitivity analysis factors. There are two different situations about sensitivity analysis factor choice. The first case is that the optimal values for some parameters in PerSiCon and related algorithms are not decided yet. For instance, although rolling horizon approach has been applied in vehicle-based adaptive signal control, there is no conclusion about the optimal value for planning duration. Therefore, different planning duration values will be adopted in PerSiCon-Junction evaluation, which is incremented from 10s to 60s with a step of 10s to test the influences of the planning horizon towards PerSiCon-Junction. The different values of weighted factor δ from 0 to 1 in Equation (4-2) should also be tested in PerSiCon-Junction.

Another case is that different situations happen in the real world traffic dynamics and all signal control algorithms are essential to be tested in these scenarios to observe the changes in their performance. For instance, the traffic flows fluctuate at different times of days and on different dates. Therefore, simulation scenarios with different flow levels are carried out in the evaluation framework. The penetration rate of CV also changes over the years as the value is predicted higher in future. The proposed algorithm is tested in different CV penetration rate evaluation scenarios. Similarly, various bus occupancy levels are considered in different evaluation scenarios.

The most commonly used KPIs in vehicle-based controls and person-based controls are summarized in Table 2.1 and Section 3.1 respectively. In this research, average vehicle delay, average vehicle number of stop, average person delay and average person number of stop are selected to evaluate the algorithms in each scenario based on the following considerations:

- Average vehicle delays and number of stop are primary optimization components in fixed-time calibrated signal plans TRANSYT to execute the signal timing plans;
- The objective function of VehSiCon is to minimise average vehicle delay;
- PerSiCon is proposed to minimise average person delay;
- Average person delay and average person number of stop can reflect the performance of person-based controls and are widely adopted in related researches. Average person delay can measure the delay suffered by each passenger in the vehicle. The average number of stop is not merely a KPI to measure the fuel consumption and fuel emissions, it can also reflect the passenger travelling experiences in vehicles. Fewer average person number of stop can improve the travelling experience of each person.

Delay is described as the excess time one vehicle takes to complete its travelling routes compared to the free-flow travel time. The free-flow travel time is defined as the time vehicle takes to finish its journey by free travelling status under road speed limits, without the disturbances of external factors such as signalized junctions, surrounding vehicles or traffic infrastructures. The free-flow travel time can be tested by implementing a series of vehicles travelling in a non-signalized junction, recording time spent and calculating the average value. The actual travel time of one vehicle equals to time step it leaves the simulation minus the time step it appears in the simulation. The delay of one vehicle equals actual travel time minus free-flow travel time. The delays of all passengers inside the vehicle are the same as the value of vehicle delay. Therefore, the total delay of passengers in one vehicle equals the number of passengers multiply vehicle delay. The number of stops for one vehicle during the entire journey is recorded by simulation. The passenger number of stops in one vehicle equals the number of passengers multiply vehicle number of stops.

3. 8 Summary

This chapter highlights the research gaps in urban signal controls by reviewing the most relevant state-of-the-art person-based controls and flexible signal timing literature and lists the contributions of this project to respond to the aim and objectives. To fill in the gaps, the chapter elaborates on the general methodologies that should be adopted for the new proposed person-based algorithm by analysing its challenges and requirements. Moreover, the evaluation framework for validating the performance of the proposed algorithm by comparing it with reference algorithms is constructed, which has been summarized in Table 3.4. All of the signal control algorithms are evaluated in the same vehicle environments and criteria. Both vehicle-based metrics and person-based metrics are adopted in Table 3.4 to ensure the fairness of the evaluation. Next chapter provides detailed descriptions of the proposed person-based algorithm PerSiCon-Junction, PerSiCon-Bus and PerSiCon-Network to respond to objectives.

Table 3. 4 Key points in harmonised evaluation and validation framework

<table>
<tr><td>Junction scale</td><td>Isolated junction</td><td colspan="2">Multiple junctions</td></tr>
<tr><td>Evaluation signal control algorithms</td><td>TRANSYT,
ILACA,
VehSiCon,
PerSiCon-Bus</td><td>TRANSYT-Network,
ILACA-Network,
VehSiCon-Network,
PerSiCon-Network</td><td>PerSiCon-Network with EUVO algorithm</td></tr>
<tr><td>Performance indicators</td><td colspan="3">Average vehicle delay, average vehicle number of stop, average person delay, average person number of stop</td></tr>
<tr><td>Sensitivity analysis factors</td><td colspan="2">Traffic flow level, CV penetration rate, planning horizon, weighted factor δ, bus occupancy level</td><td>CV penetration rate, distance from detection area to cross line, loops and cameras activation interval</td></tr>
</table>

Chapter 4 The detailed methodologies of proposed person-based control algorithms

Chapter 3 briefly introduces the proposed person-based algorithms PerSiCon-Junction, PerSiCon-Bus, and PerSiCon-Network and their evaluation framework. This chapter describes the detailed methodology of these three algorithms. Section 4.1 lists the simplifying assumptions made for three algorithms to point out their limitations and constraints, which are expected to be improved in future works. Section 4.2 lists definitions of all sets, variables and parameters used in this chapter. Section 4.3 provides the details for the adaptive person-based signal control approach PerSiCon-Junction proposed to minimise average person delay in an urban isolated junction, to correspond to objective 2 of this project. It describes the controller decision-making operational mechanism of associating traffic signal plans with corresponding person-based performance measures, considering the occupancy level of each vehicle according to real-time information from the interaction of junction controller and connected vehicles through wireless communication. Dynamic programming is an efficient and powerful technique for integer programming solution algorithms, applied when signal optimization problems can divide into sub-problem with recursive structures. An innovative three-level dynamic programming signal optimization algorithm is developed in this project as the core of PerSiCon-Junction after collecting and processing connected vehicle data, which can explore all of the possible signal timing strategies in a certain planning horizon, predict the vehicle-based controls and efficiently figure out their person-based value function for determining optimal solutions. In this way, PerSiCon-Junction can implement in an urban isolated junction with passenger vehicles for the person-based signal control system.

The vehicle constitution is assumed to be all passenger vehicles on road in Section 4.3. However, road traffic consists of different vehicle types in some cases. PerSiCon-Junction is a scalable framework which can join different vehicle modes into the algorithm as it calculates and estimates the possible discharging time of each vehicle during the optimization process. In Section 4.4, buses are incorporated into modelling situations as a representative of special vehicle modes because it is most widely considered as a vehicle type with more passenger capacity in TSP strategies and other person-based methods. The proposed method is called an Adaptive Person-based Signal Control Algorithm with Buses (PerSiCon-Bus), which uses the same optimization framework as PerSiCon-Junction, but more specific treatments are distinguished by passenger cars and buses in some equations. Section 4.5 develops PerSiCon-Network to understand how adaptive person-based control formulates and implements in multiple junctions and how it affects junction performance in terms of average person delay and number of stops.

4. 1 Assumptions and limitations of proposed algorithms

Traffic signal control optimization is a complicated problem and it is proper to make some assumptions to simplify the optimization model. This chapter describes three person-based controls PerSiCon-Junction, PerSiCon-Bus and PerSiCon-Network. Their respective assumptions and limitations are listed below.

For PerSiCon-Junction in Section 4.3, the assumptions and limitations include:

- The vehicle compositions on road are assumed to be consisted of conventional vehicles and CVs, without the presence of AVs. AVs can send vehicular data to junction controllers and receive trajectory recommendations from controllers. Their changeable trajectories have minor influence on the vehicle arrival predictions and person-related performance, however, result in more complicated vehicle trajectory planning to reduce fuel consumption and emissions. Future works should take into account AVs in vehicular environments to achieve multiple objective function targets.
- Vehicle lane-changing behaviours are assumed to be perfect in this project. Vehicles are assumed to change to their targeted lanes at the earliest chance once they enter the discharging lanes to the junction. In vehicle arrival prediction theories lane-changing behaviours are not considered and it is assumed that all of the vehicles would be discharged from their detected lane by default. In the real world, the vehicle may change its lanes after the data collection and signal timing optimization process. This phenomenon makes disturbance to the vehicle arrival sequence and number of vehicle predictions, which degrades the prediction accuracy and person-based performance. Future works should consider the impacts of vehicle lane-changing behaviours in signal control optimization.
- To simplify the CV data collection process, it is assumed that there is no communication delay and data measurement error from CVs to junction controllers. The packet loss of CV data message is assumed to be 0%. In reality, the communication delay, data measurement error and packet loss will affect the quality of data inputs and degrade the performance of the proposed algorithm. Future works should develop enhanced signal control algorithms in more realistic scenarios.
- Pedestrians and other vehicle modes are not considered in vehicle environments. Pedestrians have their special lanes to cross the junction and they will increase the computational complexity of flexible signal plan exploration. The individual car-following models and vehicle travelling behaviours of special vehicle modes may also cause

inaccurate vehicle arrival predictions. Future works can incorporate more vehicle modes into person-based controls.

For PerSiCon-Bus in Section 4.4, the additional assumptions and limitations include:

- The bus dwell time at the bus stop, bus lane-changing behaviours, and acceleration and deceleration process to approach and leave the bus stop are not considered in this research, assuming any bus stop near the junction area. The factors mentioned above will cause higher delays for buses and bus lane-changing behaviours will also disrupt the travelling of other vehicles. The improvement measurements to these influences should be solved in future works.
- The calculation of headway between two vehicles is assumed to be only decided by the saturated flow of the former vehicle. This simplification is justified by the calculation of headway only relying on the front vehicle, so does not significantly degrade the results (Yang et al, 2018).

For PerSiCon-Network in Section 4.5, the additional assumptions and limitations include:

- The communication range of the junction controller to receive CV data is defined as 250m in this research. The communication range is typically 250 – 300m. The shorter the distance communication range is, the fewer CV data can be received by the junction controller. The data transmissions of those CVs which are out of the communication range suffer heavier delay if considering data transmission latencies from CV to junction controller then to adjacent controller. In addition, the arrival times of those vehicles which are out of the communication ranges of two junction centres need to be predicted by former information. Although data transmission latency is not considered in this research, the 250m communication range is adopted as the worst scenario to develop PerSiCon-Network.
- PerSiCon-Network assumes there is no data transmission between two adjacent junctions. Similar to the communication delay between CVs and junction controllers, the communication delay between two adjacent junctions will affect the quality of data inputs and degrade the performance of the proposed algorithm, which should be considered in future research.

4. 2 Definitions of sets, decision variables and parameters

This section provides all of the sets, variables and parameters used in three new proposed person-based controls in Table 4.1.

Table 4. 1 Definitions of sets, decision variables and parameters for PerSiCon-Junction, PerSiCon-Bus and PerSiCon-Network

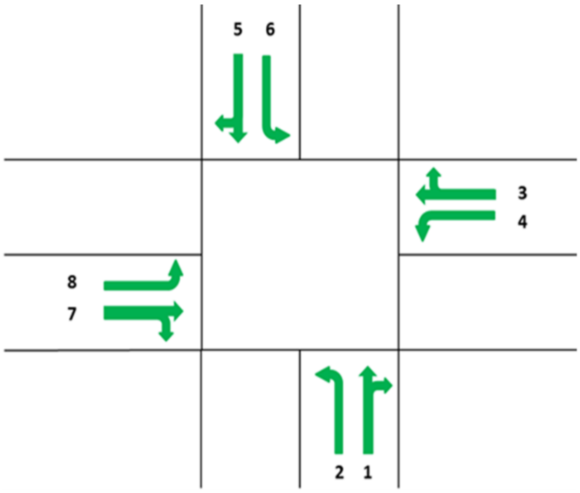
Sets	Description	Unit
T	Set of all steps in the planning horizon, expressed in form of time step.	—
P	Set of all phases in an isolated junction.	—
D	Set of all possible traffic signal plans in a junction (assign green traffic light to which phase).	—
$D_t(s_t)$	Set of feasible control decisions at time step t, given state variable s_t.	—
S_t	Set of possible traffic light phase states at step step t.	—
L	Set of state transition linkage allowing junction state transfer from last step to current step.	—
$E(p)$	Set of all compatible phases given phase index t in isolated junction.	—
Sets		
p	Index of phases in phase set P.	—
t	Planning time step index in time step set T, expressed in form of time step.	—
i	Index of a vehicle (car or bus) in a specific lane at a specific time step, counting from the vehicle nearest stop line.	—
g_p	Total number of constantly green traffic lights time steps given for phase p before initial time step 0, 0 if red light.	s
m_t^p	Traffic light state in phase p at time step t, represented by binary variables. 0 if red and 1 if green.	—
$D_V(i,p)$	Virtual arrival time of vehicle i in phase p to the junction with free flow speed.	s
$D_C(i,p)$	Actual departure time of vehicle i in phase p from the junction.	s
$T_{ACC}(i,p)$	Accumulative waiting time of vehicles from the first time it detected by junction controller to start of current planning time step 0.	s
$Tc(i,p)$	Time spent for vehicle i in phase p from beginning time step to when it crosses the stop line.	s
$A(i,p)$	Occupancy level of vehicle i in phase p at beginning time step. More specifically, it is also written as $\mathrm{a(i,t,p,s}_t)$ which refers to occupancy level of vehicle i in phase p at time step t, given state variable s_t in detailed formulas.	per
$A_c(i,p)$	Occupancy level of vehicle i in phase p at beginning time step if it is a car. More specifically, it is also written as $a_c(i,t,p,s_t)$ which refers to occupancy level of car i in phase p at time step t, given state variable s_t in detailed formulas to reflect the update of index of vehicle with occupancy due to different discharging states.	per
$A_b(i,p)$	Occupancy level of vehicle i in phase p at beginning time step if it is a bus. More specifically, it is also written as $a_b(i,t,p,s_t)$ which refers to occupancy level of bus i in phase p at time step t, given state variable s_t in detailed formulas to reflect the update of index of vehicle with occupancy due to different discharging states.	per
$v_0^p(i)$	Instantaneous speed of vehicle i from stop line to its location in phase p at initial time step 0 in meters per second.	m/s
S_{n+i}	The distance from cross line of planning junction A to $(n+i)$th vehicle S_{n+i}.	m
P_{n+i}	The distance from cross line of adjacent junction B to $(n+i)$th vehicle S_{n+i}.	m
$D(A,B)$	The distance between junction A and junction B.	m

$Q(t)$	Vehicle queue length at time step t	veh
$C(n+i)$	Time needed for $(n+i)$th vehicle to be discharged from adjacent junction B at the initial time step if it is not on link road.	s
T_{n+i}	The initial predictive time of $(n+i)$th vehicle	s
$f(t)$	Vehicle arrival rate at time step t	veh/s
$g(t)$	Vehicle discharging rate at time step t	veh/s
Decision variables		
d_t	Control variable denoting traffic control decision made by junction controller, transferring from state s_{t-1} at time step $t-1$ to state s_t at time step t. Also written as $\langle s_{t-1}, s_t \rangle$.	—
s_t	State variable denoting current state of traffic light phase at time step t, which value is represented by (p_t^1, p_t^2. p_t^1, p_t^2 represents phase index given green traffic lights in phase group (1,3,6,8) and (2,4,5,7) respectively in state s_t. If all of phases in phase group (1,3,6,8) or (2,4,5,7) are given red light, $p_t^1 = r_j$ or $p_t^2 = r_j$. j means total time step has been lasting for all red state.	—
$Vc_t^p(i, s_t)$	Predictive departure time of vehicle i in phase p at time step t, given state variable s_t assuming constant green light given for the phase in following steps.	s
$Sc_t^p(i, s_t)$	A binary variable represents predictive status of vehicle i in phase p when it cross stop line at time step t, given state variable s_t, 1 represents free travelling status and 0 represents queuing/slow-down status.	—
$c_t(s_t, d_t)$	Performance measure for passenger delay at time step t, given state variable s_t and control variable d_t.	s
$f(t, s_t)$	Function value at time step t which represents the accumulated person-based performance measure for current step and all of the previous step, given state variable s_t.	s
Constants		
F	Intergreen time interval in seconds.	s
α	Start-up lost time in seconds.	s
δ	Coefficient of accumulative waiting time of vehicles	—
h_s	Saturation headway in seconds.	s
T'	Planning duration in seconds.	s
i_p	Number of vehicles in phase p at the beginning of planning.	veh
p'	Total number of phases in junction.	—
S_c	Saturation flow rate if all vehicles are cars.	veh/h
S_b	Saturation flow rate if all vehicles are buses.	veh/h
A_0	Occupancy limit of passenger vehicles.	per
A_C	Occupancy limit of passenger cars.	per
A_B	Occupancy limit of buses.	per
v_s	Speed of vehicles discharging from queue.	m/s
v_{car}	Speed of cars discharging from queue.	m/s
v_{bus}	Speed of buses discharging from queue.	m/s

R	CV communication range.	m
V_d	Vehicle free-flow travelling velocity.	m/s
a	Vehicle constant acceleration.	m/s²
t_a	The time needed for vehicle acceleration process.	s
D_a	The distance vehicle travelled throughout the acceleration process.	m
Q_0	Initial queue length.	veh
$Q_{\max}$	Queue length maximum constraint.	veh

4. 3 Detail description of signal control algorithm PerSiCon-Junction

This section describes the proposed algorithm PerSiCon-Junction to optimize signal timing plans using information from CVs. A signalized junction with approaches from four directions is considered, which is shown in Figure 4.1. Each approach contains a dedicated left-turning lane which exclusively serves conflicting left-turning vehicles and a right-turning and through lane for those right-turning vehicles or vehicles that go straight. The phase number allocated for each lane and phase conflicting map are also illustrated in Figure 4.1 to indicate the vehicle movements at the junction.



(a)

	Phase 1	Phase 2	Phase 3	Phase 4	Phase 5	Phase 6	Phase 7	Phase 8
Phase 1	--	1	0	0	1	0	0	0
Phase 2	1	--	0	0	0	1	0	0
Phase 3	0	0	--	1	0	0	1	0
Phase 4	0	0	1	--	0	0	0	1
Phase 5	1	0	0	0	--	1	0	0
Phase 6	0	1	0	0	1	--	0	0
Phase 7	0	0	1	0	0	0	--	1
Phase 8	0	0	0	1	0	0	1	--

(b)

Figure 4. 1 (a) Junction layout and signal phase number (b) Phase conflicting map adopted in this section

The PerSiCon-Junction integrates real-time vehicular-related data with junction control information for optimization. The position, speed, occupancy and ID of every CV received by PerSiCon-Junction originated from the BSM data framework under the SAE J2735 message set, which broadcasts at 10HZ frequency (USGAO, 2015). BSMs are through IEEE 802.11p communication protocol which describes the hierarchy of DSRC designing for high-speed vehicular movements. The time step of the proposed adaptive signal timing approach is set as 1s. The connected junction control region is defined as 250m as a far enough reliable communication range in a four-leg isolated junction, where the messages can be received accurately under IEEE 802.11p DSRC networks (He et al., 2012).

A three-layered dynamic programming optimization procedure is developed to find out the maximum performance values and corresponding signal plans at a certain time. As shown in Figure 4.2, the algorithm receives vehicle ID, position, speed and road occupancy level, and processes them to produce the vehicle state list and initial departure time list as inputs for the first layer in Section 4.3.2. The first layer then calculates sub-performance values for different possible signal strategies at every time step (1 s) using Dynamic Programming (DP). The minimum performance value is recorded for the current step after figuring out all nodes of a certain step. The details of DP structure in the first layer are described in Section 4.3.3. To search all branches at each node when operating the DP algorithm, a signal phase transition exploration algorithm is developed to explore any potential traffic signal timing strategies in the middle layer (see Section 4.3.4). The vehicle trajectory and car-following theories are also adopted to understand vehicle trajectory influences caused by different signal plan selections and related costs/benefits on every branch are determined (see Section 4.3.5). In the third layer in Section 4.3.6, the algorithm finds the maximum person-based performance measure benefits at the end of the planning horizon and uses a backward recursion DP to search for an optimal signal timing plan. The rolling horizon procedure repeats to execute the optimization framework when the arranged signal plans are implemented.

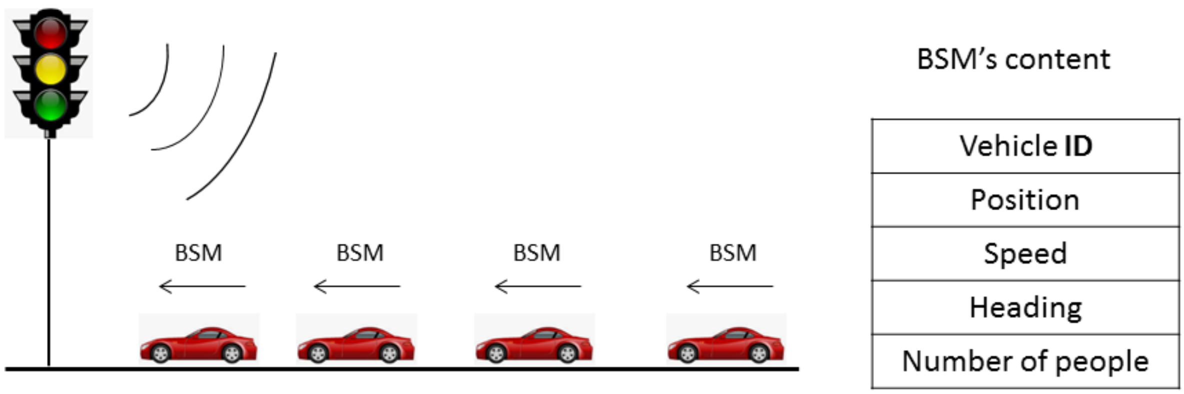


Figure 4. 2 CV data collecting process and contents of BSM

4.3.1 Model formulation

The algorithm aims to minimise average passenger delay in an urban isolated junction without following any strict phase sequence and phase duration. PerSiCon-Junction describes the controller decision-making operational mechanism of associating traffic signal plans with corresponding person-based performance measures, considering the occupancy level of each vehicle according to real-time information from the interaction of junction controller and CVs. All sets, variables and parameters used to formulate PerSiCon-Junction are listed in Table 4.1:

The objective of the PerSiCon-Junction is to minimise the total passenger delay of vehicles which can be detected by CV technology around the junction. The passenger delay is calculated by the product of vehicle delay and the number of people in vehicles separately. The vehicle delay equals the difference value of the vehicle predicted departure time from the junction and virtual arrival time to the junction with free flow speed, which is shown in Equation (4-1):

$$min\sum_{p=1}^{P'}\sum_{i=1}^{i_p}A(i,p)[D_C(i,p)-D_V(i,p)] \tag{4-1}$$

However, the summation of delays of all detected vehicles is difficult to be measured in signal optimization procedure as not all the vehicles from upcoming lanes can be discharged in a limited planning duration T. The departure times of those vehicles that failed to be discharged are unknown in the current optimization horizon. Therefore, the increment of total people time savings is adopted in this paper to replace the summation of people delay reduction. A mixed integer linear program is developed in PerSiCon-Junction to maximise the total number of people discharging time savings. As minimum green time is satisfied in flexible signal plans, the accumulated waiting time of the vehicle, from the first time it is detected to the initial step of the current optimization process with coefficient, is added to the objective function to guarantee the weight of low occupancy vehicle queuing for a longer time. The occupancy level factor is incorporated into the objective function to assign fairly priorities to different occupancy vehicles. The person-based objective function is formulated in Equation (4-2).

$$max\sum_{p=1}^{P'}\sum_{i=1}^{i_p}A(i,p)[T'+1-Tc(i,p)+\delta T_{ACC}(i,p)] \tag{4-2}$$

$$s.t.$$

$$0\ \le A(i,p)\le\ A_0,\ \ i\,=1,2,\ldots,i_p,\forall p\ \in P \tag{4-3}$$

$$0\le Tc(i,p)\le T'+1, i=1{,}2,\ldots,i_p,\forall p\in P \tag{4-4}$$

$$0\le\sum_{p=1}^{p'}m_t^p\le 2,\forall t\in T \tag{4-5}$$

$$Vc_t^p(i,s_t)<Vc_t^p(i+1,s_t)i=1{,}2,\ldots,i_p-1,\forall p\in P,\forall t\in T,\forall s_t\in S_t \tag{4-6}$$

$$d_t\in D_t(s_t),s_t\in S_t,\forall t\in T \tag{4-7}$$

Constraint (4-3) limits the value range of occupancy level parameter in each vehicle. Constraint (4-4) limits the value of time spent on the departure time of a specific vehicle starting from time step 0. This value equals $T' + 1$ if the vehicle fails to cross in planning duration. Equation (4-5) constrains the number of green traffic light phases m_t^p available to be assigned at the same time, which should be no more than 2 to obey the rules of non-conflicting phases in a standard 8-phases isolated junction to avoid vehicle collision. Constraint (4-6) sets out the relationships of predictive departure time among those vehicles in the same lane assuming no lane-changing behaviours near the junction.

Constraint (4-7) claims that all of the state variables $s_t$and decision variables d_t need to be selected from their separate sets at time t. The determinations of state set and control decision set depend on phase transition regulation and state set in last step $t-1$, which are represented in Equations (4-8) and (4-9) respectively. The details are described in Sections 4.3.3 – 4.3.6.

$$S_t = \{s_t \vee \langle s_{t-1}, s_t \rangle \in L, s_{t-1} \in S_{t-1}\} \forall t \in T \tag{4-8}$$

$$D_t(s_t) = \{\langle s_{t-1}, s_t \rangle \vee \langle s_{t-1}, s_t \rangle \in L, s_{t-1} \in S_{t-1}\} \forall t \in T \tag{4-9}$$

4.3.2 PerSiCon-Junction overview and data source processing

PerSiCon-Junction is developed to provide a method for solving the optimization problem formulated, finding out the maximum performance values and corresponding signal plans over a certain period. The system overview of PerSiCon-Junction is presented in Figure 4.3. As shown in Figure 4.3, the algorithm receives vehicle ID, position, speed and road occupancy level, and processes them to produce the vehicle state list and initial departure time list as inputs at t = 0 using Equations (4-10) – (4-13). A three-layered DP algorithm is the core part of PerSiCon-Junction to figure out the optimal solution with DP structure. Dynamic programming is adopted to divide the whole optimization problem into sub-problem in every time step with recursive structure. The optimal solution for the substructure is recorded and can be retrieved in the following optimization process to avoid repetitive calculations, which is more effective than the enumeration method. The three-layered DP algorithm (as seen in Figure 4.3) is constructed by a forward recursion algorithm (Algorithm 1) at the upper and middle layers and a backward recursion algorithm (Algorithm 3) at the lower layer. Algorithm 1 describes the upper and middle layers of PerSiCon-Junction with a forward recursion DP structure. Algorithm 2 is a phase transition algorithm operating every step inside Algorithm 1, to explore all of the possible signal plans in the next step based on the signal plan in the current step. After determining the maximum objective function value, Algorithm 3 performs a backward recursion DP structure to figure out the optimal solution.

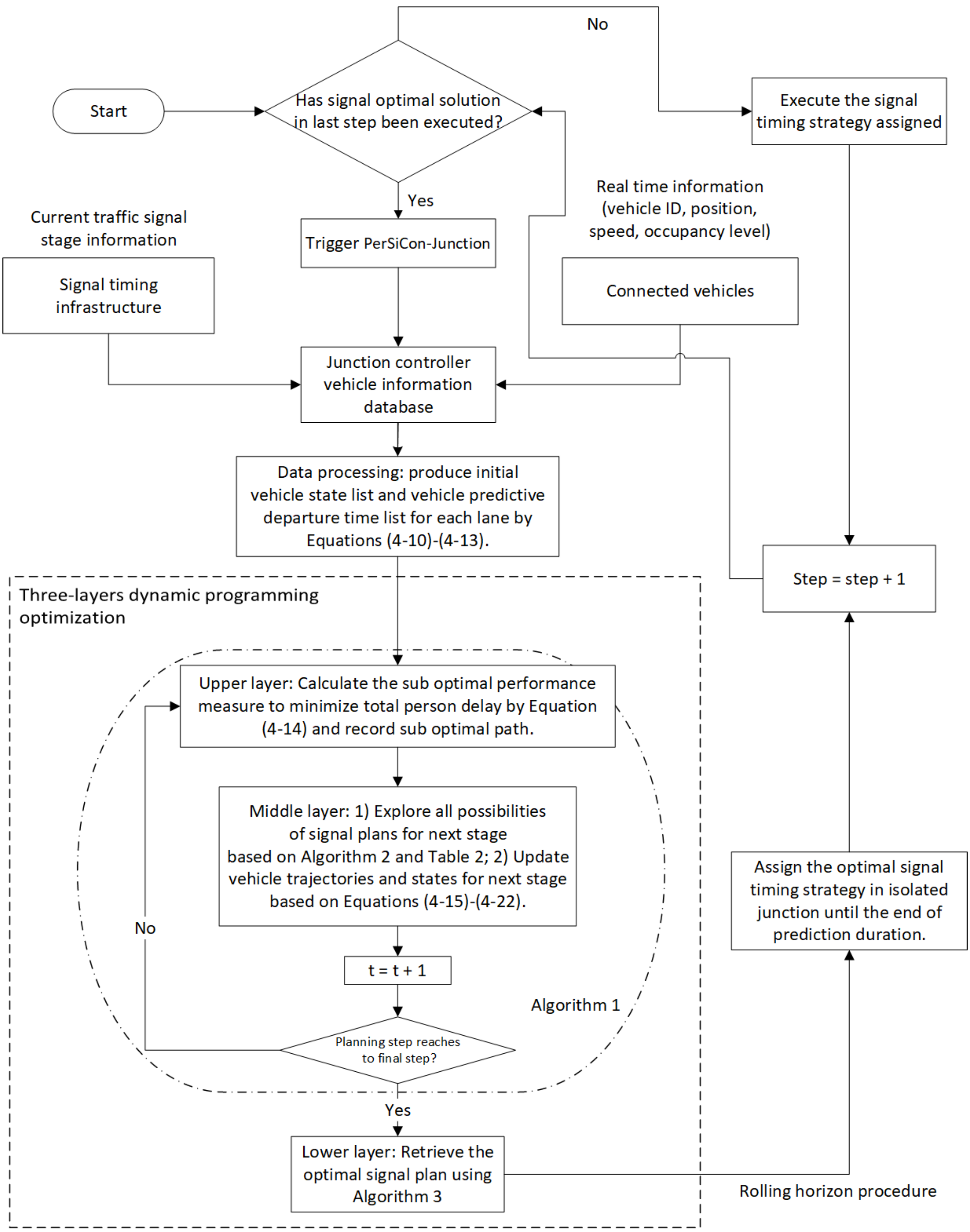


Figure 4. 3 Conceptual framework flowchart of PerSiCon-Junction

Before the operation of the optimal solution algorithm, all pieces of BSM from CVs are managed to form vehicle information lists sorted by phase index. The purpose of this process is to generate initial predictive departure time lists for the fleet based on the vehicle trajectory theories shown in Figure 4.4.

Every CV can only send real-time information about its individual characteristics and trajectories to the junction management infrastructure. The distances from those CVs travelling within range of the detection region and approaching towards the junction centre to the cross line of each lane can be calculated with location information. The location lists are then sorted CVs by their distance to the cross line from nearest one to furthest in detection range. The instantaneous speed and occupancy level lists are produced by recording fleet information by following the order of distances.

Given positions and speeds of vehicle i in phase p, the initial departure time for vehicles in queue and arrivals can be predicted at the start of optimization supposing that the next step for this lane will be constantly activated with green lights, which are expressed in Equations (4-10) and (4-11). The prediction method is originated from the kinematic wave theory principles adopted in person-based control (Christofa et al, 2016) and (Mohammadi et al, 2019), which is used for describing vehicle trajectories in the fleet with the influence of adjacent vehicles. In this paper, the acceleration and deceleration process of vehicles when they merge into queues or start-up for discharging are simplified to reduce the operational complexity of algorithm optimization. Four cases of different fleet trajectory patterns (see Figure 4.4) are considered in this method in the case of no less than three vehicles in arriving fleet:

1. All vehicles are discharged with free-flow speed
2. All vehicles are discharged from queue
3. Following vehicles with free-flow speed arrive before the queue has been discharged
4. Following vehicles with free-flow speed arrive after the queue has been discharged.

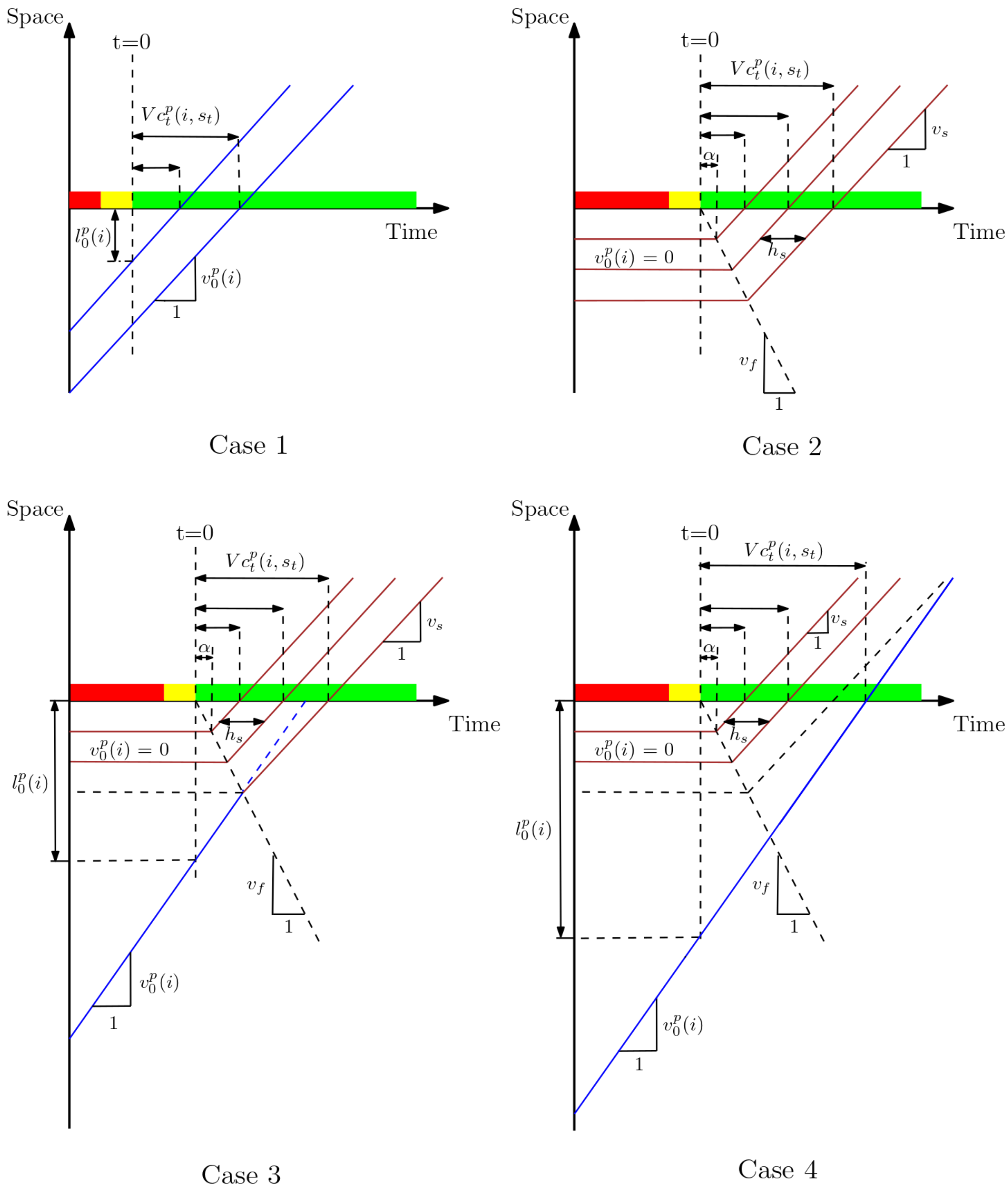


Figure 4. 4 Different cases of fleet trajectory representations assuming constantly green light given

The different departing cases in Figure 4.4 analyse vehicle trajectories and statuses with the knowledge of speeds and distances to junction cross line. The horizontal axis represents different time steps. Red, yellow and green colours on the horizontal axis are junction signal timing plans at different time steps in the individual lane. The vertical axis represents the distance of a vehicle to the cross line. The negative values in the vertical axis mean that vehicles are in the approaching lane and positive values mean that vehicles have crossed the junction. Each line represents the trajectory of a vehicle, in other words, the relationships between time steps and positions of a vehicle. The blue lines represent vehicles travelling under free-flow speed with a slop of vehicle free-flow travelling speed $v_0^p(i)$. The brown lines represent vehicles in queues or slow-down processes if the slope of a vehicle $v_0^p(i)$ is less than the threshold value v_s. At the initial time step t = 0, the position of each vehicle $l_0^p(i)$ represents the distance from it to the cross line. Given constant green time after the initial time step, the time needed for a vehicle to cross the junction $Vc_t^p(i, s_t)$ equals to its vertical axis value when $l_0^p(i) = 0$. If there is no queue, the vehicle can cross the junction with the free-flow speed as shown in case 1 in Figure 4.4. If a queue exists, as illustrated in cases 2, 3 and 4 in Figure 4.4, each vehicle in queue discharges with a discharging speed v_s saturated headway h_s and start-up time loss for first vehicle α due to driver reaction and vehicle platoon acceleration. The rate of backward recovery shock wave starting from congestion occurred equals to a slope of v_f.

The first difference of scenarios is to judge whether there is a queue exists at the junction at the moment of the green light is given or not. If the speed of the first vehicle in approach fleet $v_0^p(i)$ is higher than the threshold speed parameter v_s, it can be regarded as a free-flow status vehicle, whose departure time equals the distance to the junction cross line divided by instantaneous speed. The following vehicles also cross the junction without stop and delay, which is shown in case 1 in Figure 4.4. If the speed of the first vehicle in the platoon is detected as 0, it stops at the junction to form a queue. When the green light is awarded to this lane, the vehicle suffers a start-up loss time α due to driver reaction time and acceleration time lost, then crosses the junction with saturated flow speed v_s. All queuing vehicles (see case 2 in Figure 4.4) successively accelerate to speed v_s and discharge keeping a saturation time headway $h_s$with the adjacent front vehicle for the sake of avoiding collision. If a free travelling vehicle is detected approaching the end of the queue, it will either merge into the queue before the front vehicles have been discharged (see case 3 in Figure 4.4) or cross the junction with free-flow speed after the queue has been eliminated when it is far away enough (see case 4 in Figure 4.4). The challenge is to compare the value of free speed discharging time with the predictive departure time of previous vehicles plus the saturation headway. Case 3 occurs if the summation of predictive departure time of previous vehicles plus the saturation headway is greater than discharging time under free-flow speed, otherwise the vehicle will drive without the disruption of the queue in case 4.

According to the theories explained above in Figure 4.4, the initial departure time of the first vehicle in the fleet is formulated separately, which is shown in Equation (4-10). This is because the trajectory of the first vehicle is not affected by any following vehicles and start-up loss time should be taken into account. The initial departure times of the following vehicles are calculated by Equation (4-11) sequentially.

$$Vc_0^p(1,s_0) = \begin{cases} \alpha + h_s - g_p, if v_0^p(1) = 0 \wedge g_p < \alpha + h_s \\ min[\alpha + h_s - g_p, l_0^p(1)/v_0^p(1)], if 0 \le v_0^p(1) \le v_s \wedge g_p < \alpha + h_s \forall p \in P \\ l_0^p(1)/v_0^p(1), if v_0^p(1) > v_s \vee g_p \ge \alpha + h_s \end{cases} \quad (4\text{-}10)$$

$$Vc_0^p(i,s_0) = \begin{cases} \mathrm{Vc}_0^p(i-1,s_0) + h_s, & if\ v_0^p(i) \le v_s \\ \max[l_0^p(i)/v_0^p(i),\ \mathrm{Vc}_0^p(i-1,s_0) + h_s], & if\ v_0^p(i) > v_s \end{cases} \forall p \in P, i \ge 2 \quad (4\text{-}11)$$

The travelling status of each vehicle when it leaves the approaching lane is defined by binary variables. This variable is judged after the initial departure time is determined for the convenience of updating the departure time of the vehicle in the following steps. The transition of two status modes is an irreversible process. Once a vehicle driving at free flow speed changes to queuing status, this status will stay constant until it is discharged. The statuses of the first vehicle and following vehicles in the lane counted from the stop line are expressed in Formulas (4-12) and (4-13) respectively.

$$Sc_0^p(1,s_0) = \begin{cases} 1, if v_0^p(1) > v_s \\ 0, if v_0^p(1) \le v_s \end{cases} \forall p \in P \quad (4\text{-}12)$$

$$Sc_0^p(i,s_0) = \begin{cases} 1, if\ v_0^p(1) > v_s\ and\ Vc_0^p(i,s_0) > l_0^p(i)/v_0^p(i) \\ 0, \quad other\ cases \end{cases} \forall p \in P,\ i \ge 2 \quad (4\text{-}13)$$

3.4.3 Three-layered DP and forward recursion algorithm

This sub-section introduces the proposed three-layered DP algorithm and Algorithm 1 applied at the upper and middle layers in PerSiCon-Junction. Figure 4.5 presents a sketch illustration of a three-layered DP algorithm. This multi-step DP applies a forward recursion and a backward recursion algorithm to solve the signal timing optimization problem on a certain planning horizon. The upper layer calculates sub-performance values for different possible signal strategies at every time step (1 s) based on the state variables and decisions using Equation (4-14) in Algorithm 1. The sub-optimal performance value is then recorded for the current step after figuring out all nodes of a certain step. The details of the DP structure in the upper layer are described in this Section. In order to search all branches at each node when operating the DP algorithm, a signal phase transition exploration algorithm (Algorithm 2) is developed to explore any potential traffic signal timing strategies in the middle layer (see Section 4.3.4). The vehicle trajectory and car-following theories are also adopted to match vehicle trajectory influences caused by different signal plan selections and related costs/benefits on every branch are determined by Equations (4-15) - (4-22) in Algorithm 1 (see Section 4.3.5). In the bottom layer, the algorithm finds the maximum person-based performance measure benefits at the end of the planning horizon and uses a backward recursion DP in Algorithm 3 (see Section 4.3.6) to search for an optimal signal timing plan. The rolling horizon procedure repeats to execute the optimization framework when the arranged signal plans are implemented.

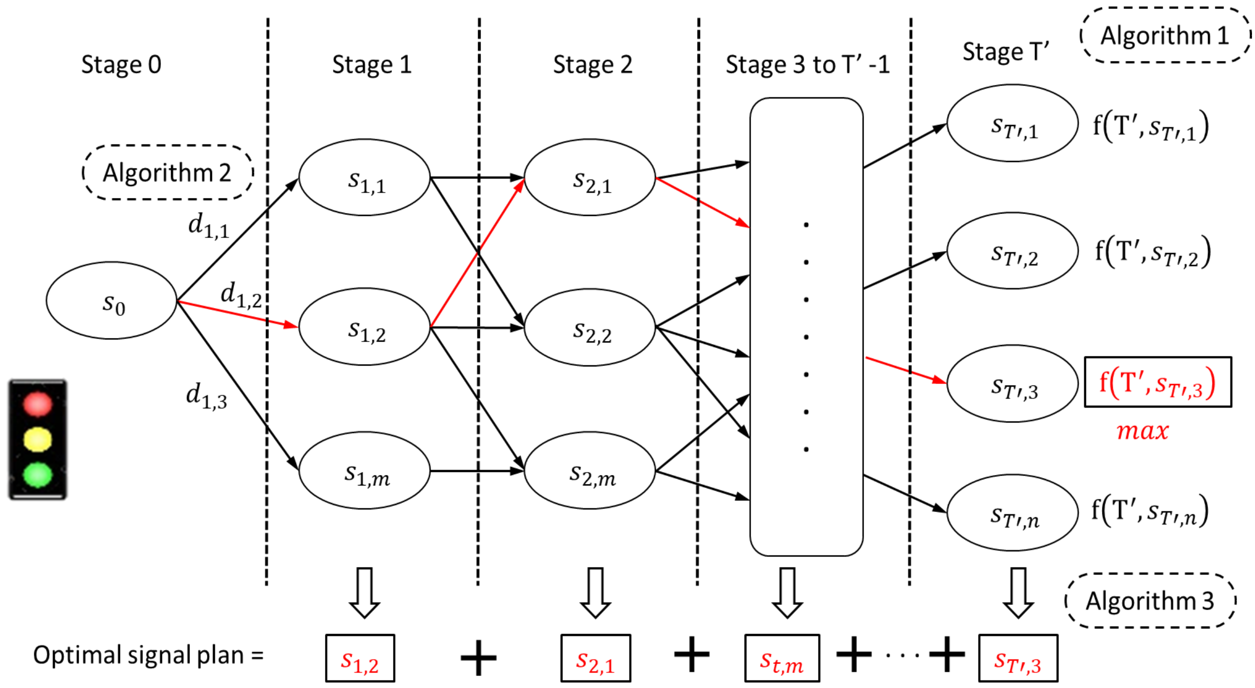


Figure 4. 5 Multi-steps sketch for three-layered dynamic programming algorithm constituted by Algorithm 1, 2 and 3

In Figure 4.5, the signal timing optimization algorithm triggers at step 0 and collects state information from CVs. There are several available choices (e.g. $d_{1,1,}d_{1,2,}d_{1,3}$in step 1 in Figure 4.5) for the junction controller to implement as different phase allocation schemes, transferring vehicle environments and signal phases to different states (e.g. $s_{1,1,}s_{1,2,}s_{1,3}$in step 1 in Figure 4.5) with varying passenger discharging benefits. The signal optimization algorithm accumulates this performance measure in every step and figures out the optimal solutions at the final step based on the performance value function. The three-layered DP optimization algorithm assigns flexible signal phase sequences and durations to achieve maximum value of performance value function based on predictive vehicle departure time. Step represents time step in the algorithm and is discretized to 1 s intervals in order to enable the algorithm to identify all of the possibilities and relative benefits of signal plan transition in every step. The junction controller determines the phase allocation in every step at the final step by performing the optimization over a predetermined planning horizon.

All of the feasible states s_t and junction decisions d_t at time step t are derived from the sets of possible states S_t and control decisions $D_t(s_t)$ in equation (4-8) and (4-9). The details of forward recursion are described as follows:

Algorithm 1 Forward recursion dynamic programming algorithm in the upper and middle layer of PerSiCon-Junction

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Input: Speed, location, vehicle ID and occupancy data of vehicle (car or bus) $i = 1,2,\dots,i_p, \forall p \in P$. Junction signal information s_0 at initial time step 0.

Output: Optimal solution for signal timing state $s^*_{T'}$ at final time step T' with maximum accumulated function value $f(T', s_{T'})$; dictionary with sub optimal solution path O^*.

1: predict the initial departure time $Vc_0^p(i, s_0)$ initial vehicle statue $Sc_0^p(i, s_0)$ of vehicle (car or bus) $i = 1,2,\dots,i_p, \forall p \in P$ at time step 0 using Equation (4-10) – (4-13)

2: set $t \leftarrow 1$, $f(0, s_0) \leftarrow 0$, $O^* \leftarrow$ empty dictionary

3: **while** $t \leq T'$ **do**:

4:     **for** each $s_{t-1} \in S_{t-1}$:

5:         get state variable set S_t and decision variable set $D_t(s_t)$ at time step t using Algorithm 2 and Table 4.2

6:     **for** each $s_t \in S_t$ and $d_t \in D_t(s_t)$:

7:         calculate sub performance measure $c_t(s_t, d_t)$ using Equation (4-14)

8:         $f(t, s_t) \leftarrow max_{s_t}$

9:         record $s^*_{t-1} \leftarrow O^*[t, s_t]$ as sub optimal solution **if** $c_t(s_t, d_t) + f(t-1, s_{t-1}) = f(t, s_t)$

10:         **while** $t < T'$ **do**:

10:             **for** each $p \in P$:

11:                 **if** $p == p_t^1$ **or** $p == p_t^2$:

12:                     update $Vc_t^p(i, s_t)$, $Sc_t^p(i, s_t)$ and $a(i, t, p, s_t)$ using Equation (4-15) – (4-17)

13:                 **else**:

14:                     update $Vc_t^p(i, s_t)$, $Sc_t^p(i, s_t)$ and $a(i, t, p, s_t)$ using Equation (4-18) – (4-22)

15:     $t \leftarrow t + 1$

16: $f(T', s^*_{T'}) = max$

The forward recursion in the upper layer starts the optimization at step 1 by assigning cumulative value representing the person-based objective function to 0. For each step, the upper layer of DP calculates the performance measure of passenger discharging benefits, determining and recording the optimal solution $O^* d_t(s_t)$ combining with the cumulative value function in the last step for each state variable s_t. At the final step, the optimization algorithm compares function values of different states to decide the optimal signal timing plans with the highest objective function value.

A series of phase allocations for each step reaching to the optimal state are searched by a backward recursion in the lower layer in Section 4.3.6. The performance measure $c_t(s_t, d_t)$ of passenger benefits from the last step to the current step is a function of state variables and control decisions. The performance measure is calculated in response to the person-based objective function by judging whether the first index vehicle after the stop line in lanes given green traffic light in state s_t is able to cross the stop line or not. The value $c_t(s_t, d_t)$ is calculated in Equation (4-14):

$$c_t(s_t,d_t) = \begin{cases} [a(1,t-1,p_t^1,s_{t-1}) + a(1,t-1,p_t^2,s_{t-1})]\left(T' + 1 - t + \delta T_{ACC}(1,p_t^1) + \delta T_{ACC}(1,p_t^2)\right), \\ if\ p_t^1 \in \{1,3,6,8\}, p_t^2 \in \{2,4,5,7\}, 0 < Vc_{t-1}^{p_t^1}(1,s_{t-1}) \le 1, 0 < Vc_{t-1}^{p_t^2}(1,s_{t-1}) \le 1 \\ [a(1,t-1,p_t^1,s_{t-1})]\left(T' + 1 - t + \delta T_{ACC}(1,p_t^1)\right), \\ if\ p_t^1 \in \{1,3,6,8\}\ and\ 0 < Vc_{t-1}^{p_t^1}(1,s_{t-1}) \le 1, p_t^2 \notin \{2,4,5,7\}\ or\ Vc_{t-1}^{p_t^2}(1,s_{t-1}) > 1 \\ [a(1,t-1,p_t^2,s_{t-1})]\left(T' + 1 - t + \delta T_{ACC}(1,p_t^2)\right), \\ if p_t^2 \in \{2,4,5,7\}\ and\ 0 < Vc_{t-1}^{p_t^2}(1,s_{t-1}) \le 1, p_t^1 \notin \{1,3,6,8\}\ or\ Vc_{t-1}^{p_t^1}(1,s_{t-1}) > 1 \\ 0, other\ cases \end{cases} \quad \forall t \in T \tag{4-14}$$

Cars and buses are constantly discharging from the approaching lanes and vehicle environments are dynamic as the proceeds of optimization. The predictive departure time, travelling status and occupancy level of vehicles in each lane determining the value of $c_t(s_t, d_t)$ need to be updated in the middle layer after the calculation of performance measure in the upper layer in every step, and returned them to the upper layer for calculation in next step.

4.3.4 Signal phase transition and exploration algorithm

The four-leg isolated junction layout and phase allocations are used in this paper and the phase conflicting map illustrating which phases are conflicted is graphed in Figure 4.1. A dual-ring controller follows fixed pre-determined phase sequences, which cannot be adopted in person-based signal control to explore the flexibility of signal timing plans (Improta and Cantarella, 1984). A flexible signal phase sequence and combinations machine are proposed in PerSiCon-Junction to solve this problem. In the middle layer of the DP optimization algorithm, the set for all feasible traffic signal phase states is produced in each step depending on the signal state set in the last step and phase transition linkages allowing junction state transfer from the last step to the current step in Equation (4-9). The phase set is originated from real-time phase information collected by traffic light infrastructure as the phase set at the initial step. Inspired by the theoretical flexible traffic light state machine proposed in (Li and Wang, 2006), the phase transition linkage and exploration algorithm is adopted in this research. It allows the efficient exploration of all flexible phase transition linkage situations by obeying the rules of avoiding conflicting vehicle flow collisions based on the phase conflicting map (Guler et al., 2016) and eliminating unnecessary linkages. Figure 4.6 shows an example. In the phase conflicting map, the number in the first row represents the subject phase index and the number in the first column represents the compatible or conflicting phase. Value 1 means the two phases are compatible and 0 means the two phases are conflicting. To elaborate on the feasible adjacent relationships, several criteria need to be satisfied meanwhile to ensure junction travelling safety and limited green time resource utilisation:

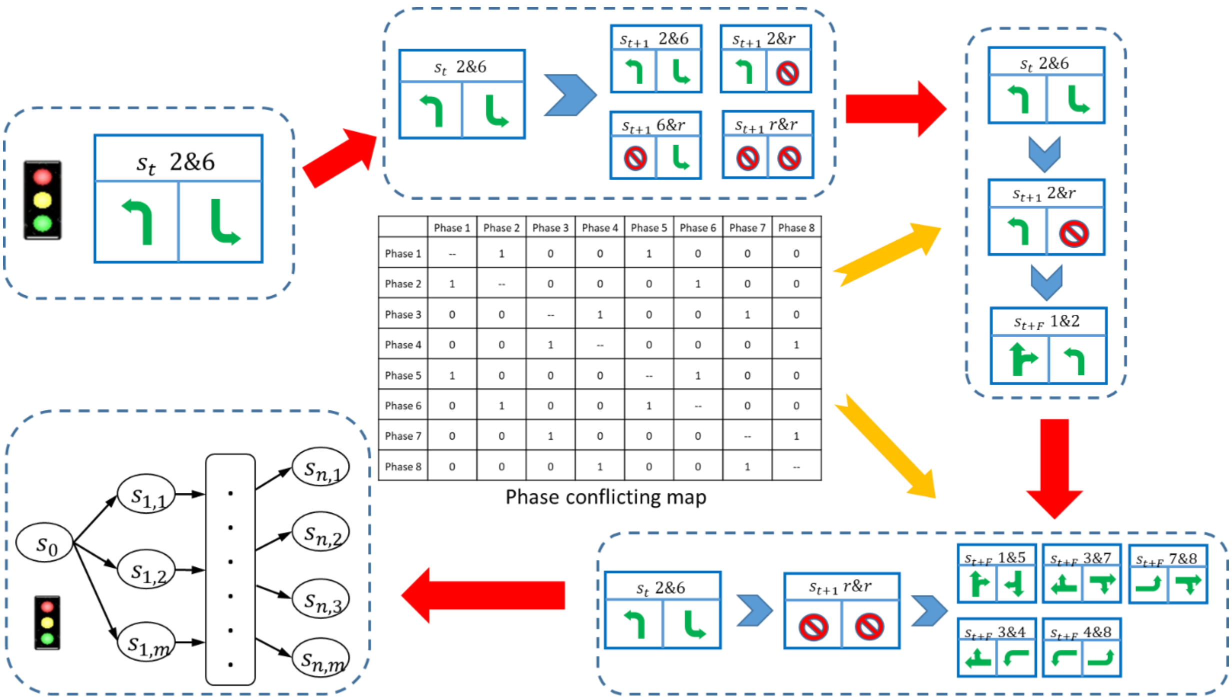

Figure 4. 6 An example of signal phase transition and exploration mechanism

▪ At any state in isolated junction, the junction controller assigns green traffic lights to at most two non-conflicting phases to ensure the vehicle flow can safely cross the junction centre area without collision. The non-conflicting relationships between any of two phases in the isolated junction have been expressed in Table 3.2. For every phase, there are two other compatible phases that allow them to proceed with vehicle flows at the same time. More specifically, given phase $p_t^1 \in P$, at state s_t, compatible phase $p_t^2 \in E(p_t^1)$. For example, if the index of the first phase is 1, the non-conflicting phase of it belongs to set $\{2,5\}$.

▪ The transitions between two states need to experience complete intergreen interval duration, each of which incorporates two non-conflicting phases with green light and all of them are completely different. However, if one of the green light phases in one state is the same as one of those green light phases in another state, this phase should keep green lights during the intergreen time. This is because the green light phase exists in two different states and the red light is unnecessary to operate to obstruct the vehicle flows. For example, phase 1 will keep the green light during state transition $(1,2)$ to $(1,5)$.

▪ The traffic signal phase state with two non-conflicting phases cannot transfer to itself after an intergreen duration. This criterion is to ensure maximising the use of green resources. For instance, state $(1,2)$ cannot transfer to $(1,2)$ by intergreen duration.

According to these rules, the steps of signal phase transition and exploration mechanism are described in Algorithm 2 as follows:

Algorithm 2 Signal phase transition and exploration algorithm

Input: Signal timing state s_{t-1} at time step $t-1$; dictionary with sub optimal solution path O^* from Algorithm 1.

Output: Signal timing state set S_t and decision set $D_t(s_t)$ at time step t.

$S_t \leftarrow [\,]$, $D_t(s_t) \leftarrow [\,]$
explore all possible $s_t = (p_t^1, p_t^2)$ based on $s_{t-1} = (p_{t-1}^1, p_{t-1}^2)$ and Table 4.2, insert each s_t into list S_t
if $t \geq F+1$:
    for each $s_t \in S_t$:
        if $p_{t-1}^1 \in \{1,2,3,4,5,6,7,8\}$ **and** $p_{t-1}^2 = r_F$:
            retrieve s_{t-F-1} $(p_{t-F-1}^1, p_{t-F-1}^2)$ from O^*
                remove s_t from S_t **if** $p_{t-F-1}^2 = p_t^2$:
        elif $p_{t-1}^1 = r_F \wedge p_{t-1}^2 = r_F$:
            retrieve s_{t-F-1} $(p_{t-F-1}^1, p_{t-F-1}^2)$ from O^*
            remove s_t from S_t **if** $p_{t-F-1}^1 = p_t^1$ **and** $p_{t-F-1}^2 = p_t^2$
        else:
            pass
for each $s_t \in S_t$:
    $d_t \leftarrow \langle s_{t-1}, s_t \rangle$
    insert d_t into $D_t(s_t)$

The middle layer of the DP optimization algorithm reproduces the flexible signal phase algorithm which satisfies all of the requirements above and modifies it as a form of an adjacent list in Table 4.2. Given the form of the traffic phase state at the last step, all feasible forms of the state at this step are listed in Table 4.2. These possible phase states constitute the set of planned steps and enable the DP to calculate different performance measures by visiting all of the elements in the set.

Table 4. 2 Set for possible traffic phase states given state in last step

The form of given state $s_{t-1} = (p_{t-1}^1, p_{t-1}^2)$ at step $t-1$	The form of possible states $s_t = (p_t^1, p_t^2)$ at step t
$p_{t-1}^1 \in \{1,3,6,8\} \wedge p_{t-1}^2 \in \{2,4,5,7\}$	1$p_t^1 = p_{t-1}^1, p_t^2 = p_{t-1}^2$ 2$p_t^1 = p_{t-1}^1, p_t^2 = r_1$ 3$p_t^1 = r_1, p_t^2 = r_1$
$p_{t-1}^1 \in \{1,2,3,4,5,6,7,8\} \wedge p_{t-1}^2 = r_j, 1 \leq j < F$	$p_t^1 = p_{t-1}^1, p_t^2 = r_{j+1}$
$p_{t-1}^1 \in \{1,2,3,4,5,6,7,8\} \wedge p_{t-1}^2 = r_F$	$p_t^1 = p_{t-1}^1, p_t^2 \in E(p_{t-1}^1) \wedge p_t^2 \neq p_{t-F-1}^2$
$p_{t-1}^1 = r_j \wedge p_{t-1}^2 = r_j, 1 \leq j < F$	$p_t^1 = r_{j+1}, p_t^2 = r_{j+1}$
$p_{t-1}^1 = r_F \wedge p_{t-1}^2 = r_F$	$p_{t-1}^1 \in \{1,3,6,8\} \wedge p_{t-1}^2 \in \{2,4,5,7\}, p_t^1 \neq p_{t-F-1}^1, p_t^2 \neq p_{t-F-1}^2$

4.3.5 Vehicle departure time updating theory

In the middle layer of PerSiCon-Junction, the initial departure time list is updated and combined with the decision of the junction signal controller for lane i to calculate the partial fragments of passenger delay reduction. The initial departure time list of the fleet for one lane is predicted in Section 4.3.2 assuming the green light is always given for the current phase in the following steps. However, this assumption in standard isolated junctions is a special situation and not suitable for all cases as there are only two phases that can be given with right of way at the same step at most to avoid vehicle collision of flows from conflicting vehicles. The different traffic phase sequences and combinations in varying states will result in different vehicle statuses, affecting the time spent arriving at the stop line. The vehicle environments are essential to be updated at every step corresponding to every generated state in the state set given green or red traffic light.

If the traffic light for phase p is green at time step t, the recalculation of predictive departure time, travelling status and occupancy level for each vehicle in each lane are expressed in Equations (4-15) - (4-17):

$$If m_t^p = 1:$$

$$Vc_t^p(i, s_t) = \begin{cases} Vc_{t-1}^p(i, s_{t-1}) - 1, & if\ Vc_{t-1}^p(1, s_{t-1}) > 1, i = 1, 2, \dots, i_p \\ Vc_{t-1}^p(i+1, s_{t-1}) - 1, & if\ 0 < Vc_{t-1}^p(1, s_{t-1}) \leq 1, i = 1, 2, \dots, i_p - 1 \end{cases} \forall p \in P, \forall t \in T \tag{4-15}$$

$$Sc_t^p(i, s_t) = \begin{cases} Sc_{t-1}^p(i, s_{t-1}), & if\ Vc_{t-1}^p(1, s_{t-1}) > 1, i = 1, 2, \dots, i_p \\ Sc_{t-1}^p(i+1, s_{t-1}), & if\ 0 < Vc_{t-1}^p(1, s_{t-1}) \leq 1, i = 1, 2, \dots, i_p - 1 \end{cases} \forall p \in P, \forall t \in T \tag{4-16}$$

$$a(i, t, p, s_t) = \begin{cases} a(i, t-1, p, s_{t-1}), & if\ Vc_{t-1}^p(1, s_{t-1}) > 1, i = 1, 2, \dots, i_p \\ a(i+1, t-1, p, s_{t-1}), & if\ 0 < Vc_{t-1}^p(1, s_{t-1}) \leq 1, i = 1, 2, \dots, i_p - 1 \end{cases} \forall p \in P, \forall t \in T \tag{4-17}$$

The predictive departure time of every vehicle in this lane is shortened according to Figure 4.4 assuming constant green light in Equation (4-15). If the algorithm determines that the first vehicle has crossed the lane, the vehicle state list and occupancy level list are updated to remove the information of the vehicle being discharged in Equations (4-16) and (4-17) respectively.

However, if the junction controller allocates a red traffic light to the planned phase in the current time step, the procession of vehicles discharging will be obstructed and none of the vehicles in this lane are able to leave. Therefore, vehicle trajectory and car-following updating theories are proposed in this paper. Four different cases of fleet trajectories need to be updated to cases in Figure 4.7, each of which corresponds to the relative case in Figure 4.4.

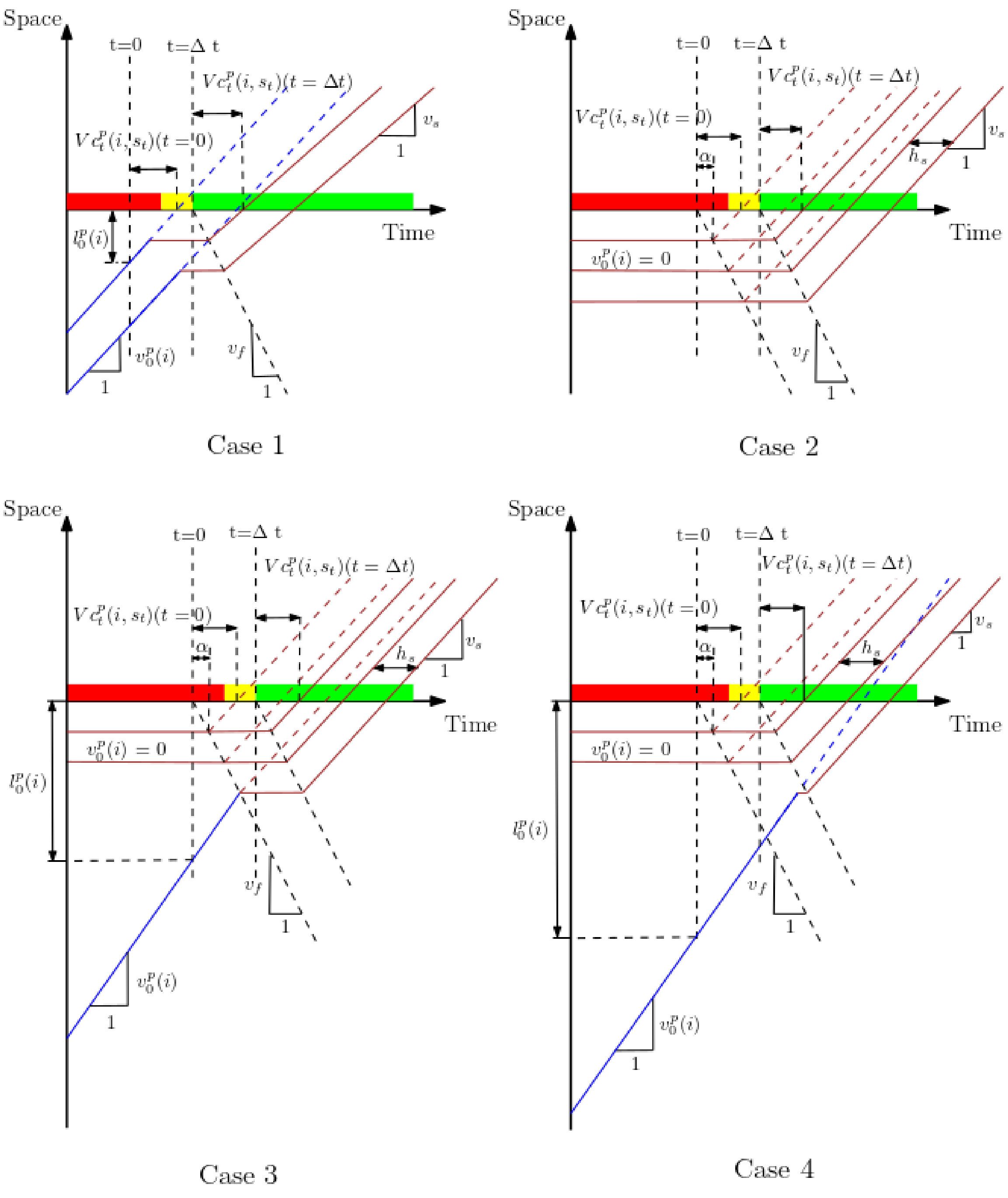

Figure 4. 7 Update for different cases of fleet trajectory representations assuming red light for next step

Figure 4.7 updates the different cases of vehicle trajectories in Figure 4.4 assuming red light is given by the junction controller. The meanings of each parameter and general principles of cases have been explained in Figure 4.4. The main difference in Figure 4.7 is that the junction controller assigns a Δt period red light after the initial time step. The blue and brown dashed lines in four cases represent the original vehicle position changed by time step. The blue and brown full lines are updated vehicle trajectories, considering that the expected discharging vehicles during Δt period are obstructed by red lights.

In case 1 in Figure 4.7, the key point is to judge whether vehicle fleets with free speed trajectories in green light given situations switch to queuing mode or not. The initial departure time for the first vehicle in fleet $Vc_t^p(1, s_t)$ minus time step spent 1 is compared with the departure time of queuing vehicle involving start-up time loss α. The maximum value is adopted as an updated departure time for the first vehicle because once the red light is given, it will last for at least an intergreen duration. The departure times and statuses of the following vehicles are successively decided by taking maximum value. The situation in case 2 stay unchanged as the queues have formed. The red light postpones the departure time of all vehicles as seen in case 2 in Figure 4.4. The situation of case 3 is extremely similar to case 2 in Figure 4.7, as the statuses of approaching vehicles to the end of the queue are judged to be queued before the front vehicles' departure. In case 4, the departure times of those vehicles with free flow speed are compared again with their queuing departure time after Δt time left is given a red light.

$$If m_t^p = 0:$$

$$Vc_t^p(1, s_t) = \begin{cases} max\left[Vc_{t-1}^p(1, s_{t-1}) - 1, \alpha\ + h_s\right], if\ Sc_{t-1}^p(1, s_{t-1}) = 1 \\ Vc_{t-1}^p(1, s_{t-1}), \qquad if\ Sc_{t-1}^p(1, s_{t-1}) = 0 \end{cases} \forall p \in P, \forall t \in T \tag{4-18}$$

$$Vc_t^p(i, s_t) = \begin{cases} max\left[Vc_{t-1}^p(i, s_{t-1}) - 1,\ Vc_{t-1}^p(i\ - 1, s_{t-1})\ + h_s\right], if\ \ Sc_{t-1}^p(i, s_{t-1}) = 1 \\ Vc_{t-1}^p(i, s_{t-1}), \qquad if\ Sc_{t-1}^p(i, s_{t-1}) = 0 \end{cases} i \geq 2, \forall p\ \in P, \forall t\ \in T \tag{4-19}$$

Equations (4-18) and (4-19) update of vehicle predictive departure times for the first index and others consider different criteria in Figure 4.7. The departure time of those vehicles recognized as queuing or slowing-down vehicles remains unchanged until the green traffic light is given in the following steps. The thresholds of different vehicles' travelling statuses are set for vehicles in each lane to judge the vehicle status in this step. If vehicles are determined to be discharged following the saturated flow, the vehicle departure time and travelling status will be adjusted accordingly. Otherwise, the vehicle still travels towards the end of the vehicle queue at free travelling speeds.

$$Sc_t^p(i, s_t) = \begin{cases} 0,\ \ if\ \ Vc_t^p(i, s_t) =\ \ \mathrm{Vc}_{t-1}^p(i\ - 1, \mathrm{s}_{t-1})\ + h_s \\ 1,\ \ \ if\ Vc_t^p(i, s_t) \neq\ \ \mathrm{Vc}_{t-1}^p(i\ - 1, \mathrm{s}_{t-1})\ + h_s \end{cases} \quad i \geq 2, \forall p\ \in P, \forall t\ \in T \tag{4-20}$$

$$Sc_t^p(1, s_t) = \begin{cases} 0, & if \ Vc_t^p(1, s_t) = \alpha + h_s \\ 1, & if \ Vc_t^p(1, s_t) \neq \alpha + h_s \end{cases} \quad \forall p \in P, \forall t \in T \tag{4-21}$$

$$a(i, t, p, s_t) = a(i, t-1, p, s_{t-1}) \quad i = 1, 2, \dots, i_p, \forall p \in P, \forall t \in T \tag{4-22}$$

The adjustments for vehicle travelling status are represented in Equations (4-20) and (4-21). As red traffic lights cause obstacles for all of the vehicles in the lane, the number of vehicles and their respective occupancy levels keep the same value during the planning step, which is shown in Equation (4-22). These traffic parameters are then updated and passed to the upper layer to calculate the performance measure for the next step.

4.3.6 Backward recursion algorithm at lower layer

The upper layer and middle layer execute the DP algorithm to the final step and find the optimal solution with the highest person-based objective function in PerSiCon-Junction. In the lower layer, a backward recursion is applied to retrieve the optimal policy for the whole planning duration starting from the final step and operating backwards. After all optimal decisions reacting to every state made in all steps are calculated, the optimal decision of each step can be retrieved by backward recursion described in Algorithm 3 as follows:

Algorithm 3 Backward recursion algorithm in the lower layer of PerSiCon-Junction when $t = T'$

Input: Signal timing state $s_{T'}^*$ at final time step T' with maximum accumulated function value $f(T', s_{T'})$; dictionary with sub optimal solution path O^* from Algorithm 1.

Output: Optimal signal timing plan list Sig^* reaching to signal timing state $s_{T'}^*$

optimal signal timing plan list $Sig^* \leftarrow [\,]$, insert $s_{T'}^*$ into Sig^*, $t \leftarrow T'$

while $t \geq 2$ **do**:

  retrieve s_{t-1}^* from $O^*[t, s_t^*]$

  insert s_{t-1}^* as first element in Sig^*

  $t \leftarrow t - 1$

The optimal plan with a series of junction controller decision choices in every step is recorded after the backward algorithm. A rolling-horizon approach is applied for PerSiCon-Junction where the problem is solved again when one stage (barrier group) is executed to include more recent vehicle data from CVs. The proposed approach collects data at a certain time step, predicts traffic state for a certain planning duration constituted by a number of time steps, and finds optimal signal timing parameters with the highest objective function values, implementing it in the isolated junction over the prediction period. At the end of implementation, the data collection system and three-layered optimization algorithm will be triggered again to repeat the commands.

4.4 Detail description of signal control algorithm PerSiCon-Bus

This subsection describes PerSiCon-Bus modified from PerSiCon-Junction which is adopted in vehicle states of all passenger cars. Two vehicle modes (cars and buses) are considered in this chapter. The buses are assumed to be travelled on the mixed lanes with cars. Notably, the proposed algorithm can be extended to incorporate other vehicle modes. However, this person-based approach focuses on buses due to their unique occupancy number against passenger cars. To simplify the proposed algorithm, the bus stops and vehicle lane-changing behaviours are not considered in this research.

As the optimization process of PerSiCon-Junction introduced in Section 4.3 estimates and updates each vehicle departure time for every time step, the framework of PerSiCon-Bus can also be achieved by using Figure 4.3 and Algorithms 1-3. Buses are considered a kind of special vehicle mode over passenger vehicles, with unique mechanics for determining occupancy, saturated flow, queuing discharging speed and headway. The development of PerSiCon-Bus is proper and important because there are minor changes to the optimization algorithm and the statuses and departure times of buses can be estimated under different signal plans for person delay reduction, resulting in the enhancement of proposed person-based control adaptability in variety mixture vehicle situations. In this way, the algorithm and framework of PerSiCon-Bus are almost the same as PerSiCon-Junction described in Section 4.3. However, the parameters of buses are different from passenger cars, which needs to be treated differently in some equations. In this section, parts of the equations are clarified more specifically to update the theoretical method and other equations which are not mentioned keep unchanged. The rest sets, variables and parameters for PerSiCon-Bus are also supplied in Table 4.1.

The objective of PerSiCon-Bus is to minimise the total passenger delay of cars and buses which can be detected by CV technology around the junction. The passenger delay is calculated by the product of vehicle delay and the number of people in cars and buses separately. The occupancy level factor is incorporated into the objective function to assign fairly priorities to different occupancy vehicles. The person-based objective function is formulated in Equation (4-23). More specifically, the occupancy level of cars and buses are expressed respectively in Equation (4-24). Therefore, Equation (4-2) in PerSiCon-Junction is modified to Equations (4-23) and (4-24) in PerSiCon-Bus.

$$max \sum_{p=1}^{P'} \sum_{i=1}^{i_p} A(i,p)[T' + 1 - Tc(i,p) + \delta T_{ACC}(i,p)] \tag{4-23}$$

$$A(i,p) = \begin{cases} A_c(i,p), if\ vehicle\ i \in phase\ p\ is\ a\ car \\ A_b(i,p), if\ vehicle\ i \in phase\ p\ is\ a\ bus \end{cases} i = 1,2,\dots,i_p, \forall p \in P \tag{4-24}$$

Constraints (4-25) and (4-26) replace the original Constraint (4-3) in PerSiCon-Junction to limit the value range of occupancy level parameter in each car or bus because passenger cars and buses have different occupancy capacities A_C and A_B.

$$0 \leq A_c(i,p) \leq A_C \; i = 1,2, \dots, i_p, \forall p \in P \tag{4-25}$$

$$0 \leq A_b(i,p) \leq A_B \; i = 1,2, \dots, i_p, \forall p \in P \tag{4-26}$$

In PerSiCon-Junction, the initial departure time estimation of vehicles in a lane in Equations (3-10) and (3-11) relies on saturated flow headway h_s between two vehicles, which is a constant when both vehicles are passenger vehicles. However, the saturated flow headway of buses is different because buses have different acceleration rates, vehicle lengths and saturated flow speeds than passenger cars. Therefore, Equations (4-27) and (4-27) are inserted behind Equations (4-10) and (4-11) in PerSiCon-Bus to consider the different cases of saturated flows headway h_s and speed of vehicles discharging from queue v_s.

$$h_s = \begin{cases} 3600/S_c \,, if vehicle i - 1 (i \geq 2) \vee vehicle 1 is a car \\ 3600/S_B \,, if vehicle i - 1 (i \geq 2) \vee vehicle 1 is a bus \end{cases} \forall p \in P \tag{4-27}$$

$$v_s = \begin{cases} v_{car}, if vehicle i is a car \\ v_{bus}, if vehicle i is a bus \end{cases} i = 1,2, \dots, i_p, \forall p \in P \tag{4-28}$$

Equation (4-27) represents that buses and cars have different saturated flows and the headways between two vehicles are decided by the saturation flow of the front vehicle. This simplification is justified by the calculation of headway only relying on the front vehicle, so does not significantly degrade the results (Yang et al, 2018). Equation (4-28) indicates that the speeds of cars and buses discharging from the queue, which are used for judging vehicle status, are also different.

In PerSiCon-Bus, the performance measure $c_t(s_t, d_t)$ of passenger benefits from the last step to the current step is also a function of state variables and control decisions. Therefore, the value $c_t(s_t, d_t)$ is calculated by Equations (4-14) and (4-29) with different car and bus occupancy levels. Equation (4-29) is inserted behind (4-14) as follows:

$$a(i,t,p,s_t) = \begin{cases} a_c(i,t,p,s_t), & if \;\; vehicle \; i \; is \; a \; car \\ a_b(i,t,p,s_t), & if \;\; vehicle \; i \; is \; a \; bus \end{cases} \quad i = 1,2, \dots, i_p, \forall p \; \in P \tag{4-29}$$

4.5 Detail description of signal control algorithm PerSiCon-Network

4.5.1 The coordinated control in traditional and state-of-the-art urban signal controls

The person-based signal control designed for multiple junctions is more meaningful than isolated junctions as vehicle travel is defined as movement from origin to a destination within a certain range over one junction. The vehicle leaving information from one junction can inform another junction in advance through connected vehicle technology to achieve junction coordination. Signal control coordination can provide efficient movements for vehicle platoons passing through proximal junctions. Vehicles leaving out of the current junction will appear in approaching lanes of one of its neighbours, all of whose trajectories and passenger delays are possible to be planned by coordinated signal controls. However, it is noted that not all of the signal controls are worthy of coordination. The distance between two proximal junctions should be close enough and traffic flow demands coming from upstream are not random and substantial. The Federal Highway Administration reported that junction coordination could be considered when the distance between two proximal junctions is less than 0.75 miles (Henry, 2005).

The existing coordinated urban signal controls and state-of-the-art CV adaptive vehicle-based signal control reviewed in Chapter 2, which has shown that a lot of researches have been done to develop coordinated signal control in urban road networks. The relevant coordinated signal control systems are classified into three categories based on their objective optimization architectures and optimal solution levels: central, hierarchal, and decentralized signal control approaches.

4.5.1.1 Central coordinated signal control approach

The majority of signal timing approaches applied in multiple junctions adopt central junction coordination. The vehicle state and optimization objective in central approaches are formulated into a global-level mathematical program. All of the signal timing parameters, such as cycle length, phase duration and offset are determined through central optimization algorithms. SCOOT is an example of central coordination approach operated in a few proximal junctions. The central computer program in SCOOT calculated the optimal solutions for fixed cycle, offsets and green durations in order to reduce the total vehicle delays and stops on the basis of value prediction by implementing different signal timing parameters. However, notably that signal control coordination is a Non-deterministic Polynomial (NP) problem (Hajbabaie, 2012) and it is challenging to find globally optimal solutions for junction control objectives when the scales of road networks expand. Those central approaches are not scalable to be implemented in multiple junctions if network scales increase.

4.5.1.2 Hierarchal coordinated signal control approach

Hierarchal approaches decompose the signal control optimization problem in multiple junctions into several levels and try to solve the different objectives in separate levels. The core principle of most hierarchal approaches is to make slow-varying and wide-area-level decisions in the upper network layer and execute the junction area and real-time optimization in the lower level. The sub-optimal problems at the junction level are interconnected through a central control unit. SCATS (Lowrie, 1990) is such a hierarchal approach adopting two-level signal control composition. The strategic control is carried out by a regional computer to determine the signal timing parameters and offsets according to average prevailing traffic conditions. The local controllers at the tactical level can adjust the green time of one junction, making it flexible to correspond to the fluctuating real-time flow demand. Other cases of hierarchal approaches, such as OPAC, UTOPIA, and RHODES, have been detailed in Chapter 2. The hierarchal approaches are able to find the optimal solution more efficient than central approaches in the amount of time. However, the connections among central control units and sub-optimal computers in hierarchal approaches require a considerable cost on infrastructures. Moreover, the central objective controls in the upper level are slow-varying processes, difficult to be accomplished in real-time and compete with distinct objectives in the junction control level.

4.5.1.3 Decentralized signal control approach

The decentralized approaches decompose the planning network into varying regions, involving a single junction in each of them. The connected controller infrastructures gather vehicular information surrounding the local target junction and optimize vehicle objectives to calculate sub-optimal solutions. This sort of approach can be extended on large network scales and operate in a real-time environment. More recently, adaptive vehicle-based CV adaptive signal controls have developed in multiple junctions. An adaptive signal control algorithm aiming at minimising total queue length at each junction was proposed by Priemer and Friedrich (2009), separating road network areas with a number of junctions into individual junctions. While there is no coordinated information exchange among the junctions thus the signal control is not coordinated. Similarly, the predictive microscopic simulation algorithm (PMSA) proposed by Goodall et al. (2013) also lacks considering coordination among adjacent junctions. A cumulative Travel-Time Responsive (CTR) junction control algorithm was proposed by Lee et al. (2013) to ensure the smooth trajectory of vehicle platoons on major streets with the introduction of weighting factors. However, not test the performance of the approach. More recently, a novel DC technical signal timing optimization is presented to decide the green time termination or continuation at junction level, also make them be coordinated by informing information from adjacent junctions to make them towards global optimality. Compared to the above two sorts of approaches, the decentralized approaches are more convenient to be applied in larger network case studies as they consider less about the coordination among proximal junctions. The challenge of decentralized approaches is that their signal timing policies are more inclined to explore local solutions and sub-optimal solutions rather than global objectives.

4.5.1.4 Coordination paradigm consideration for this research

The central approaches and hierarchal approaches are not scalable as the extension of road network scales and are difficult to be real-time. In terms of the proposed person-based signal control approach, it adopts flexible stage sequences and phase combinations to explore a better way of optimizing person-based measures. The central approaches and hierarchal approaches are not suitable in this case as greater computational complexity caused by flexible signal timing options makes it challenging to calculate global optimal solutions. The decentralized approaches will be considered to be more appropriate to implement person-based adaptive CV signal control in urban large scales with a varying number of junctions. However, the developed DC signal timing optimization inspires that the approaching vehicle number and flow information from neighbouring junctions may be useful for individual junctions, to make them coordinated towards global optimality.

This project will develop decentralized coordinated person-based CV adaptive signal controls, making use of arrival and leaving vehicle information from proximally connected junctions. The inadequately connected vehicle detection region of isolated junction controllers can be complemented by infrastructures of neighbouring junctions. The vehicles leaving out of current junctions will also be captured by a signal controller to predict the travel time it will approach the departure lane of the proximal junction and inform through wireless communication. In this way, the proximal junctions will be coordinated to reduce person delay and improve passenger travelling experience. The holding back problem (Doan and Ukkusuri, 2012) probably occurs in multiple junctions where overhanging queues accumulated in departure lanes obstruct subsequent vehicles from joining into the end of the queues. To avoid this phenomenon, the maximum number of queuing vehicles one lane can have will be modelled in the following constraints. Once the vehicles have reached the limit value, the green duration for this phase will be provided regardless of the person's delays in other lanes.

A Coordinated Person-based signal Control algorithm (PerSiCon-Network) to extend PerSiCon-Junction from isolated junction to multiple junctions. With the implementation of the proposed algorithm, every junction controller updates the vehicle occupancy list and departure predictive list by making use of information received from adjacent junctions. To evaluate its influence, the coordinated signal control algorithm will be tested under varieties of scenarios with different CV penetration rates, traffic flow demands and prediction horizons. The indicator results will be compared to those in benchmarking models including fixed-time coordinated control and vehicle-based control in multiple junctions to analyse the performance of the proposed algorithm.

4.5.2 Approach proposed for PerSiCon-Network

PerSiCon-Network assumes that the local controller at every junction operates PerSiCon-Junction described in Chapter 3 based on CVs data within its wireless communication range to optimize person-based signal plans. The proposed algorithm figures out signal timing plans for a given horizon period and will be triggered to carry out for the next period when the scheme has been completely executed. The general procedure of it can be summarized in five steps below:

Step 1: Collecting information from every CV near junction A and arranging them according to their approaching lanes, the location list $S(A) = [S_1, S_2, \dots, S_n]$, instantaneous speed list $V(A) = [V_1, V_2, \dots, V_n]$ and occupancy level lists $O(A) = O_1, O_2, \dots, O_n]$ at every lane are generated assuming there are n vehicles detected. The elements in those lists are sorted by their distances to the cross line from nearest one to furthest within detection range.

Step 2: Given the position list and speed list of each lane, the initial departure time list for vehicles $T(A) = [T_1, T_2, \dots, T_n]$ can be predicted at the start of optimization supposing that the next step for this lane will be constantly activated with green lights.

Step 3: The upper layer of the three-layer DP optimization algorithm captures a sub-optimal function value for a special traffic situation by the proposed DP framework and removes any other strategies to avoid recalculation from the initial step.

Step 4: In order to calculate performance measures, the middle layer of three-layer DP optimization algorithm updates the vehicle departure time list in every step, which also explores all kinds of possible signal plans based on a flexible traffic light state machine.

Step 5: At the lower layer, the algorithm finds the optimal person-based performance measure at the end of the planning horizon and uses a backward recursion DP to search for a signal timing plan resulting in this value function.

According to Section 4.5.1, the central architecture and hierarchical structure make junction controllers more complex or less flexible to implement real-time signal control under CV environments. Therefore, the decentralized structure is chosen as a general coordination framework in this paper to enable local controllers to operate their adaptive signal control algorithms. Compared to signal controls in multiple junctions without coordination, it receives more comprehensive real-time vehicular data to realize surrounding environments. Meanwhile, as shown in Step 1 and 2 in Section 4.3, the objective benefits of PerSiCon-Junction in the previous study is calculated based on vehicle arrival prediction and explicit occupancy level as data inputs. To make less interruption to local algorithm operation and provide more CV data to adjacent junctions to promote decision, PerSiCon-Network is adopted by combing decentralized structure and vehicle trajectories estimation approach from upstream. The occupancy level and trajectory information of undetected vehicles will be processed as inputs of the trajectories estimation approach to predict their arrival time for local controllers. Another reason for proposing PerSiCon-Network is that it can predict queue lengths of connected lanes at any optimizing time steps to prevent the holding-back phenomenon of a high-demand vehicle platoon. The model formulation and operating algorithms of PerSiCon-Network are described in Section 4.5.3 and Section 4.5.4 respectively.

4.5.3 PerSiCon-Network model formulation

The distributions of local controllers and surrounding vehicles in multiple junctions are illustrated in Figure 4.8. It can be seen that the communication range R of junction A cannot completely cover the link road between junction A and B. However, those undetected vehicles on the link road, especially for vehicle platoon with high occupancy levels, have chances to cross junction A if the adequate green time is given under person-based delay reduction strategy to save travel time for more passengers. While junction B is capable of learning data of these vehicles and delivering them to junction A with the assumption of no transmission packet loss and communication delay. In order to provide a comprehensive vehicular environment for the person-based algorithm and reduce interference to local signal decisions, the coordinated model formulation will make changes to Steps 1 and 2 of PerSiCon-Junction to update vehicle location, speed, occupancy level and initial prediction time list.

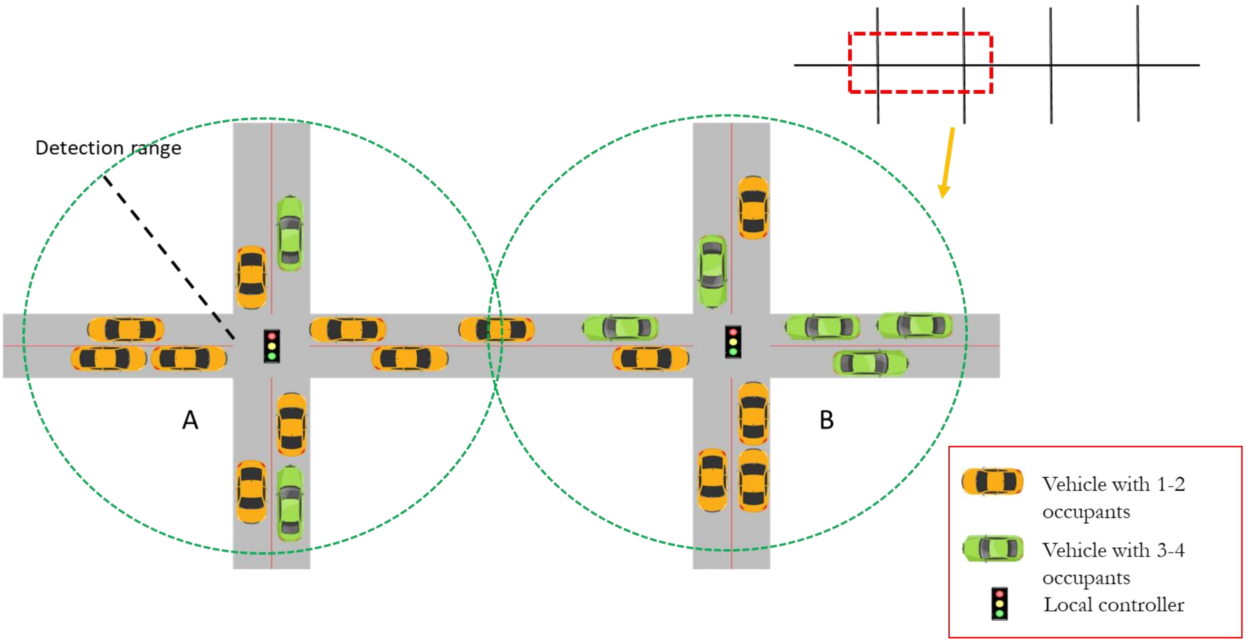

Figure 4. 8 Diagram illustrating coordinated control and vehicle distributions at multiple junctions

As is seen in Figure 4.8, junction A can detect n vehicles and additionally m vehicles have the potentials to cross the junction during planning horizon. $D(A,B)$ represents the distance between two junctions and Q_{n+i} is the distance from the cross line of junction B to $(n+i)$th undetected vehicle. For distance from the cross line of junction A to $(n+i)$th undetected vehicle S_{n+i} on link road, there is:

$$S_{n+i} = D(A,B) - Q_{n+i}, \quad 1 \le i \le m \tag{4-30}$$

Otherwise if undetected vehicle S_{n+i} is not on link road, it should satisfies:

$$S_{n+i} = D(A,B) + Q_{n+i}, \quad 1 \le i \le m \tag{4-31}$$

The distance between two junctions $D(A,B)$ is a constant value. Figure 4.9 illustrates four cases of relationships between junction distance and communication range, which are:

a. The distance of junction $D(A,B)$ is no higher than the communication range R.

b. The distance of junction $D(A,B)$ is higher than the communication range R but no higher than $2R$.

c. The distance of junction $D(A,B)$ is higher than the double communication range $2R$ but no higher than the coordination distance recommendation value 0.75 miles.

d. The distance of junction $D(A,B)$ is higher than 0.75 miles.

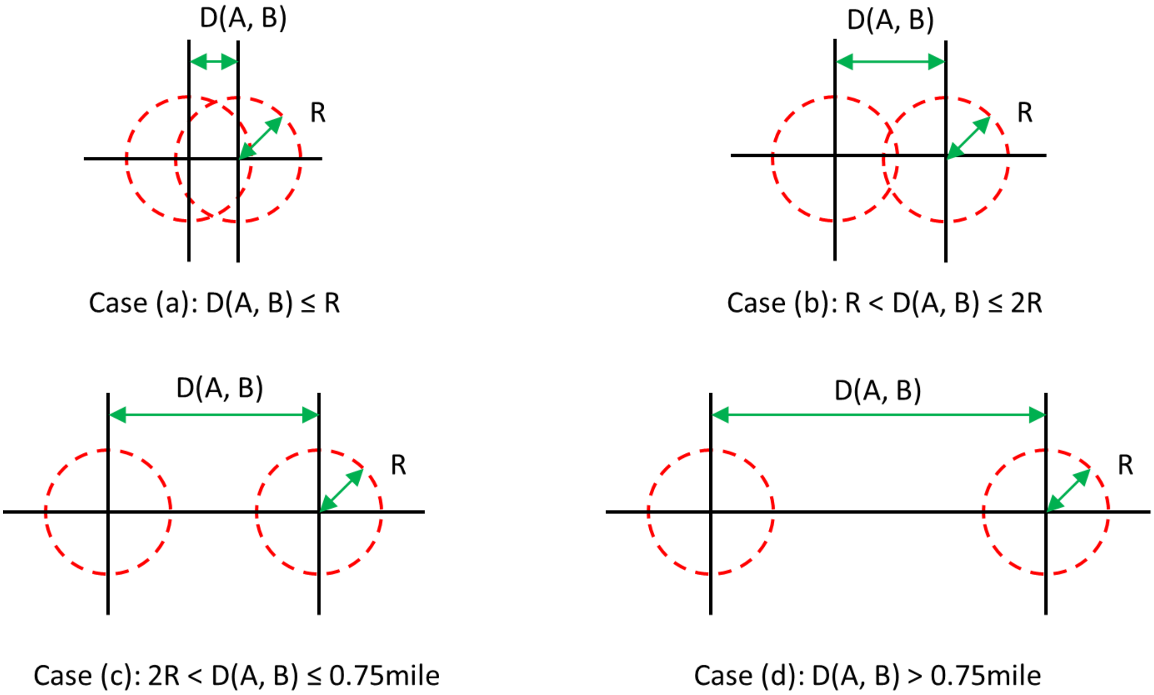

Figure 4. 9 Four cases of relationships of distance between two junctions $D(A, B)$ and communication range R

In different cases, the distance from the cross line of junction B to $(n + i)$th undetected vehicle Q_{n+i} is determined in different ways. When implementing PerSiCon-Network in a new location, the distance between two junctions $D(A, B)$ needs to be measured first and the flowchart in Figure 4.10 is used to judge how to acquire the value Q_{n+i} to calculate S_{n+i} using Equations (4-30) and (4-31).

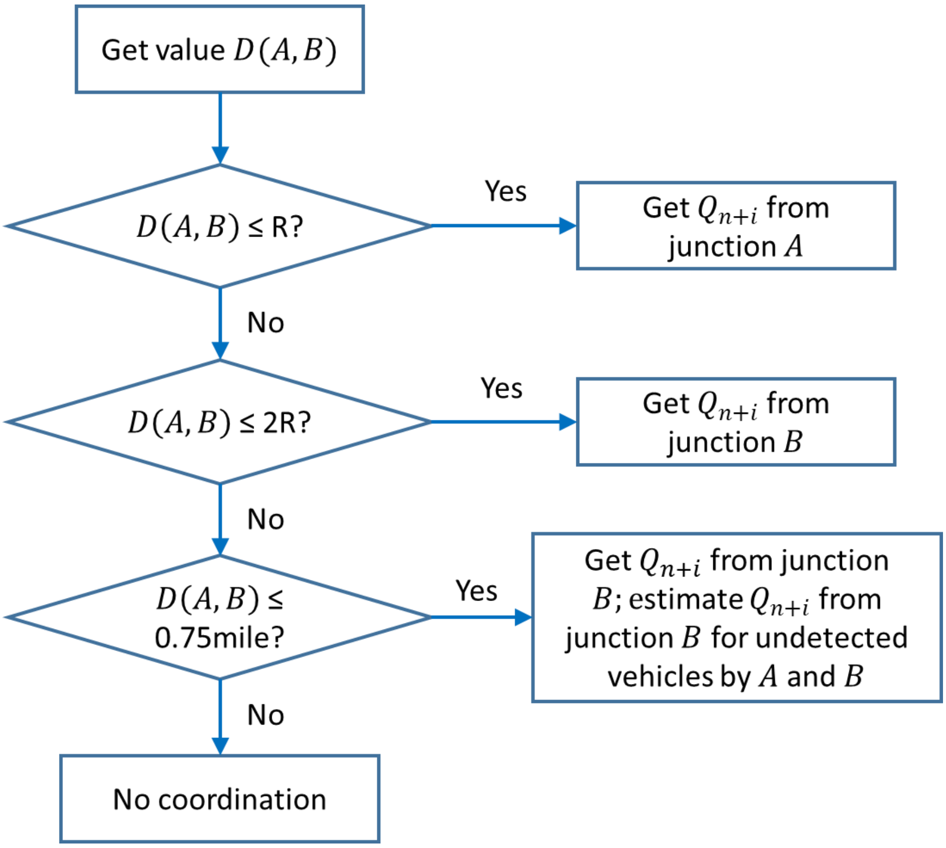

Figure 4. 10 Flowchart of determining Q_{n+i} in different relationships of $D(A, B)$ and R

The vehicle location can be directly determined by junction A if $D(A, B)$ satisfies the criteria in case a, or calculated by junction B in case b. If $D(A, B)$ satisfies the criteria in case c, junction B need to detect the vehicle travelling from B to A with several time steps before the optimization. The value of the time step from detection to optimization equals to gap distance $D(A, B) - 2R$ divided by free-flow travelling speed V_d. Then those vehicles in the gap between two communication ranges can be estimated by the distances between them at the detection time step. If $D(A, B)$ exceeds than coordination recommendation distance value, there would be no coordination for the link. In such a way, vehicle location, speed, and occupancy level list can be updated as $S(A) = [S_1, S_2, \dots, S_n, S_{n+1}, \dots\ S_{n+m}]$, $V(A) = [V_1, V_2, \dots, V_n, V_{n+1}, \dots\ V_{n+m}]$, $O(A) = O_1, O_2, \dots, O_n O_{n+1}, \dots\ O_{n+m}]$ separately.

If vehicle queue forms at the approaching lane in junction B (such as situation (a) in Figure 4.11) due to red light, the undetected vehicle will first try to discharge from junction B with time $T(l)$ on the green. It then experiences an acceleration process, from the initial discharging velocity at saturated flow V_0 to free-flow travelling velocity V_d, with constant acceleration a. The time needed for the acceleration process t_a satisfies:

$$t_a = \frac{V_d - V_0}{a} \tag{4-32}$$

The distance vehicle travelled throughout the acceleration process D_a can be calculated as follows:

$$D_a = \frac{{V_d}^2 - {V_0}^2}{2a} \tag{4-33}$$

The vehicle will then approach with constant speed V_d to cross junction A on the green, or stop at the end of queue formed on the link road to wait for discharge. Therefore, the initial predictive time of $(n+i)$th vehicle T_{n+i} takes the maximum value of two cases, which is calculated as:

$$T_{n+i} = \max(T_{n+i-1} + h_s, T(l) + D_a + \frac{D(A,B) - D_a}{V_d}), \quad 1 \le i \le m \tag{4-34}$$

Where T_{n+i-1} is the predictive discharging time of the previous vehicle and h_s is saturated headway of discharging queue. In case (b) of Figure 4.11, the $(n+i)$th vehicle crosses junction B with free-flow travelling velocity V_d. It will also keep this status to cross junction A unless existing vehicle queue on link road blocks its trajectory. To judge this, the predictive time of the vehicle T_{n+i} can be calculated as follows:

$$T_{n+i} = \max(T_{n+i-1} + h_s, \frac{S_{n+i}}{V_d}), \quad 1 \le i \le m \tag{4-35}$$

To ensure that the $(n+i)$th vehicle of both two cases in Figure 4.11 are possible to be discharged within planning horizon T, the time predictions under free-flow travelling status are constrained as:

$$0 < \frac{S_{n+i}}{V_d} < T(l) + D_a + \frac{D(A,B) - D_a}{V_d} \le T, \quad 1 \le i \le m \tag{4-36}$$

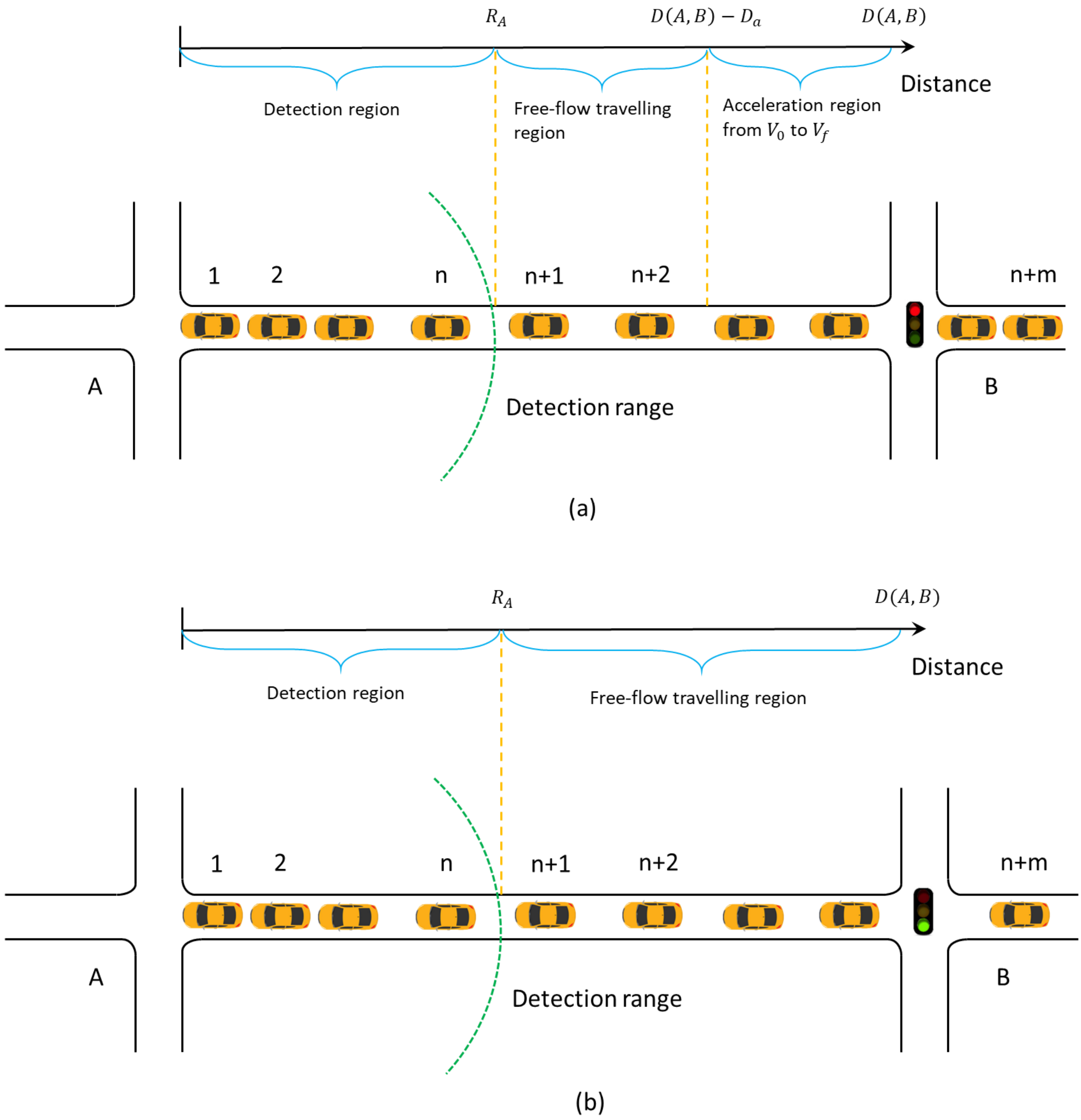

Figure 4. 11 Vehicle situations on link road between junction A and B in case (a) red light and case (b) green light at junction B

To avoid the potential flow holding back problems (Doan and Ukkusuri 2012) in coordinated junctions, the maximum queue length is defined as Q_{max} on the link road that at any time step t in the planning horizon T, queue length $Q(t)$ cannot exceed the maximum queue length Q_{max}. The constraint is presented as follows:

$$Q(t) < Q_{max}, \qquad 0 \leq t \leq T \tag{4-37}$$

The queue length $Q(t)$ at time step t is determined by:

$$Q(t) = \begin{cases} Q_0, & t = 0 \\ Q(t-1) + f(t) - g(t), & 0 < t \leq T \end{cases} \tag{4-38}$$

Where Q_0 is the initial queue length at time step 0 by counting the number of vehicles with stopped status on link road. $f(t)$ and $g(t)$ refer to vehicle arrival rate and the discharging rate at time step t. Suppose that queue length equals to $i-1$, and the arrival rate is judged by whether ith vehicle will be stopped at the end of the queue or not, which is presented as:

$$f(t) = \begin{cases} 1, & T_i = T_{i-1} + h_s \\ 0, & T_i > T_{i-1} + h_s \end{cases} \tag{4-39}$$

As for discharging rate $g(t)$ at time step t, its value determines on the basis of the predictive time of the first vehicle T_1 and signal plans $Sig(t)$ at junction A. The criterion is presented as follows:

$$g(t) = \begin{cases} 1, & if\ 0 < T_1 \leq 1 \text{ and } Sig(t) = \text{green} \\ 0, & other\ cases \end{cases} \tag{4-40}$$

4.5.4 Description of coordinated control algorithm

By incorporating the formulated model above at a coordinated level, PerSiCon-Junction aims to have enhanced performance in multiple junctions. As part of the coordinated person-based control algorithm, Algorithm 4, the coordinated data supplement algorithm, was developed to supply extra data sources to the local controller with received information from the adjacent junction. The essential location list, velocity list, occupancy level list and time prediction list are firstly created by following steps 1 and 2 in PerSiCon-Junction. The locations of those undetected vehicles are calculated and appended to the location list, combined with information from junction B and Equations (4-30) and (4-31). After updating the velocity list and occupancy level list, the initial prediction times of undetected vehicles are calculated using Equations (4-32) – (4-36) and appended to the prediction time list. The new lists will replace the original ones as data inputs for the local controller to implement the person-based optimization algorithm (Algorithm 5).

Algorithm 4 Coordinated data supplement algorithm

Data collection and processing procedure (ID, location, speed, occupancy, lane ID of CVs):
For each approaching lane i of junction A:
Generate location list $S(i, A)$ based on lane ID
Generate velocity list $V(i, A)$, occupancy level list $O(i, A)$ according to sequence of CV's ID in location list
Generate initial time prediction list $T(i, A)$ based on $S(i, A)$ and $V(i, A)$
If lane i is road link between junction A and B:
Generate location list $T(i, B)$, velocity list $V(i, B)$, occupancy level list $O(i, B)$
Update $S(i, A)$, $V(i, A)$, $O(i, A)$ based on Equation (4-30)
For each approaching lane of junction B except link road:
Update $S(i, A)$, $V(i, A)$, $O(i, A)$ based on Equation (4-31)
Update $T(i, A)$ based on $S(i, A)$, $V(i, A)$ and Equation (4-32) - (4-35)
Remove the following elements in $T(i, A)$ if their values exceed planning horizon T based on equation (4-36)
Remove relative elements in $S(i, A)$, $V(i, A)$, $O(i, A)$
Else:
Pass
End procedure

Algorithm 5 operates the three-layer DP optimization algorithm developed in PerSiCon-Junction by incorporating dynamic queue length check and flow holding back prevention procedure. The algorithm keeps calculating queue length on the link road at any time step after assigning the signal plan for the current step. If queue length exceeds the maximum value, the weight of discharging vehicles on this lane dramatically increases and the signal controller will intend to switch the traffic light to green. Once the time step reaches to planning horizon, Algorithm 5 will search out a strategy achieving minimum objective value and retrieve it ready for implementation. The pseudocode of Algorithm 5 is presented below.

Algorithm 5 Coordinated control optimization algorithm

Coordinated person-based control optimization procedure:
Generate $S(i, A)$, $V(i, A)$, $O(i, A)$, $T(i, A)$ for approaching lane i of junction A based on algorithm 1, get current phase P_0 at time step 0
For time step t from 1 to T:
Create possible signal plan set in next step based on signal adjacent list and P_{t-1}
For each in signal plan set:
Calculate queue length based on Equation (4-38), (4-39) and (4-40)
If queue length reaches to maximum constraint based on Equation (4-37)
Switch green light to light
Else:
Pass
Calculate sub-optimal performance value to minimum person delay based on $T(i, A)$ from PerSiCon-Junction
Update time predictive list $T(i, A)$ and $O(i, A)$
Record signal plan path to sub-optimal value
Find out optimal performance value from all possible strategies at time T
Retrieve signal plans reaching to optimal performance value

16: End procedure

4.6 Summary

This chapter clarifies the detailed methodology for developing a person-based signal control approach PerSiCon-Junction in an urban isolated junction transferring from the vehicle-based approach. In order to solve those challenges and implement the person-based approach in CV environments, PerSiCon-Junction with a three-level signal optimization algorithm is introduced with the realization of its conceptual framework. The details of PerSiCon-Junction are also explained to understand how the proposed algorithm figures out the optimal signal timing plan to achieve person-based objectives with completely flexible signal plans and an update of vehicle departure time prediction. PerSiCon-Bus and PerSiCon-Network are then developed to incorporate person-based control with bus mode and extend to network scales.

Chapter 5 Experiments and evaluations of person-based controls in isolated junction and road networks

Chapter 4 provides the details of proposed algorithms to explore the new paradigm of adaptive signal control for person-based controls using CV data. To initially validate the performance of person-based controls, real-world case studies including isolated junction and road networks need to be constructed in microscopic simulation to test whether the person-based controls offer improved measures compared to benchmarking models. A case study located in Birmingham, UK is selected where the isolated junction and road networks can be reproduced in microsimulation and traffic flow demand data for this place can be acquired to imitate the traffic operation conditions for different periods. As bus routes exist in both isolated junction and road networks case study, PerSiCon-Bus and PerSiCon-Network are correspondingly evaluated in isolated junction and road networks in vehicular environments mixture by passenger cars and buses. This chapter describes the junction layouts, flow demands, signal phase settings and vehicle parameters of two case studies to implement the control algorithm in evaluation experiments. The results from simulation experiments in various scenarios are also presented to analyse the performance of PerSiCon-Bus and PerSiCon-Network in different cases compared to fixed-time control, actuated control and vehicle-based control in CV environments.

5.1 Assumptions and limitations

Chapter 3 discusses that the simulation tool is the most appropriate selection to evaluate the performance of urban signal controls. This research builds simulation environments with observed traffic flow demands and operates all of the signal controls in simulation to imitate their practical performance in the real-world case study. However, the simulation experiments cannot completely simulate and replace real-world operations. Some assumptions are made in this section to acknowledge the limitations of the evaluation framework as follows:

The number of passengers in passenger cars and buses is assumed to follow the Poisson distribution. The assumptions of passenger number distributions have been justified in Chapter 2 given the mean value of vehicle occupancy. The Poisson distribution probabilities are used in simulation to decide the number of passengers in each car and bus. The actual state may not be the same as this assumption, resulting in different vehicle occupancy rates and affecting the performance of person-based controls.

Vehicle generation distribution departed from the entrance of the simulation road network is assumed to be uniform. The O-D matrix determines the number of vehicles that enter the simulation road network in a certain period. From the perspective of simulation traffic flow generation, in each simulation time step, there is at most one vehicle entering the road network from one lane. Poisson distribution is not suitable to be adopted in this case as it is more used to estimate the number of vehicles in a certain time interval and two or more vehicles are possible to be generated in one second, which is conflicted with the traffic flow generation mechanism. Therefore, uniformed distribution is assumed to imitate the vehicle generation distribution and decide whether there is a departing vehicle in every time step.

Krauß car-following model adopted in experiments is assumed to represent the actual behaviours of vehicles on road. The actual states of vehicles may be different from the behaviours simulated in the car-following model. This results in inaccurate vehicle arrival prediction to degrade the performance of person-based control. The performance generated by simulation may also not reflect real-world conditions.

The rates of the bus in vehicle types are assumed to be the same at different times of day, which is equal to the statistics of bus rates in different vehicle types. In the real world, the rate of the bus would be higher during peak periods. This is because the bus operation frequency increases with higher traffic demand during peak periods. The different rates of the bus at different times of day may affect the performance of person-based control.

The vehicle flows and their routes from originations and destinations in the case study area are assumed to be consistent with the real states. Besides the planning networks, there are also some branches distributed around the main road and share a part of traffic demands. However, the traffic flow across these branches cannot be collected. The road network in simulation experiments is simplified and O-D matrixes are constructed to ensure that the traffic flows travelling through the detectors are consistent with the recorded data. In real states, the vehicle routes are more complicated than those in simulation experiments and traffic flows have various originations and destinations, which cannot reflect the real traffic dynamics. This is a limitation of the evaluation framework.

0.01m/s speed threshold is assumed to judge whether a vehicle is stopped or not. The reorganization of a stopped vehicle is an important component in person-based control algorithms and the number of stop measurements. A strict speed threshold value contributes to accurately detecting a vehicle stop event. In SUMO simulation the speed of all stopped vehicles is observed to be lower than 0.01m/s. Therefore, 0.01m/s is taken as a threshold. In practice, the speed of a vehicle can be measured by a speed odometer and data measurement errors need to be considered to take the speed threshold. The data measurement error may cause the speed of a stopped vehicle is illustrated to be higher than the strict threshold and detection fail. The speed threshold taken should relatively higher in practice to satisfy that the speed measurements of most of the stopped vehicles (e.g. 95% or 99% of the vehicles in experiments) are below this value.

5.2 Location of case study and junction layout

To validate the performance of the proposed person-based algorithm and other traffic signal controls, realistic real-world case study models need to be constructed. As discussed in Chapter 3, microsimulation is the most suitable way to model the signal control experiments in the current stage. To reproduce the traffic behaviours on road networks and urban junctions, both junction and road network geometry layouts and traffic flow recorded data surrounding the junctions are required. At the time stage of this research, Birmingham City Council provides great quantities of recorded traffic data in the areas of Birmingham and West Midlands, covering a large number of inductive loop stations and urban junctions (Birmingham City Council, 2019). The dataset can be accessed online to generate the traffic demands for the urban area to model the road networks. After comparison, a road network consisting of 5 signalized junctions in the Newtown area of Birmingham is selected as a realistic case study to validate the proposed method, which is shown in Figure 5.1.

Figure 5. 1 Map of the case study location in the Newtown area of Birmingham. The locations of inductive loops are marked with yellow probes. The lane approaches are represented by red lines

The case study is considered as the most appropriate place to evaluate the proposed PerSiCon-Network for the following reasons:

1. The area covers a long route corridor (around 2km) with 5 successive urban junctions and 36 inductive loops. The ratio of the number of loops and junctions is highest in this area. The high coverage of inductive loops ensures traffic flows in this area can be reproduced in simulation with adequate accuracy.

2. The distance between two junctions is suitable to adopt coordinated person-based control, neither too long nor too narrow.

3. The area contains large residential areas, and key educational and sports points such as Nishkam high school, JD Gyms Birmingham and the University of Law, Birmingham to produce and attract trips so that a great number of traffic flows can be observed.

4. The geometry layout of crossroad junctions is standard to implement signals, rather than providing roundabouts and dedicated left turn lane for vehicles before the approach to the junction area, with sufficient phases to make person-based control to be feasible to implement.

As different versions of person-based controls are proposed in Chapter 4, the selected case study area is used to construct isolated junction and road networks to evaluate the person-based controls. As buses exist in both isolated junction and road networks, PerSiCon-Bus and PerSiCon-Network are operated to test their performance in two cases respectively. The junction layouts of the two case studies are introduced below.

5.2.1 Isolated junction case study

The isolated junction case study is adopted to test the isolated junction version of person-based control PerSiCon-Bus. It is one of the junctions in the selected case study area. An isolated junction located at New John Street West & A34 junction in the Newtown area of Birmingham is modelled in the open-source microscopic simulation package SUMO. Figure 5.2 (a) illustrates the junction layouts and 8-options signal phase diagram. Figure 5.2 (b) presents the planned origin and destination zones of traffic flows travelling through this junction. The junction is selected for the isolated junction case study as the highest traffic volumes travel across this junction and the 8-options signal phase diagram is flexible to apply person-based control.

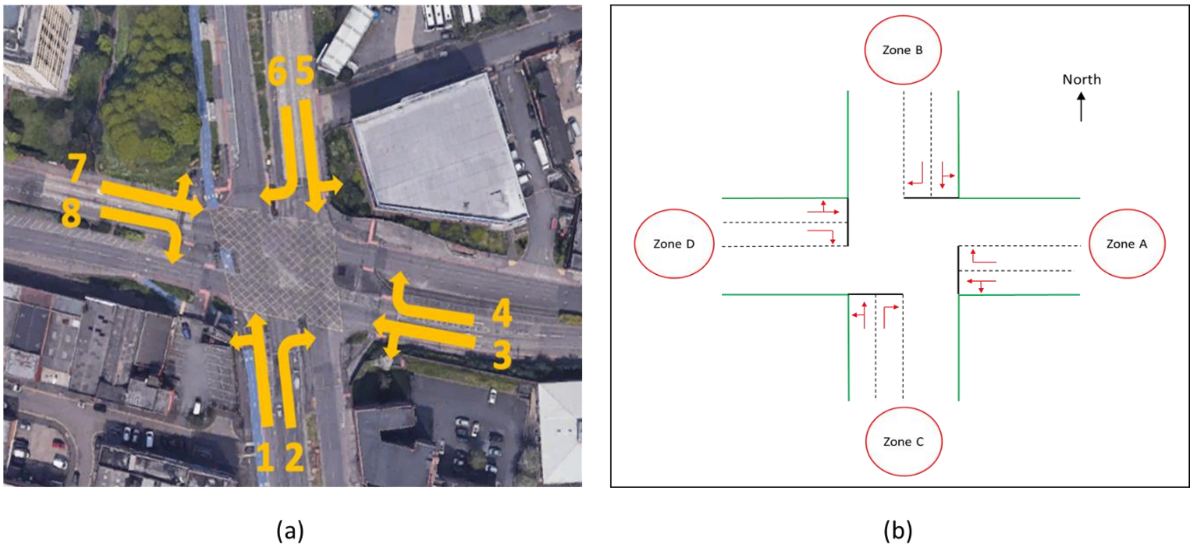

Figure 5. 2 (a) Geometry and signal phase diagram; (b) origin and destination zones of isolated junction at New John Street West & A34 junction

5.2.1 Road network case study

The modelled urban corridor consisting of 5 successive junctions is illustrated in Figure 5.3 with red lines where the surrounding inductive loops are distributed to collect traffic flow data. The interlocking part of roads B4100 and A4540 at the top left corner of the map is an overpass without a turning lane rather than a signalized junction. The geometry road map data for this area from Open Street Map (OSM) are used to reproduce the road network with 5 signalized junctions (represented by traffic light icons in Figure 5.3) in SUMO (OSM, 2019). Figure 5.3 illustrates the simulated road network.

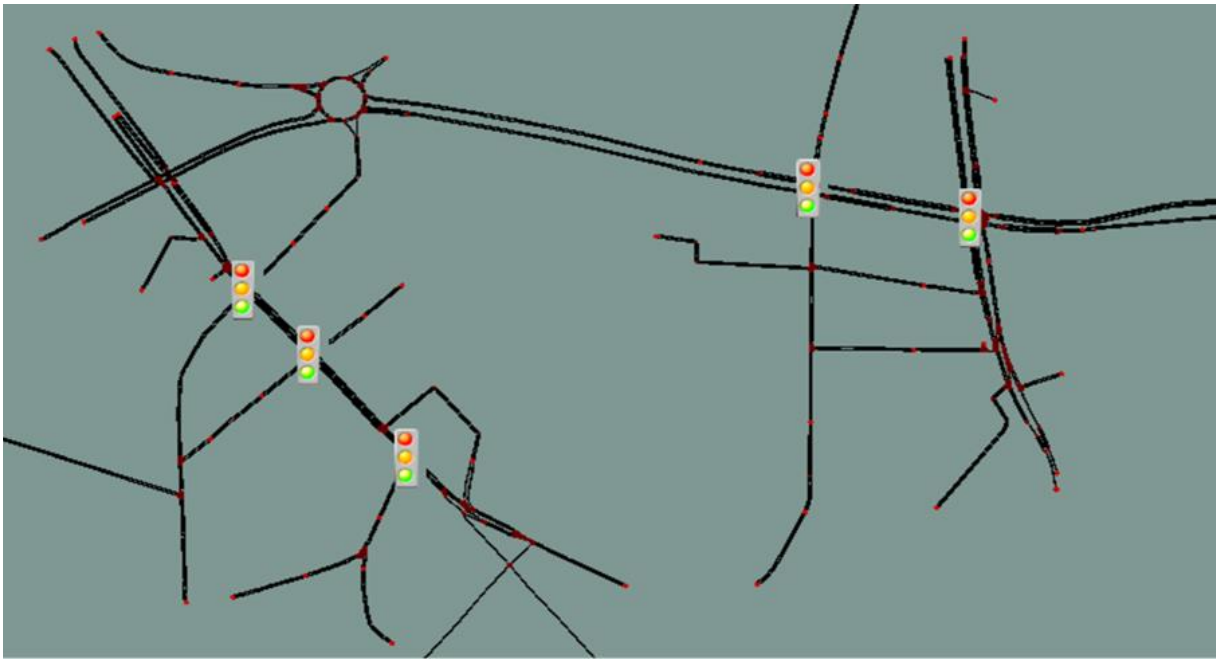

Figure 5. 3 Simulated road network in SUMO. The signalized junctions are marked with traffic light icons

5.3 Traffic flow data for case study

To generate the traffic flow demands for the modelling road network, two types of datasets are collected from the case study: manual traffic survey and recorded flow data from inductive loops. The manual traffic data are used to ensure that the dataset from the online database matches the data in the real site. The traffic demands from the online dataset are collected and processed to generate the traffic flows crossing the case study area. The procedures are described in this section.

5.3.1 Manual traffic survey

A manual traffic survey of the selected case study has been carried out over two days in October 2020. A manual traffic survey aims to observe the traffic data from real site locations of the case study to ensure that the traffic dataset used online is consistent with the actual state of vehicular situations. The contents of the manual traffic survey include:

1. 15 minutes of traffic flow counts for each approach at 5 junctions in the selected case study area;

2. Signal stage patterns and sequence at each signalized junction;

3. The proportions of different vehicle types.

The detailed collected results of the manual traffic survey are placed in Appendix B-D. The traffic flow counts are observed to compare with the traffic data from the online dataset. The signal stage observations are used to determine the stage patterns and sequences for benchmarking models in simulation. The vehicle type constitution is to make sure that the vehicle type ratio statistics from DfT are reliable to be used to estimate the bus numbers in Chapter 7.

5.3.2 Traffic dataset from Birmingham City Council

Birmingham City Council provides the Birmingham and West Midlands with real-time traffic data which can be accessible for public use (Birmingham City Council). The datasets include traffic counts, vehicle speed, ID and geometry locations of inductive loops over the past 10 years until 2018. In this project, the traffic flow counts from inductive loops illustrated in Figure 5.1 between 2017 and 2018 are used to generate the traffic flow volumes for the case study area. The traffic flow counts from each inductive loop are recorded at a frequency of 5-minutes intervals. The data files for these inductive loops are downloaded and aggregated from 5-minute interval traffic counts to 1-hour interval traffic counts over 24 hours each day as the daily flow patterns can be formed and observed to decide which part of the data is used to reproduce the traffic flows.

Three types of traffic flow counts are considered to be adopted as data for traffic volume generation: average flow for weekdays excluding public holidays, average flow for public holidays and weekends, and average flow for all dates. An example of traffic flow daily patterns of three types in an inductive loop coded with N51131R is shown in Figure 5.4.

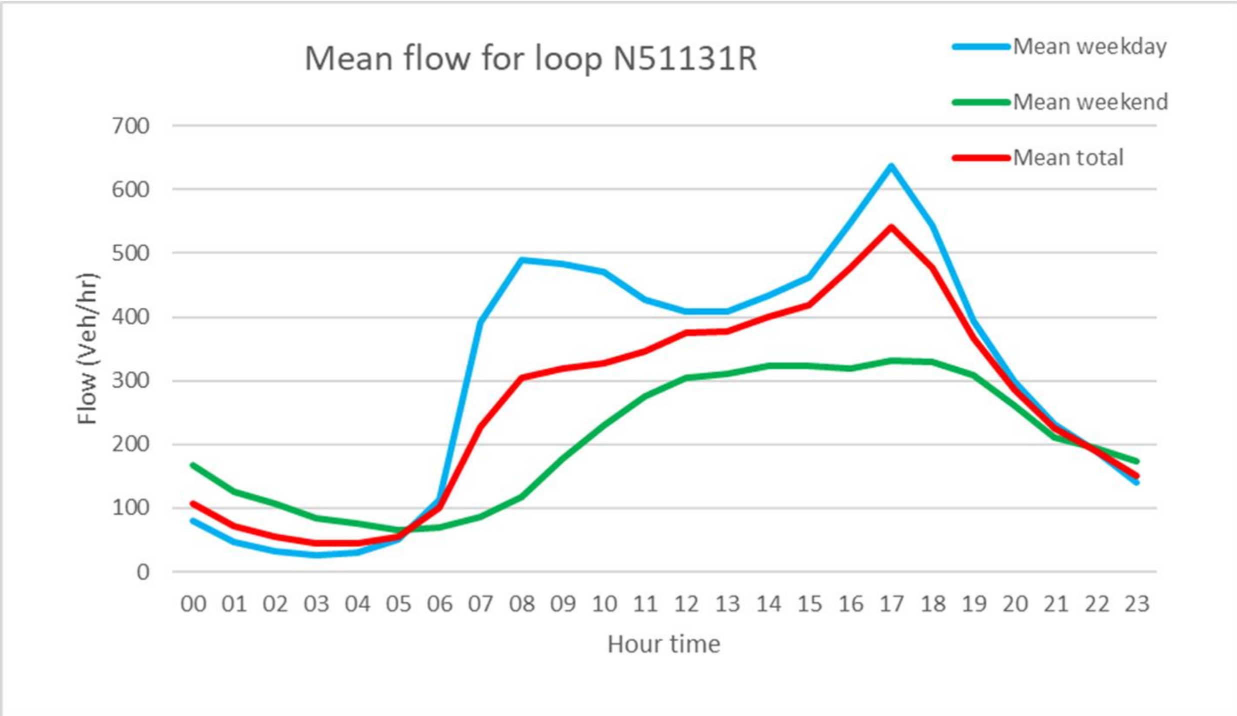

Figure 5. 4 An example of the daily flow patterns in weekdays, weekends and total average flow for inductive loop detector N51131R

Figure 5.4 illustrates that the average daily flow profile on weekdays has two peak hour periods, the inter-peak period from 7 a.m. to 7 p.m. and the off-peak period from 8 p.m. to 6 a.m. the next day. This allows the signal control to be evaluated at different traffic flow levels including peak periods and off-peak periods. However, there is no obvious traffic flow characteristic from the weekend daily flow profile like peak hour periods. The mean flow profile combined weekdays and weekends also has no such characteristic. The traffic counts from weekdays are selected to use as they conduct various traffic flow levels to make traffic signal control evaluations challenging and meaningful to understand how the proposed method works in different traffic states. As a result, the traffic flow data for weekends and public holidays are removed from the dataset for 2017 to 2018 to generate the average traffic volumes crossing through these inductive loops during weekdays.

In order to test the performance variances of PerSiCon-Bus and PerSiCon-Network to the changes in traffic flow demands, different traffic flow level scenarios are arranged in simulation experiments according to the daily flow profile of average flow. The grey lines in Figure 5.5 present separate daily flow patterns of an example inductive loops on weekdays. Figure 5.5 illustrates that the range surrounded by low and high (±25% of average flow) daily flow patterns covers the majority of daily flows experienced by inductive loop N51131R on the weekdays of the whole year. +25% of the average flow is also an empirical limit value to prevent heavy traffic congestion to occur in TRANSYT fixed-time controls. Therefore, ±25% of the average flow is defined to be high and low traffic levels in simulation experiment scenarios.

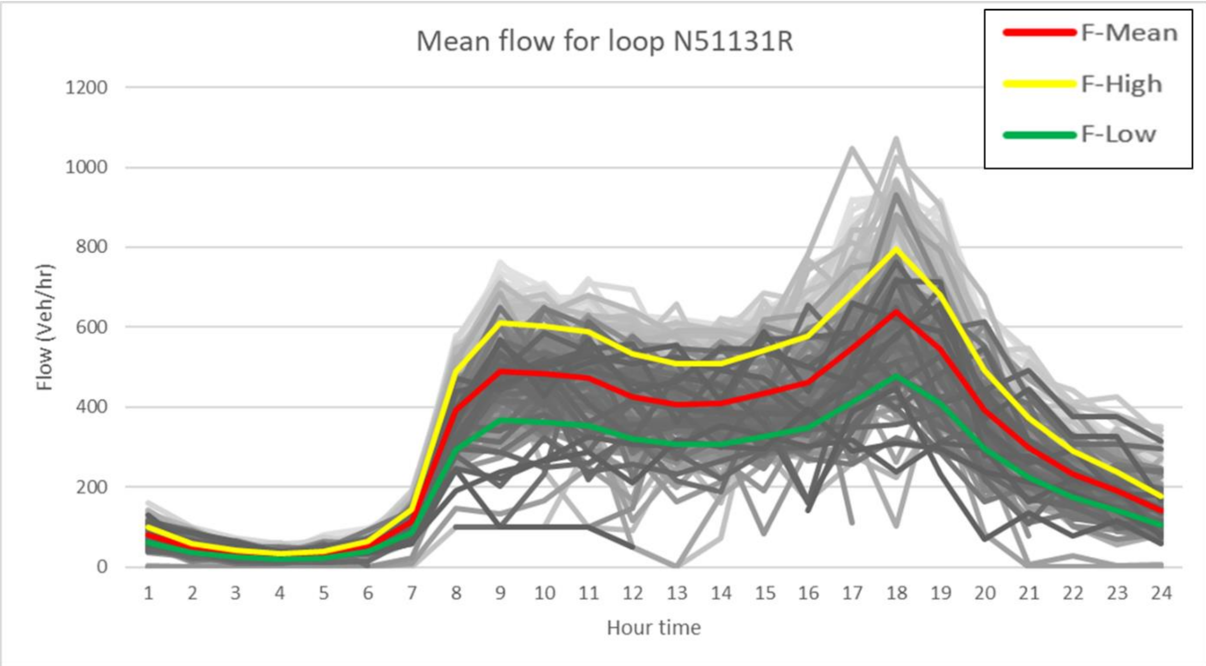

Figure 5. 5 An example of the daily flow patterns on weekdays and average flow profile in low, average and high levels. The grey lines represent separate daily flow patterns on weekdays. The yellow, red and green lines represent the daily flow profile in low (-25% average), average and high (+25% average) levels respectively

5.4 Convert flow data from inductive loops to O-D matrix

In this project, hourly traffic volumes are generated to imitate traffic flows crossing case study area over 24 hours as a comprehensive consideration of balancing daily flow pattern formation (compared to examples like 2-hours traffic flows) and massive statistical work like traffic counts in 5/15-minutes intervals. Hourly flow volumes experienced by inductive loops need to be processed to form O-D matrix, which is a critical data input to product traffic volumes for the case study (examples illustrated in Table 4.1 and 5.1). The most widely used approach to model traffic demand is Four-Step Model (FSM) (De Dios Ortúzar and Willumsen, 2011) with inputs of user activity data and geometry layouts of road networks. The steps of FSM include trip generation, trip distribution, mode choice and route choice, which are briefly described in following sub sections combing real states of case study.

5.4.1 Trip generation

The traditional trip generation method estimates traffic volumes produced and attracted by each zone by a wide range of surveys involving trip categories, number of households, number of dwelling units, etc. In this research, as traffic volumes counted by inductive loops are given, the locations of zones are defined at the far side of inductive loop sites so that all of the traffic travelling from and to the dedicated zone can be detected by corresponding inductive loops. The origin and destination zones with numbers A to D for the isolated junction are allocated in Figure 5.2(b). The locations of zones with numbers A to K for producing and attracting traffic flows in the road network area are allocated in Figure 5.6.

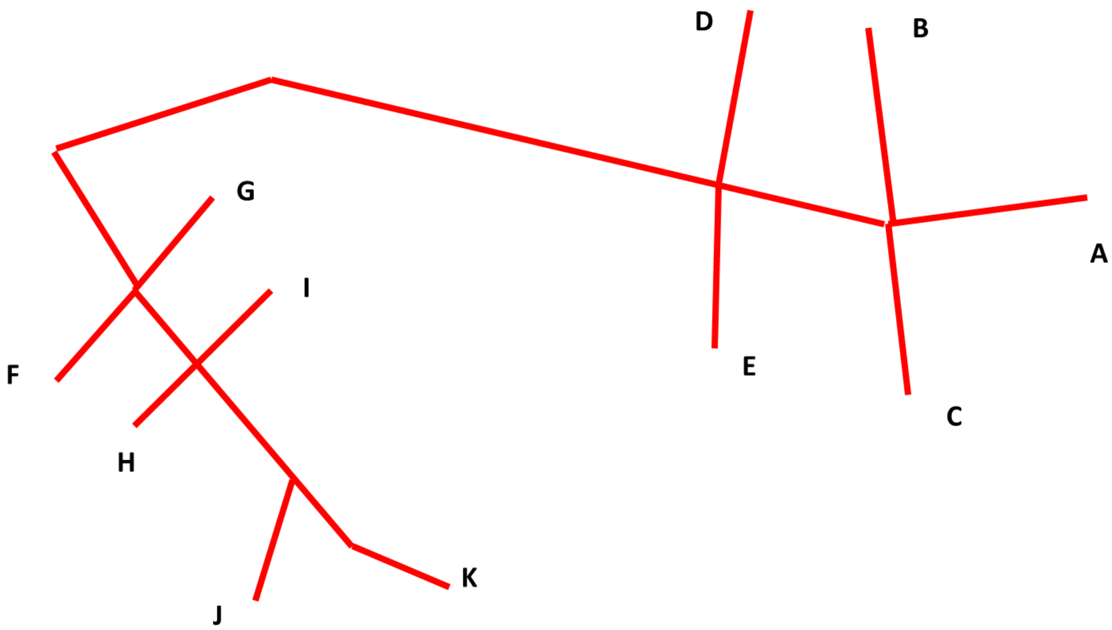

Figure 5. 6 The locations of zones with numbers A to K in the sketch of case study junctions

The traffic volume values detected by inductive loops located at upcoming approaching lanes from zones to junctions are equal to the trip generation summation of related zones. The traffic values from inductive loops at discharging lanes from junctions to zones represent the trip attraction summation. The hourly summation of trips generated and attracted by zones A to K can be realized from the corresponding inductive loops over 24 hours on weekdays.

5.4.2 Trip distribution

Trip distribution aims to sort the summation of trip production/attraction from each zone to other origin/destination zones to form an O-D matrix. As no prior travel survey information and vehicle turning counts data can be available, an initial trip assignment needs to be carried out to proportional assign the trips based on the weighted factor before the calibration with values from trip generation (De Dios Ortúzar and Willumsen, 2011). The weighted factor used for assigning summation production/attraction trips in this research is defined as a product of the number of lanes and speed limit of lanes from each approach, which is regarded as an index of road capacity.

The initial trip assignment estimates the values of the O-D matrix. However, as both origin and destination trip summation are known in this research, double proportional assignments would result in the trips being over or under-assigned and not consistent with one of the origin/destination values. The O-D matrix needs to be calibrated after assignments. The Furness model (Furness, 1965) is considered to be the most suitable method in this study to calibrate the O-D matrix values. The Furness model is a double-constrained growth factor method so that it can execute trip distribution calibration without other information requirements (such as expansion ratio in the growth factor model) and the summation of trips can be adjusted to fit both origin and destination values (compared to single-constrained model). In this way, the traffic flow counts from inductive loops are converted to hourly O-D matrix over 24 hours on weekdays. For the isolated junction, 4 zones located in 4 different directions in Figure 5.2(b) are assumed to generate and attract traffic volumes to consist of vehicles arriving and discharging from different routes. An example of an hourly O-D matrix of 4 zones for the isolated junction is presented in Table 5.1. Table 5.2 provides an example of road network O-D matrix results after iterations of calibration.

Table 5. 1 An example of O-D matrix assignment during morning peak period for isolated junction

Hourly flow demand (pcu)		Destination zone			
		A	B	C	D
Origin zone	A	-	135	137	244
	B	130	-	205	364
	C	133	207	-	374
	D	222	365	393	-

Table 5. 2 An example of O-D matrix assignment during morning peak period for road network after Furness model calibration

Hourly flow demand (pcu)		Destination zone										
		A	B	C	D	E	F	G	H	I	J	K
Origin zone	A	-	135	137	20	33	20	26	27	16	28	73
	B	130	-	205	30	49	31	39	40	24	42	109
	C	133	207	-	30	50	31	40	41	25	43	112
	D	21	33	34	-	8	5	7	7	4	7	18
	E	30	47	48	7	-	7	9	9	6	9	25
	F	15	25	26	4	6	-	5	5	3	5	14
	G	21	34	35	5	9	5	-	7	4	7	18
	H	30	48	50	7	11	7	9	-	6	9	26
	I	26	40	43	6	11	6	8	8	-	8	22
	J	30	47	47	7	11	7	9	9	6	-	26
	K	57	90	93	13	22	14	18	18	11	19	-

5.4.3 Mode choice

The mode choice is to determine the vehicle volumes from the O-D matrix in different vehicle types. The UK Department for Transport provides statistics about the ratios of different vehicle types in the VEH0104 dataset in 2018 (UK Govt. Dept. Transport, 2018b). The vehicle type distributions were also counted from the manual survey to ensure that the statistics are consistent with the real vehicular situations in the case study area, which can be found in Appendix C. The vehicle types from datasets include passenger cars, buses, LGV, Heavy Goods Vehicle (HGV) and Motorcycle (MC). In this section, the evaluation experiments put more emphasis on understanding the benefits of person-related indicators from the proposed method under passenger car circumstances with different occupancies. The simulation scenarios assume that all vehicles on road are passenger vehicles. In the next chapter, bus mode is incorporated into the vehicle fleets. Other vehicle types can also be considered with different vehicle models and priority levels in future research.

5.4.4 Route choice

In the traditional FSM model, if few alternative routes allow vehicles to travel from origin to destination point, the vehicle volume needs to be assigned on these routes following the rules such as the shortest path principle. Although there is not only one route that can be found from defined origin zones to destination zones in Figure 5.1, the traffic volumes from those branches cannot be detected as no inductive loop site locates. In this research, the sketch of isolated junction in Figure 5.2 and multiple junctions in Figure 5.6 is adapted to provide the optional routes from origin to destination as these approaches are distributed with inductive loops. As a result, there are limited ways can be chosen from each origin-destination pair. The traffic volumes allocated in each route may not reflect the real states of traffic situations in this area but they are the best way to make the traffic flows generated by simulation to be consistent with recorded traffic count information from inductive loops.

5.5 Model calibration and validation

Traffic modelling guidelines version 4.0 published by DfT (DfT, 2021) suggest GEH values are used to calibrate and validate the traffic flows within the model simulation to match traffic counts to an acceptable level of accuracy. The GEH statistic is calculated as follows:

$$GEH = \sqrt{\frac{2(F_{sim} - F_{obv})^2}{F_{sim} + F_{obv}}} \tag{6-1}$$

Where F_{sim} is the traffic volumes generated in simulation from the FSM approach and F_{obv} is the traffic volumes observed by inductive loops. The model flow counts should satisfy the criteria that GEH statistics of more than 85% of the cases should be less than 5%.

The flow counts in the average level were used to be calibrated in this research. High and low flow levels can be adjusted accordingly. The GEH statistics were calculated using hourly flow counts obtained from inductive loops and hourly flow generated by the FSM approach over 24 hours. If the GEH values fail to satisfy the requirements, the hourly traffic volumes produced by FSM are sent back to be recalibrated. This procedure will be repeated until GEH values meet the criteria. The results of GEH values are indicated in Figure 5.7. From Figure 5.7 all of the GEH values over 24 hours are below the 5% criteria baseline, which means that the traffic flows used in the simulation are well calibrated to represent the real state traffic flows.

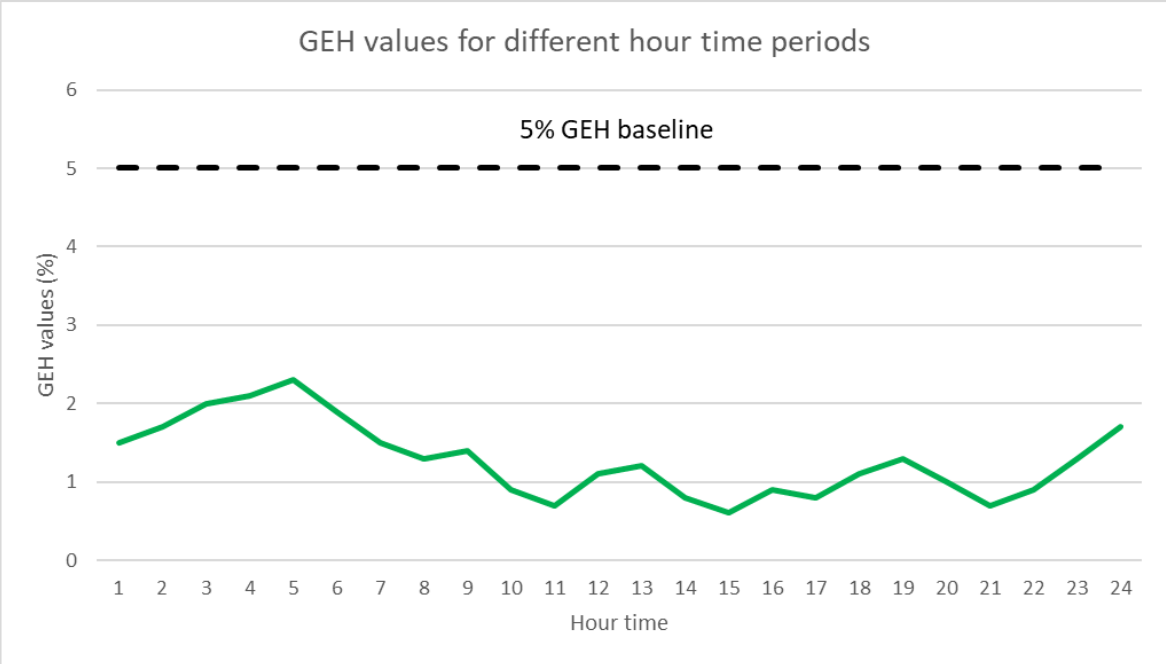

Figure 5. 7 GEH values for different hour time periods over 24 hours

5.6 Junction settings and vehicle parameters

5.6.1 Stage patterns

The fixed-time control, actuated control and vehicle-based control using CV data apply a fixed stage sequence. The green phases operated in one stage need to follow the phase non-conflicting rules. In isolated junction, the stage sequence and phase combinations are observed from the survey of the case study. Left-turning, straight movements and dedicated right-turning movements in the same direction are combined to form one stage. The stage sequence applied in three benchmarking models is graphed in Figure 5.8. For road networks, a traffic manual survey gathers the stage sequences of 5 junctions and applies them in simulation experiments, the detailed information has been placed in Appendix B.

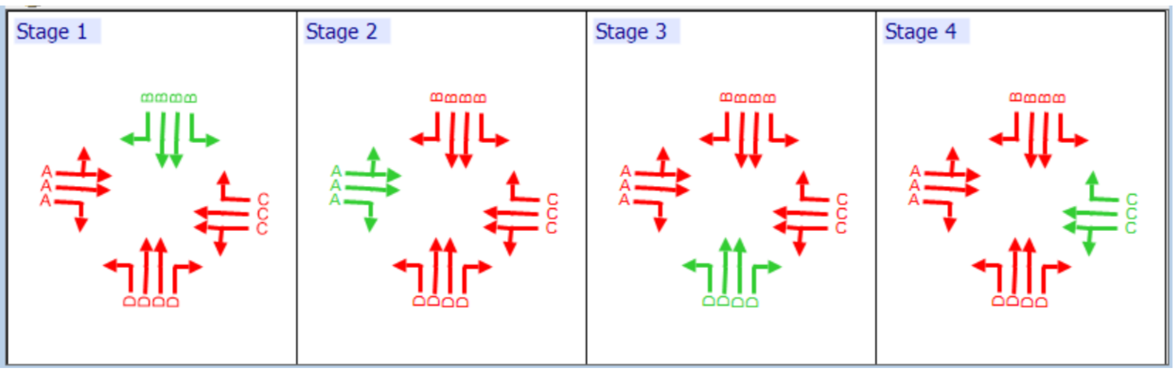

Figure 5. 8 Stage sequence for isolated junction case study

5.6.2 Intergreen time, minimum green time and maximum green time configuration

The intergreen time is the duration of phase transition to ensure the safety of vehicle movements at the junction. The intergreen time duration is derived from the UK government guidelines presented in Table 5.3, which is related to the distance from the crossline to probable collision points.

Table 5. 3 Determining intergreen time duration by DfT (DfT, 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

Minimum green time and maximum green time are important parameters in actuated control to constraint the green duration for each stage to satisfy queue clearance requirement. The vehicle-based control using CV data also adopt the configuration settings of minimum and maximum green time as it follows fixed stage sequence. The recommended minimum and maximum green duration are given by Traffic Signal Timing Manual in Table 5.4. The minimum and maximum green time in this research are set to 2 and 10 times intergreen duration.

Table 5. 4 Typical minimum and maximum green interval durations

Phase	Facility Type	Maximum Green (s)	Minimum Green (s)
Through	Major Arterial (speed limit exceeds 40 mph)	50 to 70	10 to 15
	Major Arterial (speed limit is 40 mph or less)	40 to 60	7 to 15
	Minor Arterial	30 to 50	4 to 10
	Collector, Local, Driveway	20 to 40	2 to 10
Left Turn	Any	15 to 30	2 to 5

5.6.3 Signal timing parameters

5.6.3.1 Signal timing parameters for TRANSYT fixed-time control

Hourly O-D matrix of zones in Table 5.1 and Table 5.2 are adopted as traffic volume data inputs of TRANSYT and TRANSYT-Network fixed time optimization. Cycle length is another input parameter to decide the green operation duration for each stage. The DfT recommends that the cycle time of the fixed time plan should not exceed 120 seconds regularly to prevent drivers from being frustrated to wait too long at red lights (DfT, 2006). TRANSYT 16 provides a Cycle Time Optimizer function as optional support to the difficult task of selecting cycle time. Cycle Time Optimizer provides information for a wide range of cycle length selections and figures out the relative results of the Performance Index involving practical reserve capacity or total delay. The cycle length optimization results for the isolated junction are graphed as an example in Figure 4.4.

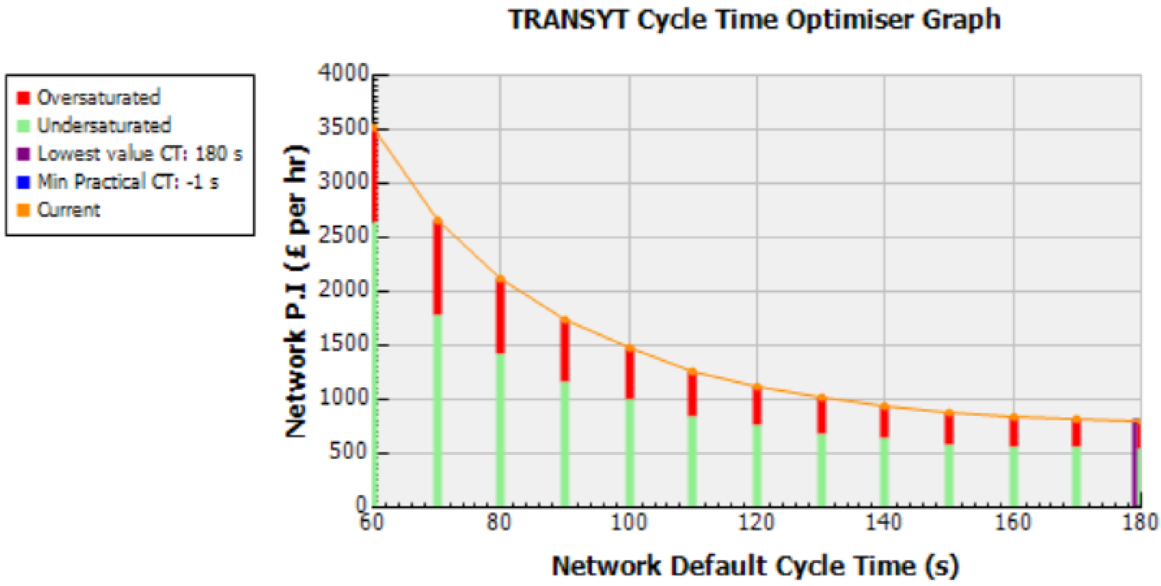

Figure 5. 9 Cycle time optimization result for isolated junction with cycle length from 60s to 180s with a step of 10s

Figure 5.9 indicates that the Performance Index decreases as the cycle length increases and there is no obvious decline when the cycle length is longer than 120 seconds. The cycle length of 120 seconds is selected for TRANSYT signal plans. The optimized signal timing plans are produced in Table 5.5.

Table 5. 5 TRANSYT signal timing plans for isolated junction (Stage ID are shown in Figure 5.8)

Stage ID	Stage start (s)	Stage end (s)	Duration (s)
4	0	15	15
1	21	44	23
2	50	83	33
3	89	114	25

5.6.3.2 Signal timing parameters for actuated signal control ILACA

Some parameters for control strategies responsive to traffic flow should be decided based on junction layouts to operate the algorithms. For instance, the start time loss at the start of green time and saturated flow for each lane in the isolated junction is observed to be 1.8s and 1400 veh/h separately in this junction. The 1400 veh/h saturated flow equals to flow of 0.38 veh/s, therefore the time needed to clear 1 vehicle in the queue is estimated to be 2.6s. For the inductive loop actuated control algorithm (ILACA), each approach lane installs inductive loops at 6m and 18m from their stop lines (Highways Agency, 2002) so that the vehicle flows can be detected. At the actuated control decision point (see figure 6.2), if vehicle flow is greater than 80% of the saturated flow (0.8×1400veh/h = 1120veh/h = 0.31veh/s →≈3s/veh), the vehicle can be detected less than 3s from the last detection time between detectors. Thus the unit extension time will be extended for this lane corresponding to high vehicle demand. The typical value of extension time is suggested to be a range from 0.1s to 2s in (Koonce et al., 2008), so 1s extension time will be accepted here to related to the time step.

5.6.4 Vehicular parameters for cars and buses

As claimed in Chapter 3, Krauß car-following model is the most appropriate model to reproduce the vehicle behaviours in this project. The Krauß car-following model parameters for passenger cars and buses are described in Table 5.6.

Table 5. 6 The Krauß car-following model parameters for passenger cars and buses (DLR, 2018)

Description	Unit	Value	
Vehicle type	-	Passenger car	Bus
Maximum acceleration	m/s2	2.6	1.0
Maximum deceleration	m/s2	4.5	3.5
Vehicle length	m	5.0	12.0
Vehicle min gap	m	2.5	2.5
Driver imperfect value	-	0.5	0.5
Driver reaction time	s	1.0	1.0
Maximum Speed	m/s	50	23.6

5.7 Passenger occupancy estimation

Although there are no specific distribution proportions of different car occupancies released from UK DfT or detailed survey information from the case study area, the number of passengers in a car (excluding drivers so that the value can start from 0) can be assumed to follow Poisson distribution when the number of independent trials is large and the probability of occurrence in one experiment is very small. The mean values of vehicle occupancy at different times of day on weekdays are provided in Table 2.3. In different hour periods, the corresponding mean vehicle occupancy value is considered as the mean occupancy of passenger vehicles in the case study area. Given the mean value, Table 5.7 provides an example of probability estimation for passenger cars with different occupancy levels from 1 to 4 assuming they follow the Poisson distribution. For each new generated vehicle, the probabilities of the number of people inside it can be decided in Table 5.7.

Table 5. 7 Different probabilities of cars occupancies from 1 to 4 in a vehicle assumed Poisson distribution with a mean of 1.6

Car occupancy	0	1	2	3
Probability	54%	33%	10%	3%

Similarly, the bus occupancies can be assumed to follow the Poisson distribution. The distribution of different vehicle types in the VEH0104 dataset provided by DfT can be used to determine the model choice in the traditional FSM method (UK Govt. Dept. Transport, 2018b). The statistics from the dataset are compared with the results collected from the manual survey in the case study location to make sure that the statistics are consistent with the real state, which can be seen in Appendix C. In this research, two vehicle modes, passenger cars and buses are considered. As there is no statistic for vehicle type distribution under different hour periods, the traffic volumes of buses are calculated by total traffic volume multiples the summation percentage of bus distribution to determine the bus flows in different periods.

From average vehicle occupancies sorted by vehicle types provided by DfT in Table 2.3, the average bus occupancy (with driver) is 13.2 in 2000 and the average growth rate until 2036 is 0 (UK Govt. Dept. Transport, 2021b). In this research, it is assumed that the average bus occupancy (with driver) in the case study area is 13.2 and the distribution of passengers follows the Poisson distribution. The bus capacity is determined by the local bus operator National Express West Midlands in the case study area. The buses consist of 30% single-decker buses with 45 passenger capacity (Alexander Dennis, 2019a) and 70% double-decker buses with 86 passenger capacity (Alexander Dennis, 2019b). The estimations of different occupancy excluding drivers are listed in Table 5.8 as follows.

Table 5. 8 Different probabilities of buses with occupancy from 1 to capacity assumed Poisson distribution with a mean of 13.2

Bus occupancy	1 - 5	6 - 10	11 - 15	16 - 20	21 - Capacity
Ratio	1%	22%	53%	22%	2%

As bus occupancy values are varied, the distribution ratios of different passenger numbers are calculated in groups with a step of 5 passengers. The bus occupancy number in each group is assigned uniformly to form the ratio of the corresponding group to estimate bus occupancy.

5.8 Evaluation experiments

To validate the performance of PerSiCon-Network, the road networks and generated traffic flows of the case study in the Newtown area of Birmingham were implemented in SUMO. Table 3.4 provides an evaluation outline. To evaluate the performance in different flow demand levels, the proposed algorithm was simulated in three kinds of flow levels: low, average and high. The low and high flow levels are defined as ±25% of average hourly flow levels. The car occupancy distributions and car-following model parameters are described in the above sections. Three benchmarking models: TRANSYT, ILACA and VehSiCon and their coordination versions were programmed and operated in simulation.

The penetration rate, which is the rate of CVs to non-CV cars, is set to vary between 10% and 100% with a step of 10% in simulation to test the performance of the proposed algorithm to change to CV penetration rate. The communication range is set to be 250m and situations of data measurement and transmission processes are assumed to be perfect (no packet loss, data measurement error and data transmission delay). Meanwhile, different planning duration values will be adopted in the PerSiCon-Bus and PerSiCon-Network evaluation. The planning duration is incremented from 10s to 60s with a step of 10s to test the influences of the planning horizon towards PerSiCon-Bus and PerSiCon-Network. Besides the various scenarios to different traffic flows, prediction horizons and CV penetration rates, a range of bus occupancy levels are tested in simulation, with a step of 10 from 10 to 50 and with a step of 2 below 10, to analyse the sensitivity of the proposed algorithm to bus occupancy. The different values of weighted factor δ from 0 to 1 in Equation (3-2) are adopted in PerSiCon-Junction to observe the changes in performance. The performance of buses and passenger cars are also expressed respectively to understand how the proposed algorithm works in the mixture of vehicular environments.

Each experimental scenario was operated 30 times with different random seeds to avoid the influences of randomness on generated traffic demands and occupancy sequences. The experiments were carried out on a laptop with Windows 10 system and Intel Core i7 CPU (2.9 GHz) and computational cost is recorded for each simulation. The average computation time for each time step (1s decision step and 29s execution step for every 30s) and each decision point is 0.174s and 0.378s for isolated junction experiments, 0.204s and 0.531s respectively for road network experiments, both of which are less than 1s.

In order to identify whether there are significant differences in PerSiCon-Network and benchmarking models, the hypothesis tests are carried out between mean person-related values of them. As all of the evaluation results collected from the proposed method and benchmarking models are samples and they may not reflect the actual mean values of signal controls, two sample T-test hypothesis tests are adopted for this research in the case that the actual mean values are unknown and cannot be captured.

5.9 Results and discussions for isolated junction case study

The proposed person-based controls PerSiCon-Bus and PerSiCon-Network are operated in isolated junction and road networks respectively to validate the person-based control effectiveness in different traffic environments. This section presents and analyses the results of PerSiCon-Bus which is evaluated in the isolated junction case study, including general results of PerSiCon-Bus in 100% CV penetration rates and performance to different sensitivity factors.

5.9.1 General results

The results in Table 5.9 show the average person delays and average vehicle delays sorted by occupancy levels from PerSiCon-Bus and comparisons of three benchmarking models. Table 5.10 presents the average person number of stops and average vehicle number of stops of PerSiCon-Bus and three reference models. The average vehicle-related values: average vehicle delay and average vehicle number of stops, divided by the total number of people and number of vehicles are also summarized in two tables. To illustrate the priority policies and actual effects of the proposed approach PerSiCon-Bus to different occupancy level vehicles, the performance of evaluated vehicles in different signal control simulations are recorded separately by different occupancy levels. The numbers in the last two columns in Tables 5.9 and 5.10 represent the collected output data of average person/vehicle delay and average person/vehicle number of stops values per person. Meanwhile, the data in the first four columns present person/vehicle delay and stop values per person categorized by occupancies. All values are collected under 100% CV penetration rate.

Tables 5.11 and 5.12 illustrate the p-values results of two sample T-test carried out between outputs collected from PerSiCon-Bus and benchmarking models in different demand levels in a 95% confidence degree. In each experiment, if the p-value is less than 0.05, one group of data is identified to have a significant difference compared to another group of data. The hypothesis test results are contributed to verify whether PerSiCon-Bus achieves significant improvements or not against another reference signal control method.

The general results are discussed in further detail in the following part of Section 5.9.1.

Table 5. 9 Comparison of average passenger delay (s/per) and average vehicle delay (s/veh) of the proposed algorithm and benchmarking algorithms under three flow scenarios in 100% CVs penetration rate with a mixture of cars and buses

Flow level	Control methods	Cars with 4 occups	Cars with 3 occups	Cars with 2 occups	Cars with 1 occup	Buses with 30 occups	Average person delay	Average vehicle delay
Low	TRANSYT	104.39	103.67	102.92	103.15	103.81	103.29	103.62
	ILACA	80.13	81.12	81.73	80.72	82.41	81.08	81.38
	VehSiCon	55.25	56.02	54.21	56.24	54.31	55.23	55.38
	PerSiCon-Bus	35.31	38.47	43.63	72.05	20.21	49.81	58.87
Average	TRANSYT	110.05	112.37	111.84	111.16	111.04	111.56	111.47
	ILACA	87.25	88.82	88.56	88.03	87.92	88.31	88.28
	VehSiCon	67.04	67.82	66.73	68.32	67.36	66.98	67.43
	PerSiCon-Bus	45.62	51.93	56.37	86.04	22.46	62.37	71.48
High	TRANSYT	130.93	128.83	131.85	129.48	130.42	130.44	130.34
	ILACA	107.15	107.84	108.94	108.64	108.72	108.52	108.39
	VehSiCon	83.21	84.02	84.72	82.34	83.01	83.66	83.56
	PerSiCon-Bus	62.24	67.13	72.45	101.67	32.57	77.94	87.48

Table 5. 10 Comparison of average passenger stop (num/per) and average vehicle stop (num/veh) of the proposed algorithm and benchmarking algorithms under three flow scenarios in 100% CVs penetration rate with a mixture of cars and buses

Flow level	Control methods	Cars with 4 occups	Cars with 3 occups	Cars with 2 occups	Cars with 1 occup	Buses with 30 occups	Average passenger delay	Average vehicle delay
Low	TRANSYT	1.21	1.25	1.24	1.23	1.24	1.24	1.23
	ILACA	0.92	0.97	0.95	0.98	0.94	0.96	0.96
	VehSiCon	0.58	0.55	0.56	0.56	0.57	0.56	0.56
	PerSiCon-Bus	0.35	0.42	0.48	0.73	0.19	0.50	0.59
Average	TRANSYT	1.43	1.40	1.40	1.44	1.45	1.40	1.41
	ILACA	1.11	1.16	1.12	1.17	1.13	1.15	1.14
	VehSiCon	0.66	0.64	0.66	0.67	0.65	0.66	0.66
	PerSiCon-Bus	0.45	0.48	0.57	0.84	0.29	0.61	0.70
High	TRANSYT	1.63	1.60	1.60	1.64	1.65	1.60	1.61
	ILACA	1.39	1.34	1.36	1.38	1.36	1.36	1.37
	VehSiCon	0.93	0.95	0.91	0.90	0.91	0.91	0.92

PerSiCon-Bus	0.60	0.65	0.69	1.29	0.35	0.86	0.96

Table 5. 11 P-values in average person delay and average vehicle delay comparisons for PerSiCon-Bus and three benchmarking models in different traffic flow demands with a mixture of cars and buses in 100% CV penetration rate and 30s prediction horizon

Average person delay comparison	P-values			Average vehicle delay comparison	P-values		
	TRANSYT	ILACA	VehSiCon		TRANSYT	ILACA	VehSiCon
Low	0.000	0.000	0.004	Low	0.000	0.000	0.043
Average	0.000	0.000	0.010	Average	0.000	0.000	0.018
High	0.000	0.000	0.003	High	0.000	0.000	0.024

Table 5. 12 P-values in average person stop and average vehicle stop comparisons for PerSiCon-Bus and three benchmarking models in different traffic flow demands with a mixture of cars and buses in 100% CV penetration rate and 30s prediction horizon

Average person stop comparison	P-values			Average vehicle stop comparison	P-values		
	TRANSYT	ILACA	VehSiCon		TRANSYT	ILACA	VehSiCon
Low	0.000	0.000	0.013	Low	0.000	0.000	0.027
Average	0.000	0.000	0.025	Average	0.000	0.000	0.047
High	0.000	0.000	0.017	High	0.000	0.000	0.032

It can be found from Table 5.9 that the proposed PerSiCon-Bus reduces 40.2% - 51.8%, 28.2% - 38.6% and 6.8% - 9.8% of average passenger delay of all vehicles compared to the TRANSYT, ILACA and VehSiCon benchmark algorithms in the vehicular environments under three flow scenarios. Table 5.10 demonstrates similar reductions of average passenger stop for the proposed algorithms against the benchmark algorithms, which are 46.3% - 59.7%, 36.8% - 47.9% and 5.5% - 10.7% respectively. Meanwhile, the average vehicle delay and average vehicle stop of the proposed algorithm also is not heavily degraded in each scenario even if VehSiCon is selected as a baseline. Although Table 5.11 and Table 5.12 show significant differences in average vehicle delay and average vehicle stop of PerSiCon-Bus compared to VehSiCon, the average vehicle delay and stop of the proposed algorithm are only 4.7% - 6.3% and 4.3% - 6.1% higher than those of VehSiCon. The signal control methods using CV data achieve fewer average person delays and average vehicle stops, as CV data inputs can provide a more accurate estimation of vehicle crossing time than infrastructure sensors such as inductive loops or pre-determined off-line signal optimization. The higher average delay and stop in ILACA can be attributed to an imprecise estimation of road conditions, queue length discharging time, stage switching and green extension by inductive loop sensors. The detectors in ILACA can partially react to flow demand and adjustments for signal plans are not as accurate as VehSiCon and PerSiCon-Bus in the absence of vehicle instantaneous trajectories from CVs, resulting in a higher frequency of mode switching between queuing and discharging statuses to cause more average stops.

The results indicate that the application of connected vehicle technology is more beneficial to road network signal control than inductive loops under 100% penetration rate situation. The proposed PerSiCon-Bus achieves obvious average person delay reductions even compared to VehSiCon, which reflects the effects of the proposed person-based control algorithm in this project. The P-values results from hypothesis tests in Table 5.11 and Table 5.12 also identify the improvements of the proposed PerSiCon-Bus on average person delay and average person stop. Table 5.11 and Table 5.12 illustrate that the PerSiCon-Bus has significant differences in average person delay and average person stop in high, average and low traffic demand scenarios against TRANSYT, VehSiCon, where the P-values results are all below 0.05 at 95% confidence level.

Among three different traffic demand levels, PerSiCon-Bus achieves the highest average person delay and average person stop reductions against three benchmarking models when the traffic demand level is low. On the contrary, PerSiCon-Bus reduce the average person's delay and stop at minimal degrees when the traffic demand level is high. This is because more vehicles arrive at the junction with dynamic occupancy level combinations when traffic demand is higher and PerSiCon-Bus have to first give priority to some low occupancy level vehicles before the vehicles with high occupancy levels. For instance, in high-level traffic demands, 1-occupancy vehicles are more likely to be stopped before 4-occupancy vehicles, so 4-occupancy vehicles can only be discharged after the green light is given for 1-occupancy vehicles. Therefore, high flow level influences the performance of PerSiCon-Bus to a certain extent.

More specifically, it can be observed from Table 5.9 and Table 5.10 that the average delay and stop of high-occupancy cars (cars with 2, 3 or 4 occupants) and buses are significantly reduced compared to the summations of average passenger delay. In terms of cars with 4 occupants and buses, the average delays of them are 25.2% - 36.1% and 60.8% - 66.7% less than those in the vehicle-based approach VehSiCon using CVs data to minimise vehicle delay in all cases. The average person stops of them are also significantly less than those in VehSiCon. However, the average delay and stop of 1-occupancy vehicles are 23.5% - 28.1% and 25.4% - 43.3% larger than those in VehSiCon. As expected, the reason is that the proposed algorithm reduces delays of high-occupancy vehicles and scarifies the travel time of 1-occupancy vehicles through more flexible signal timing plans in 8-phases junction to reduce the average delay of all drivers and passengers.

5.9.2 Sensitivity analysis to CV penetration rate

In order to understand how the proposed PerSiCon-Network performs under a variety of mixture vehicle environments of conventional vehicles and CVs, the sensitivity analysis experiments are tested for different approaches. Figure 5.10 illustrates sensitivity test results of average delays (Figure 5.10 (a), (c) and (e) for average person delays and Figure 5.11 (b), (d) and (f) for average vehicle delays) respectively of different controls from 10% to 100% CV penetration rate with a step of 10%. Figure 5.11 illustrates how the proposed algorithm and benchmarking models change with CV penetration rates (Figure 5.11 (a), (c) and (e) for average person stop and Figure 5.11 (b), (d) and (f) for average vehicle stop) assuming situations of all passenger cars. Table 5.13 - Table 5.16 are hypothesis test results for average person/vehicle delays and stops in different CV penetration rate scenarios respectively.

The plots in Figure 5.10 show similar variation trends of average person/vehicle delays among signal controls using CV data under three traffic flow levels. The average person/vehicle delays of signal controls using CV data (VehSiCon and PerSiCon-Bus) increase as the CV penetration rate decreases regardless of their objectives or signal plan flexibilities. The average person/vehicle delays of the connected control methods perform worse than ILACA when the CV penetration rate is less than 50%, and perform worse than TRANSYT when the CV penetration rate is less than 30%. Compared to VehSiCon, the advantage of reducing passenger delay in the proposed algorithm is gradually reduced by reducing the CV penetration rate. This can be proved by the hypothesis test results in Tables 5.13 and 5.14. The average person/vehicle delays of PerSiCon-Bus are not significantly different to those of VehSiCon when the CV penetration rate decrease to 60% - 80%. Figure 5.11, Table 5.15 and 5.16 illustrate that there are similar influences on trends of average passenger/vehicle stops in Figure 5.10, Table 5.13 and 5.14 of all operational algorithms under three flow levels. The reason is that the gradual absence of CVs reduces the data sources of signal optimization algorithms using CV data, making them cannot realize the entire vehicle situation at multiple junctions. As the CV penetration rate decreases, VehSiCon/PerSiCon-Bus can only acquire part of vehicular information. The optimization outputs of their algorithms cannot reach the perfect objective function targets of minimising person/vehicle delay. The values of TRANSYT and ILACA remain the same as they do not rely on the information sent from CVs.

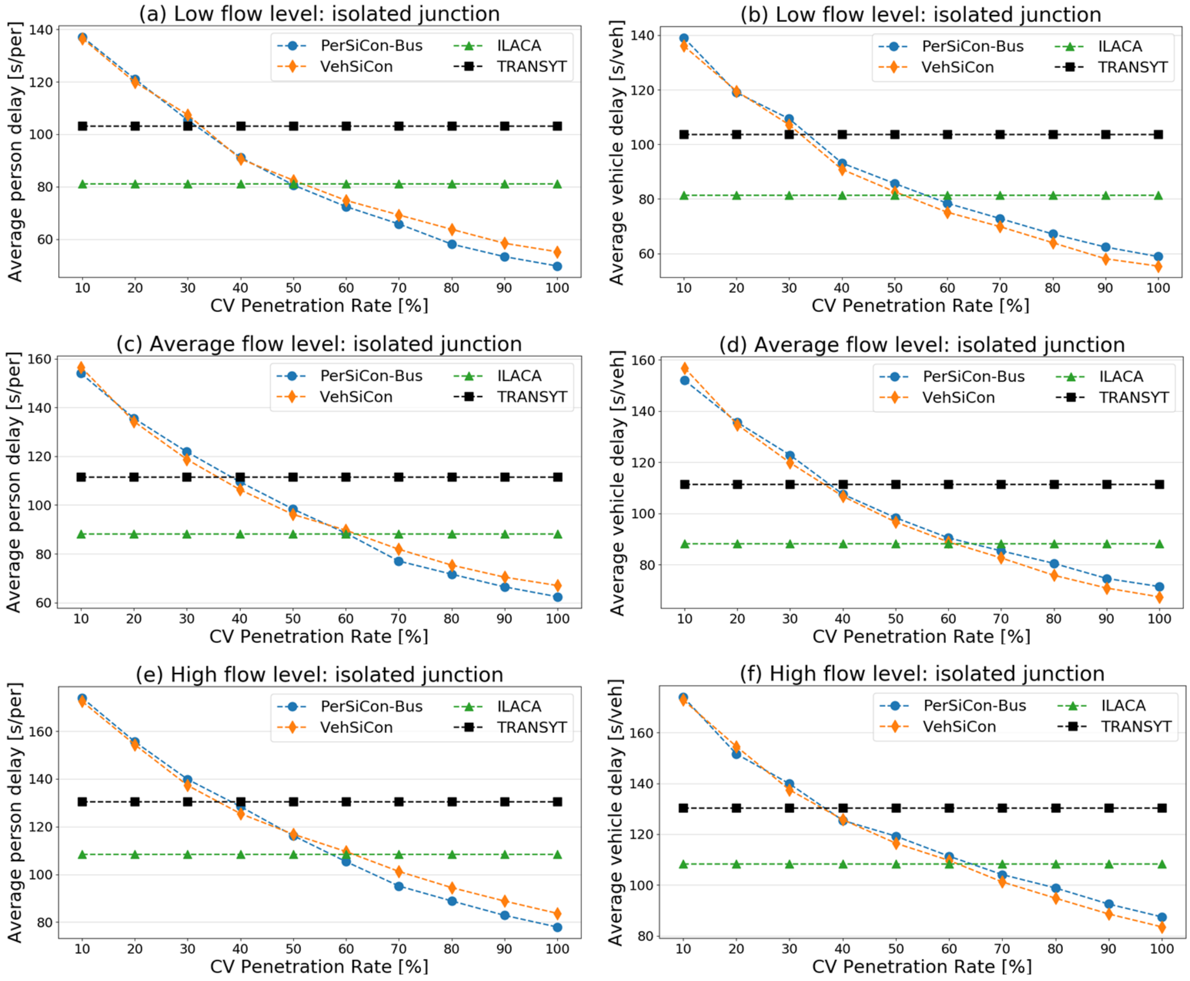

Figure 5. 10 Comparison of average passenger delay (s/per) and average vehicle delay (s/veh) of proposed algorithm PerSiCon-Bus and benchmarking algorithms in isolated junction under variety CV penetration rates and three flow levels

Table 5. 13 P-values in average person delay comparison for PerSiCon-Bus and three benchmarking models in isolated junction in different traffic flow demands and different CV penetration rates

	P-values for average person delay								
Flow level	Low			Average			High		
Signal controls	TRANSYT	ILACA	VehSiCon	TRANSYT	ILACA	VehSiCon	TRANSYT	ILACA	VehSiCon
100%	0.000	0.000	0.004	0.000	0.000	0.010	0.000	0.000	0.003
90%	0.000	0.000	0.009	0.000	0.000	0.022	0.000	0.000	0.009
80%	0.000	0.000	0.016	0.000	0.000	0.024	0.000	0.000	0.008
70%	0.000	0.000	0.027	0.000	0.000	0.037	0.000	0.000	0.025
60%	0.000	0.000	0.069	0.000	0.418	0.072	0.000	0.046	0.044
50%	0.000	0.143	0.082	0.000	0.000	0.115	0.000	0.000	0.735

40%	0.000	0.000	0.175	0.291	0.000	0.893	0.375	0.000	0.254
30%	0.083	0.000	0.225	0.000	0.000	0.346	0.000	0.000	0.437
20%	0.000	0.000	0.417	0.000	0.000	0.842	0.000	0.000	0.577
10%	0.000	0.000	0.258	0.000	0.000	0.618	0.000	0.000	0.782

Table 5. 14 P-values in average vehicle delay comparison for PerSiCon-Bus and three benchmarking models in isolated junction in different traffic flow demands and different CV penetration rates

	P-values for average vehicle delay								
Flow level	Low			Average			High		
Signal controls	TRANSYT	ILACA	VehSiCon	TRANSYT	ILACA	VehSiCon	TRANSYT	ILACA	VehSiCon
100%	0.000	0.000	0.043	0.000	0.000	0.018	0.000	0.000	0.024
90%	0.000	0.000	0.031	0.000	0.000	0.029	0.000	0.000	0.029
80%	0.000	0.000	0.045	0.000	0.000	0.007	0.000	0.000	0.037
70%	0.000	0.000	0.058	0.000	0.048	0.034	0.000	0.041	0.054
60%	0.000	0.046	0.074	0.000	0.210	0.096	0.000	0.067	0.133
50%	0.000	0.008	0.094	0.000	0.000	0.085	0.000	0.000	0.094
40%	0.000	0.000	0.146	0.006	0.000	0.269	0.005	0.000	0.865
30%	0.001	0.000	0.325	0.000	0.000	0.168	0.000	0.000	0.644
20%	0.000	0.000	0.490	0.000	0.000	0.641	0.000	0.000	0.429
10%	0.000	0.000	0.272	0.000	0.000	0.658	0.000	0.000	0.718

From Table 5.13, PerSiCon-Bus has significant differences in average person delay against VehSiCon when the CV penetration rate is higher than or equal to 70% in low/average traffic flow scenarios and 60% in high traffic flow scenarios at a 95% confidence level. Table 5.14 illustrates that the average vehicle delays of PerSiCon-Bus and VehSiCon only have significant differences when the CV penetration rate is higher than or equal to 80% in low traffic demand levels and 70% in average/high demand levels. Tables 5.15 and Table 5.16 provide similar dynamics about the average person/vehicle stop performance of these two controls. The P-values results for average person delay indicate high-level requirements of CV penetration rate for PerSiCon-Bus to achieve the obvious advantages of reducing average person delay, 60% - 80% against vehicle-based control using CV data. This is because fewer CV penetration rate makes signal controllers have less vehicle environment realization and execute signal timing plans less precise to the objective functions. The signal timing plans are not optimal in PerSiCon-Bus/VehSiCon so they are less likely to achieve significant improvements in reducing average person/vehicle delays and stops.

In most cases, the performance of PerSiCon-Bus in Table 5.13 – Table 5.16 are significantly different to those of TRANSYT and ILACA. However, there are still a few special situations where p-values are higher than 0.05, for instance, 30% CV penetration rate compared to TRANSYT and 50% CV penetration rate compared to ILACA in low demand level in Table 5.13. The reason is that KPIs of PerSiCon-Bus increase as the CV penetration rate decreases and the rising values are very close to the unchanged values in TRANSYT or ILACA at a CV penetration rate. In this case, the mean difference is a minor value, which leads to a large p-value as it is a critical component to calculate p-values.

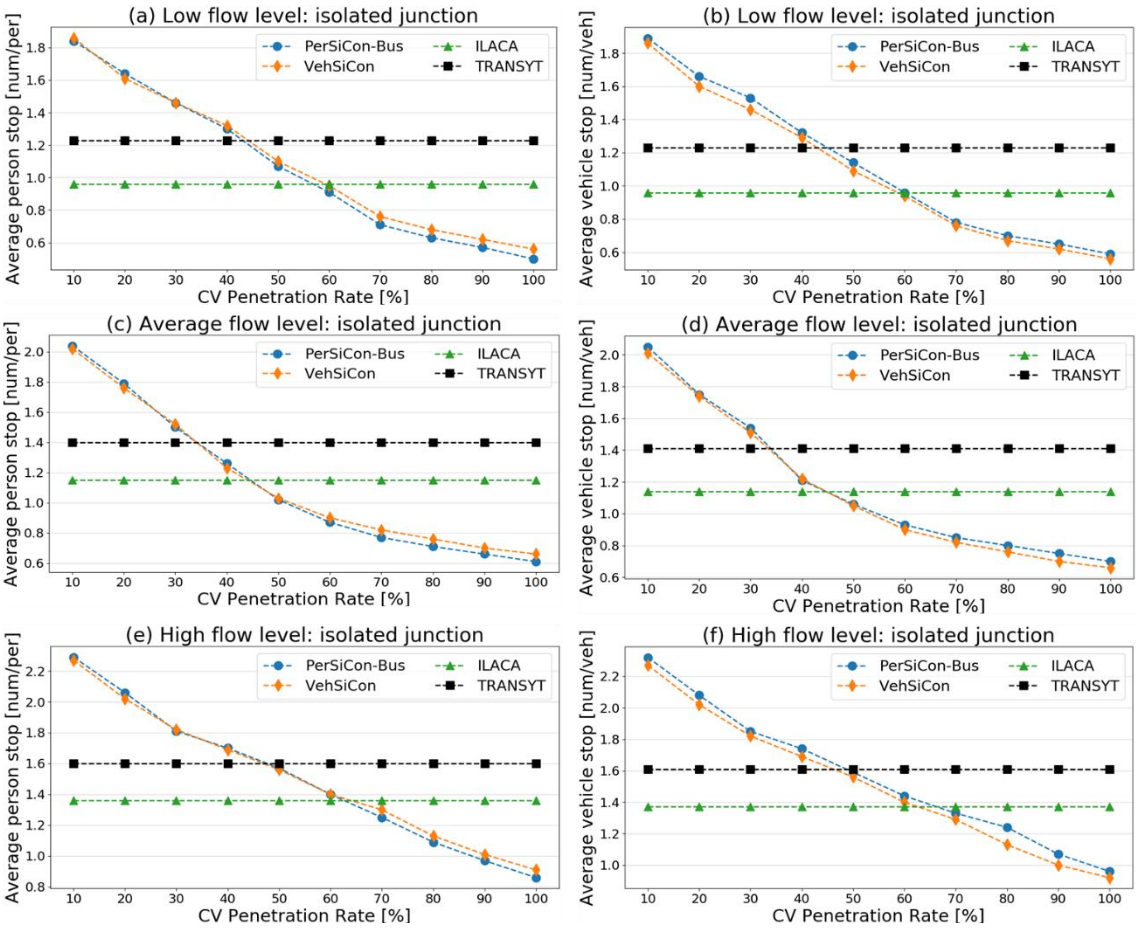

Figure 5. 11 Comparison of average passenger stop (num/per) and average vehicle stop (num/veh) of proposed algorithm PerSiCon-Bus and benchmarking algorithms in isolated junction under variety CV penetration rates and three flow levels

Table 5. 15 P-values in average person stop comparison for PerSiCon-Bus and three benchmarking models in isolated junction in different traffic flow demands and different CV penetration rates

	P-values for average person stop								
Flow level	Low			Average			High		
Signal controls	TRANSYT	ILACA	VehSiCon	TRANSYT	ILACA	VehSiCon	TRANSYT	ILACA	VehSiCon
100%	0.000	0.000	0.013	0.000	0.000	0.025	0.000	0.000	0.017
90%	0.000	0.000	0.016	0.000	0.000	0.031	0.000	0.000	0.030
80%	0.000	0.000	0.024	0.000	0.000	0.027	0.000	0.000	0.028
70%	0.000	0.000	0.037	0.000	0.000	0.038	0.000	0.000	0.044
60%	0.000	0.015	0.048	0.000	0.000	0.071	0.000	0.040	0.537
50%	0.000	0.000	0.082	0.000	0.000	0.211	0.000	0.000	0.199
40%	0.000	0.000	0.249	0.000	0.000	0.376	0.000	0.000	0.582
30%	0.000	0.000	0.913	0.000	0.000	0.240	0.000	0.000	0.625
20%	0.000	0.000	0.190	0.000	0.000	0.558	0.000	0.000	0.817
10%	0.000	0.000	0.572	0.000	0.000	0.362	0.000	0.000	0.762

Table 5. 16 P-values in average vehicle stop comparison for PerSiCon-Bus and three benchmarking models in isolated junction in different traffic flow demands and different CV penetration rates

	P-values for average vehicle stop								
Flow level	Low			Average			High		
Signal controls	TRANSYT	ILACA	VehSiCon	TRANSYT	ILACA	VehSiCon	TRANSYT	ILACA	VehSiCon
100%	0.000	0.000	0.027	0.000	0.000	0.047	0.000	0.000	0.032
90%	0.000	0.000	0.042	0.000	0.000	0.035	0.000	0.000	0.005
80%	0.000	0.000	0.039	0.000	0.000	0.041	0.000	0.000	0.012
70%	0.000	0.000	0.119	0.000	0.000	0.076	0.000	0.036	0.038
60%	0.000	0.871	0.378	0.000	0.000	0.213	0.000	0.000	0.083
50%	0.000	0.000	0.192	0.000	0.000	0.156	0.361	0.000	0.237
40%	0.000	0.000	0.485	0.000	0.003	0.712	0.000	0.000	0.411

30%	0.000	0.000	0.283	0.000	0.000	0.368	0.000	0.000	0.394
20%	0.000	0.000	0.423	0.000	0.000	0.871	0.000	0.000	0.347
10%	0.000	0.000	0.694	0.000	0.000	0.536	0.000	0.000	0.514

5.9.3 Changes to prediction horizons

As explained above, the suitable planning horizon for the proposed PerSiCon-Bus is uncertain. Therefore, it is essential to make a sensitivity analysis of the performance of the developed approach under a group of different predictive horizons. Figure 5.12 and Table 5.13 are sensitivity test results of average person/vehicle delay and stop values in different DP prediction horizons (10s, 20s, 30s, 40s, 50s, 60s) in different signal control methods. Table 5.17 – Table 5.20 are hypothesis test results.

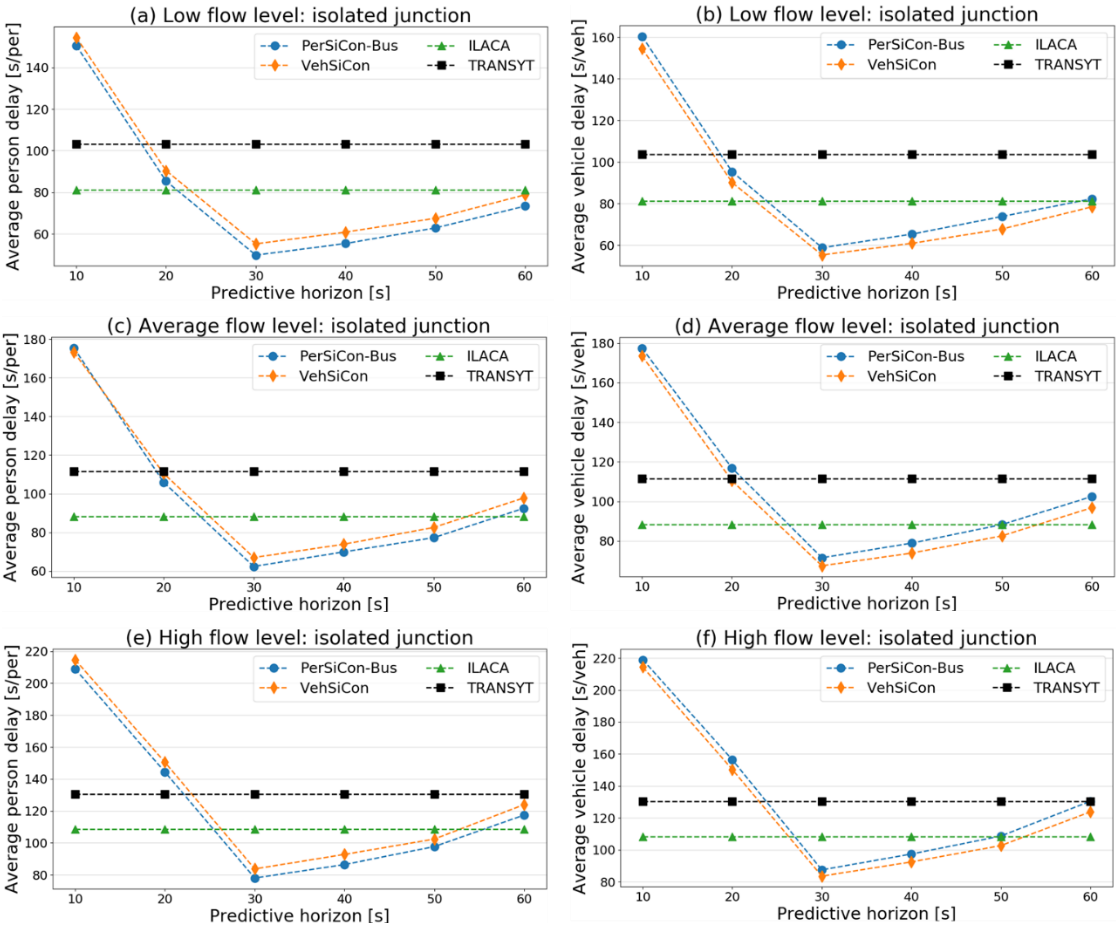

Figure 5. 12 Line charts of average person delay (s/per) and average vehicle delay (s/veh) of proposed algorithm and benchmarking algorithms in isolated junction under variety predictive horizons (s) and three flow levels. CV penetration rate is assumed to be 100%

Table 5. 17 P-values in average person delay comparison for PerSiCon-Bus and three benchmarking algorithms in isolated junction in different traffic flow demands and different prediction horizons (100% CV penetration rate)

	P-values for average person delay								
Flow level	Low			Average			High		
Signal controls	TRANSYT	ILACA	VehSiCon	TRANSYT	ILACA	VehSiCon	TRANSYT	ILACA	VehSiCon
10s	0.000	0.000	0.386	0.000	0.000	0.911	0.000	0.000	0.176
20s	0.000	0.015	0.013	0.000	0.000	0.004	0.000	0.000	0.006
30s	0.000	0.000	0.004	0.000	0.000	0.010	0.000	0.000	0.003
40s	0.000	0.000	0.018	0.000	0.000	0.019	0.000	0.000	0.008
50s	0.000	0.000	0.010	0.000	0.000	0.008	0.000	0.000	0.011
60s	0.000	0.000	0.014	0.000	0.000	0.017	0.000	0.000	0.021

Table 5. 18 P-values in average vehicle delay comparison for PerSiCon-Bus and three benchmarking algorithms in isolated junction in different traffic flow demands and different prediction horizons (100% CV penetration rate)

	P-values for average vehicle delay								
Flow level	Low			Average			High		
Signal controls	TRANSYT	ILACA	VehSiCon	TRANSYT	ILACA	VehSiCon	TRANSYT	ILACA	VehSiCon
10s	0.000	0.000	0.259	0.000	0.000	0.397	0.000	0.000	0.271
20s	0.000	0.000	0.032	0.007	0.000	0.034	0.000	0.000	0.027
30s	0.000	0.000	0.043	0.000	0.000	0.018	0.000	0.000	0.024
40s	0.000	0.000	0.037	0.000	0.000	0.026	0.000	0.000	0.035
50s	0.000	0.000	0.029	0.000	0.967	0.015	0.000	0.643	0.018
60s	0.000	0.421	0.040	0.000	0.000	0.022	0.814	0.000	0.014

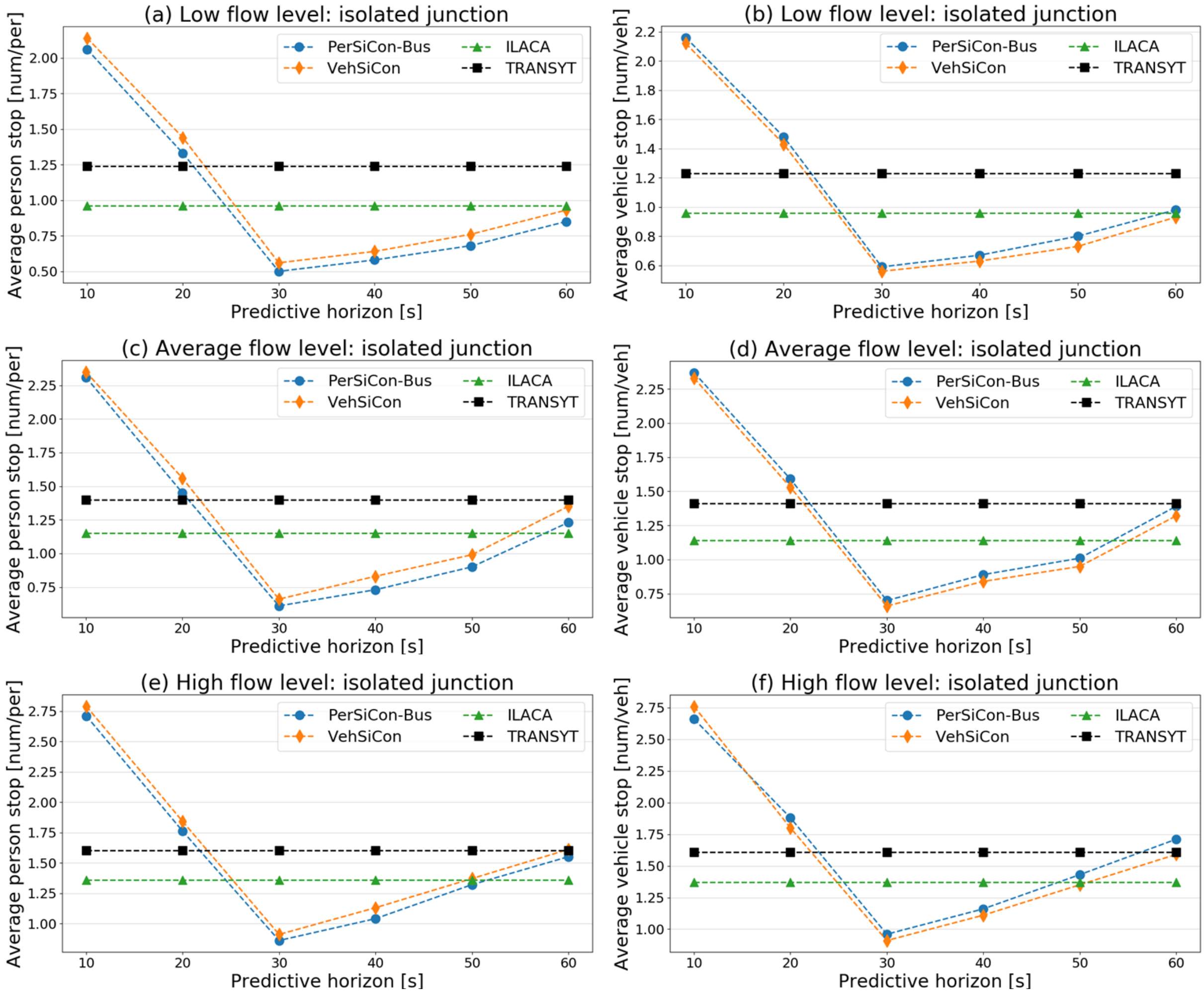

Figure 5. 13 Line charts of average person stop (num/per) and average vehicle stop (num/veh) of proposed algorithm and benchmarking algorithms in isolated junction under variety predictive horizons (s) and three flow levels. CV penetration rate is assumed to be 100%

Table 5. 19 P-values in average person stop comparison for PerSiCon-Bus and three benchmarking algorithms in isolated junction in different traffic flow demands and different prediction horizons (100% CV penetration rate)

	P-values for average person stop								
Flow level	Low			Average			High		
Signal controls	TRANSYT	ILACA	VehSiCon	TRANSYT	ILACA	VehSiCon	TRANSYT	ILACA	VehSiCon
10s	0.000	0.000	0.095	0.000	0.000	0.087	0.000	0.000	0.213
20s	0.000	0.000	0.002	0.027	0.000	0.021	0.000	0.000	0.005
30s	0.000	0.000	0.013	0.000	0.000	0.025	0.000	0.000	0.017
40s	0.000	0.000	0.022	0.000	0.000	0.016	0.000	0.000	0.026
50s	0.000	0.000	0.016	0.000	0.000	0.028	0.000	0.045	0.013

60s	0.000	0.000	0.009	0.000	0.007	0.031	0.036	0.000	0.008

Table 5. 20 P-values in average vehicle stop comparison for PerSiCon-Bus and three benchmarking algorithms in isolated junction in different traffic flow demands and different prediction horizons (100% CV penetration rate)

	P-values for average vehicle stop								
Flow level	Low			Average			High		
Signal controls	TRANSYT	ILACA	VehSiCon	TRANSYT	ILACA	VehSiCon	TRANSYT	ILACA	VehSiCon
10s	0.000	0.000	0.096	0.000	0.000	0.468	0.000	0.000	0.104
20s	0.000	0.000	0.021	0.000	0.000	0.031	0.000	0.000	0.019
30s	0.000	0.000	0.027	0.000	0.000	0.047	0.000	0.000	0.032
40s	0.000	0.000	0.026	0.000	0.000	0.037	0.000	0.000	0.026
50s	0.000	0.000	0.012	0.000	0.000	0.020	0.000	0.025	0.017
60s	0.000	0.288	0.009	0.419	0.000	0.017	0.001	0.000	0.012

From Figures 5.12 and 5.13, the performance of person/vehicle delay and stop in PerSiCon-Bus/VehSiCon present a similar tendency. As seen in Figures 5.12 and 5.13, there is a visible trough located at the planning duration 30s for the rolling horizon approach in the proposed PerSiCon-Bus/VehSiCon. The performance of TRANSYT and ILACA keep unchanged in different prediction horizon scenarios as the rolling horizon approach is only adopted in PerSiCon-Bus/VehSiCon. The average person/vehicle delays and stops of PerSiCon-Bus/VehSiCon rapidly decrease from 10s, 20s to 30s horizon, and slightly increase from 30s to 60s duration at a step of 10s. The results indicate that setting the planning horizon too short significantly degrades the performance of NPerSiCon-Network/ PerSiCon-Network in terms of people's number of stops due to limited signal plan choices and biased function values. The blanking periods of intergreen interval and start-up loss time occupying a considerable part of too short a planning horizon leads to no benefits to people discharging. The results are heavily biased when determining the traffic signal executions as signal schemes are generated based on the highest value function with rarely vehicles can be discharged, regardless of effects on signal phase switching for following saturated flows. The effects on cumulative deviation in long-time vehicle discharging prediction (40s, 50s, 60s) are comparable to less negative influences on the performance of ILACA. 30s are suggested to be selected as planning horizon and signal scheme operation cycles combing objective understanding of value function and accurate vehicle travel prediction in the group of six planning horizon choices.

Table 5.17 – Table 5.20 indicate the similar tendency of p-values of average person/vehicle delay and stop in different planning horizon plans in PerSiCon-Bus compared to reference models. PerSiCon-Bus presents significant improvements against VehSiCon when the prediction horizon is higher than or equal to 20s in all cases. However, when the prediction horizon is 10s, all of the p-values are above 0.05. The reason has been claimed above that 10s are not sufficient for implementing optimal solutions of PerSiCon-Bus/VehSiCon, resulting in a heavily degraded of their performance. Similar to the abnormal p-values in Section 5.9.3, there are also a few special cases where the p-values are higher than 0.05s with comparisons of TRANSYT or ILACA. For instance, 60s prediction horizon in low demand levels in Table 5.18 when compare to ILACA. The reason is also that the increasing mean values of average delay and stop are very close to the values in TRANSYT and ILACA in some special cases and the minor mean differences result in high p-values.

5.9.4 Changes to accumulation time weighted factors

Figures 5.14 and 5.15 illustrate the performance of average person/vehicle delay and stop of PerSiCon-Bus under different numbers of accumulation time weighted factor δ from 0 to 1 in Equation (3-2). Table 5.21 – Table 5.24 are hypothesis test results of PerSiCon-Bus and reference models in different accumulation time weighted factors. From Figures 5.14 and 5.15 the performance of PerSiCon-Bus present a similar tendency. The average person/vehicle delay and stop of PerSiCon-Bus/VehSiCon increase as the weighted factor δ rises. Figures 5.14 and 5.15 (a), (c) and (e) illustrate that the change ranges of average person delay and stop of PerSiCon-Bus are higher than those of VehSiCon.

On the contrary, the change ranges of average vehicle delay and stop of PerSiCon-Bus are lower than those of VehSiCon according to Figures 5.14 and 5.15 (b), (d) and (f). This is because the PerSiCon-Bus algorithm provides more right of ways to those low occupancy vehicles with high accumulation time and scarifies the crossing chances of high occupancy vehicles when the accumulation time weighted factor is high. The changes in accumulation time weighted factor also make negative influences the decision-making process of VehSiCon. However, the negative influences on VehSiCon are less than those on PerSiCon-Bus as all of the vehicles have the same priority levels.

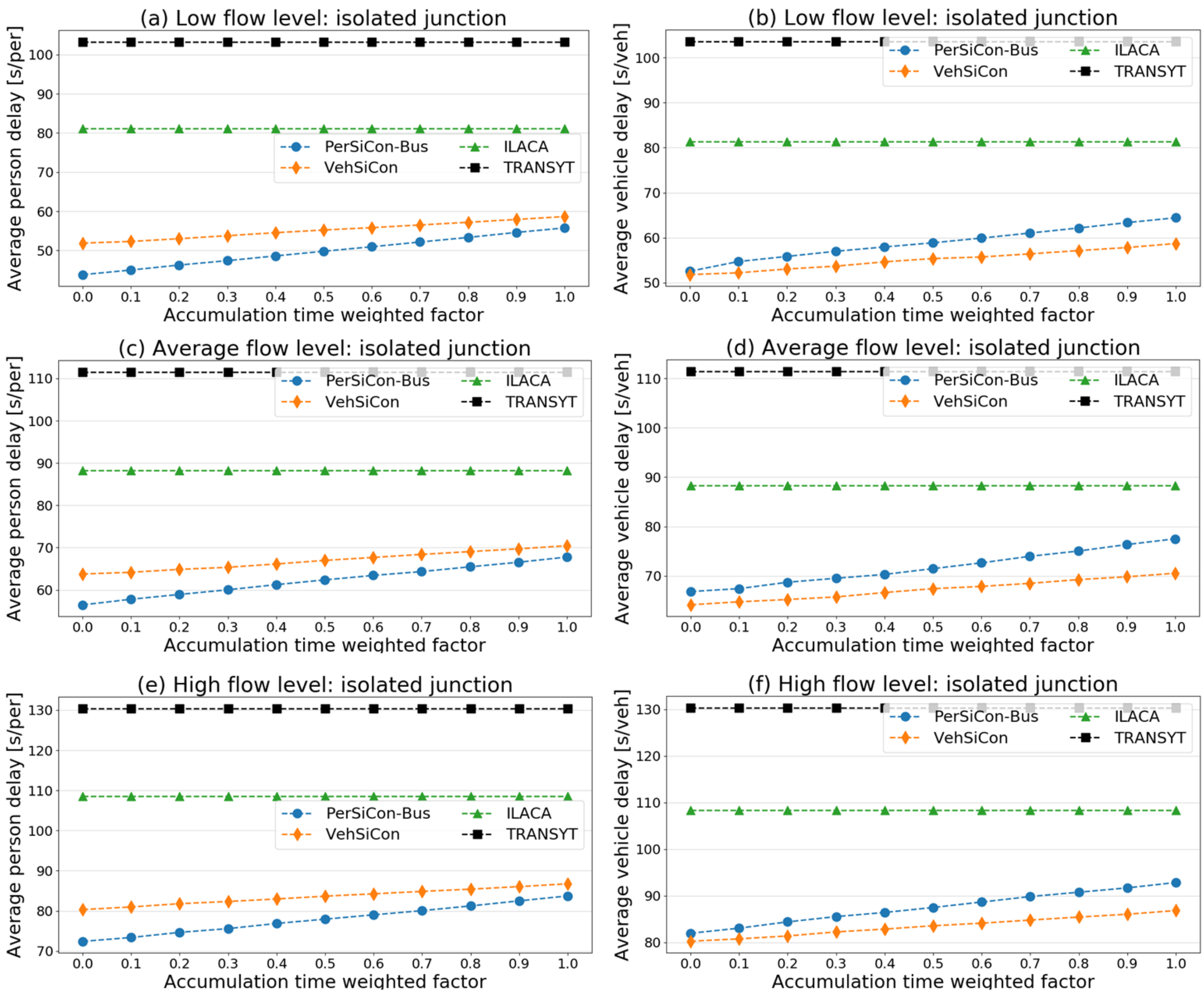

Figure 5. 14 Line charts of average person delay (s/per) and average vehicle delay (s/veh) of proposed algorithm and benchmarking algorithms in isolated junction under variety accumulation time weighted factors and three flow levels. CV penetration rate is assumed to be 100%

Table 5. 21 P-values in average person delay comparison for PerSiCon-Bus and three benchmarking algorithms in isolated junction in different traffic flow demands and different accumulation time weighted factors (100% CV penetration rate)

	P-values for average person delay								
Flow level	Low			Average			High		
Signal controls	TRANSYT	ILACA	VehSiCon	TRANSYT	ILACA	VehSiCon	TRANSYT	ILACA	VehSiCon
0	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
0.1	0.000	0.000	0.000	0.000	0.000	0.001	0.000	0.000	0.000
0.2	0.000	0.000	0.002	0.000	0.000	0.003	0.000	0.000	0.002
0.3	0.000	0.000	0.007	0.000	0.000	0.012	0.000	0.000	0.005

0.4	0.000	0.000	0.009	0.000	0.000	0.013	0.000	0.000	0.009
0.5	0.000	0.000	0.004	0.000	0.000	0.010	0.000	0.000	0.003
0.6	0.000	0.000	0.023	0.000	0.000	0.024	0.000	0.000	0.029
0.7	0.000	0.000	0.031	0.000	0.000	0.028	0.000	0.000	0.038
0.8	0.000	0.000	0.038	0.000	0.000	0.037	0.000	0.000	0.034
0.9	0.000	0.000	0.044	0.000	0.000	0.043	0.000	0.000	0.043
1.0	0.000	0.000	0.063	0.000	0.000	0.059	0.000	0.000	0.051

Table 5. 22 P-values in average vehicle delay comparison for PerSiCon-Bus and three benchmarking algorithms in isolated junction in different traffic flow demands and different accumulation time weighted factors (100% CV penetration rate)

	P-values for average vehicle delay								
Flow level	Low			Average			High		
Signal controls	TRANSYT	ILACA	VehSiCon	TRANSYT	ILACA	VehSiCon	TRANSYT	ILACA	VehSiCon
0	0.000	0.000	0.103	0.000	0.000	0.095	0.000	0.000	0.175
0.1	0.000	0.000	0.073	0.000	0.000	0.084	0.000	0.000	0.080
0.2	0.000	0.000	0.082	0.000	0.000	0.069	0.000	0.000	0.059
0.3	0.000	0.000	0.057	0.000	0.000	0.061	0.000	0.000	0.049
0.4	0.000	0.000	0.044	0.000	0.000	0.035	0.000	0.000	0.017
0.5	0.000	0.000	0.043	0.000	0.000	0.018	0.000	0.000	0.024
0.6	0.000	0.000	0.030	0.000	0.000	0.026	0.000	0.000	0.019
0.7	0.000	0.000	0.024	0.000	0.000	0.017	0.000	0.000	0.006
0.8	0.000	0.000	0.017	0.000	0.000	0.004	0.000	0.000	0.004
0.9	0.000	0.000	0.005	0.000	0.000	0.001	0.000	0.000	0.000
1.0	0.000	0.000	0.001	0.000	0.000	0.000	0.000	0.000	0.000

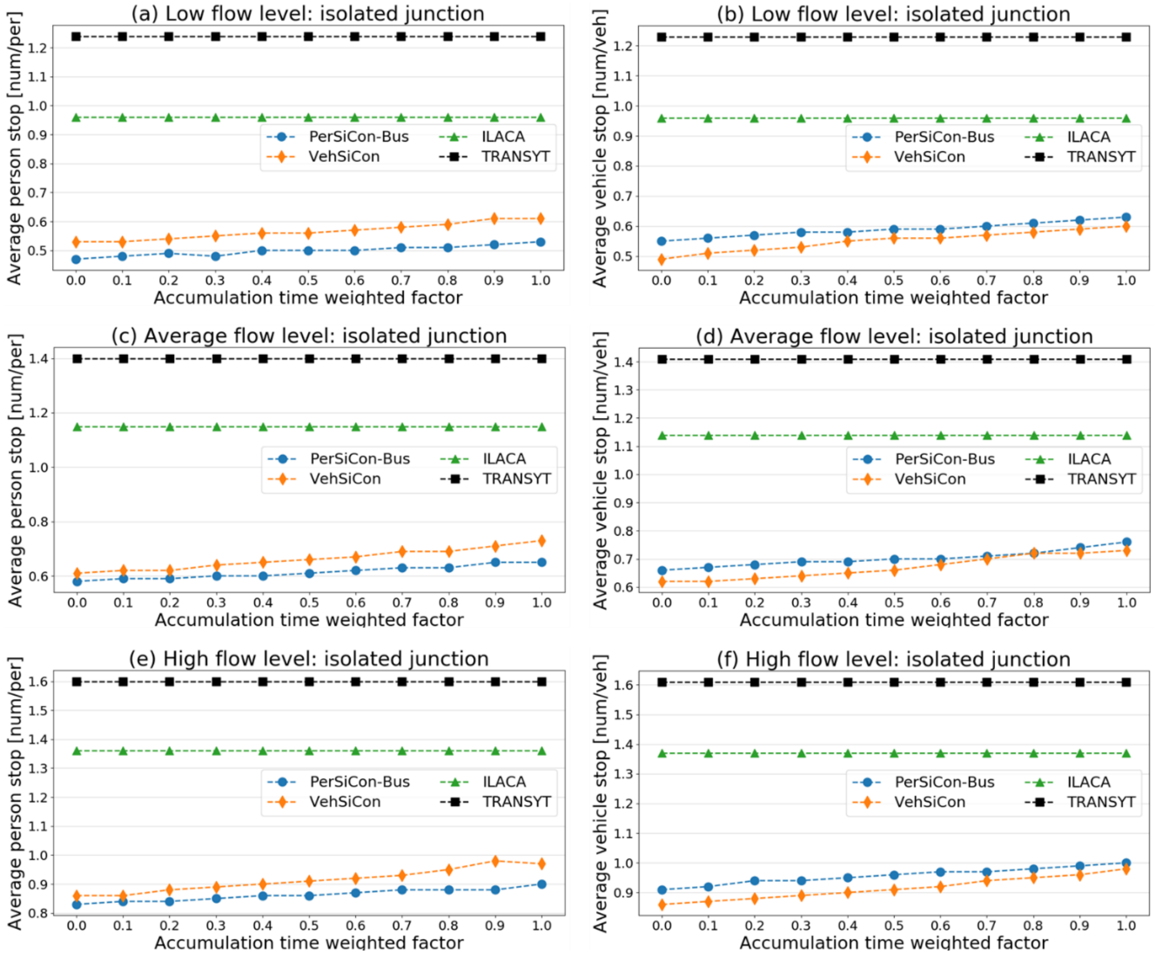

Figure 5. 15 Line charts of average person stop (num/per) and average vehicle stop (num/veh) of proposed algorithm and benchmarking algorithms in isolated junction under variety accumulation time weighted factors and three flow levels. CV penetration rate is assumed to be 100%

Table 5. 23 P-values in average person stop comparison for PerSiCon-Bus and three benchmarking algorithms in isolated junction in different traffic flow demands and different accumulation time weighted factors (100% CV penetration rate)

	P-values for average person stop								
Flow level	Low			Average			High		
Signal controls	TRANSYT	ILACA	VehSiCon	TRANSYT	ILACA	VehSiCon	TRANSYT	ILACA	VehSiCon
0	0.000	0.000	0.007	0.000	0.000	0.011	0.000	0.000	0.033
0.1	0.000	0.000	0.012	0.000	0.000	0.004	0.000	0.000	0.032
0.2	0.000	0.000	0.009	0.000	0.000	0.010	0.000	0.000	0.024
0.3	0.000	0.000	0.015	0.000	0.000	0.019	0.000	0.000	0.017
0.4	0.000	0.000	0.011	0.000	0.000	0.015	0.000	0.000	0.026
0.5	0.000	0.000	0.013	0.000	0.000	0.025	0.000	0.000	0.017

0.6	0.000	0.000	0.031	0.000	0.000	0.023	0.000	0.000	0.033
0.7	0.000	0.000	0.028	0.000	0.000	0.034	0.000	0.000	0.019
0.8	0.000	0.000	0.039	0.000	0.000	0.036	0.000	0.000	0.036
0.9	0.000	0.000	0.044	0.000	0.000	0.047	0.000	0.000	0.041
1.0	0.000	0.000	0.047	0.000	0.000	0.068	0.000	0.000	0.073

Table 5. 24 P-values in average vehicle stop comparison for PerSiCon-Bus and three benchmarking algorithms in isolated junction in different traffic flow demands and different accumulation time weighted factors (100% CV penetration rate)

	P-values for average vehicle stop								
Flow level	Low			Average			High		
Signal controls	TRANSYT	ILACA	VehSiCon	TRANSYT	ILACA	VehSiCon	TRANSYT	ILACA	VehSiCon
0	0.000	0.000	0.051	0.000	0.000	0.062	0.000	0.000	0.048
0.1	0.000	0.000	0.046	0.000	0.000	0.043	0.000	0.000	0.035
0.2	0.000	0.000	0.023	0.000	0.000	0.039	0.000	0.000	0.038
0.3	0.000	0.000	0.036	0.000	0.000	0.034	0.000	0.000	0.031
0.4	0.000	0.000	0.029	0.000	0.000	0.025	0.000	0.000	0.026
0.5	0.000	0.000	0.027	0.000	0.000	0.047	0.000	0.000	0.032
0.6	0.000	0.000	0.034	0.000	0.000	0.041	0.000	0.000	0.029
0.7	0.000	0.000	0.025	0.000	0.000	0.036	0.000	0.000	0.015
0.8	0.000	0.000	0.019	0.000	0.000	0.027	0.000	0.000	0.020
0.9	0.000	0.000	0.008	0.000	0.000	0.023	0.000	0.000	0.018
1.0	0.000	0.000	0.031	0.000	0.000	0.011	0.000	0.000	0.023

The change ranges of average person/vehicle delays and stops of PerSiCon-Bus and VerSiCon are also reflected in hypothesis test results in Table 5.21 – Table 5.24. It can be found that in some cases in Tables 5.21 and 5.23 when accumulation time weighted factor equals 1, there is no significant difference between average person delay and stop of PerSiCon-Bus and VerSiCon. On the contrary, in some cases in Tables 5.22 and 5.24 when the weighted factor equals 0, the average vehicle delay and stop of PerSiCon-Bus are not significantly different against VerSiCon.

The reason is that with the increments of weighted factor δ, PerSiCon-Bus incorporates more considerations of those low occupancy vehicles which wait quite a long time at the junction. The adjustments of signal control decisions provide more opportunities to provide the green time for low occupancy vehicles and thus the summation values of average person/vehicle delay and number of stop increase with higher change ranges than VerSiCon. As a result, the most appropriate value of weighted factor δ is considered to be 0.5 to make a balance between providing priorities to high occupancy vehicles and taking into account the accumulation time of low occupancy vehicles.

5.9.5 Changes to bus occupancy levels

Figures 5.16 and 5.17 show the average person/vehicle delay and stop of vehicles of the proposed algorithm PerSiCon-Bus under three flow scenarios if bus occupancy ranges from 2 to 50 passenger/veh. Table 5.25 – Table 5.28 present p-values of PerSiCon-Bus compared to reference models in various experiments. It can be seen from Figures 5.16 and 5.17 that KPIs of PerSiCon-Bus keep unchanged when bus occupancy is higher than or equal to 8 passenger/veh. The average person delay and stop slightly increase, but the average vehicle delay and stop slightly decrease when bus occupancy is lower than 8 passengers/veh. Meanwhile, the performance of PerSiCon-Bus have only minor fluctuations so they are significantly different to the performance of reference models in all scenarios in Table 5.25 – Table 5.28. The causes of the phenomenon are buses only make up a very small part of vehicle dynamics and their performance changes have minor influences on the summation. In PerSiCon-Bus, the priority levels of buses are determined by comprehensive results of bus occupancy, bus length, bus headway, and predictive arrival and departure time. Discharging a bus costs a higher green time right of way than discharging a vehicle. Therefore, the junction controller provides the right of way for a car rather than a bus if their priority levels of them are the same, which heavily increases the travelling delay of buses.

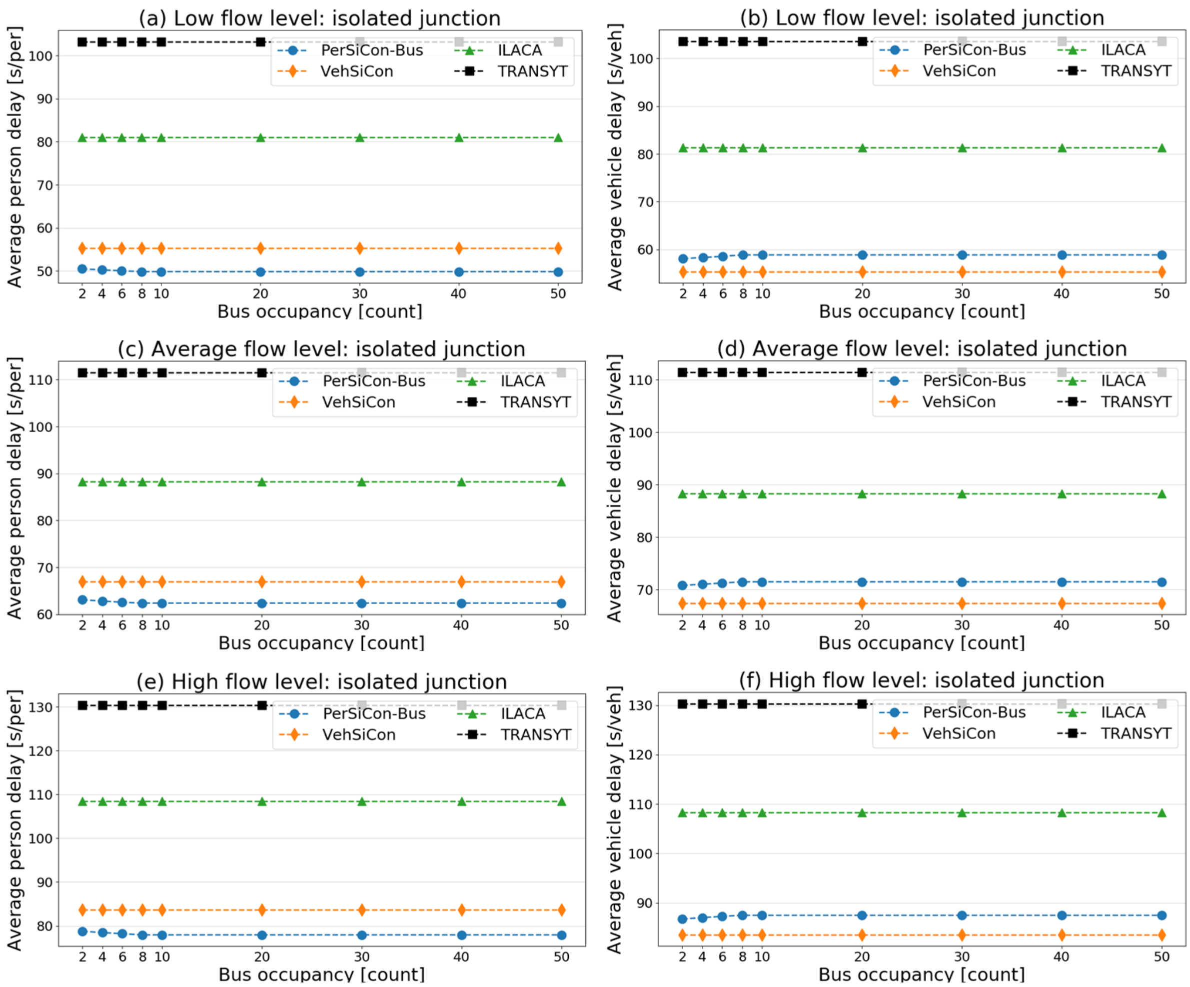

Figure 5. 16 Line charts of average person delay (s/per) and average vehicle delay (s/veh) of proposed algorithm and benchmarking algorithms in isolated junction under variety bus occupancy levels and three flow levels. CV penetration rate is assumed to be 100%

Table 5. 25 P-values in average person delay comparison for PerSiCon-Bus and three benchmarking algorithms in isolated junction in different traffic flow demands and different bus occupancy levels (100% CV penetration rate)

	P-values for average person delay								
Flow level	Low			Average			High		
Signal controls	TRANSYT	ILACA	VehSiCon	TRANSYT	ILACA	VehSiCon	TRANSYT	ILACA	VehSiCon
2	0.000	0.000	0.013	0.000	0.000	0.019	0.000	0.000	0.007
4	0.000	0.000	0.008	0.000	0.000	0.012	0.000	0.000	0.002
6	0.000	0.000	0.005	0.000	0.000	0.016	0.000	0.000	0.005
8	0.000	0.000	0.004	0.000	0.000	0.010	0.000	0.000	0.003
10	0.000	0.000	0.004	0.000	0.000	0.010	0.000	0.000	0.003

20	0.000	0.000	0.004	0.000	0.000	0.010	0.000	0.000	0.003
30	0.000	0.000	0.004	0.000	0.000	0.010	0.000	0.000	0.003
40	0.000	0.000	0.004	0.000	0.000	0.010	0.000	0.000	0.003
50	0.000	0.000	0.004	0.000	0.000	0.010	0.000	0.000	0.003

Table 5. 26 P-values in average vehicle delay comparison for PerSiCon-Bus and three benchmarking algorithms in isolated junction in different traffic flow demands and different bus occupancy levels (100% CV penetration rate)

	P-values for average vehicle delay								
Flow level	Low			Average			High		
Signal controls	TRANSYT	ILACA	VehSiCon	TRANSYT	ILACA	VehSiCon	TRANSYT	ILACA	VehSiCon
2	0.000	0.000	0.047	0.000	0.000	0.021	0.000	0.000	0.028
4	0.000	0.000	0.044	0.000	0.000	0.016	0.000	0.000	0.027
6	0.000	0.000	0.045	0.000	0.000	0.018	0.000	0.000	0.022
8	0.000	0.000	0.043	0.000	0.000	0.018	0.000	0.000	0.024
10	0.000	0.000	0.043	0.000	0.000	0.018	0.000	0.000	0.024
20	0.000	0.000	0.043	0.000	0.000	0.018	0.000	0.000	0.024
30	0.000	0.000	0.043	0.000	0.000	0.018	0.000	0.000	0.024
40	0.000	0.000	0.043	0.000	0.000	0.018	0.000	0.000	0.024
50	0.000	0.000	0.043	0.000	0.000	0.018	0.000	0.000	0.024

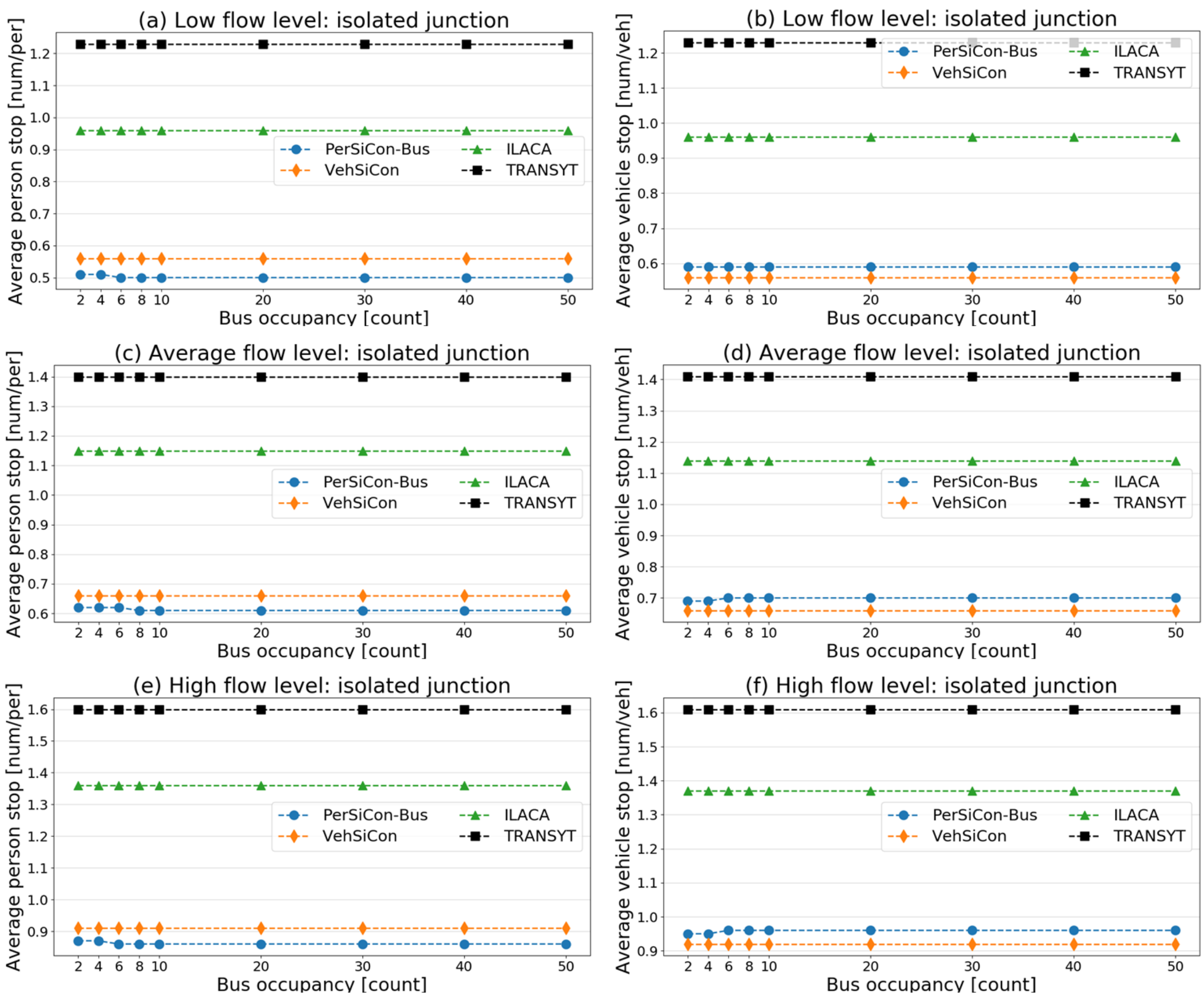

Figure 5. 17 Line charts of average person stop (num/per) and average vehicle stop (num/veh) of proposed algorithm and benchmarking algorithms in isolated junction under variety bus occupancy levels and three flow levels. CV penetration rate is assumed to be 100%

Table 5. 27 P-values in average person stop comparison for PerSiCon-Bus and three benchmarking algorithms in isolated junction in different traffic flow demands and different bus occupancy levels (100% CV penetration rate)

	P-values for average person stop								
Flow level	Low			Average			High		
Signal controls	TRANSYT	ILACA	VehSiCon	TRANSYT	ILACA	VehSiCon	TRANSYT	ILACA	VehSiCon
2	0.000	0.000	0.019	0.000	0.000	0.020	0.000	0.000	0.019
4	0.000	0.000	0.017	0.000	0.000	0.028	0.000	0.000	0.016
6	0.000	0.000	0.014	0.000	0.000	0.024	0.000	0.000	0.021
8	0.000	0.000	0.013	0.000	0.000	0.025	0.000	0.000	0.017
10	0.000	0.000	0.013	0.000	0.000	0.025	0.000	0.000	0.017

20	0.000	0.000	0.013	0.000	0.000	0.025	0.000	0.000	0.017
30	0.000	0.000	0.013	0.000	0.000	0.025	0.000	0.000	0.017
40	0.000	0.000	0.013	0.000	0.000	0.025	0.000	0.000	0.017
50	0.000	0.000	0.013	0.000	0.000	0.025	0.000	0.000	0.017

Table 5. 28 P-values in average vehicle stop comparison for PerSiCon-Bus and three benchmarking algorithms in isolated junction in different traffic flow demands and different bus occupancy levels (100% CV penetration rate)

	P-values for average vehicle stop								
Flow level	Low			Average			High		
Signal controls	TRANSYT	ILACA	VehSiCon	TRANSYT	ILACA	VehSiCon	TRANSYT	ILACA	VehSiCon
2	0.000	0.000	0.033	0.000	0.000	0.049	0.000	0.000	0.031
4	0.000	0.000	0.028	0.000	0.000	0.044	0.000	0.000	0.034
6	0.000	0.000	0.030	0.000	0.000	0.048	0.000	0.000	0.032
8	0.000	0.000	0.027	0.000	0.000	0.047	0.000	0.000	0.032
10	0.000	0.000	0.027	0.000	0.000	0.047	0.000	0.000	0.032
20	0.000	0.000	0.027	0.000	0.000	0.047	0.000	0.000	0.032
30	0.000	0.000	0.027	0.000	0.000	0.047	0.000	0.000	0.032
40	0.000	0.000	0.027	0.000	0.000	0.047	0.000	0.000	0.032
50	0.000	0.000	0.027	0.000	0.000	0.047	0.000	0.000	0.032

To make things clearer, Figure 5.18 lists the average person delay and stop of passenger cars and buses separately. 5.18 illustrates that the average passenger delays of buses and cars keep unchanged when bus occupancy is higher than or equal to 8 passenger/veh. However, the average passenger delay of buses is significantly degraded if bus occupancy is lower than 8 passengers/veh, and is even worse than the average passenger delay of cars when bus occupancy is 2 passengers/veh. Meanwhile, the average passenger delay of cars slightly improves as bus occupancy decreases. The results indicate that the priority levels of buses are less than those of cars with the same occupants as the predictive discharging time of buses is relatively high compared with cars. Since the average person's delay and stop of passenger cars only make minor changes and they occupy a large proportion of vehicle compositions on road, the summation delay and stop of PerSiCon-Bus do not change obviously. Table 5.25 – Table 5.28 prove that the summation average person delay and stop of PerSiCon-Bus have a significant difference against other control methods in all kinds of bus occupancy levels.

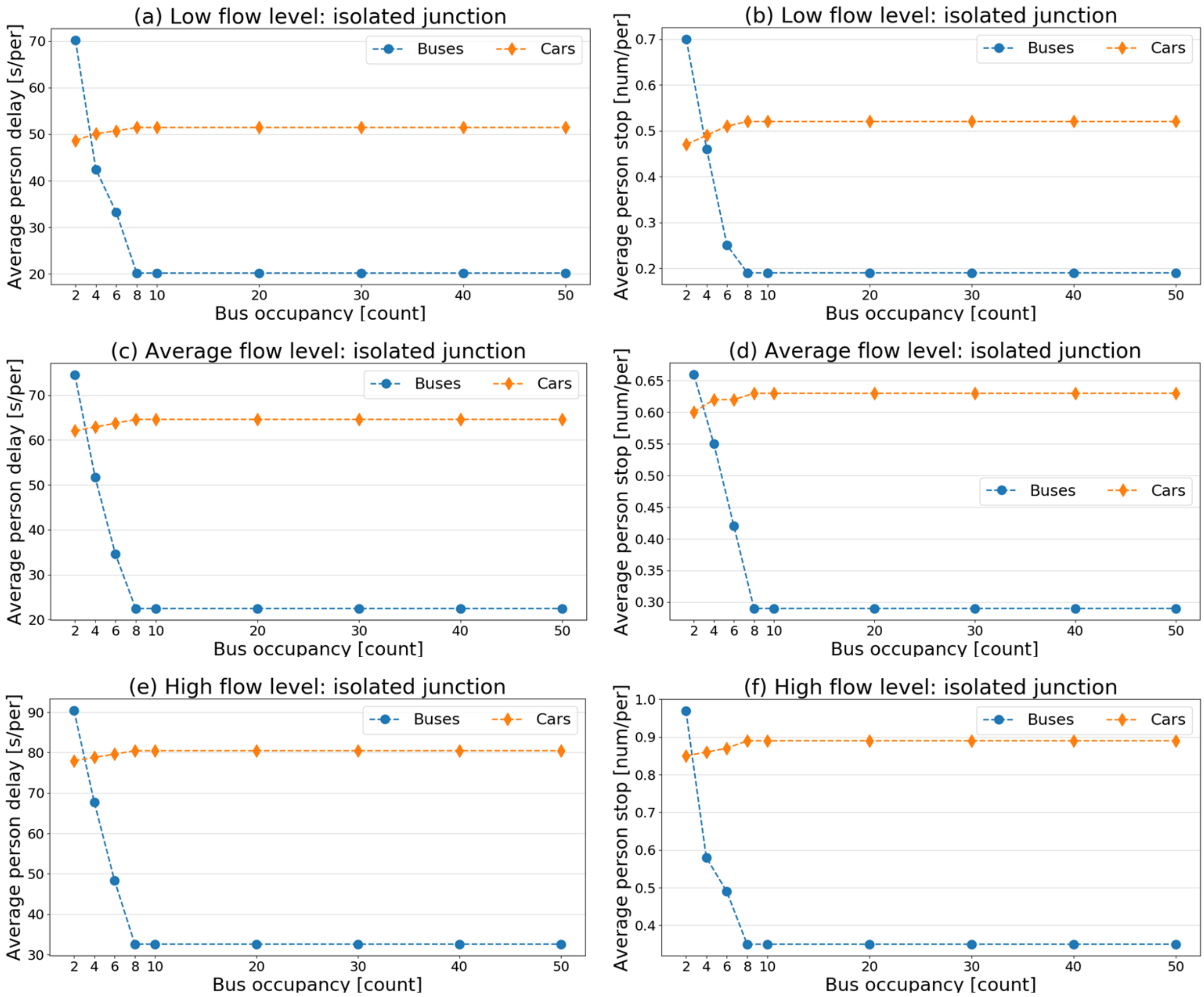

Figure 5. 18 Average person delay (s/per) and average person stop (num/per) of cars and buses respectively of proposed algorithm PerSiCon-Bus and under variety bus occupancy levels and three flow levels with mixture of cars and buses

5.10 Results and discussions for road network case study

Section 5.9 presents and analyses the results of PerSiCon-Bus in an isolated junction. This section presents and analyses the results of the coordination version of the proposed algorithm PerSiCon-Network, which is evaluated in the road network case study. The detailed performance of PerSiCon-Network and reference algorithms in various experiments with different sensitivity factors are also illustrated in this section.

5.10.1 General results

This section presents the general simulated results of PerSiCon-Network with benchmarking models in mixture vehicle environments in the road network. Tables 5.29 and 5.30 compare the average person/vehicle delay and stop of the proposed PerSiCon-Network to those obtained from TRANSYT-Network, ILACA-Network and VehSiCon-Network under three different flow levels (low, average and high), in the vehicular mixtures of cars and buses respectively. The summations of average person delay, average vehicle delay and average delays of cars and buses in different occupancy levels are also represented in Table 5.29. Table 5.30 shows the average person stop, average vehicle stop and average stops of vehicles with different occupancy levels. Table 5.31 and Table 5.32 show the hypothesis test results of average person/vehicle delay and stop of PerSiCon-Network against three benchmarking models at a 95% confidence level. The null hypothesis is that the average performance of PerSiCon-Network do not have a significant difference from another control method. The details are discussed below.

Table 5. 29 Comparison of average passenger delay (s/per) and average vehicle delay (s/veh) of the proposed algorithm and benchmarking algorithms under three flow scenarios in 100% CVs penetration rate with a mixture of cars and buses

Flow level	Control methods	Cars with 4 occups	Cars with 3 occus	Cars with 2 occups	Cars with 1 occup	Buses with 30 occups	Average passenger delay	Average vehicle delay
Low	TRANSYT- Network	127.62	128.79	127.18	129.07	129.27	127.45	128.15
	ILACA- Network	97.31	98.43	97.18	96.95	98.25	97.38	97.49
	VehSiCon- Network	68.85	68.16	68.91	67.82	68.19	68.34	68.42
	PerSiCon- Network	47.86	53.82	59.13	84.46	25.63	63.88	71.91
Average	TRANSYT- Network	133.24	134.52	134.68	132.07	132.56	134.23	133.71
	ILACA- Network	104.02	105.03	104.11	103.87	105.62	104.27	104.58
	VehSiCon- Network	77.43	76.08	76.92	75.49	76.21	76.32	76.26
	PerSiCon- Network	52.77	58.19	61.65	93.06	29.27	69.12	79.15
High	TRANSYT- Network	156.54	155.46	155.89	154.51	155.85	155.87	155.84
	ILACA- Network	122.68	123.87	122.85	124.03	123.76	123.44	123.59
	VehSiCon- Network	95.90	96.68	94.73	94.93	95.31	95.25	95.41
	PerSiCon- Network	72.57	77.69	83.39	111.07	44.23	89.14	98.43

Table 5. 30 Comparison of average passenger stop (num/per) and average vehicle stop (num/veh) of the proposed algorithm and benchmarking algorithms under three flow scenarios in 100% CVs penetration rate with a mixture of cars and buses

Flow level	Control methods	Cars with 4 occups	Cars with 3 occups	Cars with 2 occups	Cars with 1 occup	Buses with 30 occup	Average passenger delay	Average vehicle delay
Low	TRANSYT- Network	1.80	1.78	1.81	1.82	1.80	1.81	1.81
	ILACA- Network	1.16	1.18	1.15	1.17	1.13	1.17	1.16
	VehSiCon- Network	0.73	0.74	0.75	0.73	0.75	0.74	0.73
	PerSiCon- Network	0.59	0.64	0.73	0.92	0.33	0.70	0.76
Average	TRANSYT- Network	1.86	1.84	1.87	1.83	1.86	1.85	1.85
	ILACA- Network	1.25	1.25	1.24	1.26	1.24	1.25	1.25

	VehSiCon- Network	0.80	0.77	0.79	0.81	0.79	0.80	0.79
	PerSiCon- Network	0.68	0.70	0.77	0.99	0.45	0.74	0.82
High	TRANSYT- Network	2.07	2.05	2.06	2.05	2.08	2.06	2.05
	ILACA- Network	1.48	1.50	1.47	1.49	1.48	1.48	1.48
	VehSiCon- Network	1.20	1.18	1.17	1.21	1.16	1.18	1.19
	PerSiCon- Network	0.69	0.78	0.83	1.55	0.56	1.04	1.23

Table 5. 31 P-values in average person delay comparison for PerSiCon-Network and three benchmarking models in different traffic flow demands with a mixture of cars and buses in 100% CV penetration rate road network

Average person delay comparison	P-values			Average vehicle delay comparison	P-values		
	TRANSYT-Network	ILACA-Network	VehSiCon-Network		TRANSYT-Network	ILACA-Network	VehSiCon-Network
Low	0.000	0.000	0.005	Low	0.000	0.000	0.039
Average	0.000	0.000	0.001	Average	0.000	0.000	0.046
High	0.000	0.000	0.002	High	0.000	0.000	0.025

Table 5. 32 P-values in average person stop comparison for PerSiCon-Network and three benchmarking models in different traffic flow demands with a mixture of cars and buses in 100% CV penetration rate road network

Average person stop comparison	P-values			Average vehicle Stop comparison	P-values		
	TRANSYT-Network	ILACA-Network	VehSiCon-Network		TRANSYT-Network	ILACA-Network	VehSiCon-Network
Low	0.000	0.000	0.018	Low	0.000	0.000	0.031
Average	0.000	0.000	0.002	Average	0.000	0.000	0.043
High	0.000	0.000	0.000	High	0.000	0.000	0.036

The general results of signal control operations with their coordination versions in the road network are very similar to the results of signal control operations in the isolated junction. From Table 5.29, the results show that the proposed PerSiCon-Network outperforms other control methods in average person delay of all vehicles in the presence of buses, with reductions of 42.8% - 49.9% against TRANSYT-Network, 27.8% - 34.4% against ILACA-Network and 6.4% - 9.4% against

VehSiCon-Network respectively in the road network. Table 5.30 also illustrates similar results that PerSiCon-Network reduces average person stop by 49.5% - 61.3% compared to TRANSYT-Network, 29.7% - 40.8% compared to ILACA-Network and 7.5% - 16.7% compared to VehSiCon-Network. The hypothesis test results from Tables 5.31 and 5.32 can also be evident that average person delay and stop of PerSiCon-Network are significantly different to any one of the control methods in three flow levels, where the null hypothesis should be rejected at a 95% confidence level.

Similar to the general results in the isolated junction case study in Section 5.9.1, the signal control methods using CV data achieve fewer average person delays and stops because vehicular data from CVs provide a more accurate estimation of vehicle crossing time than infrastructure sensors such as inductive loops or pre-determined off-line signal optimization. The optimization process of TRANSYT-Network cannot react to the real-time traffic dynamics, which heavily degrades the performance of TRANSYT-Network. ILACA-Network also causes higher average person delay and stop due to imprecise estimation of road conditions, queue length discharging time, stage switching and green extension by inductive loop sensors. The detectors in ILACA-Network only partially react to flow demand and adjustments for signal plans are not as accurate as VehSiCon-Network and PerSiCon-Network in the absence of vehicle instantaneous trajectories from CVs, resulting in a higher frequency of mode switching between queuing and discharging statuses to cause more average stops.

More precisely, it can be observed from Table 5.29 and Table 5.30 that the average delays and stops of high-occupancy cars (cars with 2, 3 or 4 occupants) and buses with a mean of 13.2 passengers in PerSiCon-Network are significantly reduced compared to those in benchmarking models. In terms of cars with 4 occupants and buses, the average delay them are 24.3% - 31.8% and 53.6% - 62.4% less than those in vehicle-based approach VehSiCon-Network using CVs data with the objective of minimising vehicle delay in all cases. However, the average delays of 1-occupancy vehicles in PerSiCon-Network are larger than those in VehSiCon-Network. As expected, the proposed algorithm provides more crossing opportunities for high-occupancy vehicles and scarifies the travel time of 1-occupancy vehicles through more flexible signal timing plans in 8-phases junction to reduce the average delay of all drivers and passengers. Therefore, the vehicles with high occupancy levels cross the junction at the earliest chance and they suffer fewer vehicle delays and stops. The summation person delay and stop in PerSiCon-Network can be reduced as the delays and stops of more passengers in high occupancy levels are decreased.

5.10.2 Sensitivity analysis to CV penetration rate

As claimed in Section 5.8, a group of scenarios are carried out with different parameters of CV penetration rates, prediction horizons, accumulation time weighted factors and bus occupancy levels. Figures 5.19 and 5.20 illustrate how the KPIs of the proposed algorithm and benchmarking models change with different CV penetration rates (average person/vehicle delay in Figure 5.19 and average person/vehicle stop in Figure 5.20 with mixture situations of cars and buses on the road network. Table 5.33 - Table 5.36 are hypothesis test results for different CV penetration rates at a 95% confidence level.

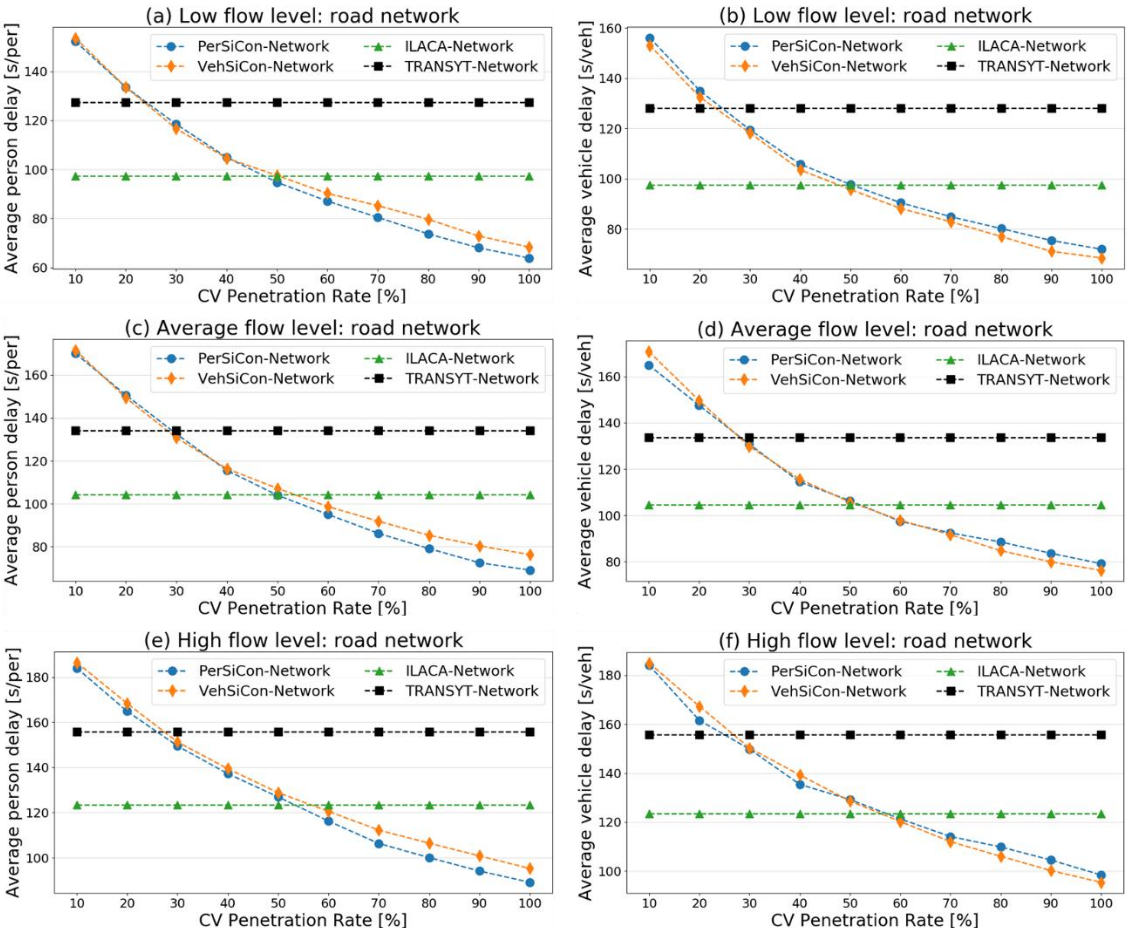

Figure 5. 19 Comparison of average passenger delay (s/per) and average vehicle delay (s/veh) of proposed algorithm PerSiCon-Network and benchmarking algorithms in road network under variety CV penetration rates and three flow levels

Table 5. 33 P-values in average person delay comparison for PerSiCon-Network and three benchmarking models in road network in different traffic flow demands and different CV penetration rates

	P-values for average person delay		
Flow level	Low	Average	High

Signal controls	TRANSYT	ILACA	VehSiCon	TRANSYT	ILACA	VehSiCon	TRANSYT	ILACA	VehSiCon
100%	0.000	0.000	0.005	0.000	0.000	0.001	0.000	0.000	0.002
90%	0.000	0.000	0.011	0.000	0.000	0.0004	0.000	0.000	0.011
80%	0.000	0.000	0.021	0.000	0.000	0.013	0.000	0.000	0.016
70%	0.000	0.000	0.034	0.000	0.000	0.032	0.000	0.000	0.030
60%	0.000	0.000	0.045	0.000	0.000	0.043	0.000	0.000	0.037
50%	0.000	0.073	0.064	0.000	0.382	0.052	0.000	0.084	0.280
40%	0.000	0.000	0.093	0.000	0.000	0.276	0.000	0.000	0.367
30%	0.000	0.000	0.147	0.155	0.000	0.359	0.080	0.000	0.310
20%	0.003	0.000	0.326	0.000	0.000	0.320	0.000	0.000	0.173
10%	0.000	0.000	0.417	0.000	0.000	0.498	0.000	0.000	0.441

Table 5. 34 P-values in average vehicle delay comparison for PerSiCon-Network and three benchmarking models in road network in different traffic flow demands and different CV penetration rates

	P-values for average vehicle delay								
Flow level	Low			Average			High		
Signal controls	TRANSYT	ILACA	VehSiCon	TRANSYT	ILACA	VehSiCon	TRANSYT	ILACA	VehSiCon
100%	0.000	0.000	0.039	0.000	0.000	0.046	0.000	0.000	0.025
90%	0.000	0.000	0.036	0.000	0.000	0.043	0.000	0.000	0.037
80%	0.000	0.000	0.041	0.000	0.000	0.041	0.000	0.000	0.028
70%	0.000	0.000	0.205	0.000	0.000	0.158	0.000	0.041	0.257
60%	0.000	0.000	0.157	0.000	0.011	0.832	0.000	0.031	0.625
50%	0.000	0.195	0.336	0.000	0.246	0.347	0.000	0.240	0.510
40%	0.000	0.000	0.674	0.000	0.000	0.559	0.000	0.000	0.267
30%	0.231	0.000	0.813	0.127	0.000	0.416	0.036	0.000	0.756
20%	0.000	0.000	0.549	0.000	0.000	0.742	0.041	0.000	0.315
10%	0.000	0.000	0.357	0.000	0.000	0.467	0.000	0.000	0.823

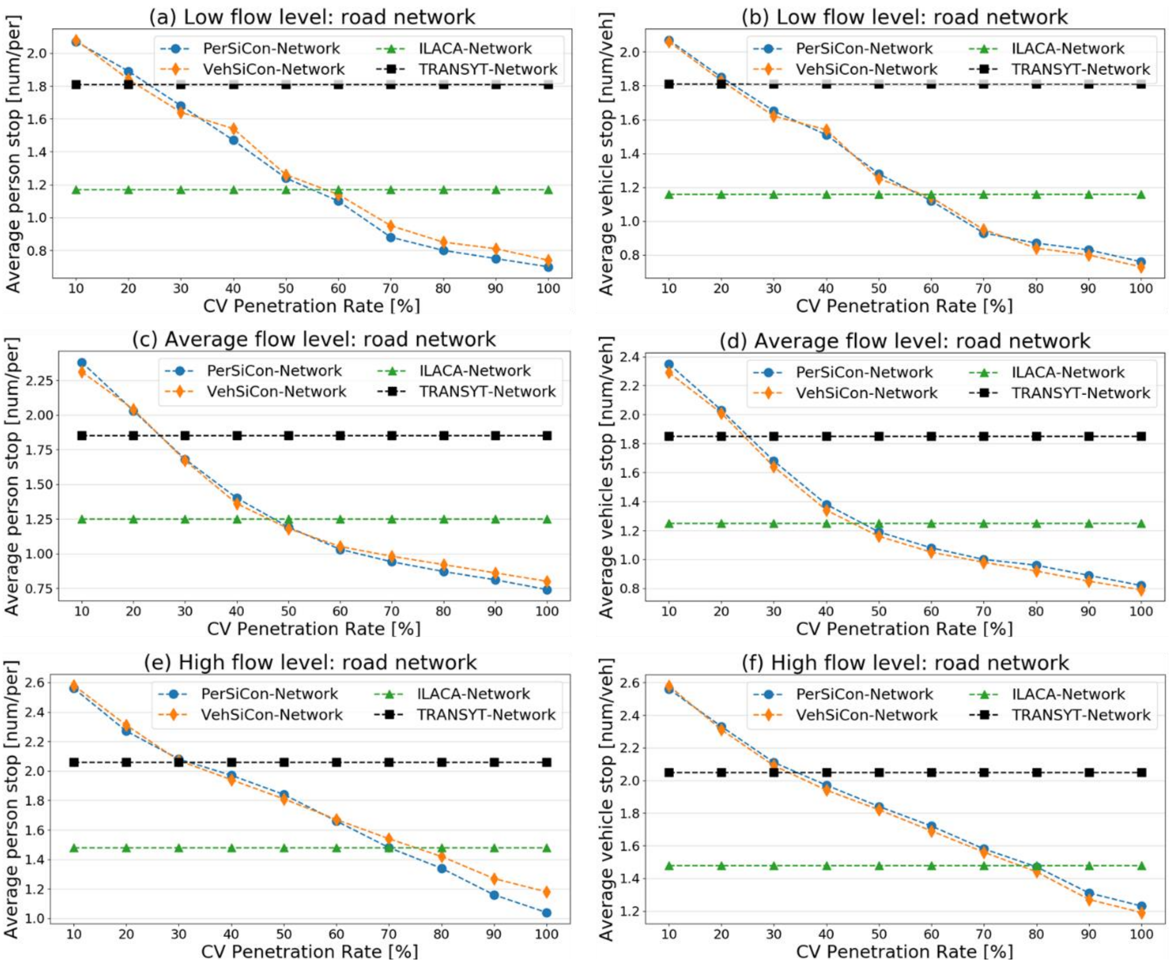

Figure 5. 20 Comparison of average passenger stop (num/per) and average vehicle stop (num/veh) of proposed algorithm PerSiCon-Network and benchmarking algorithms in road network under variety CV penetration rates and three flow levels

Table 5. 35 P-values in average person stop comparison for PerSiCon-Network and three benchmarking models in road network in different traffic flow demands and different CV penetration rates

	P-values for average person stop								
Flow level	Low			Average			High		
Signal controls	TRANSYT	ILACA	VehSiCon	TRANSYT	ILACA	VehSiCon	TRANSYT	ILACA	VehSiCon
100%	0.000	0.000	0.018	0.000	0.000	0.002	0.000	0.000	0.000
90%	0.000	0.000	0.013	0.000	0.000	0.016	0.000	0.000	0.003
80%	0.000	0.000	0.025	0.000	0.000	0.032	0.000	0.000	0.011
70%	0.000	0.000	0.039	0.000	0.000	0.041	0.000	0.877	0.024
60%	0.000	0.000	0.042	0.000	0.000	0.082	0.000	0.000	0.064

50%	0.000	0.000	0.238	0.000	0.013	0.238	0.000	0.000	0.127
40%	0.000	0.000	0.095	0.000	0.000	0.098	0.000	0.000	0.472
30%	0.000	0.000	0.146	0.000	0.000	0.341	0.314	0.000	0.489
20%	0.000	0.000	0.118	0.000	0.000	0.319	0.000	0.000	0.264
10%	0.000	0.000	0.083	0.000	0.000	0.276	0.000	0.000	0.368

Table 5. 36 P-values in average vehicle stop comparison for PerSiCon-Network and three benchmarking models in road network in different traffic flow demands and different CV penetration rates

	P-values for average vehicle stop								
Flow level	Low			Average			High		
Signal controls	TRANSYT	ILACA	VehSiCon	TRANSYT	ILACA	VehSiCon	TRANSYT	ILACA	VehSiCon
100%	0.000	0.000	0.031	0.000	0.000	0.043	0.000	0.000	0.026
90%	0.000	0.000	0.040	0.000	0.000	0.041	0.000	0.000	0.038
80%	0.000	0.000	0.036	0.000	0.000	0.047	0.000	0.716	0.044
70%	0.000	0.000	0.351	0.000	0.000	0.761	0.000	0.000	0.242
60%	0.000	0.140	0.275	0.000	0.000	0.267	0.000	0.000	0.188
50%	0.000	0.000	0.258	0.000	0.035	0.177	0.000	0.000	0.171
40%	0.000	0.000	0.187	0.000	0.000	0.268	0.000	0.000	0.367
30%	0.000	0.000	0.376	0.000	0.000	0.198	0.047	0.000	0.616
20%	0.663	0.000	0.201	0.000	0.000	0.297	0.000	0.000	0.466
10%	0.000	0.000	0.876	0.000	0.000	0.603	0.000	0.000	0.304

Similar to the sensitivity analysis results in the isolated junction in Section 5.9.2, the plots in Figures 5.19 and 5.20 show similar variation trends of average person/vehicle delays and stops in two signal controls using CV data under three traffic flow levels. In Figure 5.19, average passenger and vehicle delays of signal controls using CV data VehSiCon-Network and PerSiCon-Network increase as the CV penetration rate decreases regardless of their objectives or signal plan flexibilities. The increments of average passenger delay for the connected control methods perform worse than ILACA-Network and TRANSYT-Network below 50% and 20% CV penetration rate respectively. By comparing VehSiCon-Network with PerSiCon-Network, the advantage of reducing person delay in the proposed algorithm is gradually eliminated by reducing the CV penetration rate. The plots in Figure 5.20 illustrate a similar tendency of average passenger and vehicle stops of all operational algorithms in the presence of buses under three flow levels. Table 5.33 - Table 5.36 evident that there is no significant difference between average person delay and stop of PerSiCon-Network and VehSiCon-Network in the case that CV penetration rate is lower than 50% - 60% and 80% respectively. The reason is that the gradual absence of CVs reduces the data sources of signal optimization algorithms using CV data, making them cannot realize the entire vehicle situation at multiple junctions. As the CV penetration rate decreases, VehSiCon/PerSiCon-Bus can only acquire part of vehicular information. The optimization outputs of their algorithms cannot reach the perfect objective function targets of minimising person/vehicle delay. The performance of TRANSYT-Network and ILACA-Network keep the same in different CV penetration rates as their data inputs do not rely on the data from CVs.

The plots in Figure 5.10 show similar variation trends of average person/vehicle delays among signal controls using CV data under three traffic flow levels. The average person/vehicle delays of signal controls using CV data (VehSiCon and PerSiCon-Bus) increase as the CV penetration rate decreases regardless of their objectives or signal plan flexibilities. The average person/vehicle delays of the connected control methods perform worse than ILACA when the CV penetration rate is less than 50%, and perform worse than TRANSYT when the CV penetration rate is less than 30%. Compared to VehSiCon, the advantage of reducing passenger delay in the proposed algorithm is gradually reduced by reducing the CV penetration rate. This can be proved by the hypothesis test results in Tables 5.13 and 5.14. The average person/vehicle delays of PerSiCon-Bus are not significantly different to those of VehSiCon when the CV penetration rate decrease to 60% - 80%. Figure 5.11, Tables 5.15 and 5.16 illustrate that there are similar influences on trends of average passenger/vehicle stops in Figure 5.10, Tables 5.13 and 5.14 of all operational algorithms under three flow levels.

The reason is that the gradual absence of CVs reduces the data sources of signal optimization algorithms using CV data, making them cannot realize the entire vehicle situation at multiple junctions. As the CV penetration rate decreases, VehSiCon/PerSiCon-Bus can only acquire part of vehicular information so that they have less vehicle environment realization and execute signal timing plans less precise to the objective functions. The optimization outputs of their algorithms cannot reach the perfect objective function targets of minimising person/vehicle delay. The signal timing plans are not optimal in PerSiCon-Bus/VehSiCon. As a result, their performance do not have significant improvements in either reducing person-related or vehicle-related performance.

The values of TRANSYT and ILACA remain the same as they do not rely on the information sent from CVs.

In most cases, the performance of PerSiCon-Network in Table 5.33 – Table 5.36 are significantly different to those of TRANSYT-Network and ILACA-Network. However, some abnormal situations where p-values are higher than 0.05 also exist, for instance, 30% CV penetration rate compared to TRANSYT-Network and 50% CV penetration rate compared to ILACA-Network in average demand level in Table 5.33. These phenomenon forms as performance indicators of PerSiCon-Network gradually increase as CV penetration rate decreases and the rising values are very close to the unchanged values in TRANSYT-Network or ILACA-Network at a certain CV penetration rate in any flow demand level. In this case, the mean difference is a minor value, which leads to a large p-value as it is a critical component to calculate p-values.

5.10.3 Sensitivity analysis to prediction horizon

Figures 5.21 and 5.22 are sensitivity test results of average person/vehicle delay and stop values in different DP prediction horizons (10s, 20s, 30s, 40s, 50s, 60s) in different signal control methods in the road network case study. Table 5.37 – Table 5.40 present hypothesis test results of reference models compared to the proposed algorithm in different prediction horizons in three flow levels.

In Figures 5.21 and 5.22, the average passenger/vehicle delays and stop of all algorithms excluding TRANSYT-Network and ILACA-Network are lowest under three flow levels in the case of 30s horizon duration with a mixture of cars and buses, which illustrate the roughly similar tendency of results in isolated junction case study in Section 5.9.3. The average passenger/vehicle delays and stops of PerSiCon-Network and VehSiCon-Network slightly increase when the predictive horizon increases to 40s, 50s and 60s, and significantly increase as the predictive horizon decreases to 10s, 20s compared to 30s prediction horizon. From Table 5.37 – Table 5.40, the average person delay and stop of PerSiCon-Network with prediction horizons from 20s to 60s have significantly difference against VehSiCon-Network in three flow levels and there is no significant difference between two signal controls using CV data when the prediction horizon is 10s.

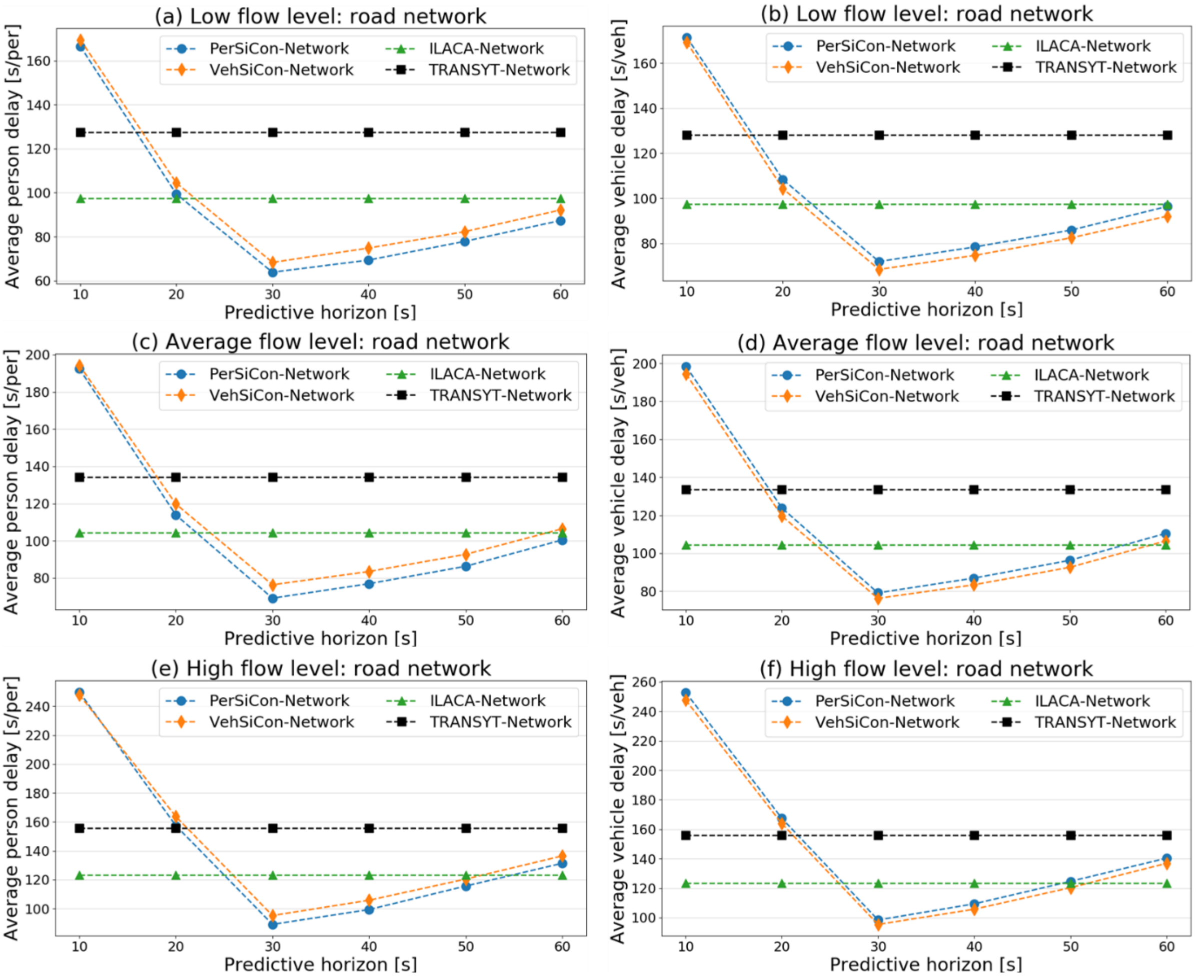

Figure 5. 21 Line charts of average person delay (s/per) and average vehicle delay (s/veh) of proposed algorithm and benchmarking algorithms in road network under variety predictive horizons (s) and three flow levels. CV penetration rate is assumed to be 100%

Table 5. 37 P-values in average person delay comparison for PerSiCon-Network and three benchmarking algorithms in road network in different traffic flow demands and different prediction horizons (100% CV penetration rate)

	P-values for average person delay								
Flow level	Low			Average			High		
Signal controls	TRANSYT	ILACA	VehSiCon	TRANSYT	ILACA	VehSiCon	TRANSYT	ILACA	VehSiCon
10s	0.000	0.000	0.160	0.000	0.000	0.241	0.000	0.000	0.477
20s	0.000	0.238	0.008	0.000	0.000	0.003	0.486	0.000	0.004
30s	0.000	0.000	0.005	0.000	0.000	0.001	0.000	0.000	0.002
40s	0.000	0.000	0.023	0.000	0.000	0.008	0.000	0.000	0.011
50s	0.000	0.000	0.015	0.000	0.000	0.017	0.000	0.000	0.018

60s	0.000	0.000	0.007	0.000	0.000	0.026	0.000	0.000	0.005

Table 5. 38 P-values in average vehicle delay comparison for PerSiCon-Network and three benchmarking algorithms in road network in different traffic flow demands and different prediction horizons (100% CV penetration rate)

	P-values for average vehicle delay								
Flow level	Low			Average			High		
Signal controls	TRANSYT	ILACA	VehSiCon	TRANSYT	ILACA	VehSiCon	TRANSYT	ILACA	VehSiCon
10s	0.000	0.000	0.259	0.000	0.000	0.137	0.000	0.000	0.291
20s	0.000	0.000	0.037	0.007	0.000	0.031	0.000	0.000	0.039
30s	0.000	0.000	0.039	0.000	0.000	0.046	0.000	0.000	0.025
40s	0.000	0.000	0.046	0.000	0.000	0.016	0.000	0.000	0.026
50s	0.000	0.000	0.018	0.000	0.000	0.032	0.000	0.952	0.029
60s	0.000	0.296	0.027	0.000	0.186	0.021	0.000	0.000	0.043

The results indicate that setting the planning horizon too short significantly degrades the performance of PerSiCon-Network/VehSiCon-Network in terms of people's number of stops due to limited signal plan choices and biased function values. The blanking periods of intergreen interval and start-up loss time occupying a considerable part of too short a planning horizon leads to no benefits to people discharging. The results are heavily biased when determining the traffic signal executions as signal schemes are generated based on the highest value function with rarely vehicles can be discharged, regardless of effects on signal phase switching for following saturated flows. The effects on cumulative deviation in long-time vehicle discharging prediction (40s, 50s, 60s) are comparable to less negative influences on performance of ILACA-Network. 30s are still the most appropriate choice to be applied in PerSiCon-Network in road network case study as planning horizon and signal scheme operation cycles combing objective understanding of value function and accurate vehicle travel prediction in the group of six planning horizon choices.

Table 5.17 – Table 5.20 indicate the similar tendency of p-values of average person/vehicle delay and stop in different planning horizon plans in PerSiCon-Network compared to reference models. PerSiCon-Network presents significant improvements against VehSiCon-Network when the prediction horizon is higher than or equal to 20s in all cases. However, when the prediction horizon is 10s, all of the p-values are above 0.05. The reason has been claimed above that 10s are

not sufficient for implementing optimal solutions of PerSiCon-Network/VehSiCon-Network, resulting in a heavily degraded of their performance. Similar to the abnormal p-values in Section 5.9.3, there are also a few special cases where the p-values are higher than 0.05 with comparisons of TRANSYT-Network or ILACA-Network. For instance, in Table 5.37 p-value of PerSiCon-Network is higher than 0.05 when compare to ILACA-Network at a low demand level and compare to TRANSYT-Network at a high demand level if the prediction horizon is 20s. The reason is also that the increasing mean values of average delay and stop are very close to the values in TRANSYT-Network and ILACA-Network in some special cases and the minor mean differences result in high p-values.

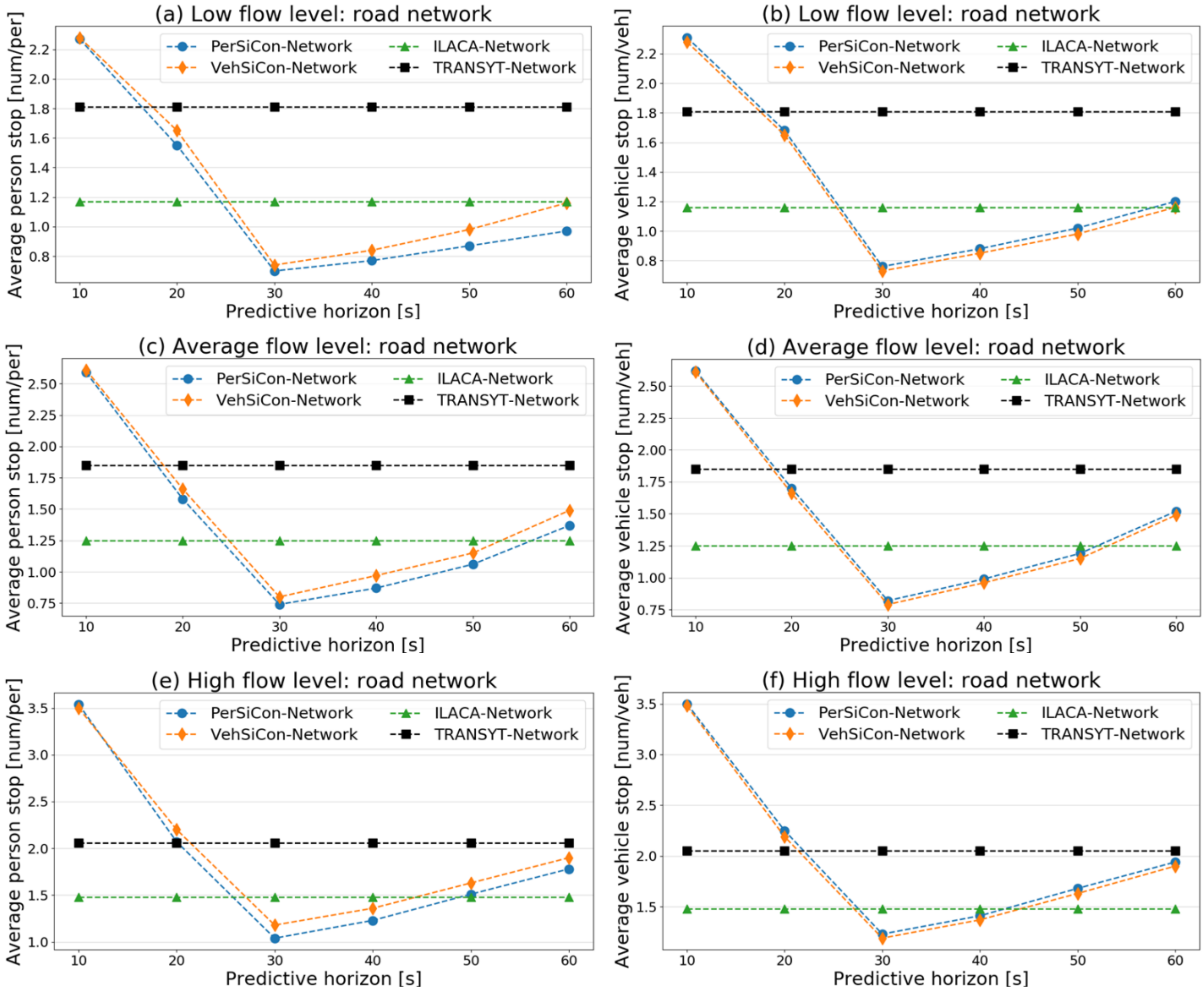

Figure 5. 22 Line charts of average person stop (num/per) and average vehicle stop (num/veh) of proposed algorithm and benchmarking algorithms in road network under variety predictive horizons (s) and three flow levels. CV penetration rate is assumed to be 100%

Table 5. 39 P-values in average person stop comparison for PerSiCon-Network and three benchmarking algorithms in road network in different traffic flow demands and different prediction horizons (100% CV penetration rate)

	P-values for average person stop								
Flow level	Low			Average			High		
Signal controls	TRANSYT	ILACA	VehSiCon	TRANSYT	ILACA	VehSiCon	TRANSYT	ILACA	VehSiCon
10s	0.000	0.000	0.284	0.000	0.000	0.349	0.000	0.000	0.319
20s	0.000	0.000	0.005	0.000	0.000	0.014	0.615	0.000	0.000
30s	0.000	0.000	0.018	0.000	0.000	0.002	0.000	0.000	0.000
40s	0.000	0.000	0.019	0.000	0.000	0.003	0.000	0.000	0.000
50s	0.000	0.000	0.023	0.000	0.000	0.007	0.000	0.357	0.003
60s	0.000	0.000	0.006	0.000	0.000	0.019	0.000	0.000	0.005

Table 5. 40 P-values in average vehicle stop comparison for PerSiCon-Network and three benchmarking algorithms in road network in different traffic flow demands and different prediction horizons (100% CV penetration rate)

	P-values for average vehicle stop								
Flow level	Low			Average			High		
Signal controls	TRANSYT	ILACA	VehSiCon	TRANSYT	ILACA	VehSiCon	TRANSYT	ILACA	VehSiCon
10s	0.000	0.000	0.436	0.000	0.000	0.732	0.000	0.000	0.282
20s	0.000	0.000	0.021	0.000	0.000	0.042	0.000	0.000	0.034
30s	0.000	0.000	0.031	0.000	0.000	0.043	0.000	0.000	0.026
40s	0.000	0.000	0.017	0.000	0.000	0.027	0.000	0.021	0.027
50s	0.000	0.000	0.025	0.000	0.000	0.022	0.000	0.000	0.015
60s	0.000	0.225	0.036	0.000	0.000	0.029	0.001	0.000	0.036

5.10.4 Sensitivity analysis to accumulation time weighted factor

Figures 5.23 and 5.24 illustrate the performance of average person/vehicle delay and stop of PerSiCon-Bus under different numbers of accumulation time weighted factor δ from 0 to 1 in the road network case study. Table 5.41 – Table 5.44 are hypothesis test results of PerSiCon-Network and reference models in different accumulation time weighted factors. Like the results in Section 5.9.4, the performance of PerSiCon-Network in Figures 5.23 and 5.24 present a similar tendency to those in the isolated junction case study. The average person/vehicle delay and stop of PerSiCon-Network/VehSiCon-Network increase as the weighted factor δ rises. Figures 5.23 and 5.24 (a), (c) and (e) illustrate that the change ranges of average person delay and stop of PerSiCon-Network are higher than those of VehSiCon-Network. On the contrary, the change ranges of average vehicle delay and stop of PerSiCon-Network are lower than those of VehSiCon-Network according to Figures 5.23 and 5.24 (b), (d) and (f). The reason is that the PerSiCon-Network algorithm provides more right of ways to those low occupancy vehicles with high accumulation time and scarifies the crossing chances of high occupancy vehicles when the accumulation time weighted factor is high. The increments of accumulation time weighted factor make negative influences on the decision-making process of VehSiCon-Network. However, the negative influences on VehSiCon-Network are less than those on PerSiCon-Network as the optimization mechanism of VehSiCon-Network treats all of the vehicles with the same priority and the accumulation time of any vehicle would not be a great value.

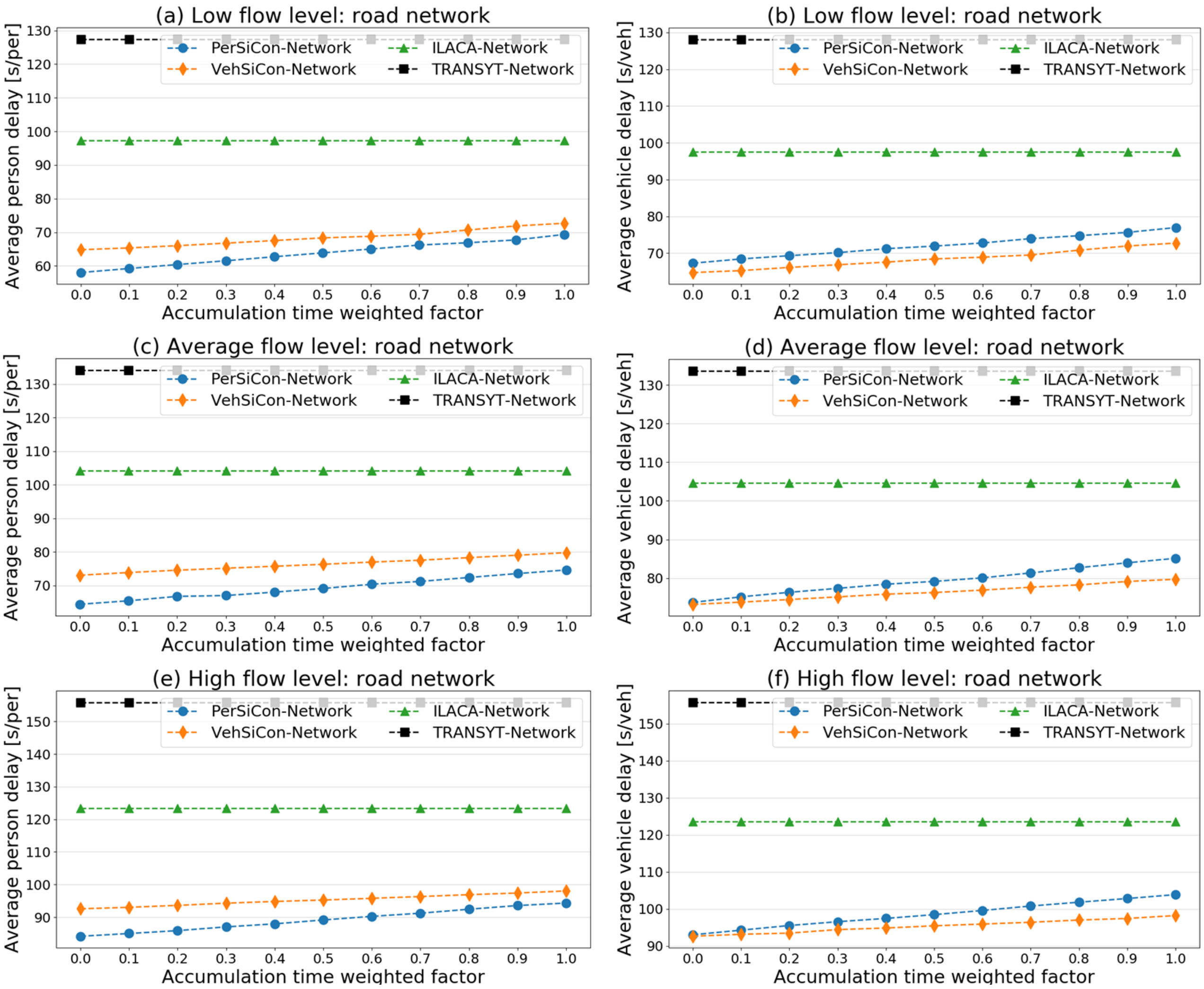

Figure 5. 23 Line charts of average person delay (s/per) and average vehicle delay (s/veh) of proposed algorithm and benchmarking algorithms in road network under variety accumulation time weighted factors and three flow levels. CV penetration rate is assumed to be 100%

Table 5. 41 P-values in average person delay comparison for PerSiCon-Network and three benchmarking algorithms in road network in different traffic flow demands and different accumulation time weighted factors (100% CV penetration rate)

	P-values for average person delay								
Flow level	Low			Average			High		
Signal controls	TRANSYT	ILACA	VehSiCon	TRANSYT	ILACA	VehSiCon	TRANSYT	ILACA	VehSiCon
0	0.000	0.000	0.001	0.000	0.000	0.000	0.000	0.000	0.000
0.1	0.000	0.000	0.002	0.000	0.000	0.000	0.000	0.000	0.000
0.2	0.000	0.000	0.001	0.000	0.000	0.000	0.000	0.000	0.002
0.3	0.000	0.000	0.004	0.000	0.000	0.001	0.000	0.000	0.005
0.4	0.000	0.000	0.005	0.000	0.000	0.002	0.000	0.000	0.003
0.5	0.000	0.000	0.005	0.000	0.000	0.001	0.000	0.000	0.002
0.6	0.000	0.000	0.026	0.000	0.000	0.013	0.000	0.000	0.011
0.7	0.000	0.000	0.038	0.000	0.000	0.027	0.000	0.000	0.020
0.8	0.000	0.000	0.034	0.000	0.000	0.031	0.000	0.000	0.032
0.9	0.000	0.000	0.041	0.000	0.000	0.035	0.000	0.000	0.039
1.0	0.000	0.000	0.059	0.000	0.000	0.042	0.000	0.000	0.055

Table 5. 42 P-values in average vehicle delay comparison for PerSiCon-Network and three benchmarking algorithms in road network in different traffic flow demands and different accumulation time weighted factors (100% CV penetration rate)

	P-values for average vehicle delay								
Flow level	Low			Average			High		
Signal controls	TRANSYT	ILACA	VehSiCon	TRANSYT	ILACA	VehSiCon	TRANSYT	ILACA	VehSiCon
0	0.000	0.000	0.182	0.000	0.000	0.102	0.000	0.000	0.042
0.1	0.000	0.000	0.084	0.000	0.000	0.073	0.000	0.000	0.045
0.2	0.000	0.000	0.076	0.000	0.000	0.067	0.000	0.000	0.041
0.3	0.000	0.000	0.046	0.000	0.000	0.053	0.000	0.000	0.040
0.4	0.000	0.000	0.044	0.000	0.000	0.049	0.000	0.000	0.034

0.5	0.000	0.000	0.039	0.000	0.000	0.046	0.000	0.000	0.025
0.6	0.000	0.000	0.030	0.000	0.000	0.034	0.000	0.000	0.023
0.7	0.000	0.000	0.029	0.000	0.000	0.033	0.000	0.000	0.026
0.8	0.000	0.000	0.024	0.000	0.000	0.034	0.000	0.000	0.015
0.9	0.000	0.000	0.011	0.000	0.000	0.026	0.000	0.000	0.021
1.0	0.000	0.000	0.006	0.000	0.000	0.014	0.000	0.000	0.017

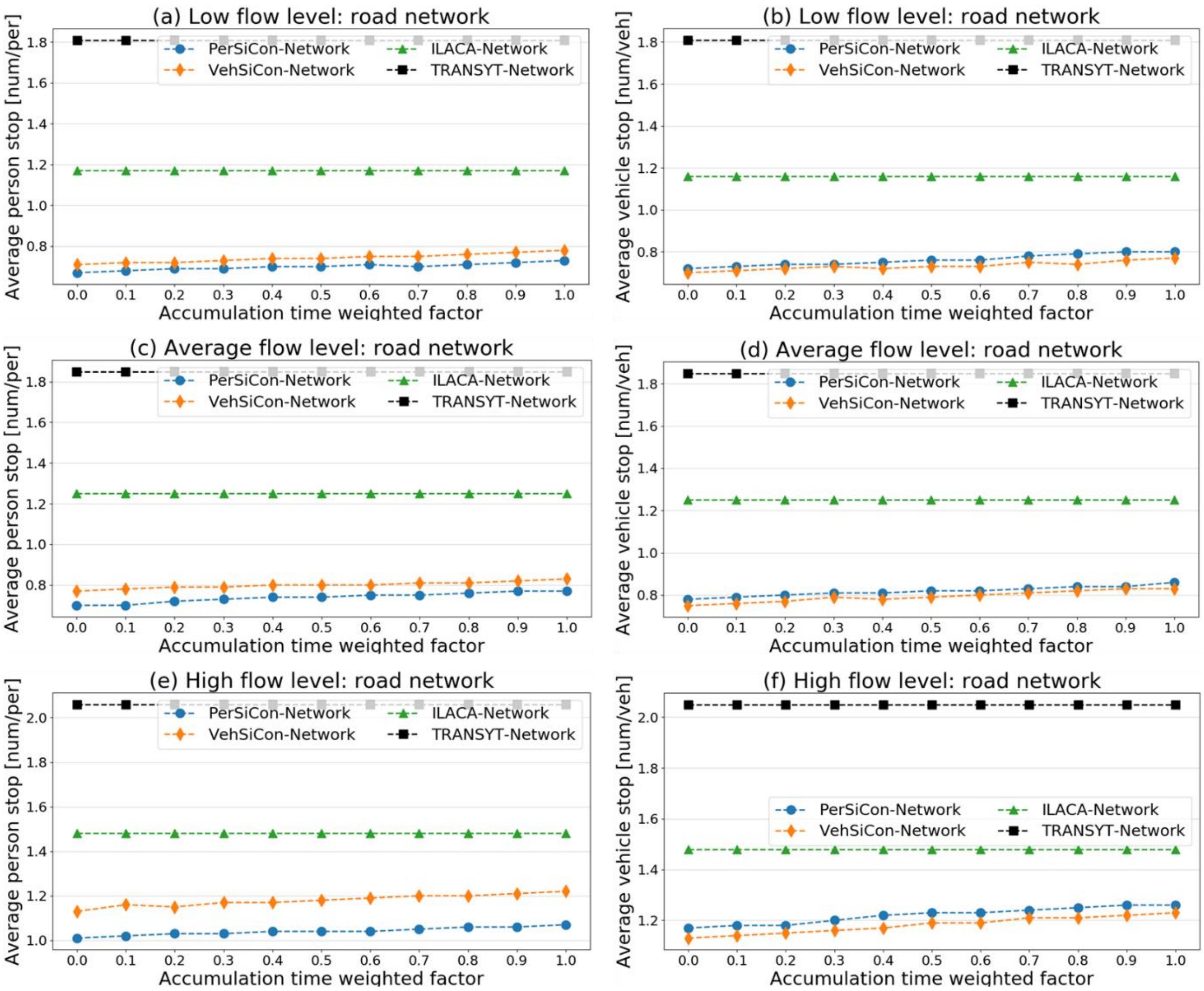

Figure 5. 24 Line charts of average person stop (num/per) and average vehicle stop (num/veh) of proposed algorithm and benchmarking algorithms in road network under variety accumulation time weighted factors and three flow levels. CV penetration rate is assumed to be 100%

Table 5. 43 P-values in average person stop comparison for PerSiCon-Network and three benchmarking algorithms in road network in different traffic flow demands and different accumulation time weighted factors (100% CV penetration rate)

	P-values for average person stop		
Flow level	Low	Average	High

Signal controls	TRANSYT	ILACA	VehSiCon	TRANSYT	ILACA	VehSiCon	TRANSYT	ILACA	VehSiCon
0	0.000	0.000	0.003	0.000	0.000	0.006	0.000	0.000	0.002
0.1	0.000	0.000	0.016	0.000	0.000	0.007	0.000	0.000	0.016
0.2	0.000	0.000	0.008	0.000	0.000	0.013	0.000	0.000	0.014
0.3	0.000	0.000	0.006	0.000	0.000	0.017	0.000	0.000	0.007
0.4	0.000	0.000	0.010	0.000	0.000	0.004	0.000	0.000	0.006
0.5	0.000	0.000	0.018	0.000	0.000	0.002	0.000	0.000	0.000
0.6	0.000	0.000	0.015	0.000	0.000	0.013	0.000	0.000	0.005
0.7	0.000	0.000	0.031	0.000	0.000	0.027	0.000	0.000	0.012
0.8	0.000	0.000	0.027	0.000	0.000	0.025	0.000	0.000	0.033
0.9	0.000	0.000	0.031	0.000	0.000	0.013	0.000	0.000	0.021
1.0	0.000	0.000	0.042	0.000	0.000	0.038	0.000	0.000	0.025

Table 5. 44 P-values in average vehicle stop comparison for PerSiCon-Bus and three benchmarking algorithms in isolated junction in different traffic flow demands and different accumulation time weighted factors (100% CV penetration rate)

	P-values for average vehicle stop								
Flow level	Low			Average			High		
Signal controls	TRANSYT	ILACA	VehSiCon	TRANSYT	ILACA	VehSiCon	TRANSYT	ILACA	VehSiCon
0	0.000	0.000	0.057	0.000	0.000	0.141	0.000	0.000	0.156
0.1	0.000	0.000	0.044	0.000	0.000	0.075	0.000	0.000	0.086
0.2	0.000	0.000	0.036	0.000	0.000	0.064	0.000	0.000	0.061
0.3	0.000	0.000	0.041	0.000	0.000	0.051	0.000	0.000	0.045
0.4	0.000	0.000	0.033	0.000	0.000	0.048	0.000	0.000	0.034
0.5	0.000	0.000	0.031	0.000	0.000	0.043	0.000	0.000	0.026
0.6	0.000	0.000	0.026	0.000	0.000	0.037	0.000	0.000	0.024
0.7	0.000	0.000	0.036	0.000	0.000	0.030	0.000	0.000	0.016
0.8	0.000	0.000	0.013	0.000	0.000	0.019	0.000	0.000	0.018

0.9	0.000	0.000	0.029	0.000	0.000	0.036	0.000	0.000	0.004
1.0	0.000	0.000	0.035	0.000	0.000	0.026	0.000	0.000	0.009

The change ranges of average person/vehicle delay and stop of PerSiCon-Network and VerSiCon-Network are also reflected in hypothesis test results in Table 5.41 – Table 5.44. It can be found that in some cases in Table 5.41 that when accumulation time weighted factor equals 1, there is no significant difference between the average person delay and stop of PerSiCon-Network and VerSiCon-Network in low and high flow demands. On the contrary, in some cases in Table 5.42 and 5.44 when the weighted factor decreases to 0 - 0.3, the average vehicle delay and stop of PerSiCon-Network are not significantly different from VerSiCon-Network. This is because with the increments of weighted factor δ, PerSiCon-Network incorporates more considerations of those low occupancy vehicles which wait quite a long time at the junction. The adjustments of signal control decisions provide more opportunities to provide the green time for low occupancy vehicles and thus the summation values of average person/vehicle delay and number of stop increase with higher change ranges than VerSiCon-Network. As a result, the most appropriate value of weighted factor δ is considered to be 0.5 to make a balance between providing priorities to high occupancy vehicles and taking into account the accumulation time of low occupancy vehicles.

5.10.5 Sensitivity analysis to bus occupancy

Figures 5.25 and 5.26 present the average person/vehicle delay and stop of vehicles of the proposed algorithm PerSiCon-Network under three flow level scenarios when bus occupancy ranges from 2 to 50 passenger/veh. Table 5.45 – Table 5.48 present p-values of PerSiCon-Bus compared to reference models in various experiments. Similar to the results in the isolated junction, the performance of PerSiCon-Network keep unchanged when bus occupancy is higher than or equal to 8 passengers/veh. The average person delay and stop slightly increase, but the average vehicle delay and stop slightly decrease when bus occupancy is lower than 8 passengers/veh according to Figures 5.25 and 5.26. The hypothesis test results in Table 5.45 – Table 5.48 prove that the performance of PerSiCon-Network always significantly outperform any of the reference models in different bus occupancies and demand levels. The causes of the phenomenon are buses constitute a very small part of vehicle dynamics and their performance changes have minor influences on the summation performance. In PerSiCon-Bus, the priority levels of buses are determined by comprehensive results of bus occupancy, bus length, bus headway, and predictive arrival and departure time. Discharging a bus costs a higher green time right of way than discharging a vehicle. In this condition, the junction controller does not necessarily provide priority to the bus and scarifies the travel time of more passenger cars. Therefore, the junction controller provides the right of way for a car rather than a bus if their priority levels of them are the same, which heavily increases the travelling delay of buses.

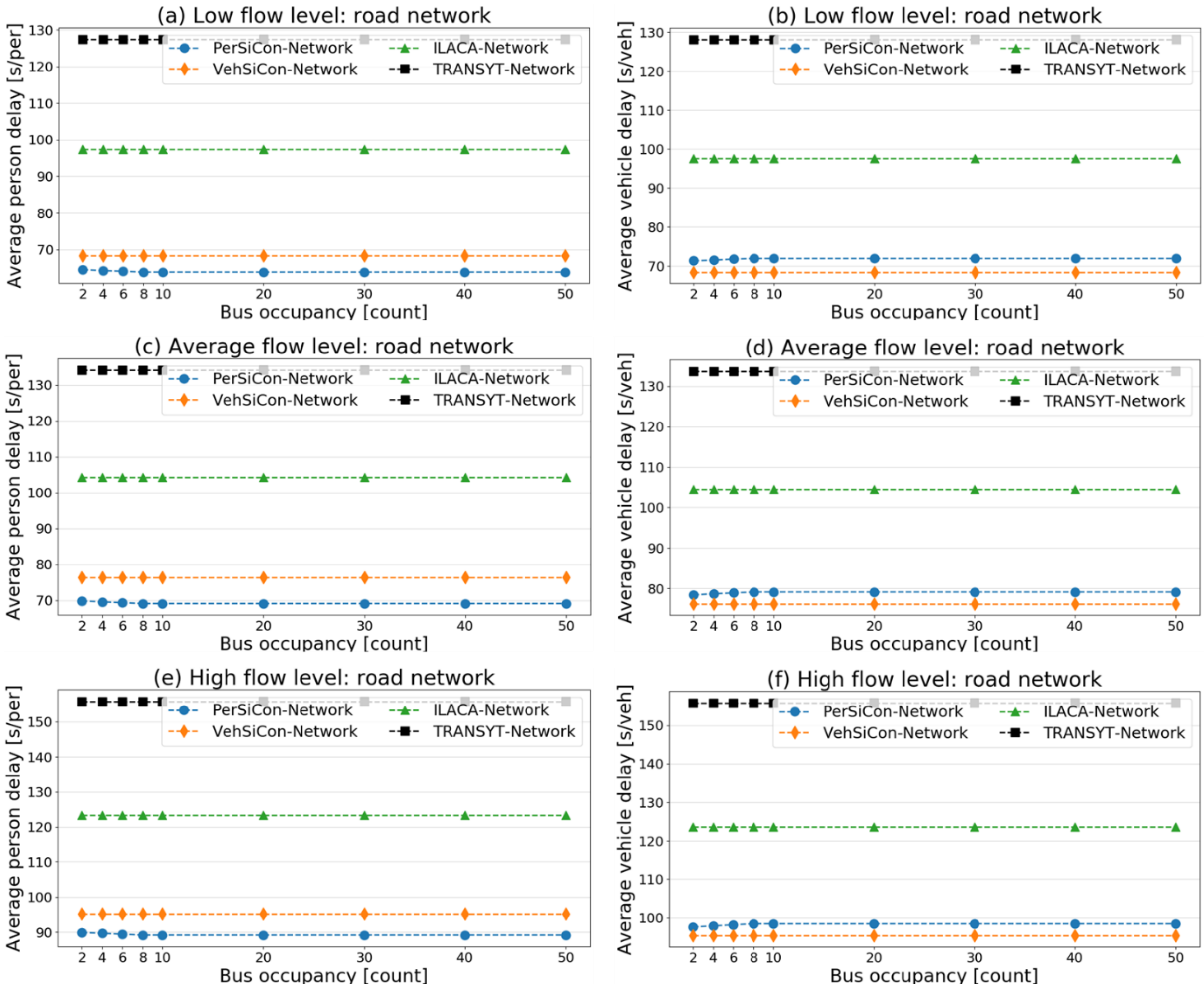

Figure 5. 25 Line charts of average person delay (s/per) and average vehicle delay (s/veh) of proposed algorithm and benchmarking algorithms in road network under variety bus occupancy levels and three flow levels. CV penetration rate is assumed to be 100%

Table 5. 45 P-values in average person delay comparison for PerSiCon-Network and three benchmarking algorithms in road network in different traffic flow demands and different bus occupancy levels (100% CV penetration rate)

	P-values for average person delay								
Flow level	Low			Average			High		
Signal controls	TRANSYT	ILACA	VehSiCon	TRANSYT	ILACA	VehSiCon	TRANSYT	ILACA	VehSiCon
2	0.000	0.000	0.014	0.000	0.000	0.004	0.000	0.000	0.009

4	0.000	0.000	0.0011	0.000	0.000	0.003	0.000	0.000	0.006
6	0.000	0.000	0.007	0.000	0.000	0.001	0.000	0.000	0.008
8	0.000	0.000	0.005	0.000	0.000	0.001	0.000	0.000	0.002
10	0.000	0.000	0.005	0.000	0.000	0.001	0.000	0.000	0.002
20	0.000	0.000	0.005	0.000	0.000	0.001	0.000	0.000	0.002
30	0.000	0.000	0.005	0.000	0.000	0.001	0.000	0.000	0.002
40	0.000	0.000	0.005	0.000	0.000	0.001	0.000	0.000	0.002
50	0.000	0.000	0.005	0.000	0.000	0.001	0.000	0.000	0.002

Table 5. 46 P-values in average vehicle delay comparison for PerSiCon-Network and three benchmarking algorithms in road network in different traffic flow demands and different bus occupancy levels (100% CV penetration rate)

	P-values for average vehicle delay								
Flow level	Low			Average			High		
Signal controls	TRANSYT	ILACA	VehSiCon	TRANSYT	ILACA	VehSiCon	TRANSYT	ILACA	VehSiCon
2	0.000	0.000	0.041	0.000	0.000	0.048	0.000	0.000	0.031
4	0.000	0.000	0.042	0.000	0.000	0.044	0.000	0.000	0.027
6	0.000	0.000	0.047	0.000	0.000	0.045	0.000	0.000	0.024
8	0.000	0.000	0.039	0.000	0.000	0.046	0.000	0.000	0.025
10	0.000	0.000	0.039	0.000	0.000	0.046	0.000	0.000	0.025
20	0.000	0.000	0.039	0.000	0.000	0.046	0.000	0.000	0.025
30	0.000	0.000	0.039	0.000	0.000	0.046	0.000	0.000	0.025
40	0.000	0.000	0.039	0.000	0.000	0.046	0.000	0.000	0.025
50	0.000	0.000	0.039	0.000	0.000	0.046	0.000	0.000	0.025

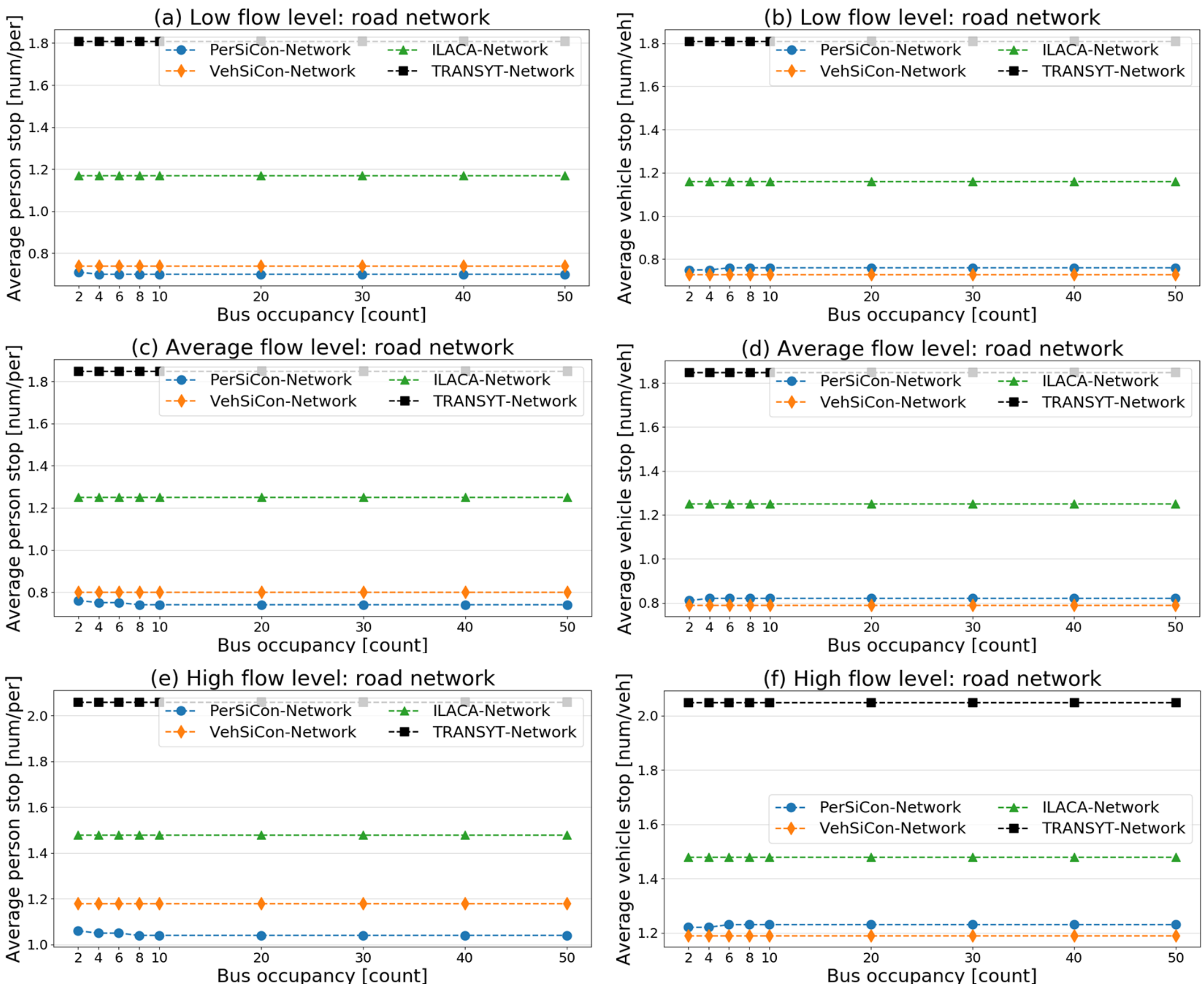

Figure 5. 26 Line charts of average person stop (num/per) and average vehicle stop (num/veh) of proposed algorithm and benchmarking algorithms in road network under variety bus occupancy levels and three flow levels. CV penetration rate is assumed to be 100%

Table 5. 47 P-values in average person stop comparison for PerSiCon-Network and three benchmarking algorithms in road network in different traffic flow demands and different bus occupancy levels (100% CV penetration rate)

	P-values for average person stop								
Flow level	Low			Average			High		
Signal controls	TRANSYT	ILACA	VehSiCon	TRANSYT	ILACA	VehSiCon	TRANSYT	ILACA	VehSiCon
2	0.000	0.000	0.027	0.000	0.000	0.011	0.000	0.000	0.004
4	0.000	0.000	0.021	0.000	0.000	0.006	0.000	0.000	0.000
6	0.000	0.000	0.017	0.000	0.000	0.003	0.000	0.000	0.001
8	0.000	0.000	0.018	0.000	0.000	0.002	0.000	0.000	0.000

10	0.000	0.000	0.018	0.000	0.000	0.002	0.000	0.000	0.000
20	0.000	0.000	0.018	0.000	0.000	0.002	0.000	0.000	0.000
30	0.000	0.000	0.018	0.000	0.000	0.002	0.000	0.000	0.000
40	0.000	0.000	0.018	0.000	0.000	0.002	0.000	0.000	0.000
50	0.000	0.000	0.018	0.000	0.000	0.002	0.000	0.000	0.000

Table 5. 48 P-values in average vehicle stop comparison for PerSiCon-Network and three benchmarking algorithms in road network in different traffic flow demands and different bus occupancy levels (100% CV penetration rate)

	P-values for average vehicle stop								
Flow level	Low			Average			High		
Signal controls	TRANSYT	ILACA	VehSiCon	TRANSYT	ILACA	VehSiCon	TRANSYT	ILACA	VehSiCon
2	0.000	0.000	0.048	0.000	0.000	0.041	0.000	0.000	0.039
4	0.000	0.000	0.043	0.000	0.000	0.047	0.000	0.000	0.044
6	0.000	0.000	0.034	0.000	0.000	0.043	0.000	0.000	0.031
8	0.000	0.000	0.031	0.000	0.000	0.043	0.000	0.000	0.026
10	0.000	0.000	0.031	0.000	0.000	0.043	0.000	0.000	0.026
20	0.000	0.000	0.031	0.000	0.000	0.043	0.000	0.000	0.026
30	0.000	0.000	0.031	0.000	0.000	0.043	0.000	0.000	0.026
40	0.000	0.000	0.031	0.000	0.000	0.043	0.000	0.000	0.026
50	0.000	0.000	0.031	0.000	0.000	0.043	0.000	0.000	0.026

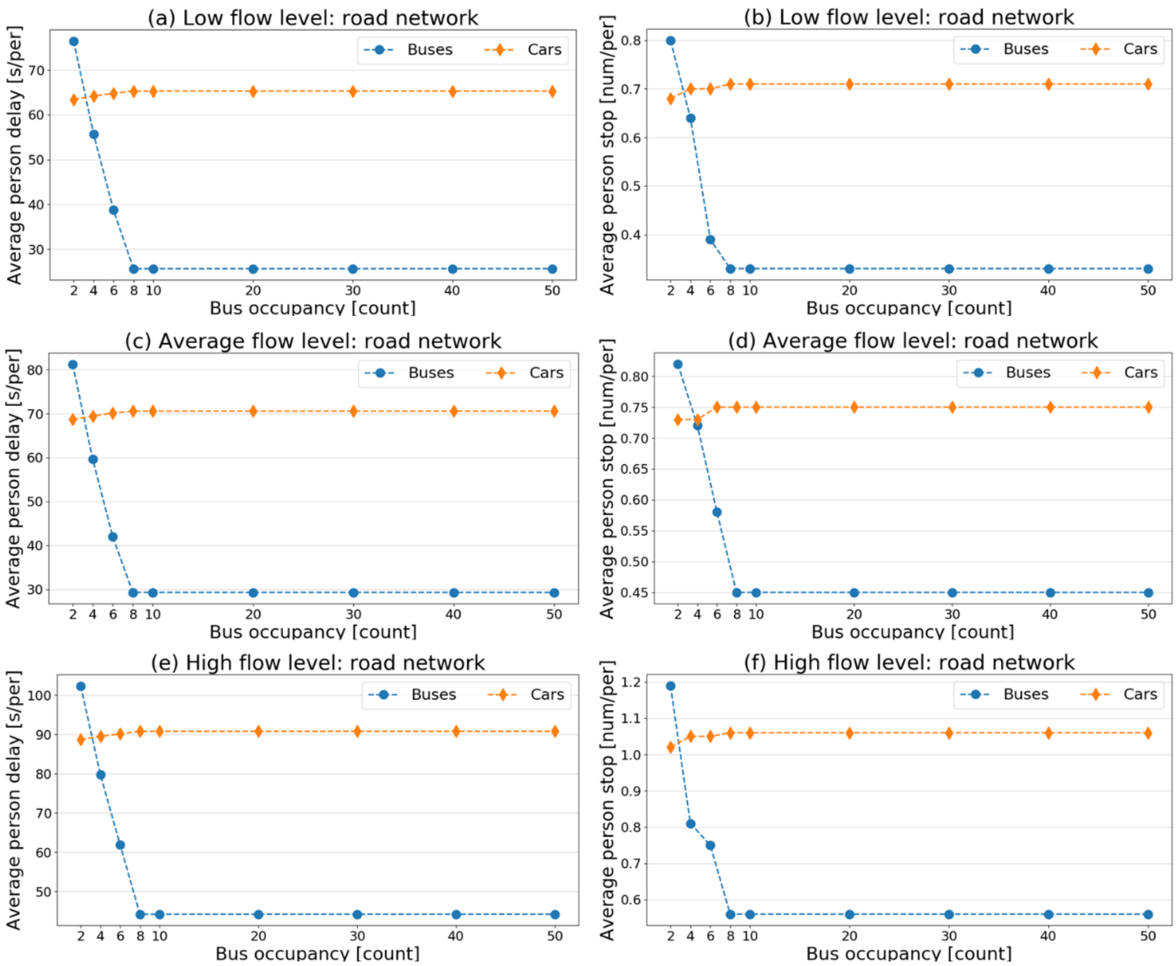

Figure 5. 27 Average person delay (s/per) and average person stop (num/per) of cars and buses respectively of proposed algorithm PerSiCon-Bus and under variety bus occupancy levels and three flow levels with mixture of cars and buses

More specifically, Figure 5.27 lists the average person's delay and stop of passenger cars and buses separately. Figure 5.27 illustrates that the average passenger delay of buses and cars keeps unchanged when bus occupancy is higher than or equal to 8 passengers/veh. However, the average passenger delay of buses is significantly degraded if bus occupancy is lower than 8 passengers/veh, and is even worse than the average passenger delay of cars when bus occupancy is 2 passengers/veh. Meanwhile, the average passenger delay of cars slightly improves as bus occupancy decreases. In contrast to those of passenger cars with 2 and 4 occupants, the average passenger delays of buses with the same occupants are 21.5% - 30.3% and 9.1% - 14.8% larger respectively. The results indicate that the priority levels of buses are less than those of cars with the same occupants as the predictive discharging time of buses is relatively high compared with cars. Since the average person delay and stop of passenger cars only make minor changes and they occupy a large proportion of vehicle compositions on road, the summation delay and stop of PerSiCon-Network do not change obviously.

5.11 Summary

This chapter describes the details of the isolated junction and road network as case studies to evaluate the performance of proposed algorithms PerSiCon-Bus and PerSiCon-Network. The junction settings, vehicle parameters, traffic demands and benchmarking models are also introduced in this chapter, which is implemented in microsimulation software SUMO for signal control operation. The vehicle environments consist of passenger cars with different occupancy levels and buses. The performance of PerSiCon-Bus and PerSiCon-Network with benchmarking signal controls are provided and analysed in this chapter with changes to CV penetration rates, prediction horizons, weighted factors and bus occupancies. The results indicate that PerSiCon-Bus performs better in average person delay and average person stop in terms of high occupancy vehicles. The PerSiCon-Bus also outperforms vehicle-based adaptive CV signal control VehSiCon in average person delay and stop of summation and high occupancy vehicles, which outstanding its effectiveness in dealing with reducing person delay in passenger vehicle environments. However, the vehicle-related performance, average vehicle delay and stop of PerSiCon-Network perform worse than VehSiCon. The performance of different signal controls with their coordination versions in the road network are similar to the results in the isolated junction case study.

The evaluation experiments to different sensitivity factors are also carried out and the results present that the average person delay and stop of overall vehicles and buses in PerSiCon-Bus/PerSiCon-Network can be significantly improved with high levels of CV penetration rates. However, the performance of PerSiCon-Bus/ PerSiCon-Network in low CV penetration rates (such as below around 60% CV penetration rate in three flow levels) do not have better performance than vehicle-based controls. The sensitivity tests also find that 30s prediction horizon and 0.5 accumulation time weighted factor are found to be the most appropriate parameters to be applied in proposed person-based algorithms. Buses can award high priority levels and suffer minor delays and stops when the average occupancy is higher than or equal to 8 passengers/veh. In next chapter, a supported algorithm used to estimate the status of unequipped vehicles in imperfect CV penetration rate is described to improve the performance of PerSiCon-Network.

Chapter 6 Improving the performance of person-based control under imperfect connected vehicle penetration rate

The proposed person-based control is evaluated in the isolated junction and road network with a mixture of buses and cars vehicular environments Chapter 5. The sensitivity test results to CV penetration rates find that the PerSiCon-Bus/PerSiCon-Network do not achieve significant improvements in person-related performance, around 60% CV penetration rate below against signal controls using CV data and 30% CV penetration rate below against fixed time control. Therefore, it is essential to improve the performance of person-based control under imperfect CV penetration rates. This chapter describes an Estimation status of Unequipped Vehicle with Occupancy (EUVO) algorithm to estimate the vehicle statuses of those unequipped vehicles based on several data types collected from CVs, inductive loops and cameras. The EUVO algorithm can be operated before the optimization process to supply the initial departure time and occupancy level estimation of unequipped vehicles. To validate the effectiveness of the EUVO algorithm, the enhanced PerSiCon-Network augmented by the EUVO algorithm is evaluated in the case study and its person-based performance are compared to those of PerSiCon-Network as introduced in Chapter 3.

6.1 Method consideration for EUVO algorithm

Few state-of-the-art researches attempted to enhance the performance of vehicle-based signal controls in mixture vehicular environments of unequipped vehicles (UVs) and CVs. Feng et al. (2015) proposed an Estimation of Location and Speed (EVLS) algorithm to estimate the positions and speeds of UVs according to the data received from CVs. Wiedemann car following model was applied to estimate locations and speeds of UVs in three regions divided by vehicle status: queuing region, slow-down region and free-flow region. However, from the results of the EVLS algorithm, the estimations of those UVs located in the slow-down region and free-flow region were not quite accurate with 25% and 50% CV penetration rates. A traffic state estimation algorithm was then proposed to estimate the locations, speeds and accelerations of UVs using data from CVs and inductive loops (Islam et al, 2020). The algorithm found the leader-follower vehicle pair and estimated the acceleration rate of a UV based on the relative velocity and headway between the leader and follower using the Wiedemann car-following model to calculate the positions and speeds of UVs in the current time step. However, this algorithm did not consider the influence of green/red traffic lights on the vehicle state. An augmenting traffic signal control system developed by Rafter et al (2020) enhanced the performance of vehicle-based signal controls using data from CVs and inductive loops in low CV penetration rates. However, the algorithm did not explicitly estimate the vehicle status of individual vehicles, which is difficult to be adopted in PerSiCon-Network. In addition, a common limitation of the above estimation algorithms is that they only estimated the vehicle states of UVs, such as locations and speeds, but failed to acquire the vehicle occupancy data. Those estimation data can satisfy the requirements of vehicle-based controls, but both vehicle state data and vehicle occupancy data are required in person-based controls. Therefore, none of them can be directly adopted in PerSiCon-Network.

The challenging thing to enhancing the proposed optimization algorithm PerSiCon-Network in imperfect CV penetration rate is that it requires predicted departure time, travelling status and occupancy level of each vehicle from each lane as data inputs. In mixture environments of UVs and CVs, the data inputs of UVs cannot be obtained by PerSiCon-Network. Although the general vehicle occupancy level ratios can be estimated by assuming that vehicle occupancy levels follow Poisson distribution, the specific vehicle occupancy level sequences are stochastic at a particular time, which makes the estimation works to be challenging to follow the real occupancy level sequences on road. However, the vehicle occupancy detection technology introduced in Section 2.4.1 can capture the occupancy level of crossing vehicles from one-side cameras, which can be used to collect vehicle occupancy data at a specific camera installation site. The inductive loops can be used to detect whether there is a vehicle crossing the site or not and it has been adopted in vehicle-based controls to estimate the states of UVs. Therefore, a EUVO algorithm is proposed in this research to estimate the vehicle status (vehicle departure time and travelling status) with the help of inductive loop detectors (E1 detectors), and match the occupancy levels of UVs by one-side cameras installed to detect vehicles at the same place with the confirmed information from CVs. The illustration layouts of the EUVO algorithm are presented in Figure 6.1.

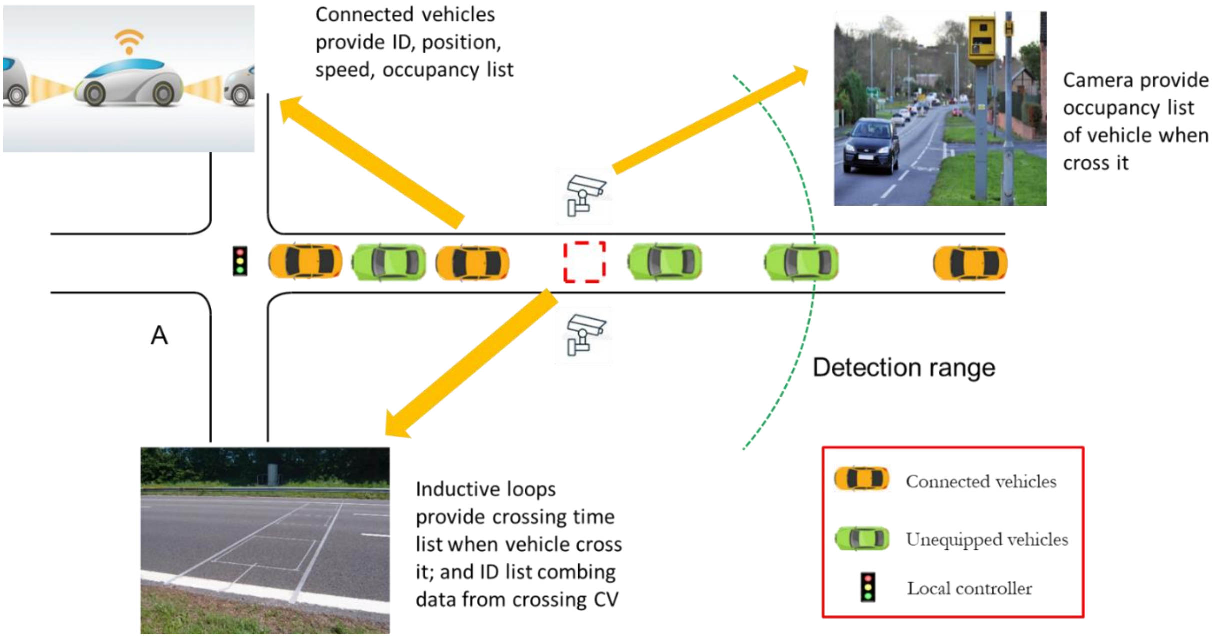

Figure 6. 1 Illustration layouts of EUVO algorithm

From Figure 6.1, one detection area of the EUVO algorithm consists of the inductive loop detectors (E1 detectors) installed on all of the discharging lanes and a one-side camera installed on the left side of the approach lanes. Vehicles travel through the detection area with installed inductive loops and cameras sequentially. The research assumes that no lane-changing behaviours happen after vehicles enter the detection area until they pass through the cross line. The time steps of vehicle detecting signal from the inductive loop of a specific lane can be recorded so that the junction controller can use the information to estimate the time needed for a vehicle with free-flow speed to cross the junction.

In the EUVO algorithm, the initial departure time and vehicle status of UVs, which are part of the data sources of the optimization process of PerSiCon-Network, can directly be estimated by data from inductive loops CVs and traffic signals. The occupancy levels of UVs, which are the rest of the data inputs, can be obtained by matching the measured occupancy from the one-side cameras to UVs detected by loop detectors based on the vehicle data from CVs.

As a result, the algorithm does not need to estimate the exact locations and positions of UVs. The occupancy information recorded from one-side cameras is matched and assigned to the vehicles travelling across the detection area. The assumptions and limitations of the EUVO algorithm and simulation experiments are listed in next section. The details of the EUVO algorithm are described in Section 6.3.

6.2 Assumptions and limitations

Besides the assumptions made in Chapters 4 and 5 for proposed algorithm methodologies and simulation experiments, some additional assumptions are listed in this section to clarify the details of the EUVO algorithm and operation settings in evaluation frameworks. The assumptions simplify some of the realistic situations and the limitations of this research need to be improved in future research. The additional assumptions made in this chapter are listed as follows:

The local highway authority is assumed to have adequate E1 detectors and one-side cameras devices to operate the EUVO algorithm. As claimed in Section 6.1, the operation of the EUVO algorithm requires extra data inputs to estimate the vehicular status and match the occupancy levels of UVs. From the illustration of Figure 6.1, the number of data collection devices required for a junction is determined by the number of approach lanes and approach directions of a junction. One E1 detectors per approach lane and two one-side cameras per junction approach direction are needed for every junction. For a four-leg typical junction with two approach lanes from each direction, 8 inductive loop detectors and 4 one-side cameras are required to implement the EUVO algorithm. The E1 detectors installed at the detection area can detect when there is a vehicle crossing a specific lane and one-side cameras can capture the occupancy level of a crossing vehicle.

Occupancy level detection accuracies from in-vehicle cameras and one-side roadside cameras are assumed to be 99% and 87% in simulation setup and experiments in SUMO. The vehicle occupancy detection works are challenging to be simulated in this research as vehicle occupancy detection technology and photos from roadside cameras are required. To simplify the simulation experiments, the detection accuracy from in-vehicle cameras and one-side roadside cameras are assumed to be consistent with the related literature. In SUMO simulation, a vehicle occupancy detection message is automatically generated when there is a vehicle crossing the detection area and the junction controller receives the message. To fit the detection accuracy, the occupancy level generated has an 87% probability to report the real occupancy level of the detected vehicle and the rest with a 13% probability to form a random value from other possibilities.

The junction controllers are assumed to receive the signals from inductive loop detectors installed in the EUVO algorithm in simulation. E1 detectors are installed at all approach lanes to the junction and they can detect and send the signals when there is a vehicle crossing the detectors. If a junction controller receives a signal at a specific time step, the message forms part of the data inputs of the EUVO algorithm.

6.3 Detail descriptions of EUVO algorithm

At the time step of the signal plan optimization process, the EUVO algorithm operates to estimate the statuses and occupancy levels of UVs after PerSiCon-Network triggers and collects vehicular data from CVs. As the index of CVs in the whole vehicle platoon is uncertain, the departure time estimations of UVs at various places (e.g. UVs in front of the first detected CVs, UVs in the middle of two detected CVs or behind the last detected CVs sorted by distances to the cross line) are different. The predicted departure time of the following vehicles can only be calculated after determining the vehicle status and discharging time of the previous one. Therefore, the EUVO algorithm procedure is executed in three steps:

1. Collecting data for EUVO algorithm from CVs, inductive loops and vehicle information storage spaces of junction controller;
2. Estimating the initial departure times, statuses and occupancy levels of UVs before first detected CVs;
3. Estimating the initial departure times, statuses and occupancy levels of CVs and those UVs between or behind them;
4. Update the vehicle information storage spaces.

EUVO algorithm is an extension of the proposed algorithm PerSiCon-Network to enhance its data inputs. Besides the sets, decision variables and parameters adopted in Table 4.1 in Chapter 4, the additional parameters and constants which are dedicated to EUVO algorithm are summarized in Table 6.1.

Table 6. 1 Definitions of parameters and constants for EUVO algorithm

Sets	Description	Unit
ID_{CV}^{P}	ID list of CVs for phase p collected at initial time step t_0.	—
V_{CV}^{P}	Speed list of CVs for phase p collected at initial time step t_0.	—
S_{CV}^{P}	Position list of CVs for phase p collected at initial time step t_0.	—
O_{CV}^{P}	Occupancy list of CVs for phase p collected at initial time step t_0.	—
T_{loop}^{p}	Vehicle crossing time list for phase p captured by inductive loop during the signal plan execution duration.	—
O_{cam}^{p}	Vehicle occupancy list for phase p captured by camera during the signal plan execution duration.	—
ID_{loop}^{p}	ID list of vehicles for phase p sorted by their loop crossing sequence during the signal plan execution duration.	—
T_{cross}^{p}	Loop crossing time step of vehicles for phase p sorted by their loop crossing sequence during the signal plan execution duration.	—
ID_{rec}^{p}	ID list of vehicles left in discharging lane for phase p recorded in junction database.	—
O_{rec}^{p}	Occupancy list of vehicles left in discharging lane for phase p recorded in junction database.	—

Parameters		
$ID_{CV}^{P}(i)$	ID of CV i in list ID_{CV}^{P} .	—
$V_{CV}^{P}(i)$	Speed of CV i in list V_{CV}^{P} .	m/s
$S_{CV}^{P}(i)$	Position of CV i in list S_{CV}^{P} .	m
$O_{CV}^{P}(i)$	Occupancy of CV i in list O_{CV}^{P} .	—
$T_{loop}^{p}(i)$	Vehicle crossing time of vehicle i in list T_{loop}^{p}.	s
$O_{cam}^{p}(i)$	Occupancy of vehicle i in list O_{cam}^{p}.	—
$ID_{loop}^{p}(i)$	ID of vehicle i in list ID_{loop}^{p}.	—
$T_{cross}^{p}(i)$	Loop crossing time of vehicle i in list T_{cross}^{p}.	s
$ID_{rec}^{p}(i)$	ID of vehicle i in list ID_{rec}^{p}.	—
$O_{rec}^{p}(i)$	Occupancy of vehicle i in list O_{rec}^{p}.	—
n_{front}^{p}	Number of vehicles stopped before the first detected CV in the queue.	—
$t_{loop,cross}^{p}(i-1)$	The actual time of last CV $i-1$ spends from inductive loop to stop line.	s
$t_{excess}^{p}(i-1)$	The excess time cost of last CV $i-1$ spends from inductive loop to stop line.	s
D_{CL}	The distance needed for CV i to accelerate to free-flow travelling speed V_d.	m
$t_{next}^{p}(i)$	The time needed for next CV/UV i to cross the lane when last CV/UV discharges from the cross line.	s
$t_{gap}(i-1,i)$	The time gap between last CV/UV and next CV/UV when they cross the inductive loop.	s
$g_{rest}^{p}(i)$	The rest of green time of phase p supposing next CV/UV i can cross the lane	s
Constants		
μ_{fir}	The constant value of the distance between the first stopped CV and the cross line.	m
l_{veh}	The length of a vehicle.	m
μ	The gap distance between two vehicles in queue.	m

The EUVO algorithm is illustrated in Algorithm 6 as follows:

Algorithm 6 EUVO algorithm

Input: ID list ID_{CV}, speed list V_{CV}, position list S_{CV}, occupancy list O_{CV} of detected CVs; Crossing time list T_{loop} and occupancy list O_{cam}, from loop and camera; ID list of UVs and CVs cross the inductive loop ID_{loop}; g_{last} and g_p; Vehicle ID list ID_{rec} and occupancy list O_{rec} from storage space.

Output: Predicted initial departure time list, status list and occupancy list of UVs and CVs in lane; Updated vehicle ID list ID_{rec}^{p} and occupancy list O_{rec}^{p}

1: If there is at least one CV in the approach lane & the speed of first detected CV is less than 0.01 m/s:

2: determine number of stopped UVs in front of it using Equation (6-1)

3: estimate predicted initial departure time of UVs using Equation (6-2)

4: Else if there is at least one CV in the approach lane & at least one CV in the discharging list during last planning duration & no UV between first detected CV and last discharged CV:

5: predict initial departure time and status using Equation (6-3) - (6-6)

6: Else:

7: retrieve $T_{loop}^{p}(i-1)$ and $T_{cross}^{p}(i-1)$ of last discharged CV/UV from storage space or loop/stop line cross time list

8: For UV(s)/CV(s) after last discharged CV/UV:
9: If UV/CV is the following vehicle next to last discharged CV/UV:
10: judge whether it can cross the lane or not using Equations (6-7) – (6-14)
11: Else:
12: judge whether it can cross the lane or not using Equations (6-11) – (6-14)
13: If it cannot cross the lane:
14: calculate initial departure time $\mathrm{Vc}_0^p(1, \mathrm{s}_0)$ and status $\mathrm{Sc}_0^p(1, \mathrm{s}_0)$ using Equation (6-15) and (6-16)
15: update value of $t_{excess}^p(1)$, $t_{next}^p(1)$ and $g_{rest}^p(1)$ using Equations (6-11) – (6-14)
16: break
17: Else if there is at least one CV in the approach lane & the UV is previous vehicle of first detected CV:
18: calculate initial departure time $\mathrm{Vc}_0^p(1, \mathrm{s}_0)$ and status $\mathrm{Sc}_0^p(1, \mathrm{s}_0)$ using Equation (6-3) to (6-6)
19: Else:
20: pass
21: update value of $t_{excess}^p(1)$, $t_{next}^p(1)$ and $g_{rest}^p(1)$ using Equations (6-11) – (6-14)
22: For vehicles from second one which cannot cross to last one detected by inductive loop:
23: If it is a UV:
24: calculate initial departure time $\mathrm{Vc}_0^p(i, \mathrm{s}_0)$ and status $\mathrm{Sc}_0^p(i, \mathrm{s}_0)$ using Equation (6-17) and (6-16)
25: Else:
26: calculate initial departure time $\mathrm{Vc}_0^p(i, \mathrm{s}_0)$ and status $\mathrm{Sc}_0^p(i, \mathrm{s}_0)$ using Equation (6-18) and (6-19)
27: update value of $t_{excess}^p(i)$, $t_{next}^p(i)$ and $g_{rest}^p(i)$ using Equations (6-11) – (6-14)
28: Create occupancy list for all vehicles by matching the corresponding indexes in either O_{rec}^p or O_{cam}^p
29: Remove data of vehicles before last discharging CV from ID_{rec}^p and O_{rec}^p
30: Append data of all UVs before first detected CV in the approach lane into ID_{rec}^p and O_{rec}^p

6.3.1 Data collection for EUVO algorithm

Compared to data inputs of PerSiCon-Network, more data sources are required for the EUVO algorithm to estimate the states of UVs. The data inputs for the EUVO algorithm originate from three parts: a) data from CVs; b) data from inductive loops and roadside cameras; c) Data from the storage space of junction controllers. Inductive loops and roadside cameras are activated every time step during the whole signal plan execution duration between two optimization processes of PerSiCon-Network. The data from the nearest CV to the cross line for every time step are also required to realize whether the first detected CV has discharged from the arrival lane. Data from the storage space of junction controllers record all of the index and occupancy levels of vehicles detected but not discharged in the last signal optimization process to recognize their states and occupancy information. The relationships of the three data resources of the EUVO algorithm are presented in Figure 6.2.

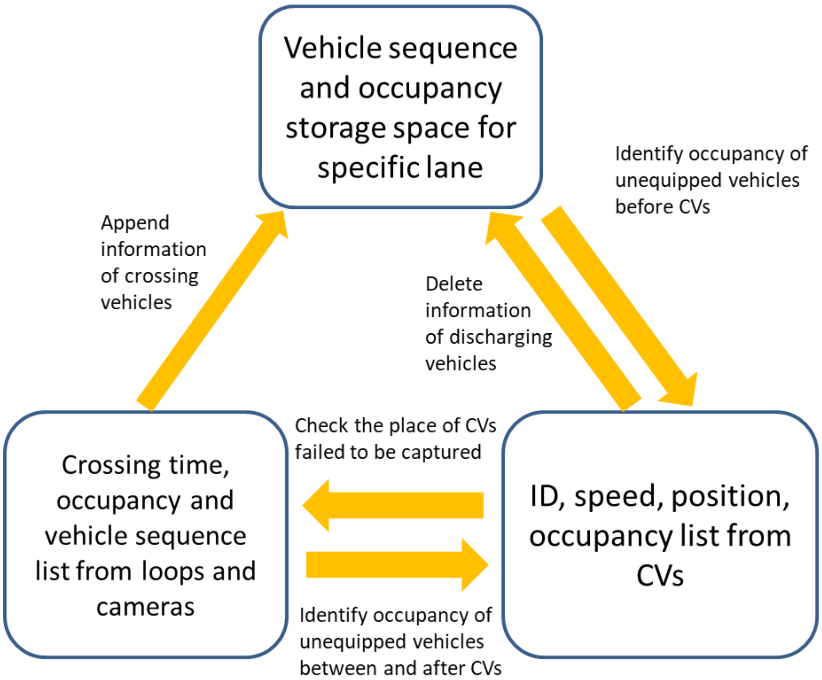

Figure 6. 2 Relationships of three data resources of EUVO algorithm

The illustration of the junction controller receiving three types of data sources as the first step of the EUVO algorithm is shown in Figure 6.3. The details of all pieces of data are listed below:

- ID list $ID_{CV}^{P} = [ID_{CV}^{P}(1), ID_{CV}^{P}(2), \ldots, ID_{CV}^{P}(n)]$, speed list $V_{CV}^{P} = [V_{CV}^{P}(1), V_{CV}^{P}(2), \ldots, V_{CV}^{P}(n)]$, position list $S_{CV}^{P} = [S_{CV}^{P}(1), S_{CV}^{P}(2), \ldots, S_{CV}^{P}(n)]$ and occupancy list $O_{CV}^{P} = [O_{CV}^{P}(1), O_{CV}^{P}(2), \ldots, O_{CV}^{P}(n)]$ of all detected CVs of phase $p \in P$ and their distance to the cross line from nearest to farthest one at an initial time step t_0. The elements with the same index in the above lists are characteristics of the same vehicle.
- Loop crossing time list $T_{loop}^{p} = [T_{loop}^{p}(1), T_{loop}^{p}(2), \ldots, T_{loop}^{p}(n)]$ and camera captured occupancy list $O_{cam}^{p} = [O_{cam}^{p}(1), O_{cam}^{p}(2), \ldots, O_{cam}^{p}(n)]$ from loop and camera respectively sorted from earliest to latest one during the signal plan execution duration. The elements with the same index in two lists are characteristics of the same vehicle.
- Locations of nearest CV for every time step and all CVs when there is a vehicle crossing the inductive loop. The former one is to identify the time step when the last CV is discharging from the cross line. The latter one is to find out whether the vehicle that crosses the inductive loop is a CV or not. The location of CVs can be used to compare with the distance from the inductive loop to the cross line to ensure this. A new ID list mixture by CVs and UVs to distinguish UV/CV type with the same sequence of their stop line cross time of phase $p \in P$ is generated as $ID_{loop}^{p} = [ID_{loop}^{p}(1), ID_{UV}^{p}(2), \ldots, ID_{loop}^{p}(n)]$. ID_{UV}^{p} refers that this vehicle is a UV. The stop line crossing time step list $T_{cross}^{p} = [T_{cross}^{p}(1), T_{cross}^{p}(2), \ldots, T_{cross}^{p}(n)]$ represents the detected or estimated time steps of CVs/UVs when they cross the stop line.

- Signal timing plan optimized by PerSiCon-Network in the last planning horizon. It is used to judge whether UVs are discharging from the cross line after the last CV and realize the green duration given for this lane before the current time step. Two parameters are important to be identified: green time last after the final detected CV or estimated UV passes through the cross line g_{rest}^{p} before the optimization time step and constantly green time given for this lane before the initial time step g_p.
- ID list mixture by CVs and UVs of vehicles in discharging lane updated at last optimization time step $ID_{rec}^{p} = [ID_{rec}^{p}(1), ID_{UV}^{p}(2), \dots, ID_{rec}^{p}(n)]$ and occupancy list sorted by the index of ID list $O_{rec}^{p} = [O_{rec}^{p}(1), O_{UV}^{p}(2), \dots, O_{rec}^{p}(n)]$. These two lists are recorded in the storage space of the junction controller and are used to determine the number of vehicles in discharging lane in the current time step and their occupancy data.

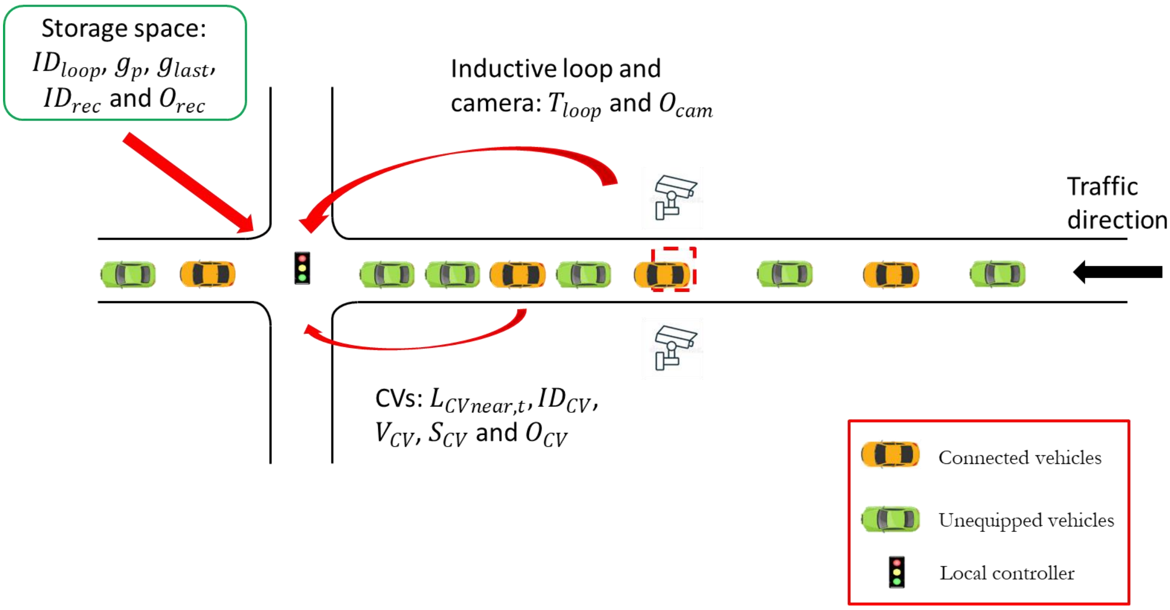

Figure 6. 3 Data collection stage for EUVO algorithm

6.3.2 Estimate states of unequipped vehicles in front of first detected CV

At the initial time step t_0, the junction controller receives data from all CVs. The initial departure time can directly be predicted using Equations (4-10) – (4-13) if all vehicles on road are CVs. However, with the presence of UVs, the number of UVs in front of the first detected CV is challenging to be required as they cannot provide their vehicular status. Therefore, it is critically important to figure out the status of the first vehicle in discharging lane and then estimate the initial departure time of all vehicles sequentially and search for their relative the occupancy level from occupancy data list O_{cam} or O_{rec}. An example has been illustrated in Figure 6.4.

As claimed in Section 6.3.1, ID_{loop} or ID_{rec} can be used to identify whether there are UVs between the first detected CV and the last discharging CV. If there is no UV between them, the first detected CV is the nearest vehicle to the cross line. Its initial departure time and status can be calculated by Equations (4-10) and (4-12). If there is at least 1 UV between two CVs, the states of UV are estimated in different cases. If the speed of the first detected CV is less than 0.01 m/s, it can be regarded as a stopped vehicle in the queue. The number of vehicles stopped in front of it n_{front} can be calculated by Equation (6-1):

$$n_{front} = (S_{CV,1} - \mu_{fir}) / (l_{veh} + \mu) \tag{6-1}$$

Where μ_{fir} is the constant value of the distance between the first stopped vehicle and the cross line, l_{veh} is the length of the first vehicle and μ is gap distance between two vehicles in queue. The initial departure time of vehicles including the first detected CV $\mathrm{Vc}_0^p(i, s_0)$ is calculated in Equation (6-2):

$$\mathrm{Vc}_0^p(i, \mathrm{s}_0) = \begin{cases} \alpha + h_s - g_p, & if\ i = 1 \\ \mathrm{Vc}_0^p(i - 1, \mathrm{s}_0) + h_s, & if\ i \geq 2 \end{cases} \tag{6-2}$$

Where α and h_s are start-up loss time and saturated headway defined in Chapter 3. The constantly green time given for this lane before initial time step is 0 if the traffic signal is a red light. All vehicle status from first stopped vehicle to the first detected CV is queuing status. The occupancy level of first detected CV can be matched either O_{cam} or O_{rec} through the index of its unique ID in the ID list ID_{CV} or ID_{loop}. The occupancy levels of all vehicles in front of it can be assigned by the occupancy list with relative indexes.

If there is at least one CV in the approach lane and at least one CV in the discharging list during the last planning duration and no UV between the first detected CV and last discharged CV, the first detected CV is the nearest vehicle to the cross line. The initial departure time for the first detected CV and following CVs in queue and arrivals can be predicted at the start of optimization supposing that the next stage for this lane will be constantly activated with green lights, which are expressed in Equations (6-3) - (6-6). The prediction of the following CVs can be found below in Equations (6-18) and (6-19). The prediction method is originated from the kinematic wave theory principles adopted in person-based control (Christofa et al, 2016) and (Mohammadi et al, 2019), which is used for describing vehicle trajectories in the fleet with the influence of adjacent vehicles. In this paper, the acceleration and deceleration process of vehicles when they merge into queues or start up for discharging are simplified to reduce the operational complexity of algorithm optimization. Four cases of different fleet trajectory patterns are considered in this method in the case of no less than three vehicles in arriving fleet:

1. All vehicles are discharged at free-flow speed
2. All vehicles are discharged from the queue
3. Following vehicles travelling at free-flow speed arrive before the queue has been discharged
4. Following vehicles travelling at free-flow speed arrive after the queue has been discharged.

$$Vc_0^p(1,s_0) = \begin{cases} \alpha + h_s - g_p, if v_0^p(1) = 0 \wedge g_p < \alpha + h_s \\ min\left[\alpha + h_s - g_p, l_0^p\,(1)/v_0^p\,(1)\right], if 0 \le v_0^p(1) \le v_s \wedge g_p < \alpha + h_s \forall p \in P \\ l_0^p\,(1)/v_0^p\,(1), if v_0^p(1) > v_s \vee g_p \ge \alpha + h_s \end{cases} \tag{6-3}$$

$$Sc_0^p(1,s_0) = \begin{cases} 1, if v_0^p(1) > v_s \\ 0, if v_0^p(1) \le v_s \end{cases} \forall p \in P \tag{6-4}$$

$$h_s = \begin{cases} 3600/S_c\,, if\ vehicle\ is\ a\ car \\ 3600/S_B\,, if\ vehicle\ is\ a\ bus \end{cases} \tag{6-5}$$

$$v_s = \begin{cases} v_{car}, if\ vehicle\ is\ a\ car \\ v_{bus}, if\ vehicle\ is\ a\ bus \end{cases} \tag{6-6}$$

More details for predicting the initial departure time and status of the first detected CV in different cases can be found in Chapter 4. Equation (6-5) represents that buses and cars have different saturated flows and the headways between two vehicles are decided by the saturation flow of the front vehicle. This simplification is justified by the calculation of headway only relying on the front vehicle, so does not significantly degrade the results (Yang et al, 2018). Equation (6-6) indicates that the speeds of cars and buses discharging from the queue, which are used for judging vehicle status, are also different.

In other cases, if the speed of the first detected CV is higher than 0.01 m/s, the status of vehicles in front of it cannot be directly decided and data of the last CV discharging from the cross line is needed. Define $t_{loop,cross}^p(i-1)$ as the actual time of the last CV $i-1$ spends from the inductive loop to the stop line. The excess time cost $t_{excess}^p(i-1)$ of the last CV $i-1$, which compares $t_{loop,cross}^p(i-1)$ with the time spent on free-flow travel time from the inductive loop to discharge from the lane, is calculated as:

$$t_{loop,cross}^p(i-1) = T_{cross}^p(i-1) - T_{loop}^p(i-1), \forall p \in P \tag{6-7}$$

$$t_{excess}^{p}(i-1) = t_{loop,cross}^{p}(i-1) - (d_{loop,cross}^{p} / v_{loop}^{p}(i-1)), if\ v_{loop}^{p}(i-1)) \geq 0.9V_d \tag{6-8}$$

$$D_{CL} = \frac{{V_d}^2 - (v_{loop}^{p}(i-1))^2}{2a} \tag{6-9}$$

$$t_{excess}^{p}(i-1) = t_{loop,cross}^{p}(i-1) - (d_{loop,cross}^{p} - D_{CL}) / V_d - (V_d - v_{loop}^{p}(i-1))/a, if\ v_{loop}^{p}(i-1)) < 0.9V_d \tag{6-10}$$

Equation (6-7) defines the calculation value of actual travel time $t_{loop,cross}^{p}(i-1)$. Equations (6-8) - (6-10) calculate the excess time cost $t_{excess}^{p}(i-1)$ of the last CV $i-1$ in either free-flow speed travelling mode or acceleration and free-flow speed travelling mode, depending on the location of the loop detection area and the speed of the vehicle when it crosses the inductive loop. If the junction controller judges the speed of vehicle $v_{loop}^{p}(i-1)$ is in the range of free-flow speed, the excess time cost $t_{excess}^{p}(i-1)$ can be calculated by Equation (6-8). Notably, cars and buses have different free-flow speed ranges, which need to be recognized separately. Otherwise, Equations (6-9) and (6-10) are used for estimating $t_{excess}^{p}(i-1)$, which represent that the vehicle first experiences an acceleration process from queue discharging status to free-flow travelling status, then cross the stop line with free-flow speed. For UVs, the free-flow speed and the speed when vehicles cross the inductive loop are originated from the empirical values observed.

The time needed for the next CV/UV i to cross the lane when the last CV/UV discharges from the cross line $t_{next}^{p}(i)$ is calculated by Equations (6-11) and (6-12):

$$t_{gap}(i-1,i) = T_{loop}^{p}(i) - T_{loop}^{p}(i-1), \forall p \in P \tag{6-11}$$

$$t_{next}^{p}(i) = \max(h_s, t_{gap}(i-1,i) - t_{excess}^{p}(i-1)), \forall p \in P \tag{6-12}$$

Where $t_{gap}(i-1,i)$ is the time gap between the last CV/UV and the next CV/UV when they cross the inductive loop. The excess time cost $t_{excess}^{p}(i)$ of vehicle i are then updated for estimating the arrival status of the next following vehicle by Equation (6-13). Formula (6-14) is used to judge whether the next CV/UV can cross the junction before the initial time step or not:

$$t_{excess}^{p}(i) = \begin{cases} 0, & if\ t_{gap}(i-1,i) - t_{excess}^{p}(i-1) \geq h_s \\ t_{excess}^{p}(i-1) + h_s - t_{gap}(i-1,i), & if\ t_{gap}(i-1,i) - t_{excess}^{p}(i-1) \geq h_s \end{cases} \tag{6-13}$$

$$g_{rest}^{p}(i) = \max(g_{rest}^{p}(i-1) - t_{next}^{p}(i), 0), \forall p \in P \tag{6-14}$$

In formula (6-14), $g^{p}_{rest}(i)$ means the rest of the green time of phase p supposing the next CV/UV i can cross the lane. If it is a negative value, CV/UV cannot cross the lane and it becomes the nearest vehicle to the cross line. The initial departure time $\mathrm{Vc}^{p}_{0}(1, \mathrm{s}_0)$ and status $\mathrm{Sc}^{p}_{0}(1, \mathrm{s}_0)$ of it is calculated by:

$$\mathrm{Vc}^{\mathrm{p}}_{0}(1, \mathrm{s}_0) = \begin{cases} t^{p}_{next}(i) - g_p, & if\ contantly\ green\ until\ t_0 \\ \alpha + h_s - g_p, & if\ other\ cases \end{cases} \tag{6-15}$$

$$\mathrm{Sc}^{\mathrm{p}}_{0}(\mathrm{i}, \mathrm{s}_0) = \begin{cases} 1, & if\ t_{gap} - t_{excess} - h_s > 0 \\ 0, & if\ t_{gap} - t_{excess} - h_s \le 0 \end{cases} \tag{6-16}$$

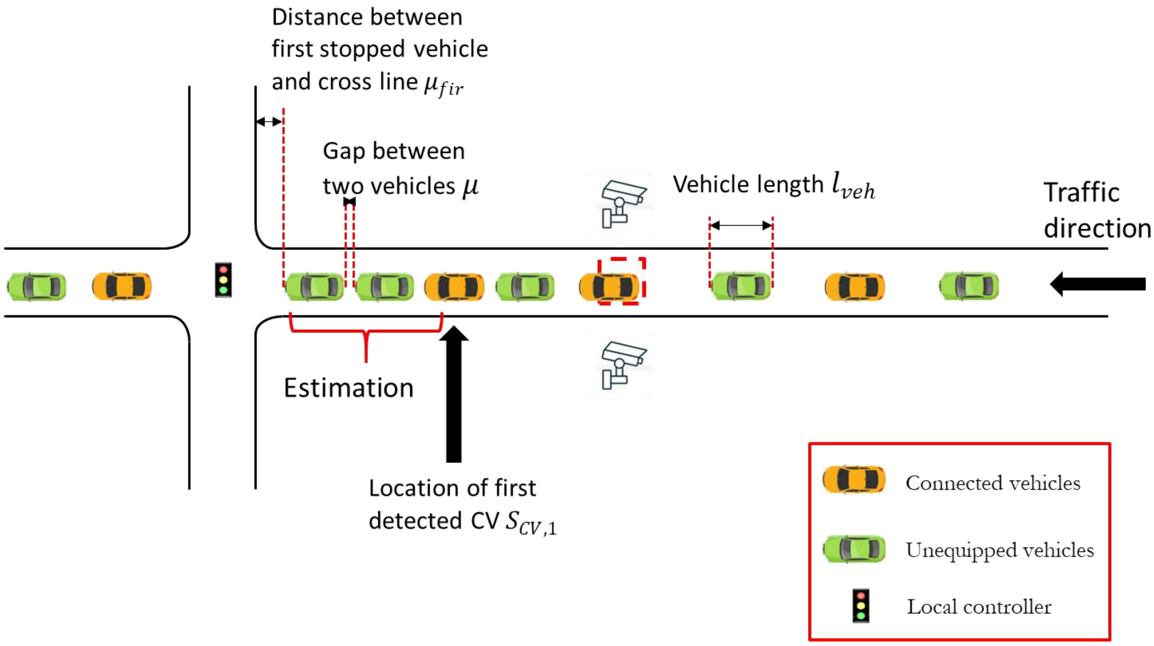

Figure 6. 4 An example of estimating states of unequipped vehicles in front of first detected CV

6.3.3 Estimate states of vehicles behind first detected CV

The initial predictive departure time and status of the first CV/UV can be determined in different cases mentioned above. After that, the next step is to estimate the following vehicles within the inductive loop and CV detection region, as shown in Figure 6.5. As each CV or bus can be recognized by its unique ID in ID_{CV} or ID_{loop}, the number of UVs/CVs/buses after the first vehicle in the discharging lane can be determined. For all of the vehicles from the second one which cannot cross to the last one detected by the inductive loop, if it is a UV, the initial departure time $\mathrm{Vc}^{p}_{0}(i, \mathrm{s}_0)$ and status $\mathrm{Sc}^{p}_{0}(i, \mathrm{s}_0)$ of vehicle i can be calculated by Equations (6-17) and (6-16):

$$\mathrm{Vc}^{\mathrm{p}}_{0}(\mathrm{i}, \mathrm{s}_0) = \mathrm{Vc}^{\mathrm{p}}_{0}(\mathrm{i} - 1, \mathrm{s}_0) + t_{next},\ i \ge 2 \tag{6-17}$$

If the next following vehicle in the lane is a bus or CV, the initial departure time $\mathrm{Vc}_0^p(i, \mathrm{s}_0)$ and status $\mathrm{Sc}_0^p(i, \mathrm{s}_0)$ can be calculated by Equations (6-18) and (6-19) considering four different cases analysing vehicle trajectories and statuses with the knowledge of speeds and distances of bus or CV to junction cross line.

$$Vc_0^{\mathrm{p}}(i, \mathrm{s}_0) = \begin{cases} \mathrm{Vc}_0^p(i-1, \mathrm{s}_0) + h_s, & if\ v_0^p(i) \leq v_s \\ \max[\, l_0^p(i)/v_0^p(i),\ \mathrm{Vc}_0^p(i-1, \mathrm{s}_0) + h_s], & if\ v_0^p(i) > v_s \end{cases} \quad \forall p \in P, i \geq 2 \tag{6-18}$$

$$Sc_0^p(i, s_0) = \begin{cases} 1, if\ v_0^p(1) > v_s\ and\ Vc_0^p(i, s_0) > l_0^p(i)/v_0^p(i) \\ 0, \quad other\ cases \end{cases} \quad \forall p \in P,\ i \geq 2 \tag{6-19}$$

After estimating the departure time $\mathrm{Vc}_0^p(i, \mathrm{s}_0)$ and status $\mathrm{Sc}_0^p(i, \mathrm{s}_0)$ of vehicle i, the occupancy values with corresponding indexes in O_{rec}^p or O_{cam}^p are assigned to vehicles to estimate the occupancy levels of UVs. In addition, the value of $t_{excess}^p(i)$, $t_{next}^p(i)$ and $g_{rest}^p(i)$ need to be updated for the preparation of calculating departure time and status for the next vehicle $i + 1$ until the last vehicle is detected by inductive loop using Equations (6-11) – (6-14).

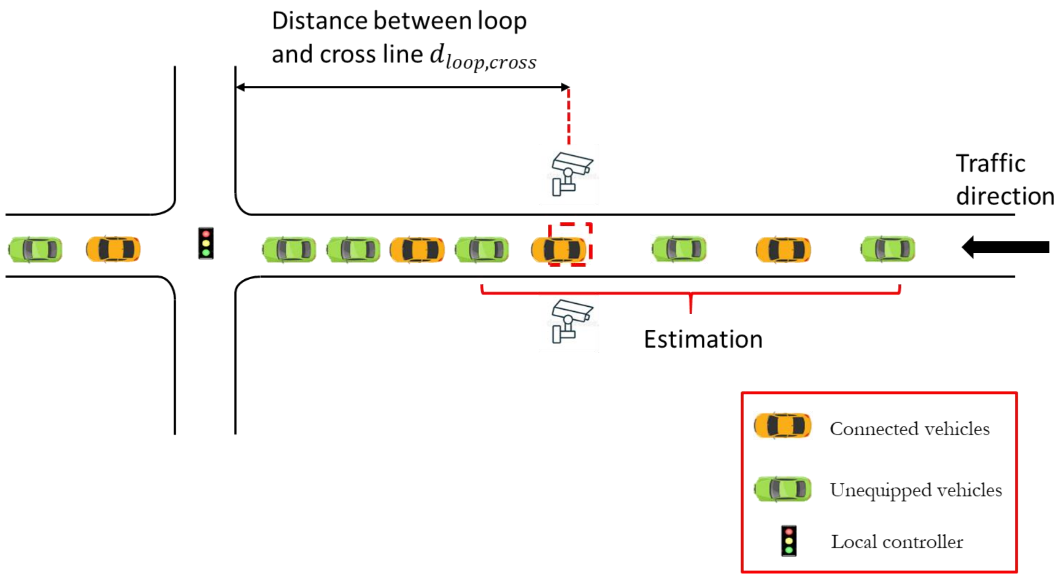

Figure 6. 5 An example of estimating states of unequipped vehicles behind first detected CV

6.3.4 Update the storage space of junction controller

The final step of the EUVO algorithm is to update the storage space of the junction controller. The purpose of this step is to record the data of all UVs and CVs in the approach lane, which is contributed to identifying the numbers, distributions and relative occupancy data of UVs for the next optimization duration. As seen in Figure 6.6, the data of those vehicles that have been discharged from the lane in the last signal plan execution duration are removed. The data of upcoming vehicles detected by inductive loops are appended to the end of the ID list ID_{rec} and occupancy list O_{rec}.

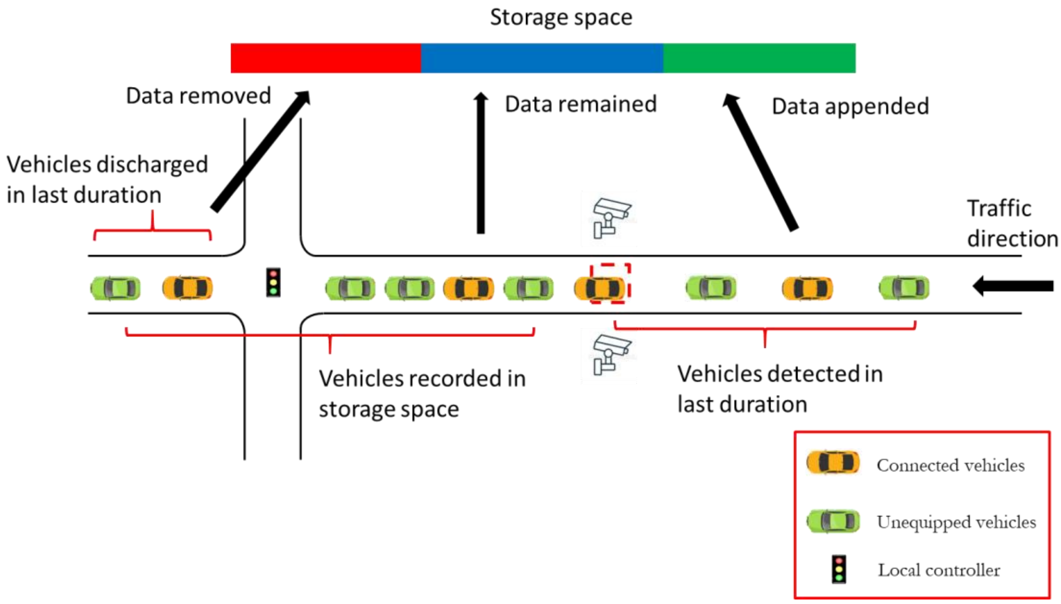

Figure 6. 6 An example of updating storage space after estimation.

6.4 Experiments and evaluations of PerSiCon- Network with EUVO algorithm

To validate the performance of the EUVO algorithm, the person-related performance of PerSiCon-Network with EUVO algorithm compared to the performance of PerSiCon-Network without UVs estimation. The experiment results of PerSiCon-Network without UVs estimation are presented in Chapter 5 and placed in this chapter as the performance of a benchmarking model. The person-based control PerSiCon-Network supported by the EUVO algorithm is operated and evaluated in the same case study provided in Chapter 5 in SUMO simulation. The vehicular parameters, junction layouts and traffic generation have been introduced in Chapter 5 and kept the same to evaluate PerSiCon-Network with the EUVO algorithm.

The data collection simulations for additional data inputs from loop detectors and roadside cameras in the EUVO algorithm have been explained in Sections 6.1 and 6.2. The occupancy detection outputs from cameras are assumed to be directly obtained in experiments due to the lack of vehicle occupancy detection technology and photo inputs. The state-of-the-art research reviewed in Chapter 2 achieved 87% vehicle occupancy detection accuracy using one-side cameras. This value is adopted and set to be the accuracy degree of occupancy detection from one-side cameras to make data sources of evaluations more realistic. If there are 2 or more lanes from one direction and 2 or more vehicles cross the inductive loop detection area at the same time step, the occupancy level of vehicles except the left one cannot be detected and their occupancy values are replaced by a uniformly random value from 1 to vehicle capacity. The occupancy level accuracy of CVs captured from in-vehicle cameras is assumed to be 99%.

Instead of the sensitivity factors that have been tested in Chapter 5, this Chapter designs some particular sensitivity factors for the EUVO algorithm to understand in which conditions it can achieve the best results. The scenarios for different CV penetration rates need to be carried out to evaluate the effectiveness of the EUVO algorithm in imperfect CV penetration rates. Besides, it is not clear where the most suitable detection area installation place is and how frequently to activate the detection area to perform the EUVO algorithm best. To observe the sensitivity of the estimation algorithm to different factors, different CV penetration rates, distances of loops and cameras to the cross line and active time interval of loops and cameras are tested respectively. The CV penetration rates are set from 10% to 100% with a step of 10%. The distances of loops and cameras to the cross line are set from 50m to 250m with a step of every 50m. 1s, 2s, 3s and 5s active time intervals of loops and cameras are used in different experiments to test the changes of EUVO algorithm. When one of the parameters is changed and tested, 50% CV penetration rate, 250m distance and 1s active time interval are used for the other two factors.

6.5 Results and discussions

6.5.1 Initial results observation

To better understand how the EUVO algorithm works and make effects on vehicle state estimations, an initial results observation is made at a certain time step when the PerSiCon-Network is triggered. The observation place is westbound two approaching lanes of the junction of New John St West and Summer Ln of Birmingham, UK, where there are two main approach lanes with massive streams of traffic. The optimization outputs made by the EUVO algorithm are compared with the outputs when the CV penetration rate is 100%. Figure 8.7 to Figure 8.9 illustrate the comparisons of estimation results from the EUVO algorithm in different settings of CV penetration rates, distances of loops/cameras to the cross line, active time intervals and baseline data representing actual states of UVs and CVs. As the PerSiCon-Network requires predictive departure time and occupancy data as inputs, the initial predictive discharging time and occupancy sequence for two lanes from west to east of the selected junction are calculated by 100% penetration rate as the baseline, which represents the actual states of vehicle data with CVs and UVs. In PerSiCon-Network with the EUVO algorithm, only data from CVs can be directly obtained.

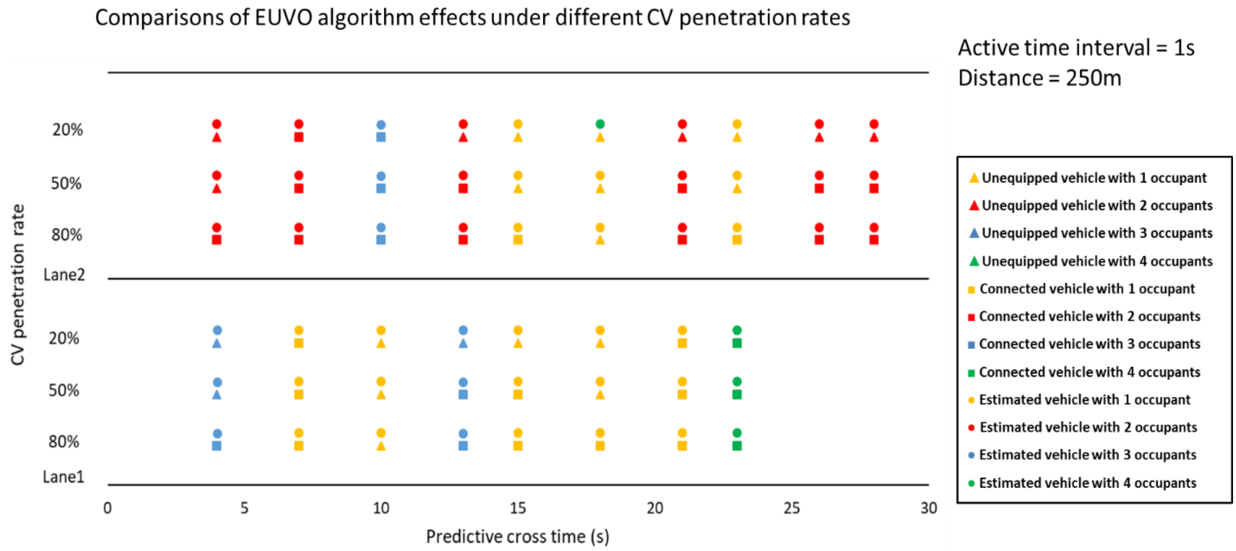

Figure 6. 7 Initial result observations of EUVO algorithm in different CV penetration rates

Figure 6.7 illustrates the vehicle state estimations made by the EUVO algorithm in 20%, 50%, 80% CV penetration rates respectively. Above the horizontal lines lane 1 and lane 2, there are three lists respectively, which represent the EUVO estimation results and baselines for lane 1 and lane 2 respectively in three different CV penetration rates. Each list responds to the CV penetration rate marked on the left side and it consists of two groups. In each list, the upper group (consisting of circle shapes) is the vehicle predictive cross-time estimations and correspond occupancy levels (represented by different colours) made by the EUVO algorithm in relative CV penetration rate. The lower group is the baseline outputs made by PerSiCon-Network when the CV penetration rate is 100%. The rectangle shapes and triangle shapes represent baseline values of CVs and UVs and different colours are their real occupancy levels. In different CV penetration rates, the EUVO algorithm can only acquire vehicle information with rectangle shapes (CVs). With different CV penetration rates EUVO algorithm receives different degrees of CV information, there are different baselines under each of the EUVO algorithm estimation outputs with circle shapes, to represent which vehicle information can be acquired by the EUVO algorithm (with rectangle shapes) in specific CV penetration rate.

Figure 6.7 illustrates that in different CV penetration rates, the estimation results for two lanes made by the EUVO algorithm produce correct predictive cross time for all vehicles, regardless of their connectivity. Only in a few cases, such as 20% CV penetration rates for lane 2, the EUVO algorithm generates an incorrect vehicle occupancy level. It could be found from this figure that penetration rate is not a critical factor to affect the performance of the estimation algorithm when loops and cameras are active every second with a distance of 250m to cross the line. In the case of 20% penetration rate, the accuracy of the estimation algorithm is still kept at a high level.

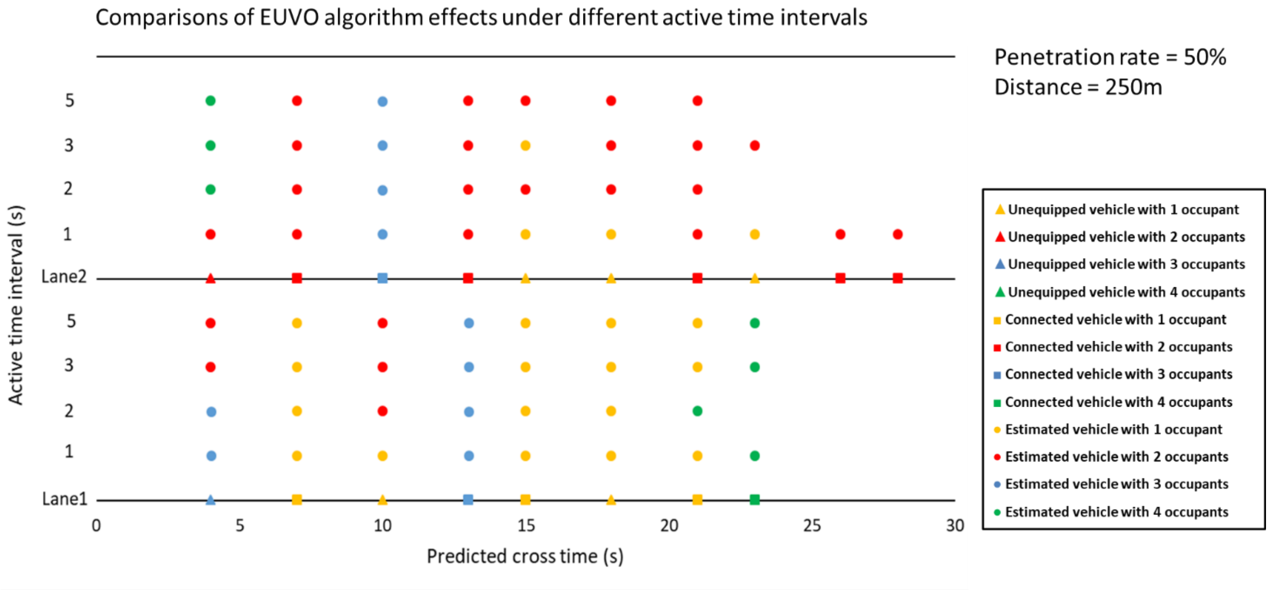

Figure 6. 8 Initial result observations of EUVO algorithm in active time intervals of cameras and loops

Figure 6.8 presents comparisons of estimation algorithm effects under active time intervals of different devices when the CV penetration rate is 50%. Similar to Figure 6.7, the rectangles and triangles on two lines represent the predictive cross time and occupancy levels of vehicles in 100% CV penetration rate as baselines. When the CV penetration rate is 50%, only CV data with rectangle shapes can be acquired by the EUVO algorithm. The groups of circle shapes with different colours on lane 1 and lane 2 lines represent the vehicle departure time estimation and occupancy level results of the EUVO algorithm, in the case that active time intervals are 1, 2, 3 and 5 seconds respectively.

It can be found in Figure 6.8 that the performance of the EUVO algorithm are significantly degraded when loops and cameras are active every 2, 3 and 5 seconds compared to those when devices are activated every second. The reason is around half of the crossing vehicles cannot be detected by loops and cameras when they are active every 2 seconds and two third cannot be found when the active interval is 3 seconds. It is hard to make an accurate estimation when a proportion of unequipped vehicle data are missing.

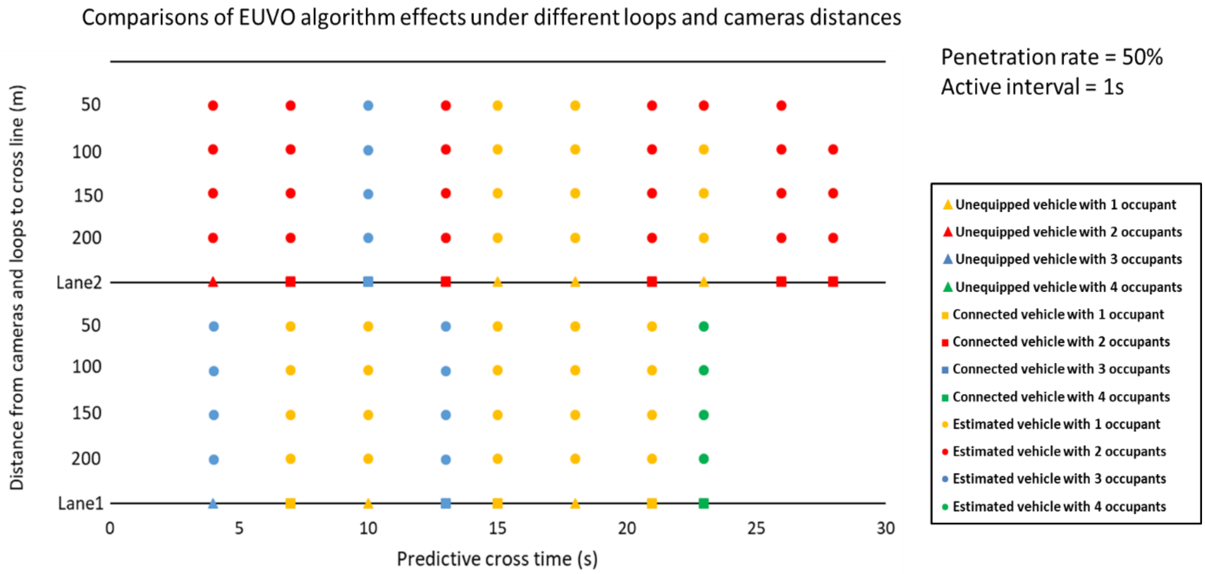

Figure 6. 9 Initial result observations of EUVO algorithm in different distances from cameras and loops to cross line

The illustration of Figure 6.9 is very similar to Figure 6.8. The rectangles and triangles on two lines represent the predictive cross time and occupancy levels of vehicles in 100% CV penetration rate as baselines. EUVO algorithm can only acquire CV data with rectangle shapes as data inputs. The circle shapes above lane 1 and lane 2 are EUVO algorithm outputs for lane 1 and lane 2 when the inductive loops and cameras are installed at 50, 100, 150, 200 and 250 meters to cross the line respectively.

Figure 6.9 shows comparisons of estimation algorithm effects under different device installation locations. The effects of the estimation algorithm do not severe drop when distances from loops and cameras to cross line change between 100 meters and 250 meters. However, the overclose distance of devices makes estimation not quite accurate as some UVs fail to cross the detection area when the EUVO algorithm works.

6.5.2 Sensitivity analysis to CV penetration rate

Figure 6.10 illustrates the performance of PerSiCon-Network with EUVO algorithm compared to PerSiCon-Network without EUVO algorithm in various CV penetration rates in three flow levels. The loops and cameras are 250m far from the cross line and active for every second. Table 6.2 shows the hypothesis test results of two control methods at 95% confidence degree. From Figure 6.10, although the average person delays and stops of PerSiCon-Network with EUVO algorithm increase as CV penetration rate decreases, the trend is rather steady and gentle compared to those performance of PerSiCon-Network without EUVO algorithm. The improvements in average person delays and stops are more significant especially when the CV penetration rate is below

50%. From the six subplots in Figure 6.10, the performance of PerSiCon-Network with EUVO algorithm at 30% CV penetration rate are even better than those of PerSiCon-Network without EUVO algorithm at 70% CV penetration rate. However, when the CV penetration rate is below 20%, the increments of average person delays and stops are relatively larger than the cases when the CV penetration rate is higher than 20%. The small proportion of CVs causes negative impacts on reducing delays and stops. The results from hypothesis tests in Table 6.2 also prove the effectiveness of the EUVO algorithm. The average person delays and stops of two control methods have significant differences when the CV penetration rate is below 90%.

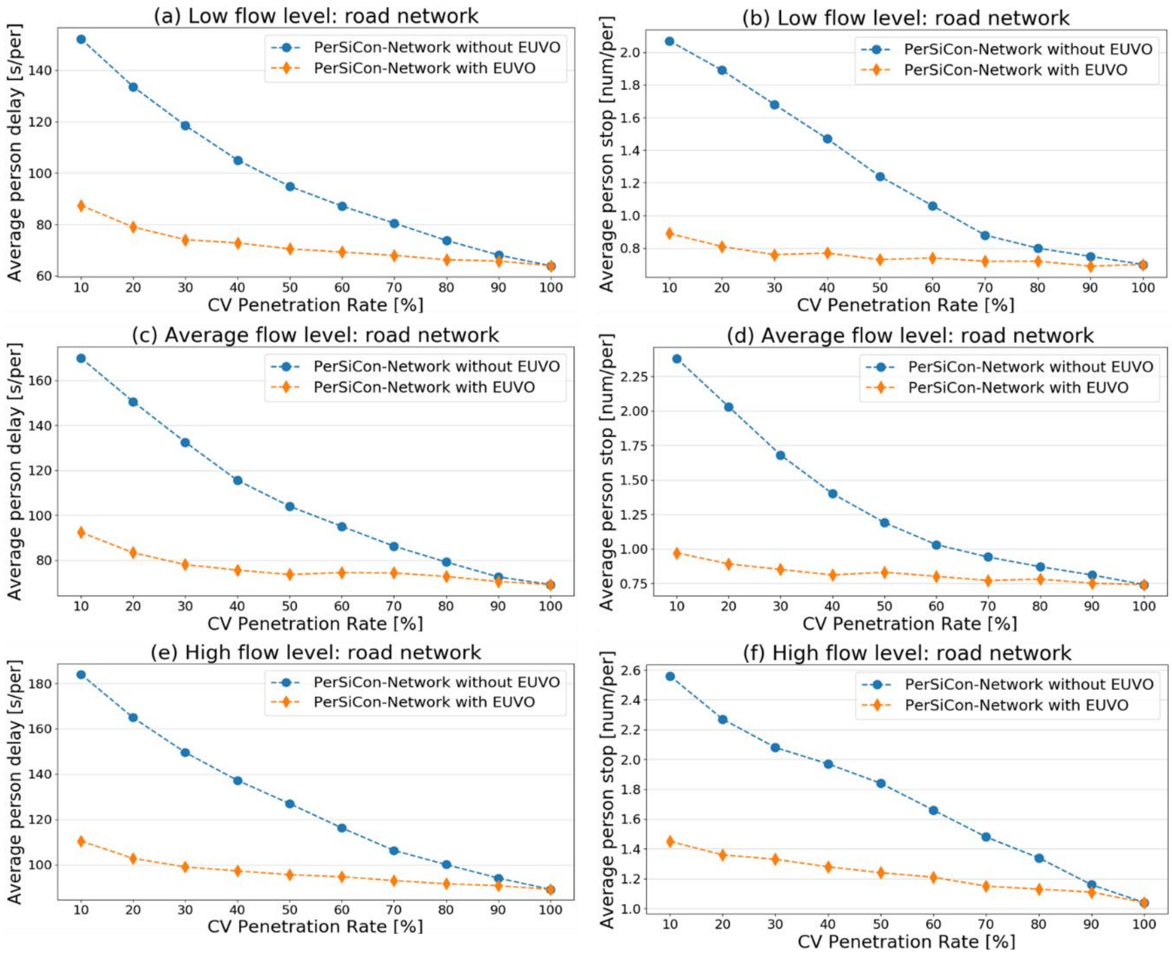

Figure 6. 10 Comparison of average passenger delay (s/per) and average person stop (num/per) of PerSiCon-Network with and without EUVO algorithms under variety CV penetration rates and three flow levels with mixture of cars and buses

Table 6. 2 P-values in average person delay and stop comparison for PerSiCon-Network with and without EUVO algorithm with mixture of cars and buses in different traffic flow demands and different CV penetration rates

	P-values for average person delay			P-values for average person stop		
Flow level	Low	Average	High	Low	Average	High
100%	1.000	1.000	1.000	1.000	1.000	1.000
90%	0.318	0.549	0.274	0.038	0.032	0.131
80%	0.020	0.042	0.009	0.006	0.003	0.000
70%	0.000	0.000	0.000	0.000	0.000	0.000
60%	0.000	0.000	0.000	0.000	0.000	0.000
50%	0.000	0.000	0.000	0.000	0.000	0.000
40%	0.000	0.000	0.000	0.000	0.000	0.000
30%	0.000	0.000	0.000	0.000	0.000	0.000
20%	0.000	0.000	0.000	0.000	0.000	0.000
10%	0.000	0.000	0.000	0.000	0.000	0.000

6.5.3 Sensitivity analysis to active time intervals

Figure 6.11 illustrates the person-related performance of PerSiCon-Network with EUVO algorithm with loops and cameras active time intervals of every 1, 2, 3 and 5 seconds in three flow levels. The CV penetration rate is set to be 50% and the distance from devices to the cross line is 250m. Similar to the observations found from the initial results presented in Section 6.5.1, the average person delays and stops of PerSiCon-Network with EUVO are significantly degraded when the devices of loops and cameras are activated every 2, 3 and 5 seconds. The reason is that in these scenarios many UVs possibly fail to be captured by loops and cameras. The hypothesis test results in Table 6.3 show that the EUVO algorithm takes significant effects on improving person-based delays and stops when the active time interval is 1, 2 or 3 seconds. In some cases when the active time interval is 5 seconds, the optimization results of PerSiCon-Network equipped with EUVO algorithm do not have obvious differences from PerSiCon- Network without EUVO algorithm.

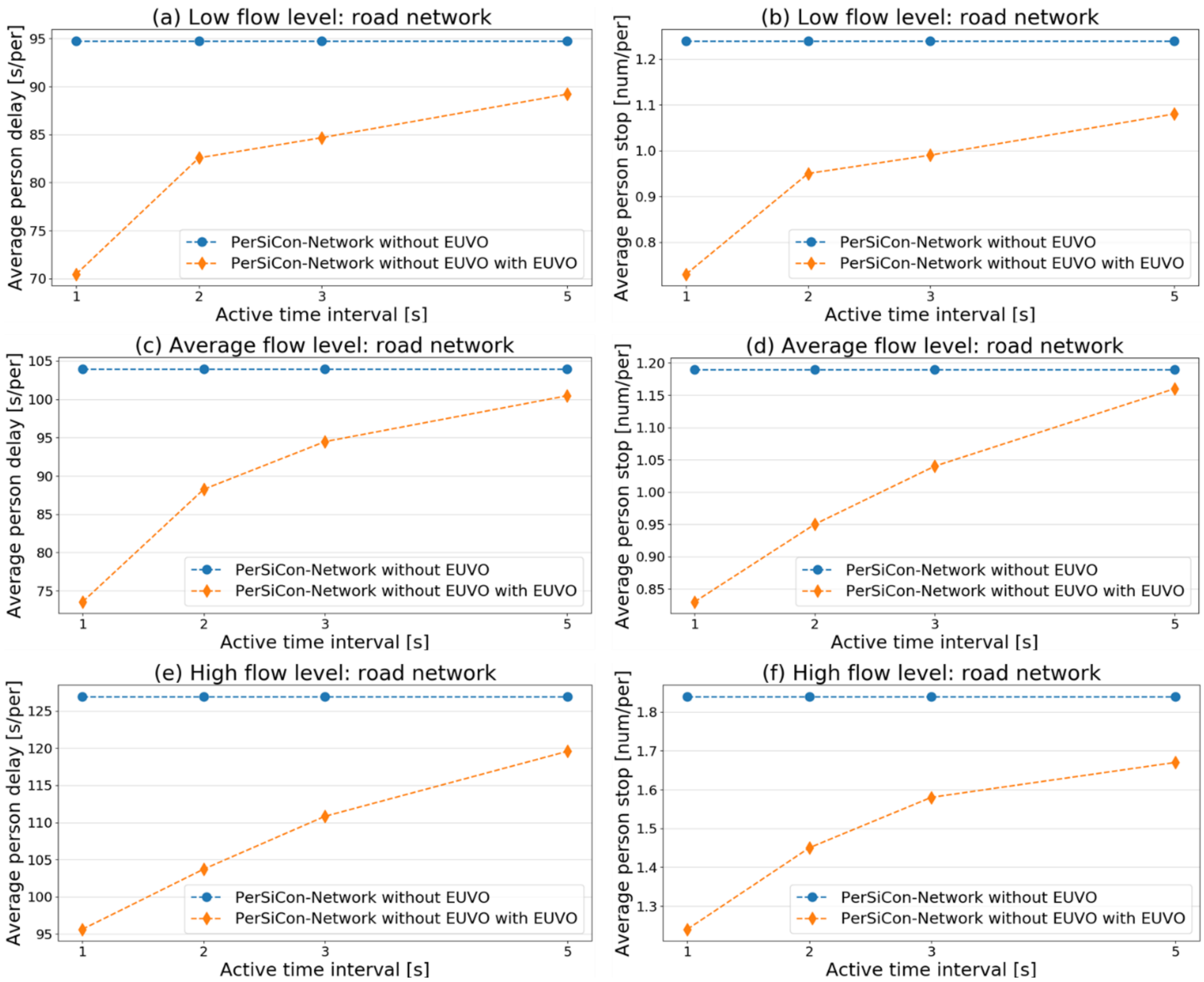

Figure 6. 11 Comparison of average passenger delay (s/per) and average person stop (num/per) of PerSiCon-Network with and without EUVO algorithms under different active time intervals and three flow levels with mixture of cars and buses

Table 6. 3 P-values in average person delay and stop comparison for PerSiCon-Network with and without EUVO algorithm with mixture of cars and buses in different traffic flow demands and different active time intervals

	P-values for average person delay			P-values for average person stop		
Flow level	Low	Average	High	Low	Average	High
1s	0.000	0.000	0.000	0.000	0.000	0.000
2s	0.000	0.000	0.000	0.000	0.000	0.000
3s	0.003	0.007	0.000	0.000	0.000	0.000
5s	0.102	0.358	0.021	0.000	0.374	0.000

6.5.4 Sensitivity analysis to distances from loops and cameras to cross line

Figure 6.12 shows the results of PerSiCon-Network equipped with EUVO algorithm in different loop and camera installation locations to the cross line in three flow levels. The performance of average person delays and stops are similar to the observation of the initial results concluded in Section 6.5.1. The average person delays and stops in three flow levels are lightly increased with the distance shortening in the range of 100m to 250m. The performance of the algorithm are degraded when the distance is 50m as the inductive loops and cameras are installed over close to the cross line, resulting in part of the UVs cannot being detected. However, the hypothesis test results in Table 6.4 indicates that the two results have significant differences at 95% confidence degree wherever the loops and cameras are located, even if they are installed 50m away from the cross line. If the detection area is too close to the cross line, the EUVO algorithm can only receive the loop signals and occupancy data of vehicles within the short range from the detection area to the cross line. This shortens the data inputs collected by the EUVO algorithm and seriously affects the performance of the EUVO algorithm.

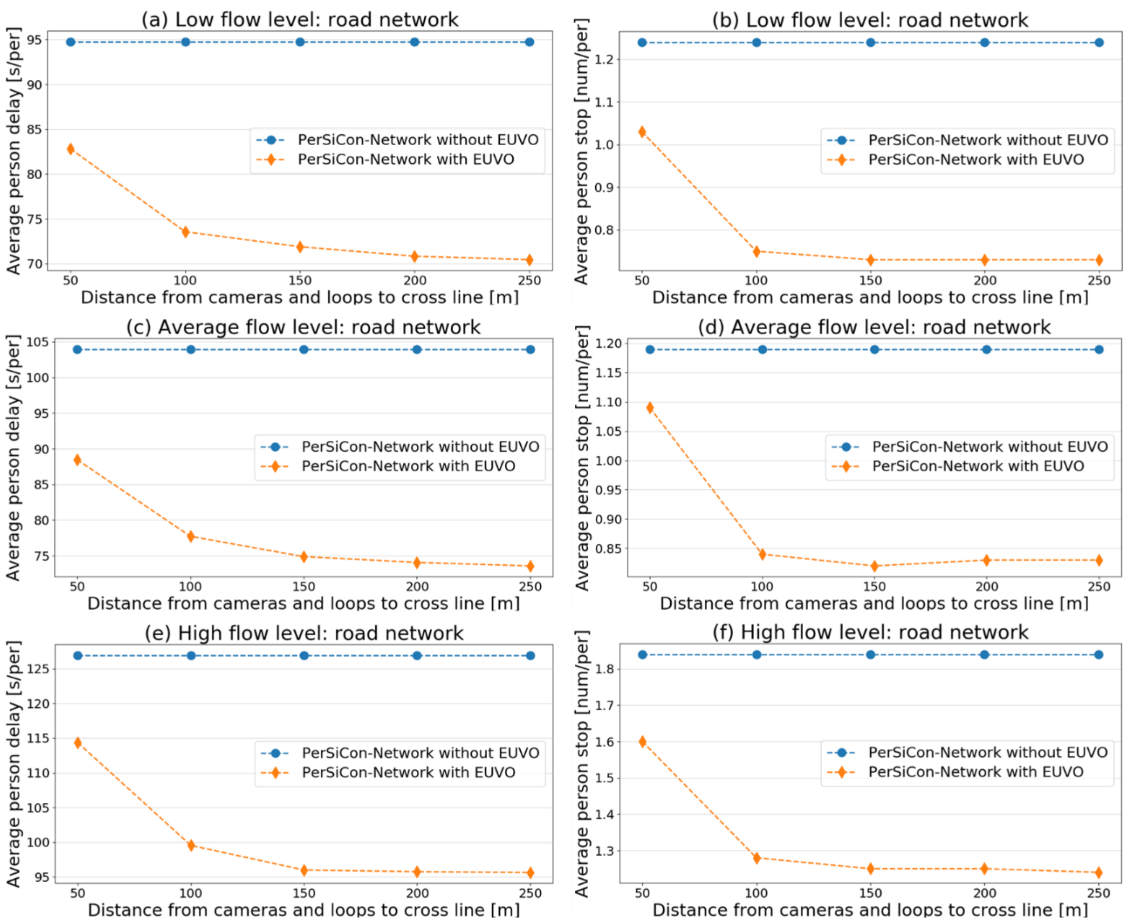

Figure 6. 12 Comparison of average passenger delay (s/per) and average person stop (num/per) of PerSiCon-Network with and without EUVO algorithms under different distances from devices to cross line and three flow levels with mixture of cars and buses

Table 6. 4 P-values in average person delay and stop comparison for PerSiCon-Network with and without EUVO algorithm with mixture of cars and buses in different traffic flow demands and different distances from cameras and loops to cross line

	P-values for average person delay			P-values for average person stop		
Flow level	Low	Average	High	Low	Average	High
50m	0.000	0.000	0.000	0.000	0.003	0.000
100m	0.000	0.000	0.000	0.000	0.000	0.000
150m	0.000	0.000	0.000	0.000	0.000	0.000
200m	0.000	0.000	0.000	0.000	0.000	0.000
250m	0.000	0.000	0.000	0.000	0.000	0.000

6.6 Summary

This chapter proposes an innovative EUVO algorithm which can estimate the predictive departure times, vehicle statuses and occupancy levels of UVs with the help of cameras and loops. The EUVO algorithm is operated before the optimization process of PerSiCon-Network to improve the degraded person-related performance of PerSiCon-Network, especially in the case the CV penetration rate is below 60%. The PerSiCon-Network supported by the EUVO algorithm is evaluated using the same case study implemented in Chapter 5 in various scenarios and its performance are compared to the results of PerSiCon- Network without the EUVO algorithm. The results indicate that the EUVO algorithm can significantly improve average person delays and stops of PerSiCon- Network when the CV penetration rate is below 90%. The inductive loops and cameras should be activated for every second to maintain the effectiveness of the EUVO algorithm. Meanwhile, the location of loops and cameras is not a critical factor to influence estimation effects until the distance between devices and the cross line is shortened to 50m. In next chapter, an overall summary of the project is given to point out the contributions of the research, how to implement the proposed method in a new location and future work directions.

Chapter 7 Conclusions and future works

In recent developments, CVs are enabled to be connected with infrastructure (V2I) and other vehicles (V2V) via wireless communication technologies (e.g. DSRC). CVs have the ability to acquire and share rich types of real-time vehicle data including positions, speeds and travel times to junction controllers. As a result, various researchers have proposed new models and algorithms to improve the performance of urban signal controls in CVs environments against traditional UTC systems such as fixed time controls, actuated controls and adaptive controls. On the other hand, a series of passenger occupancy systems, such as the APC system, bearing loading sensors and vehicle occupancy detection technology using inside/roadside cameras, are proposed to make the shift from vehicle-based controls to person-based controls to be possible. However, the development of person-based controls requires more flexible, updating vehicle trajectory theories and adaptive signal plans to achieve person-based objectives than those in vehicle-based controls inspired by TSP strategies.

This research has proposed a number of algorithms to understand how to utilise the CV data including occupancy information to achieve person-based controls in a generalized 8-phase options junction. The algorithms also extend the signal control methods to larger network scales with the data supplement from adjacent junctions and incorporate the bus mode to identify how to implement person-based controls in mixture vehicle environments. Considering the realistic situation of CV penetration rate, the algorithm is enhanced to improve the performance under imperfect CV penetration rate. A real-world case study is reproduced in simulation with various numbers of sensitivity analyses to evaluate the performance of proposed person-based control algorithms.

This chapter concludes how the research works proposed in this project fulfil the objectives point out in Chapter 1, how to make the developed algorithm generalization and operate it in a new place and what are the future work directions.

7.1 Fulfilment of the research objectives

Chapter 1 points out five research objectives for this project, this section discusses how the research achieves them and the key findings of the research.

1) Investigating the relationships between vehicle-based and person-based signal control and understanding the current state-of-the-art signal controls using connected vehicle data.

In Chapter 2, the UTC systems representing traditional vehicle-based controls and traditional transit signal priority focusing on assigning high priority levels to buses are reviewed. The person-based controls have more potentially meaningful benefits to urban traffic mobility than vehicle-based controls such as relieving traffic demand pressures and reducing direct and indirect costs of traffic congestion. However, the mechanisms of person-based controls are found to be more complicated than vehicle-based controls as more flexible signal controls should be adopted to allow high-priority vehicles to cross the junction. Meanwhile, the achievements of person-based controls need additional occupancy data of vehicles to realize their occupancy levels. The data sources of occupancy level are challenging to be provided in traditional signal controls.

The CVs are introduced to provide adequate and highly frequent real-time data sources to possibly improve the performance of signal controls and realize the achievements of person-based controls. The review of start-of-the-art researches in Chapter 2 finds great achievements to improve the performance of vehicle-based controls. According to the person-based control review in Chapter 3, only a few researchers attempt to shift vehicle-based controls to person-based controls in mixtures of cars and buses or all passenger cars environments. However, the complete flexible signal plans, updating vehicle trajectory theories, coordinated control paradigms and implementation of imperfect CV penetration rates failed to be achieved in the research and this research attempts to fill in the gaps.

2) Proposing an Adaptive Person-based Signal Control Algorithm (PerSiCon-Junction) to reduce person average delay in isolated urban junction under 100% CV penetration rate.

Chapter 3 finds the research gaps and clarifies the research contributions to fill in the gaps and achieve the aim and objectives. The person-based control PerSiCon-Junction is proposed in this research to figure out the optimal signal control plans in an isolated junction. It can be extended to vehicular environments with bus incorporation (PerSiCon-Bus) and road networks with junction coordination (PerSiCon-Network). Evaluation frameworks to test the performance of PerSiCon-Bus and PerSiCon-Network in two case studies are also outlined in Chapter 3.

Chapter 4 proposes an innovative PerSiCon-Junction to minimise person delay at isolated signalised urban junctions. PerSiCon-Junction can explore complete flexible phase combinations and stage sequences to find the optimal signal timing solution in the prediction horizon using data from CVs. A three-layered dynamic programming approach is adopted in PerSiCon-Junction with the objective of minimising person delay. A signal phase transition exploration mechanism is also developed to explore all possible signal timing plans according to non-conflicting phase rules and efficient principles. The vehicle trajectory and car-following updating theories used for predicting the discharging time of all vehicles in the platoon are also proposed considering different cases and fleet trajectories.

4) Developing Adaptive Person-based Signal Control Algorithm with Buses (PerSiCon-Bus) which integrates bus mode into vehicular environments of person-based control; constructing real-world case study to validate the performance of proposed control method in isolated junction;

Chapter 4 modifies the paradigm of PerSiCon-Junction to be PerSiCon-Bus and extends its scope of application into more complicated vehicular environments containing both buses and passenger cars. A real-world isolated junction case study in Birmingham, UK is reproduced in SUMO in the chapter evaluating the performance of PerSiCon-Bus in mixtures of passenger cars and buses. The results indicate that PerSiCon-Bus has better performance in improving average person vehicle delay, with an overall reduction of 40.2% - 51.8%, 28.2% - 38.6% and 6.8% - 9.8% compared to the TRANSYT, ILACA and VehSiCon benchmark algorithms in three flow demands. PerSiCon-Bus also achieves similar reduction of average passenger stop against the benchmark algorithms also reduced, which are 46.3% - 59.7%, 36.8% - 47.9% and 5.5% - 10.7% respectively. The results also find that the average person delay and stop of PerSiCon-Bus have significant improvements compared to those of VehSiCon, with a less average delay of 2, 3 and 4 occupancy vehicles and a higher average delay of 1 occupancy vehicles.

The sensitivity analysis tests indicate that the performance of PerSiCon-Bus below around 60% CV penetration rate in three flow levels does not have better performance than VehSiCon. The average passenger delay of buses is also significantly degraded if bus occupancy is lower than 8 passengers/veh. 30s are suggested to be selected as the planning horizon for signal scheme optimization, which combines considerations of preventing biased function value calculation in too short planning periods and failure of receiving the newest CV data in too long planning periods. The performance of overall average person values and low occupancy vehicles are observed to be stable and reached a balance with a range of 0.5 of accumulation time weighted factor δ.

4) Developing Coordinated Person-based Control (PerSiCon-Network) to extend algorithm from isolated junction to multiple road networks and evaluate its performance in road network case study;

Chapter 4 presents a PerSiCon-Network to extend the developed approach PerSiCon-Bus from an isolated junction to multiple junctions, to understand how adaptive person-based control formulates and implements in multiple junctions and how it affects junction performance in terms of average person delay and number of stops. The CV information from both surrounding CVs and adjacent junctions can be acquired to enable junction controllers to have knowledge of vehicular situations within further range. In order to incorporate further information properly for controllers to make adaptive signal timing decisions to all surrounding vehicles with different occupancies, the data from the adjacent junction will be utilised as a supplement form of predictive vehicle arrival time list according to vehicle trajectory data and signal strategy. A case study with 5 successive junctions in Birmingham, UK is built in SUMO to evaluate PerSiCon-Network. The results are very similar to the findings in an isolated junction case study. PerSiCon-Network achieves 42.8% - 49.9%, 27.8% - 34.4%, 6.4% - 9.4% average person delay reduction and 49.5% - 61.3%, 29.7% - 40.8%, 7.5% - 16.7% average person stop reduction compared to TRANSYT-Network, ILACA-Network and VehSiCon-Network. At the same time, the average vehicle delay and average vehicle stop of PerSiCon-Network are not heavily degraded. The sensitivity test results to CV penetration rate indicate that PerSiCon-Network only performs better person-related results when the CV penetration rate is above 60-80% than VehSiCon-Network. The average passenger delay and stop of buses keep unchanged until bus occupancy is lower than 8 passengers/veh. Similar to the isolated junction case study, 30s prediction horizon and 0.5 accumulation time weighted factor are still the most appropriate choices for PerSiCon-Network.
5) Proposing Estimation status of Unequipped Vehicle with Occupancy (EUVO) algorithm to improve the behaviours of PerSiCon-Network under imperfect CV penetration rate environments.

Chapter 6 develops a EUVO algorithm to estimate the vehicle statuses of those unequipped vehicles based on several data types collected from CVs, inductive loops and cameras, and storage space of junction controllers. The EUVO algorithm can be operated before the optimization process to supply the initial departure time and occupancy level estimation of unequipped vehicles and improve the performance of PerSiCon-Network in low CV penetration rates. To validate the effectiveness of the EUVO algorithm, the enhanced PerSiCon-Network with the EUVO algorithm is evaluated in the same case study for PerSiCon-Network without the EUVO algorithm in Chapter 6. The results figure out that PerSiCon-Network with EUVO algorithm performs significantly improvements of average person delay and stop against to PerSiCon-Network without EUVO algorithm when CV penetration rate is lower than or equal to 80%. Estimation effects under low CV penetration rates are not significantly degraded when loops and one-side cameras are active every second. The location of loops and cameras is also not a critical factor to influence estimation effects until close distance which causes some vehicles undetected. On the other hand, the increasing time intervals of loops and one-side cameras make estimation inaccurate as part of vehicles fail to be captured.

7.2 Implementing proposed method in a new place

This research develops person-based controls and evaluates them in a real-world case study. However, the results from various scenarios only represent behaviours of the proposed method in this specific case study, and it is uncertain whether the signal control paradigms and suggestive values are suitable in another road network as well. Hence, this subsection describes how the proposed PerSiCon-Network with EUVO algorithm can be operated in a new location.

The first important step to implementing the proposed method in a new place is to realize the geometry layouts of each junction and distributions of junctions within networks so that it would be possible to reproduce the road networks in microsimulation more realistic. For instance, the length width and speed limits may affect the free-flow speed of vehicles. The road lengths and distance between two adjacent junctions may change their coordination level of them. The scales of the junction centre area and movement lanes may influence the vehicle clearance time. The factors which may make effects vehicle travelling status, signal control strategies and signal timing parameters should be kept the same as the real situations.

The next step is to conduct comprehensive surveys of the case study area including traffic flows, vehicle types, signal patterns and vehicular parameters to reproduce traffic flows in simulation, calculate the essential parameter inputs of PerSiCon-Network and decide the strategy adopted by PerSiCon-Network. For example, the traffic flow surveys in different approaches of the case study area during different times of day periods contribute to reproducing and calibrating vehicle flow generation. The vehicle type distribution can be used to decide which types of vehicles should be incorporated into PerSiCon- Network paradigms. The vehicle parameters such as start-up time loss and saturated headway of queue discharge are required as inputs for predicting vehicle departure time. Signal patterns decide the possible formats of complete flexible signal plans that can be adopted by PerSiCon-Network.

After reproducing the case study in simulation and proposing the paradigms of PerSiCon-Network, the next step is to operate PerSiCon-Network in microsimulation in various scenarios to observe the performance of parameter changes. For instance, the suggestive planning duration, loops and cameras installation location, CV penetration rate and flow level scopes of PerSiCon-Network application can only be determined after analysing the results from a number of simulation operations.

The final step is to encode the algorithm of PerSiCon-Network for junction controller in a real place with the installation of devices such as CV data receiving infrastructures, inductive loops and roadside cameras.

7.3 Future work directions

7.3.1 Proposing person-based controls in CAVs environments

The vehicle trajectory modelling and planning in CAVs and convention vehicle environments are more complex than in the mixture environments of CVs and UVs. This is because Autonomous Vehicles (AVs) can not only send vehicle data to the junction controller but the trajectory of AVs can also be adjusted by themselves with the suggested information from controllers. Optimizing the signal controls and vehicle trajectory at the same time is a challenging task for person-based controls. In addition, how to decide the occupancy level of AVs should also be considered in future works.

7.3.2 CV data measurement error, packet loss and communication delay

The data received from CVs are assumed to be perfect in this research. In future works, the person-based control should have more realistic data-receiving conditions. For instance, the position and speed of data collection devices may cause bias errors, which leads to inaccurate CV data. The packet loss and packet latency of the CV data transmit process should also be considered in future research, as well as the transmission delay of wireless communication technology.

7.3.3 Lane changing behaviours

In this research, the lane-changing behaviours are assumed to be finished at the earliest chance when they can complete them. The future works of person-based control should consider the influences of lane-changing behaviours on the vehicle arrival time prediction and vehicle departure sequences within the detection area. The vehicle turning intention data may contribute to deciding which lane the vehicle will be in when they cross the junction and adopt relative signal control strategies.

7.3.4 Special vehicle modes and pedestrians

Bus mode is considered as a special vehicle mode in this research. Future works can incorporate more vehicle types such as LGVs, HGVs and MCs into person-based controls with different vehicle parameters and occupancy levels. The pedestrians with their dedicated movement lines could also be considered in person-based control. The paradigms of flexible signal control plans need to be updated to ensure collision avoidance between pedestrians and vehicles.

7.3.5 Flexible planning duration

In PerSiCon-Network, planning duration is a constant value to decide the duration of signal plan execution and interval of signal plan optimization. The shorter planning duration is possible more suitable than the fixed planning duration when person-based control detects a few vehicles from approaching lanes, such as during the off-peak period, as the junction controller has the chance of receiving CV data earlier. How to figure out the optimized planning duration according to the real-time vehicle states could be solved in future works.

Appendix A Contributions to the field

The conference paper and journal papers produced throughout this research are listed below:

Wu, Z., Waterson, B., Anvari, B., 2020. Adaptive Person-based Signal Control System in Isolated Connected Vehicle Junction. In *Proceedings of the Transportation Research Board 99th Annual Meeting.*

Wu, Z., Waterson, B., 2022. Urban Junction Management Strategies for Autonomous/Connected/Conventional Vehicle Fleet Mixtures. *IEEE Transactions on Intelligent Transportation Systems,* 23(8), pp. 12084-12093.

Wu, Z., Waterson, B., Anvari, B., 2022. Developing and Evaluating a Coordinated Person-based Signal Control Paradigm in a Corridor Level Network. *Transport Planning and Technology,* 45(6), pp. 498-523.

Wu, Z., Waterson, B., Anvari, B., 2022. (Under review) The Adaptive Dynamic Programming Three-layered Person-based Signal Control System in Connected Vehicle Environment. *IEEE Transactions on Vehicular Technology.*

Wu, Z., Waterson, B., Rafter, C. B., Anvari, B., 2022. (Under review) An Adaptive Three-layered Person-based Control System with Flexible Signal Plans in a Connected Vehicle and Bus Environment. *IEEE Transactions on Intelligent Transportation Systems.*

Wu, Z., Waterson, B., Rafter, C. B., Anvari, B., 2022. (Under review) An Unequipped Vehicle Status Estimation Algorithm to Improve the Performance of Person-based Control in Imperfect Connected Vehicle Penetration Rates. *IEEE Transactions on Intelligent Transportation Systems.*

Appendix B Signal pattern survey

As mentioned in Section 5.3.1, a manual traffic survey of the case study in Newtown area of Birmingham, UK was carried out over two days in October 2020. The distributions of 5 successive junctions in this case study area are presented in Figure B.1, with their individually ID labels.

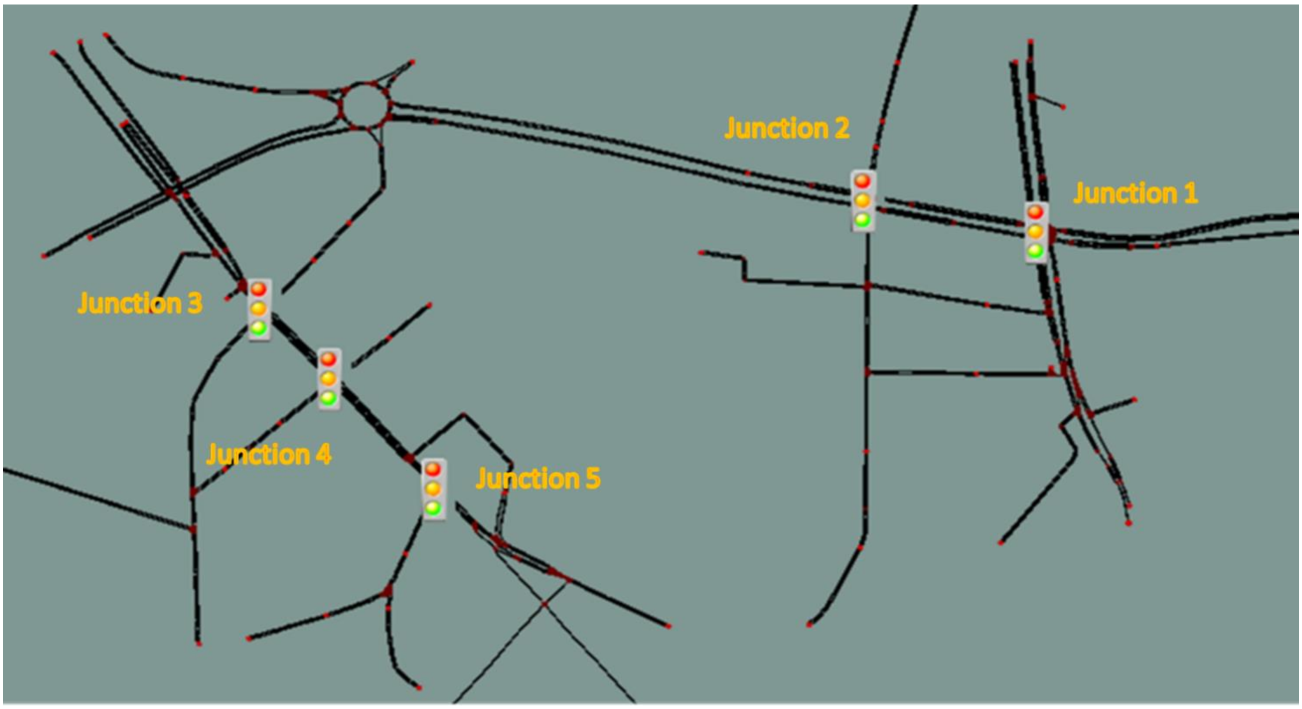

Figure B. 1 The locations of modelling junctions labelled with their IDs in the road network

Signal stage patterns and sequence at each signalized junction were observed and illustrated in Figures B.2 – B.6 respectively. The stage patterns and sequence were applied to TRANSYT, ILACA, and VehSiCon and their coordination versions in Chapter 5.

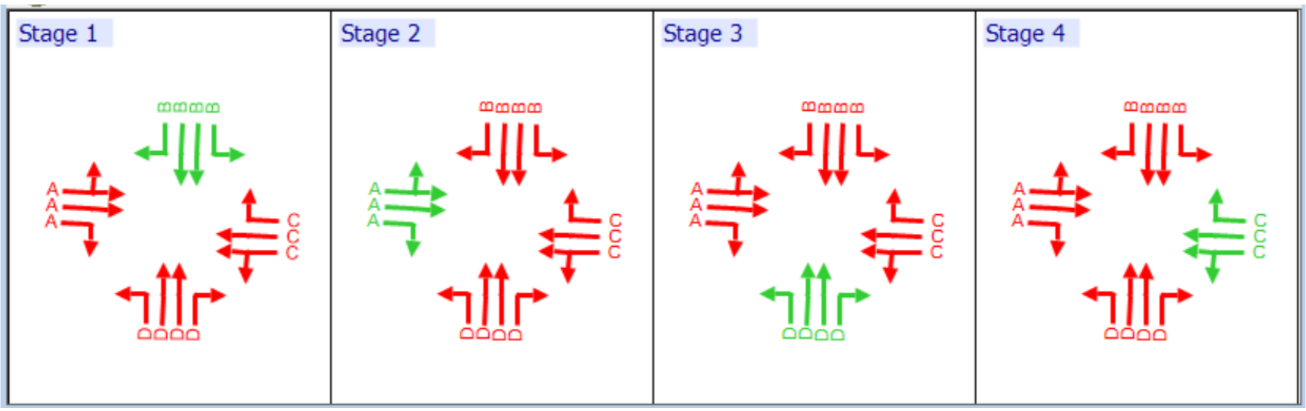

Figure B. 2 The signal stage patterns for junction 1

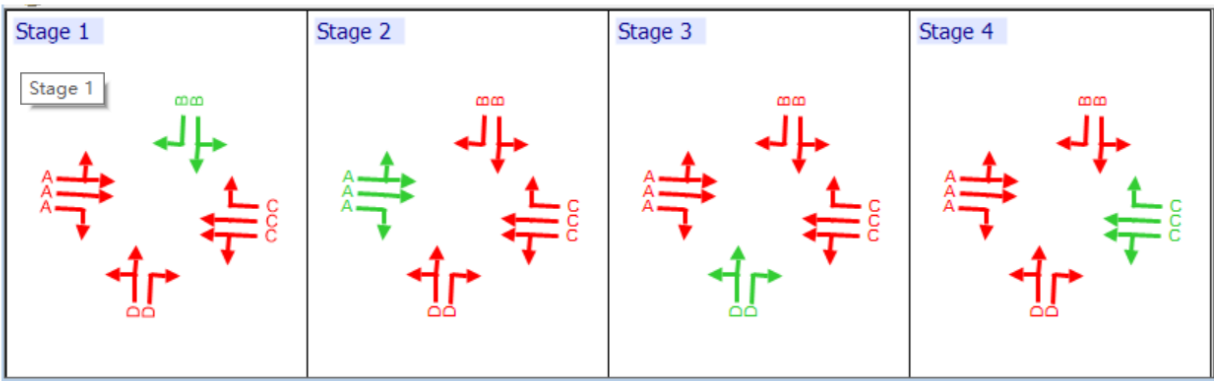

Figure B. 3 The signal stage patterns for junction 2

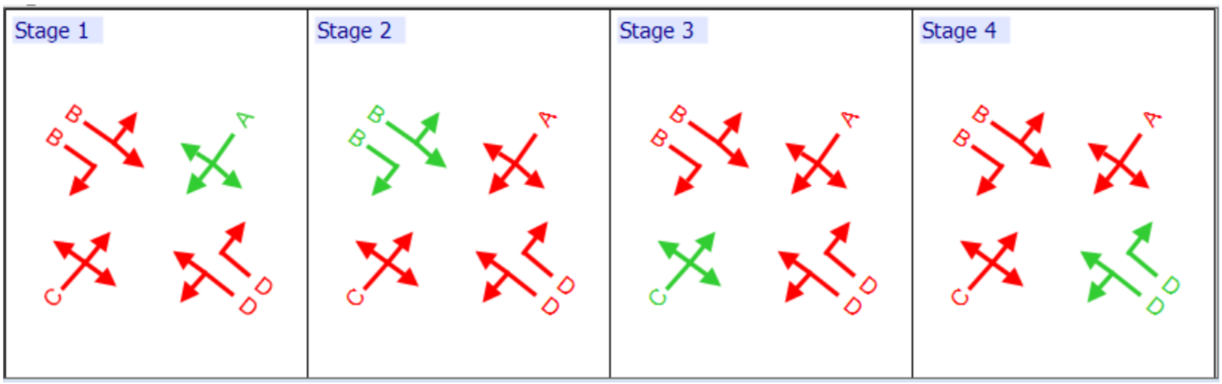

Figure B. 4 The signal stage patterns for junction 3

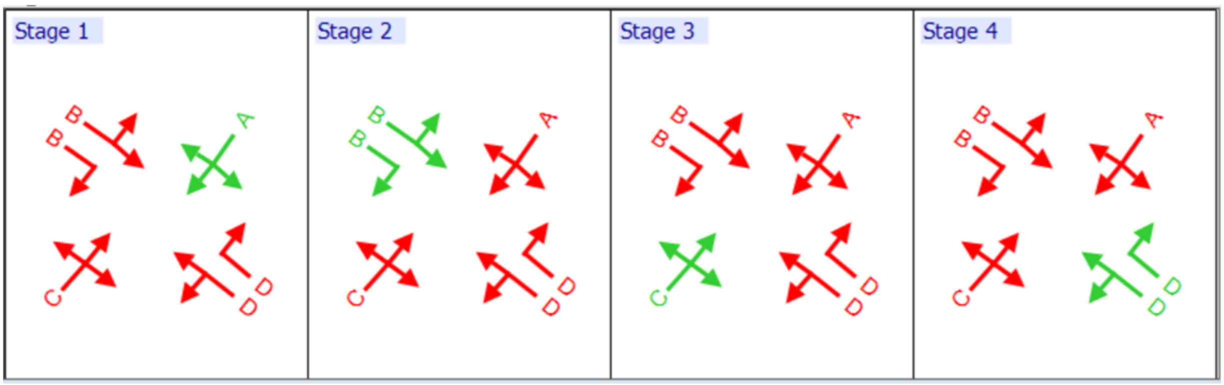

Figure B. 5 The signal stage patterns for junction 4

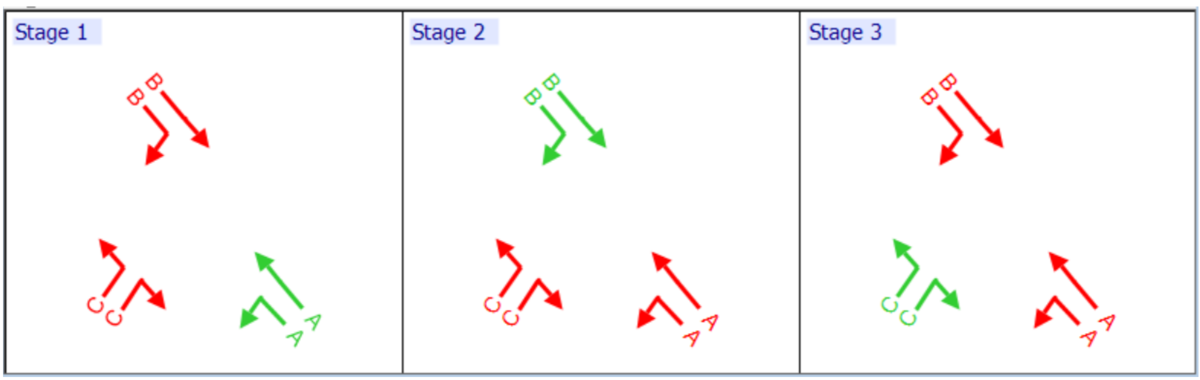

Figure B. 6 The signal stage patterns for junction 5

Appendix C Traffic flow survey

As claimed in Section 5.3.1, 15 minutes traffic flows of each stage of 5 junctions in the selected case study area during the inter-peak period and evening peak period were counted in the manual survey to make sure whether the traffic flows collected from the data portal are consistent with the real states of the case study or not. Table C.1 and Table C.2 show the vehicle counts observed in 15 minutes during the evening peak period and inter-peak period respectively. The collected data in 15 minutes were extended to hourly flow and were found to be consistent with the data from the online portal. Therefore, the data recorded from the portal are used to reproduce the traffic flows in the case study area.

Table C. 1 Vehicle counts observed of each stage of 5 junctions in road network in 15 minutes during evening peak period

Junction ID	Stage ID	Left	Straight	Right	Total
Junction 1	1	37	25	93	155
	2	71	114	66	251
	3	68	27	25	120
	4	22	97	27	146
Junction 2	1	18	4	19	41
	2	15	167	29	211
	3	36	3	42	81
	4	38	178	16	232
Junction 3	1	17	3	31	51
	2	27	189	22	238
	3	15	2	7	24
	4	11	173	17	201
Junction 4	1	10	4	29	43
	2	28	144	31	203
	3	22	3	9	34
	4	12	147	9	168
Junction 5	1	14	112	--	126
	2	--	115	54	169
	3	47	--	12	59

Table C. 2 Vehicle counts observed of each stage of 5 junctions in road network in 15 minutes during inter-peak period

Junction ID	Stage ID	Left	Straight	Right	Total
Junction 1	1	21	28	79	128
	2	72	57	70	199
	3	76	29	20	125
	4	23	68	26	117
Junction 2	1	16	3	13	32
	2	11	153	15	169
	3	25	2	26	53
	4	17	168	14	199
Junction 3	1	8	4	13	25
	2	33	170	29	232
	3	23	5	14	42
	4	16	134	13	163
Junction 4	1	9	3	26	38
	2	40	116	48	204
	3	31	4	10	45
	4	12	111	15	138
Junction 5	1	7	85	--	92
	2	--	102	41	143
	3	42	--	9	51

Appendix D Vehicle type survey

The manual survey also recorded the vehicle types of traffic flows during the inter-peak period and evening peak period. The count values of different vehicle types and their separate ratios are presented in Table D.1. The observed vehicle type distributions from the manual survey are compared with the statistics recorded in the VEH0104 dataset from DfT in the West Midlands region and comparison results are illustrated in Figure D.1. The results indicate that the observed vehicle type distributions are consistent with the statistics from DfT dataset. Therefore, the vehicle ratio of the bus is adopted to determine the bus number in the case study area in different traffic flow levels in Chapter 5.

Table D. 1 Vehicle type distributions counted from manual survey in Newtown case study area

Vehicle type	Counts	Ratio
Car	3964	83.5%
LGV	537	11.3%
HGV	115	2.4%
MC	89	1.9%
Bus	43	0.9%
Total	4748	100%

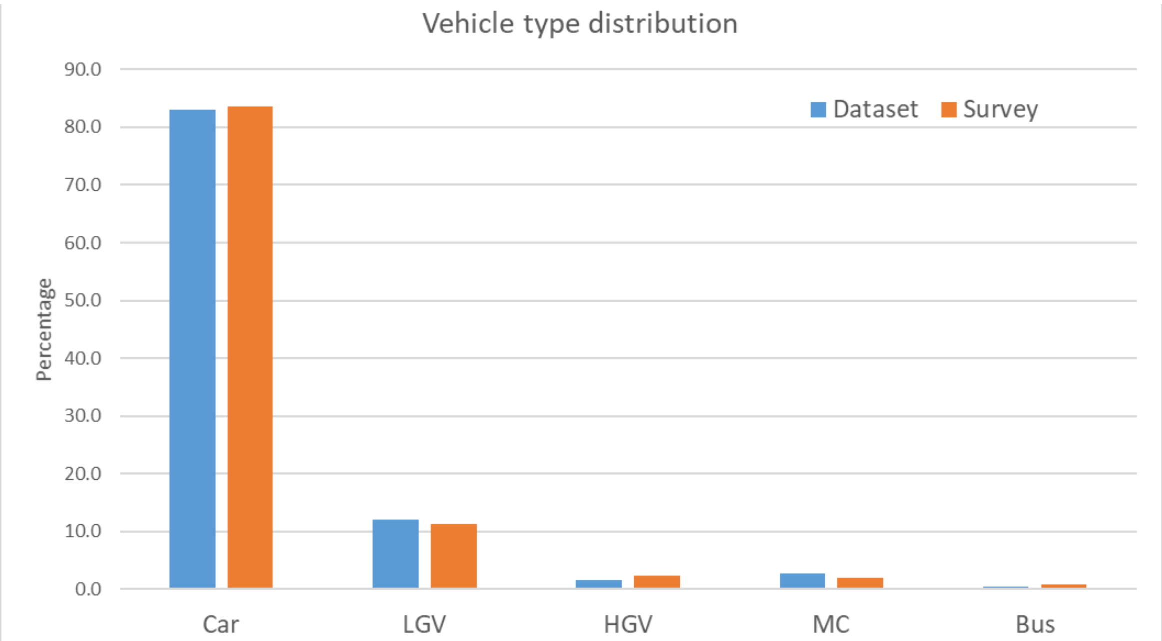

Figure D. 1 Vehicle type distribution comparisons of observed results from manual surveys and statistics from VEH0104 dataset from DfT in the West Midlands region of the UK (UK Govt. Dept. Transport, 2018b)

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