UNIVERSITY OF SOUTHAMPTON

FACULTY OF ENGINEERING AND THE ENVIRONMENT

Transportation Research Group

Improving Traffic Movement in an Urban Environment

by

Andrew Hamilton

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ABSTRACT

FACULTY OF ENGINEERING AND THE ENVIRONMENT

Doctor of Engineering

IMPROVING TRAFFIC MOVEMENT IN AN URBAN ENVIRONMENT

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This research seeks to investigate how additional data sources can be used within traffic control systems to reduce average delay and improve reliability of journey time. Current state of the art urban traffic control systems do not take full advantage of the improved granularity of data available as they use traditional, static detection methods such as inductive loops, infra-red and radar.

Therefore further research was required to fully understand what new data sources are available, how they could be used and if there are any potential benefits for traffic control systems. The transport industry is moving into an era of data abundance as more people use smart phones, satellite navigation systems, Wi-Fi and Bluetooth devices. These richer data sources could provide additional information (vehicle location, speed and destination data) but it is currently unknown as to whether they can improve the performance of the road network.

Much of the research in this thesis has been published through conference and journal papers. A novel traffic control algorithm called DEMA was developed during this research, which can significantly outperform MOVA (a leading industrial control algorithm) through reducing average delay by up to 34% when additional data sources are incorporated into the decision process. DEMA uses vehicle location, speed and turning intention information to select the most suitable stage for minimising delay.

Also a study was conducted to determine if turning intention information could be predicted from outside of a vehicle, which is a previously un-researched area. The results demonstrated that people could correctly predict turning intention with a 70% median success rate when the vehicles were 50 metres from the junction.

The outcomes of this research could have a significant impact on the future of urban traffic control systems as new data sources become more readily available in the transport industry.

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Declaration of Authorship

I, Andrew Hamilton, 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.

Improving Traffic Movement in an Urban Environment

I confirm that:

1. This work was done wholly or mainly while in candidature for a research degree at this University;
2. Where any part of this thesis has previously been submitted for a degree or any other qualification at this University or any other institution, this has been clearly stated;
3. Where I have consulted the published work of others, this is always clearly attributed;
4. Where I have quoted from the work of others, the source is always given. With the exception of such quotations, this thesis is entirely my own work;
5. I have acknowledged all main sources of help;
6. Where the thesis is based on work done by myself jointly with others, I have made clear exactly what was done by others and what I have contributed myself;
7. Parts of this work have been published: see Section 1.4 for more information:

Signed:

……………………………………………………………………………………….

Andrew Hamilton

Date: 06/05/15

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Firstly, I would like to thank my primary supervisor, Dr Ben Waterson for his continued help and challenging questions, his input was invaluable throughout the EngD. Also I would like to thank my industrial supervisor, Ian Snell for all of his practical and industrial guidance during this research project. Many people at both TRG and Siemens have been incredibly helpful and I appreciate all of the feedback and involvement at various points of the research.

I would like to thank my friends and family, especially my wife Sarah, for all of the support that they have given me over the past four years. They have shown more interest about traffic control than I could ever have hoped for.

Definitions and Abbreviations

ANPR - Automatic Number Plate Recognition

AR - Augmented Reality

BR – Burgess Road Junction

CBD – Central Business District

CVIS – Cooperative Vehicle-Infrastructure Systems

DC – Driver and Cyclist in a typical week

DD – Detection Distance

DEMA – Delay Minimisation Algorithm

Dft – Department for Transport

DSRC - Dedicated Short Range Communication

GLIDE - Green Link Determining

GPS – Global Positioning System

I - Infiltration

ITS – Intelligent Transport Systems

JT – Journey Time

Kph – Kilometres per hour

KPI – Key Performance Indicators

L - Location

MOTION - Method for the Optimization of Traffic signals In Online controlled Networks

MOVA - Microprocessor Optimised Vehicle Actuation

Mph – Miles per hour

NTCIP - National Transportation Communications in ITS Protocol

P - Passenger in a typical week

Paramics – SIAS Paramics

Pcu – Passenger Car Units

PI – Performance Index

RHODES - Real-time Hierarchical Optimized Distributed and Effective System

S – Shirley High Street Junction

Sat-nav – Satellite Navigation

SCATS - Sydney Coordinated Adaptive Traffic System

SCOOT - Split Cycle Offset Optimization Technique

Sec - Seconds

SPOT - System for Priority and Optimisation of Traffic

Definitions and Abbreviations

TfL – Transport for London

Tpm - Trillion Passenger Miles

TRANSYT - TRAffic Network StudY Tool

TRB - Transportation Research Board

TRG – Transportation Research Group

TRR – Transportation Research Record

UK – United Kingdom

USA – United States of America

UTC – Urban Traffic Control

UTMC – Urban Traffic Management and Control

UTMS - Universal Traffic Management System

UTOPIA - Urban Traffic OPtimization by Integrated Automation

V2I – Vehicle to Infrastructure

V2V – Vehicle to Vehicle

V2X – Vehicle to Vehicle or Vehicle to Infrastructure

VANET - Vehicle Adhoc Networks

VMS - Variable Messaging Signs

Chapter 1: Introduction

1.1 Research Overview – The Problem

There is an ever growing issue of congestion within urban environments around the world as the number of vehicle miles has increased dramatically over the past century. Building new roads is not a viable solution for most cities due to environmental and political concerns along with land restrictions (Wang, 2009 and Baskar et al., 2011). Throughout the past 60 years vehicle miles have increased by approximately 1000% in the UK (see Figure 1) with a similar trend globally; for example, vehicle miles travelled has grown by nearly 500% since 1940 in the USA (US Census Bureau, 2005). With evermore vehicles on the road (DfT, 2011a) the need for controlling the flow in an urban environment has become increasingly important to maximise safety and capacity, and minimise both the time loss and environmental impacts of congestion.

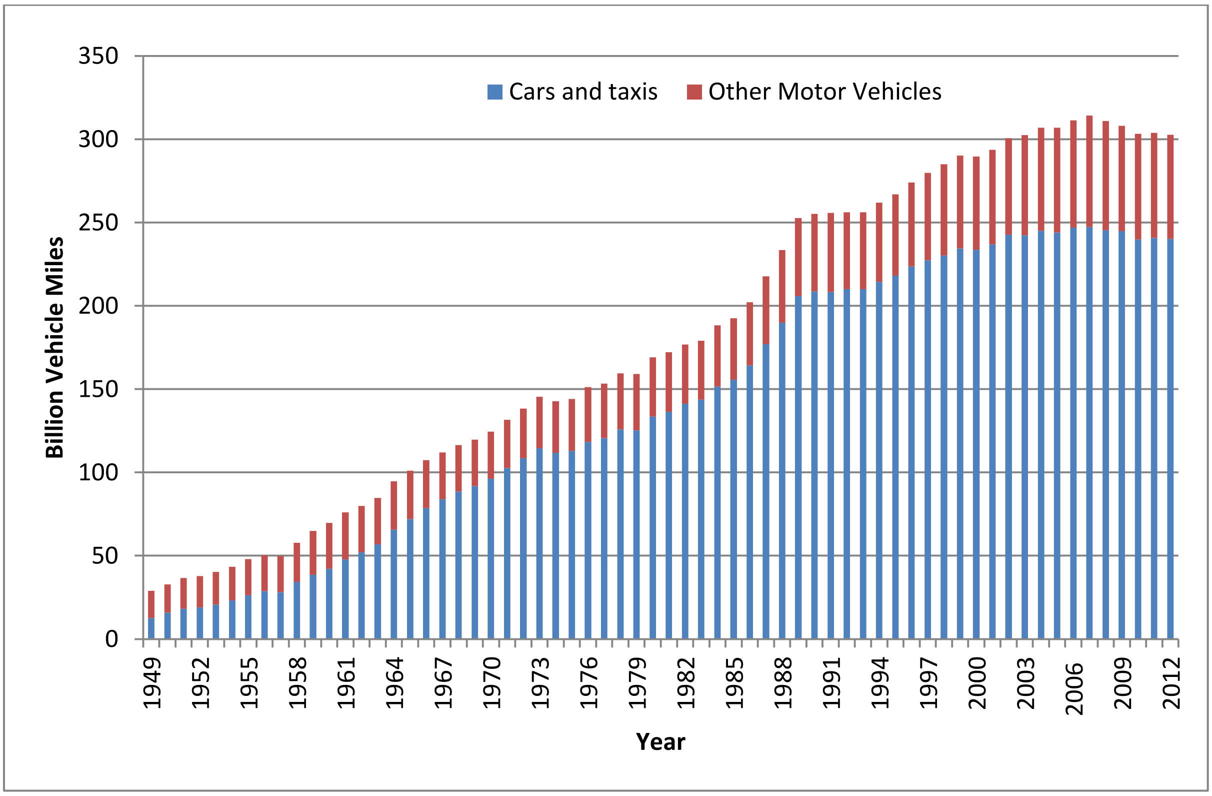

Figure 1: A graph showing the vehicle miles driven in the UK from 1949 – 2012. Adapted from: DfT, 2013a

Traffic signals have been used to help control the road network since the beginning of the 20th century (Sessions, 1971). These control systems have evolved over time but technology is advancing rapidly and existing Urban Traffic Control (UTC) systems have not kept pace (Chapter 2 will provide more detail). The current generation of UTC systems are either static (fixed time signals) or reactive to traffic conditions through sensors on the road (inductive loops, radar, infra-red); however there is great potential to move towards a more proactive control system with accurate forecasting of events using new data sources (Zhu et al., 2010).

Currently the most common traffic sensors are point detectors, such as inductive loops embedded in the road (Box and Waterson, 2010) but they only provide a brief snapshot of when a vehicle is present and therefore determining the state of the road can be quite challenging. However as new technologies seep into everyday life, new data sources become available which could provide useful information for assessing the state of the road network. Over 50% of the US and UK population have smartphones which are capable of sharing Bluetooth, Wi-Fi, cellular and GPS data (NewMedia, 2013 and Forbes, 2013). There were 7.5 million satellite navigation (sat-nav) systems in the UK in 2010 (BBC, 2010) and the use of sat-nav systems is growing so quickly that they are expected to be installed in most vehicles by 2022 (Oxford Economics, 2012). These new data sources can provide a continuous data stream of vehicle location, speed and potentially routing information, which could be used to control the road network differently.

1.2 Motivations for the Study

Siemens is the UK market leader in traffic solutions and they sponsored this project, based on a good history with the University of Southampton, to find potential solutions on how to utilise the abundance of new data sources that are available. If traffic flow can be improved through new signal control techniques then there are many potential benefits in terms of reduced travel time, lower emissions, less wasted time in congestion and a commercial benefit to Siemens of an improved UTC product. This section will investigate some of the key motives for this research being carried out.

1.2.1 Cost Reduction

A major incentive for researching this area is the potential cost savings to road users and governments. Eddington (2006) estimated that congestion costs £22 billion in lost time every year within England, and Bloomberg (2011) stated that congestion costs the USA approximately £72 billion in lost time each year. Therefore there is a significant saving to be made even with a relatively small reduction in travel time and delay. However just maintaining the current level of congestion is not a straightforward task, CVIS (2010) suggested there is already a very high pressure on London's road network but it is expected to increase by 50% by 2025 so the engineering challenge is huge.

A study suggested that adaptive traffic lights (based on wireless communication devices within vehicles) can provide much greater flexibility than current UTC systems as they have access to more detailed data sources (Gradinescu et al., 2007). This will also result in significantly lower costs due to cheaper detectors which could be in-vehicle devices such as smartphones, Vehicle to Vehicle/Infrastructure (V2X), satellite navigation systems and Bluetooth sensors.

1.2.2 Increased Pressure on the Road Network

As highlighted in Section 1.1, vehicle miles travelled has been steadily increasing over the past 60 years and this is likely to continue as people enjoy much more freedom than ever before in their personal mobility. Research suggests that car-ownership and overall vehicular travel are very likely to grow rapidly into the future. In 1950 there were approximately 1.75 trillion passenger-miles (tpm) travelled, in 2000 there were 20 tpm, whereas it is anticipated that there will be 64 tpm by 2050 – with high-speed modes and car travel accounting for 80% of this total (Moriarty and Honnery, 2008). This is a huge spatial, environmental and economic challenge for the current road network where new approaches are required to manage the ever growing volume of traffic.

1.2.3 Environmental Pressures

A recent policy change which should have a significant impact on UTC is the European Union 2011 white paper which is advocating zero carbon emissions from transport in urban centres by 2050 (European Commission, 2011). This may provide the beginnings of the policy impetus necessary to begin the process of change within the transport industry. A potential change in the way UTC systems make decisions could be to minimise carbon emissions at every junction; which would be a significant change in ethos and require additional data sources to determine priority.

1.2.4 New Technology

There is a significant amount of research being carried out into Intelligent Transport Systems (ITS) and UTC systems because of the constraints on building new roads and the potential benefits associated with improving the efficiency of the network. Existing UTC systems do not fully incorporate new data sources which are arising from the increased use of smartphones, satellite navigation systems, Bluetooth devices and V2V systems (Section 2.3 will provide more information on existing UTC systems).

CVIS (a European project) investigated the benefits of communication between vehicles and the surrounding infrastructure. CVIS (2010) have suggested that there could be a 15% reduction in travel times by using a modern architecture which enables vehicles to share information, such as the level of congestion and if there are any accidents or dangers on the road. Drivers in this project received feedback from the system to alter their driving style so that the efficiency of the road could be maximised.

ABI Research (2013b) have suggested that by 2027, there will be a 61.8% penetration rate of Vehicle to Vehicle (V2V) and Vehicle to Infrastructure (V2I) technology in new vehicles due to 12 major automotive manufacturers agreeing to install Dedicated Short Range Communication (DSRC) devices in all new vehicles. This highlights the potential for change in architecture and ability to communicate with many drivers directly, giving route guidance, traffic information and incident detection which will inevitably have an impact on network performance.

There are many other potential benefits for using Vehicle to Vehicle or Vehicle to Infrastructure (V2X) systems; if vehicles are able to communicate directly with each other then collision avoidance systems could be developed to warn other vehicles of potential incidents. It is anticipated that 79% of accidents could be avoided if V2X systems are used (Green Car Congress, 2011). ITS technologies are often researched to improve the safety record of the road network, unfortunately there were 1.24 million reported traffic fatalities in 2010 throughout the world (WHO, 2011) and 90% of road accidents are caused by some form of human error (WHO, 2004). Any traffic control system that would be developed from this research must be mindful of how it could impact road safety and if possible, reduce incidents.

However in order to develop new systems effectively, then additional data sources must be gathered to have a better understanding of the current network. Without location, speed and routing information then it would be very challenging to develop a safety system which could alert drivers of impending incidents. Therefore, further research must be carried out to determine how these data streams can be obtained and what the benefits are of using such information.

The number of connected devices (to the internet) is rapidly growing, worldwide there are 10 billion devices capable of wirelessly connecting to the internet and this is expected to grow to 30 billion by 2020 (ABI Research, 2013a). With the sheer volume of data coming from connected devices then it becomes challenging to determine what data is both reliable and relevant. Much research (especially in retail) has been carried out to make use of 'big data' and the results show that data driven decisions tend to be better decisions (McAfee and Brynjolfsson, 2012). Hence this hypothesis is carried through to traffic control, if more relevant and reliable data is available for use within traffic control, then better decisions could potentially be made. If the location, speed and vehicle routes can be known within a network then what use is this data? To answer this, three key questions must be asked of any new data sources:

1. How can the data be detected?
2. How can the data be used?
3. Is there a benefit to using the data?

1.2.5 Potential Benefits to Using Additional Data

It is important to recognise what benefits have been achieved by others from research in this field and therefore Chapter 2 explains in significant detail, the potential benefits of using new technologies. TRG have developed a number of signal control algorithms which use additional data (location and speed) and are able to outperform existing UTC systems by a considerable margin. The Highbid algorithm is able to produce 25% reductions in average delay compared to MOVA (Waterson and Box, 2010).

Box, Snell and Waterson (in press) carried out two experiments to test whether a machine learning control algorithm trained by a human expert and a machine learning controller trained by temporal difference learning, could beat SCOOT (the most commonly used, commercially available system today). The human expert trained system was able to reduce delay by 49% against SCOOT, and the temporal difference learning system outperformed SCOOT by 41%. These experiments highlight the significant improvements which could be made over the current control systems, hence why this research is focused on developing new control algorithms which incorporate new data sources.

Not only are there significant improvements to be achieved over existing UTC systems, but there are many more junctions which could be improved using intelligent control algorithms. Zhao and Tian (2012) carried out a survey to determine the number of junctions in the USA which are considered as adaptive; only 6% of all junctions were classified as adaptive and therefore there is huge potential for improvement in the USA transport network. This research project needs to investigate what benefits are possible from additional data sources but also disseminate the results to demonstrate how adaptive traffic control can outperform traditional control methods.

1.3 Aims and Objectives

The premise of this thesis is based therefore on the assumption that traffic control systems can be improved through richer data sets from new technologies. Any new algorithms will be tested against existing UTC systems to determine if there are any potential benefits.

1.3.1 Research Aim

This research will investigate the potential impact that new data sources could have on future urban traffic control systems.

1.3.2 Objectives

1. To understand 'state of the art' and future Urban Traffic Control systems, therefore highlighting any opportunities for improvement
2. To better understand how and why new technologies would be used in future UTC systems
3. Develop novel control algorithms which are able to incorporate modern data sources
4. Evaluate novel control algorithms against existing UTC systems and carry out a sensitivity analysis.
5. Provide recommendations based on the findings of any results from this research.

1.4 Contribution to the field

Significant sections of this research has been presented at academic conferences, published in journal articles and discussed at industrial meetings. Key to all engineering doctorate projects is the relevance of novel research for industrial applications. Siemens were involved in all of the major decisions throughout the research and directed the work towards industrial uses. The following papers were presented at conferences or published in journals:

Hamilton, A., Waterson, B., Cherrett, T., Robinson, A., Snell, I., 2012. *Urban Traffic Control Evolution*. In: UTSG 44th Annual Conference. University of Aberdeen, United Kingdom, 4th – 6th January 2012.

Box, S., Snell, I., Waterson, B., Hamilton, A., 2012. *A methodology for traffic state estimation and signal control utilizing high wireless device penetration*. In: 19th ITS World Congress. Vienna, Austria, 22nd – 26th October 2012.

Hamilton, A., Waterson, B., Cherrett, T., Robinson, A., Snell, I., 2013. The evolution of urban traffic control: changing policy and technology. *Transportation Planning and Technology*, 36 (1), pp. 24 – 43. Available through: http://dx.doi.org/10.1080/03081060.2012.745318

Box, S., Lees-Miller, J., Snowdon, J., Hammond, J., Hamilton, A., Gupta, S., Wilson, R.E., Waterson, B. (2013) *30 cars, figure of 8, 1 show: large scale proving ground experiments to investigate junction control*. In: 45th Annual Conference of the Universities' Transport Study Group, Oxford, GB, 2nd – 4th Jan 2013.

Box, S., Lees-Miller, J., Snowdon, J., Hammond, J., Hamilton, A., Gupta, S., Wilson, R. E., Waterson, B., 2013. *Lessons from Proving Ground Experiments to Investigate Junction Control*. 16th International IEEE Annual Conference on Intelligent Transportation Systems. The Hague, The Netherlands, 6th – 9th October 2013.

Hamilton, A., Waterson, B., Snell, I., 2014. *Human Perceptions of vehicle turning intention: Overall performance and contributory factors*. Transportation Research Board 93rd Annual Meeting. Washington D.C., United States. 12th – 16th January 2014.

Hamilton, A., Waterson, B., Snell, I., Andrews, M., 2014. *Performance evaluation of stage skipping and new data sources compared against MOVA control*. In: 17th International IEEE Conference on Intelligent Transportation Systems. Qingdao, China. 8th – 11th October 2014.

Hamilton, A., Waterson, B., Snell, I., 2015. Human Perceptions of vehicle turning intention: Overall performance and contributory factors. *Transportation Research Record: Journal of the Transportation Research Board*, 2458, pp. 8 – 15. Available through: http://dx.doi.org/10.3141/2458-02

1.5 Thesis Structure

This section will explain the structure of the thesis (see Figure 2) and provide a brief summary of each chapter.

1.5.1 Chapter 2: Evolution of Urban Traffic Control

This chapter investigates how UTC systems have evolved over time and how both policy and technological advances are shaping the next generation of traffic control systems. Many new technologies have been highlighted in this chapter, explaining what data is available and what the barriers to utilisation are.

1.5.2 Chapter 3: Key Performance Indicators

This chapter explains which Key Performance Indicators (KPI) are important to various stakeholders within the transport industry as a number of interviews were carried out at different traffic control centres. A literature review of local and network based KPI's demonstrated that delay and reliability of journey time are two important variables for assessing any new traffic control algorithms which are going to be developed from this research.

1.5.3 Chapter 4: Can turning intention data be detected?

As discussed in Section 1.2.4, one of the key questions for assessing any new data sources are how the data can be detected. As more in-vehicle technologies are being adopted (smartphones, satellite navigation systems) then additional data sources are becoming available, such as location, speed and routing for each vehicle. This chapter investigates how turning intention data can also be detected without the use of in-vehicle technology. Therefore two experiments are described which demonstrate how accurately people can predict turning intention for oncoming vehicles, how far away they are able to make accurate predictions and what influencing variables are most useful for making predictions. The results of the experiments are that people can predict turning intention with a 90% success rate from 0 – 25m from the junction, falling to 70% success when 25 – 50m away, and the most important variables are indicator usage, junction layout, turning movement, lane positioning and speed of approach.

1.5.4 Chapter 5: Turning intention data – what can it be used for?

This chapter investigates how turning intention data can be used. If a vehicle's route through the network is known then the relevant stage at the traffic light can be selected; therefore turning intention data can be used to manipulate stage diagrams by considering all possible phase combinations. This enables the control algorithm to select the best phase combination at any decision point which provides additional flexibility over existing control algorithms. The results demonstrated a maximum reduction of 24% and 15% in average delay and average journey time respectively when location, speed and turning intention data was incorporated into the control algorithm, on a theoretical junction.

1.5.5 Chapter 6: Novel signal control algorithms using new data sources

This chapter investigates if there are any benefits in using additional data sources for controlling traffic signals compared to existing algorithms. To do this, a novel traffic control algorithm had to be developed which could both adhere to real world constraints and incorporate new data sources. Using the KPI's defined in Chapter 3 a Delay Minimisation Algorithm (DEMA) was developed and tested in two real world case studies. DEMA outperformed MOVA at a T-junction by reducing the average delay by approximately 3 – 4 seconds (up to a 39% reduction) per vehicle. DEMA was also tested on an over-saturated crossroads where MOVA currently operates, and there were significant reductions in delay, ranging from 8% to 34% depending upon demand levels. However a sensitivity test was carried out to determine how DEMA would perform with imperfect data, which produced interesting results. The analysis highlighted how the detection distance should be 200 metres from the junction, and approximately 50% of vehicles need to provide additional data to achieve a 5% reduction in delay. When turning intention data was provided into DEMA, then there were drastic reductions in delay as new stages could be used to control the junction (up to a 75% reduction in delay over the current control algorithm). This chapter demonstrates that there are significant benefits in using additional data for traffic control purposes.

1.5.6 Chapter 7: Contributions of the Research and Conclusions

This chapter explains some of the limitations of the research but also many of the opportunities which have arose as a result of the work carried out.

1.5.7 Flow Diagram

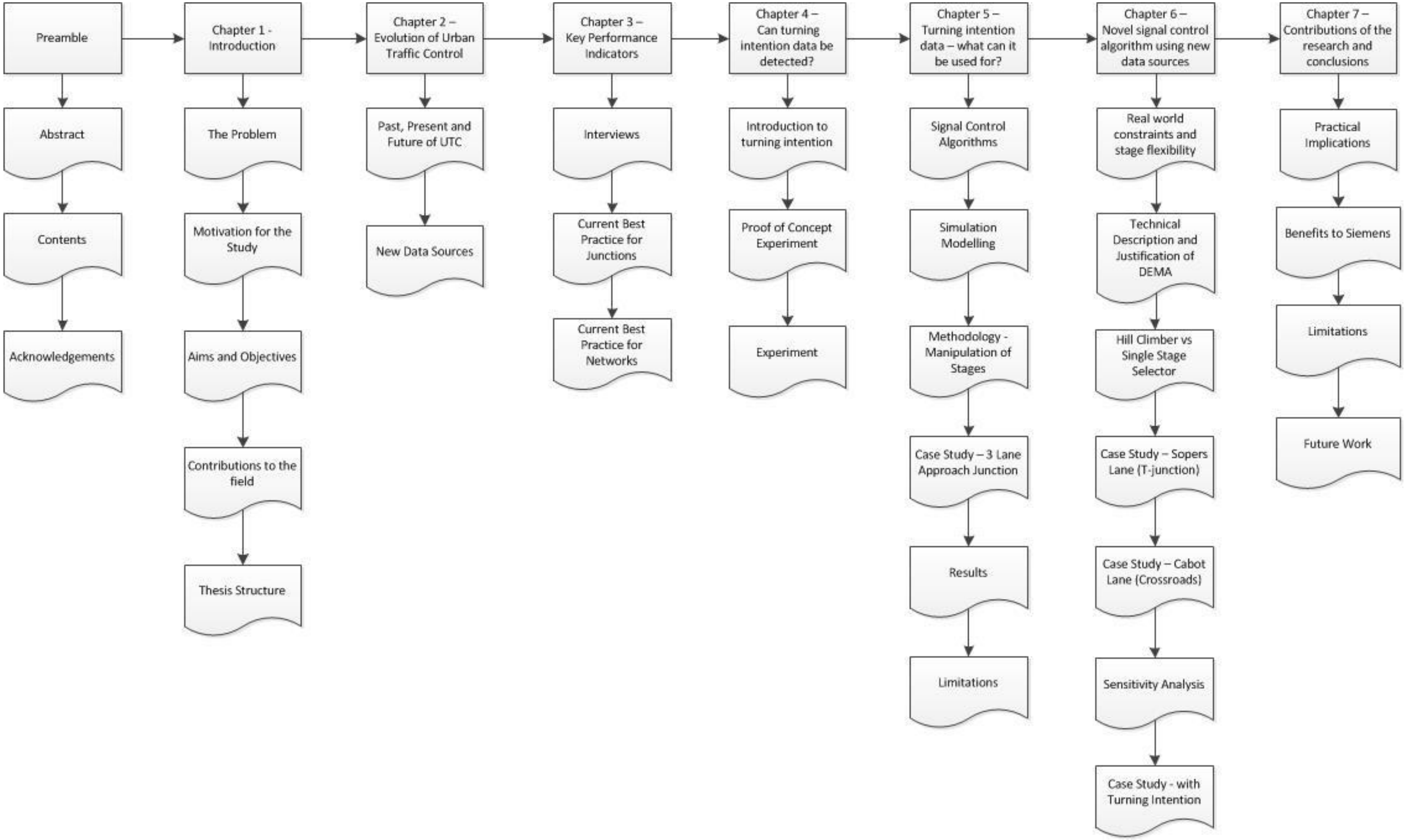

Figure 2: Structure of thesis

Chapter 2: Evolution of Urban Traffic Control

This chapter provides a thorough review of the different elements of urban traffic control which is in response to Objective 1 and 2:

1. To understand 'state of the art' and future Urban Traffic Control systems, therefore highlighting any opportunities for improvement
2. To better understand how and why new technologies would be used in future UTC systems

Urban traffic control has changed significantly from fixed time signal control to adaptive, multi-faceted network control systems. Chapter 2 explains how the evolution has occurred through influential transport policies and the use of new technologies. By reviewing 'state of the art' traffic control systems, a comparison of what data is currently used and what data will be available in the near future can be carried out to determine what opportunities are likely to arise.

Any barriers to implementation will be considered in this chapter to understand the constraints placed upon existing traffic control systems, whether these are technological, political, social or financial constraints. Much of this chapter has been published in the Journal of Transportation Planning and Technology (Hamilton et al., 2013).

2.1 Introduction

Since the earliest days of gas powered traffic lights (Day and McNeil, 1996), urban traffic control has evolved with three key influencing factors: increasing numbers of vehicles on the road network, advances in (and limitations of) technology and the desires of policy makers to maximise sustainable mobility. This chapter will highlight many of the benefits that can be observed from an efficient urban traffic control system, such as reduced congestion, increased economic efficiency and improved road safety and air quality.

There have been significant advances in vehicle detection and communications technologies which have enabled a series of step changes in the capabilities of UTC systems, from early (fixed time) signal plans to modern integrated systems. A variety of UTC systems have been implemented throughout the world, each with individual strengths and weaknesses. This section seeks to compare the leading commercial systems, and some less well known systems, to highlight the key characteristics and differences before assessing whether the current UTC systems are capable of meeting modern transport policy obligations and desires.

This chapter then moves on to consider current and future transport policy and the technological landscape in which UTC will need to operate over the coming decades; where technological advancements are expected to move UTC from an era of limited data availability to an era of data abundance.

2.2 The Past

2.2.1 PHASE 1 – Origins of Traffic Lights [1868 – 1920]

The original gas powered traffic light was based on railway designs and had only two colours, red and green. The signals were manually operated by police officers and their purpose was to improve visibility of the traffic controller as the mast was 24 feet high and could be seen on all arms of the junction (The Engineer, 1868). However the problem with this system was that it was severely limited by the technology as police officers were still required at the junction because there was no automatic control. Unfortunately the first UK traffic signals did not last long in operation, as they exploded less than a month after installation (BBC, 2009).

The subsequent electric powered traffic light was first introduced in the UK during the 1920s after observing its success in the USA and Germany. There were a number of policy objectives behind the introduction of traffic signals; primarily they were developed to relieve police officers of traffic management duties as traffic growth was rapidly increasing and many more police officers were required to direct traffic flow. This is the first example of policy driving the development of traffic signals; firstly, the members of parliament reasoned that there would be some improvement to public safety. And secondly, there was a substantial financial benefit as the installation costs were approximately £100 whereas a week's wages for a police officer was £6 to £7 and therefore the local authorities would see a rapid return on their investment (Royal Commission on Transport, 1929).

2.2.2 PHASE 2 – 'Fixed Time Plans' [circa 1920 – 1980]

This phase saw the real beginnings of UTC as rising congestion led to increased awareness of the issues amongst policy makers and consequently defined the basic objectives for all UTC systems. Congestion was highlighted as a serious issue for the United Kingdom from as early as 1964 by the Buchanan Report, when they predicted up to 40 million vehicles in the UK by 2010 (Buchanan, 1964); in 2010 there were over 34 million registered vehicles (DfT, 2011b). The Buchanan Report did encourage the government to seek alternatives to private vehicles; and in 1969 the UK policy highlighted that building evermore roads was not the solution to urban congestion (Ministry of Transport, 1969). Whereas in 1952, President Eisenhower stated a grand plan for the US to reduce metropolitan congestion through building a properly articulated highway system (Connery and Leach, 1960), this shows the different approaches taken to manage congestion in the 1950s and 1960s. In both cases however, it was still policy objectives leading the way with traffic control systems trying to match the desired outcomes.

During the late 1950s, proposals were being made to improve the original isolated fixed time plans by co-ordinating traffic signals. This involved determining offset times between neighbouring junctions so that a ‘green wave’ could be created and therefore reduce delay and congestion along arterial routes (Papageorgiou et al., 2006). To enable this local co-ordination, junctions were typically defined into small regions where the signals could be optimised in terms of split, cycle and offset times. However for fixed time plans to synchronise correctly, the cycle times must be the same length or a direct multiple, and the regional cycle time is therefore typically defined by the busiest junction in the region. By grouping junctions into small regions with the same cycle time, individual junction performance was negated for the benefit of the whole region.

The ‘cycle time’ is the total amount of time required to complete all stages at a junction. The ‘split time’ is the amount of allocated green time each stage has within a complete cycle. The ‘offset time’ is the time delay of green time between subsequent traffic signals to create smooth traffic flow. In its simplest form, the one-way offset time is the travel time between two junctions so that the downstream junction has a green light when the vehicles arrive (U.S. DoT, 2005). The offset time can be biased towards heavier traffic flow in one direction if required because the contra-flow can be insignificant in comparison (for example, morning rush hour into a city compared with flow out of the city).

Fixed time plans may be used to create green waves, give predetermined priorities, and respond to special traffic events which can be predicted, such as football matches. However fixed time plans cannot respond to unplanned incidents such as traffic accidents or road works. Fixed time plans age rapidly, particularly where traffic growth is high, and the benefits of linking may be lost in three to four years if the plans are not updated regularly, which can be an expensive process (Papageorgiou et al., 2006). Studies have shown that fixed time plans degrade by approximately three percent each year, so it is imperative that plans are regularly updated (Bell and Bretherton, 1986).

TRAffic Network StudY Tool (TRANSYT)

TRANSYT is one of the most well developed and widely used fixed time control design systems and is still in modern usage. It assumes that the flow is known and constant for a fixed period of time. TRANSYT calculates the timings off line, using historical, measured traffic data to generate optimum plans for the specific time of day, and day of the week (Gardner et al., 2009). TRANSYT can be used for designing and modelling both isolated junctions and large networks (TRL, 2015).

TRL predicted and observed a fuel consumption reduction of three to five percent in Glasgow when TRANSYT was trialled to coordinate sequential junctions (Robertson, 1982).

There are two main elements of TRANSYT; the traffic model and the signal optimiser. The traffic model represents traffic behaviour and predicts a Performance Index (PI) for a specific time plan and average set of flows on each link. The PI measures overall cost of traffic congestion, which is a weighted combination of total delay and the number of stops made by vehicles (Papageorgiou et al., 2006). Historical flow information correlated by the time of day is required by the model and a platoon dispersion model is applied to determine the offsets between junctions. The signal optimiser adjusts the signal timings in the model until the optimum PI is achieved. TRANSYT was shown to reduce journey times by 7.4 to 11.4% throughout the State of California compared with the original signal plans (Skabardonis, 2001).

2.2.3 PHASE 3 – Vehicle Actuated (Isolated) Junctions [1970's – present]

The ever growing problem of congestion was still at large, and the UK government sought after technological improvements during the 1960s. Funding was made available for research and development to individual authorities in order to find a solution to the problem; the government invested in schemes in London and Glasgow to improve the efficiency of the urban network (Ministry of Transport, 1966).

Inductive loops were developed and installed throughout the road network so that traffic signals could be triggered by vehicle presence at junctions. Isolated junctions are most commonly controlled using vehicle actuation in the UK (Gardner et al., 2009 and DfT, 2006), and the most common detection method worldwide is inductive loops (Box and Waterson, 2010). The system is reliant on traffic detectors so that green times can be allocated accordingly. This inherently requires more infrastructure than fixed time signals so there is a higher initial capital required for vehicle actuated junctions, but there are substantial financial savings in vehicle hours and maintenance time. A large amount of time and resources is required to update fixed time plans, for example, Toronto estimated that it would take 30 person years of effort to update all of the fixed time signals before they decided to upgrade to a vehicle actuated system (Quan et al., 1993).

Inductive loops are made up of coiled wire, which is embedded in the road, and a detector at the side of the road which powers the wires and creates a magnetic field around the loops. The loop resonates at a constant frequency which is monitored by the detector, and when a vehicle passes through the magnetic field, the resonant frequency increases and the detector becomes aware of a vehicle's presence (Marshproducts, 2000). These loops are typically placed upstream of a junction so that a vehicle's presence is detected with sufficient time to react to change the traffic signals.

Other common traffic sensors are infra-red cameras which are used for the detection of vehicles that request and potentially extend the green phase of traffic signals. They work through the detection of a positive or negative temperature contrast against the background and are able to detect people, animals and other objects in the detection area (Xtralis, 2013). Radar sensors are also used to detect the presence of vehicles and are able to differentiate traffic on each lane. Radars are able to "follow" the movement of an individual vehicle and can therefore be used to determine vehicle dynamics such as speed and direction of movement (Wavetronix, 2013). Radars are able to detect vehicles as far as 250 metres away from a junction (Radar Speed Signs, 2013).

Microprocessor Optimised Vehicle Actuation (MOVA)

MOVA is an advanced vehicle actuated controller, it analyses lane by lane detector data and controls signal timing to minimise delay and stops. There are approximately 3000 junctions using MOVA throughout the UK, with an installation rate of over 300 junctions per year (TRL, 2014a).

MOVA is designed to respond well to very low flows and oversaturated flows (TRL, 2014a); before the junction becomes saturated, MOVA operates in a mode which minimises delay but when the junction is saturated it operates in a maximum capacity mode. This is beneficial as no system can effectively deal with saturated conditions because there are simply too many vehicles on the road and therefore maximising capacity is a beneficial feature. Latest versions of MOVA are also capable of linking two or more junctions when they are not considered as isolated, for example, MOVA can be used in signalised roundabouts (TRL, 2014a).

In order to determine the duration of any given stage within MOVA, there are a number of sequential decisions during the green time (TRL, 2011):

1. The absolute legal minimum green period for the current green stage
2. A further variable minimum green period for each link designed to cater for those vehicles which have already crossed the detectors and for which the absolute minimum green is insufficient.
3. Following the minimum greens, a period when the queue on at least one specified link is judged to be still discharging at saturation-flow.

4. When saturated flow has ended for all specified links, a period when MOVA estimates the benefits and dis-benefits of continuing the current stage green. This optimisation process makes use of a performance index - a weighted combination of vehicle delay and vehicle stops. Unless benefits exceed dis-benefits, the green is terminated for the current stage.

These sequential decisions are based on the assumption that a predefined stage order is observed unless there is no demand for the next stage.

Determining the end of saturation flow is very important within the MOVA algorithm, as this will decide when a stage should be changed. Guidance from TRL suggests that the critical gap duration between vehicles passing over the sensors is 3.5 seconds. However this will be different when there are multiple lanes being released during the stage (TRL, 2011).

MOVA does not have a strict cycle time to adhere to because of the way in which it optimises green time; however traffic engineers will typically impose an upper limit to ensure that the waiting times do not become too large (impacting delay and the ability for pedestrians to cross). If a cycle time is imposed on MOVA, then the engineer will provide a preferred upper green time for each of the stages (TRL, 2011).

MOVA defines a lane to be oversaturated when: vehicles have been detected for an excessive period of time after the green period, or if the arrival rate becomes high. If the junction is classified as oversaturated then MOVA will attempt to maximise capacity as opposed to minimise the delay. MOVA is constantly evaluating what will maximise capacity through estimating the required green time for the other stages, and then calculating a flow efficiency rate every half second to maximise the capacity (TRL, 2011).

2.3 The Present

Inductive loops changed the way in which urban traffic control has operated; however isolated vehicle actuated junctions (e.g. MOVA) are not exploiting the full potential in an urban environment because there is no consideration of the effects on surrounding junctions. This section highlights the current potential of vehicle actuation through inductive loops, radar and infra-red detection technology, which are the main techniques used today to coordinate neighbouring junctions.

Congestion is still identified as a growing economic problem, but is also considered as an environmental and social issue (Eddington, 2006). It has been estimated that congestion costs England at least $35 billion (£22 billion) in lost time each year (Eddington, 2006). According to Bloomberg, traffic congestion in the US in 2009 cost the economy $114.8 billion (approximately £72 billion) (Bloomberg, 2011). While the underlying policy drivers are still congestion and delay minimisation, the focus has increasingly become a more holistic view of people movement rather than individual trouble spots.

2.3.1 PHASE 4 - Vehicle Actuated (Coordinated) Junctions [Late 1970s – Present]

Vehicle actuated systems which have coordinated junctions are those most often referred to as Urban Traffic Control (UTC) systems. There are many different UTC systems globally; many theoretical UTC systems have been proposed but this section will focus on those which have been adopted commercially and are used in a number of locations worldwide, see Table 1. In the US alone, there are approximately 30 different adaptive UTC systems in operation where SCATS is the most commonly used system (Zhao and Tian, 2012).

Table 1: Number of UTC System Installations

UTC System	Installations
SCOOT	More than 250 cities worldwide (TRL, 2014b)
SCATS	More than 50 locations worldwide (Zhao and Tian, 2012), 27 countries worldwide (NSW, 2014)
UTOPIA	Several cities in Italy, and also in Netherlands, USA, Norway, Finland and Denmark (KonSULT, 2009)
RHODES	4 Installations (Zhao and Tian, 2012)
MOTION	Installations in Germany (Mueck, 2008)

As with Section 2.2.3, vehicle actuated systems for coordinated junctions use on-street detector measurements to optimise signal timings on a cycle to cycle basis to better meet demand. These systems can be coordinated from a central computer (e.g. SCOOT) or have distributed intelligence and be coordinated at a local level (e.g. UTOPIA). Centrally controlled systems use less complex local controllers; whereas decentralized systems take more local decisions, with some coordination between adjacent controllers (Papageorgiou et al., 2006).

All of the major UTC systems operate on a similar basis of adjusting the split, cycle and offset times to optimise the traffic flow through a series of junctions (Papageorgiou et al., 2006). However, each UTC system has a different algorithm for adjusting these variables to achieve a higher region performance.

An advantage of isolated vehicle actuated junctions compared with a coordinated system is that there is greater flexibility to change the traffic signals because there is no consideration of the subsequent effects on neighbouring junctions (Hounsell et al., 2001). However, if every traffic signal was to operate independently then the network as a whole could potentially suffer. A 'before and after' study was carried out in Virginia, which showed a reduction of 30% in journey time between the original uncoordinated, actuated junctions and the final coordinated actuated junctions (Byungkyu and Chen, 2010).

Split Cycle Offset Optimization Technique (SCOOT)

SCOOT is the most commonly used UTC system in the world (Table 1) as it is installed in more than 250 towns and cities (TRL, 2014b). It is a dynamic UTC system which uses live traffic data to determine a suitable signalling time. SCOOT typically uses inductive loop detectors at the upstream end of links to monitor cyclic flow profiles and measure demand in real time. SCOOT has three optimisation procedures to adjust signal timings: split, cycle and offset times, which are optimised at different frequencies and using different procedures (Papageorgiou et al., 2006). Some of the first studies of SCOOT showed that SCOOT can reduce delays by up 12% in comparison to an up-to-date fixed time plan system (Hunt et al., 1981); however more recent studies have shown that in comparison to a typical fixed time plan system, which isn't fully updated, SCOOT can reduce delays by up to 20% (Shepherd, 1994).

SCOOT requires detection information very frequently to keep its plans updated, binary signals indicating the presence (or absence) of a vehicle are sent to SCOOT every second. SCOOT relies on the quality of input parameters to accurately model and react to vehicle behaviour (Wylie, 2009).

The detectors can be used to identify accidents or congestion as the velocity of vehicles is known, and there is typically additional software used alongside SCOOT to best deal with these problems, for example Comet or Stratos which provides a user friendly interface for the network operator. SCOOT makes a large number of small optimisation decisions, typically over 10,000 per hour in a network of 100 junctions (Hounsell et al., 2001), so there is a lot of information being processed.

SCOOT has flexibility in the system to override values and set parameters for different regions at different times, for example, gating strategies to protect an area from excessive traffic or bus priority measures to improve bus punctuality and regularity (Papageorgiou et al., 2006). SCOOT is able to provide differential bus priority if required by recalling, skipping or extending stages to ensure bus priority is given (Bowen, 1997).

SCOOT is able to follow trends over time in traffic flow and local short term changes; however, as the optimisation procedure only allows a small amount of change to split, cycle and offset times, then SCOOT could be constrained by this during a sudden change in flow (for example, a football match). However, a study in Toronto showed that SCOOT reduced delays after a baseball game by 61% in comparison with the previous fixed time plans (Quan et al., 1993).

Sydney Coordinated Adaptive Traffic System (SCATS)

SCATS works on a combination of coordinated vehicle actuation and fixed time plans as it uses a library of fixed time plans which have been developed to work in specific scenarios. It operates at two basic levels; the “upper level” which involves offset plan selection and the “lower level” which involves the optimisation of various junction parameters (Lowrie, 1982), such as split and cycle times (SCATS, 2012).

SCATS operates in real time and has many distributed controllers however it does not use fully comprehensive plans, it uses many smaller libraries of offsets and phase split plans. SCATS relies on incremental feedback from detectors to change the signal plans over time. There is a central control override for local junctions to implement incremental split plans which make 2% adjustments to the previous traffic signal phases. A critical junction must be named for each of the regions which the surrounding junction plans is based on. The ratio of detected flow to saturated flow is determined in each region to assess the congestion levels. (Martin, 2001).

SCATS determines offsets through “marriages and divorces”; a library of external offset options are used and a marriage is where two adjacent regions adopt the same common cycle time. Internal offsets are driven by cycle length and can be adjusted by a traffic signals engineer

(Martin, 2001). SCATS is able to change cycle time after every cycle if the road conditions have changed sufficiently.

SCATS is able to provide priority for buses and trams through a three tiered system (high, medium and low). Trams can expect to receive high priority, which results in stages being skipped to prevent trams stopping, whereas buses would typically get medium priority which involves shortened or extended stages to reduce the number of stops (Gardner et al., 2009).

SCATS biggest performance weakness is the optimisation of its offsets, which has an impact on the progression of vehicles between regions, SCATS is based on stop line detection which means that there is no concept of how long the queue is (Lowrie, 1982). SCATS does however have a useful oversaturation feature; as the road reaches saturation flow then SCATS gives all of the extra cycle time to the busiest phase to reduce the impacts of congestion. Consequently SCATS is very good at coping with heavy flows which are close to saturation, complex flow patterns and unpredictable variations (Martin, 2001).

SCATS was shown to outperform an uncoordinated set of junctions by reducing travel time up to 23%, reducing vehicle stops by 46% and a reduction of fuel usage by 12% (Shepherd, 1994).

Urban Traffic OPtimization by Integrated Automation (UTOPIA)

UTOPIA is a hierarchical, decentralised traffic signal control strategy. It aims to minimise the total time lost by vehicles, however public vehicles are prioritised highly in an attempt to prevent them from stopping at signalised junctions (Mauro and Taranto, 1990). UTOPIA is based on an optimising cost function depending upon vehicle delays and stops, delays to public transport and deviation from reference plan and historical signal timings. Optimisation is applied to both the local and network level; the local level determines the signal timings based on the cost function and is optimised for a 120 second time horizon (repeated every three seconds). At the network level, the cost function considers neighbouring junctions to build a dynamic signal co-ordination (Gardner et al., 2009).

UTOPIA has a three tiered hierarchical architectural system:

- Local Level – applies a microscopic model to estimate the state of the junction directly collecting the measurements which characterises the junction (saturation flows, turning percentages, delays). UTOPIA optimises the signal strategy over a time horizon, consisting of the next 120 seconds, where the road state is determined every 3 seconds (Shepherd, 1994).

- Area Level - less detailed traffic model to monitor the state of the whole controlled network. This level validates the local detection, checking changes in the traffic data compared with historical data
- Town Supervisor Level – integrates the congestion information given by UTOPIA with data from other systems, such as bus travel times. A macroscopic model is used at this level, which has the advantage of collecting different sources of information and having coverage of the whole city (Hounsell et al., 2001)

UTOPIA has been explicitly designed with public transport priority in mind (KonSULT, 2009); consequently UTOPIA is combined with System for Priority and Optimisation of Traffic (SPOT) which provides bus priority through shifting the 'green window' to coincide with the anticipated arrival time of buses. Bus location technology is used far upstream of signalised junctions and the system can gradually adapt the junctions to match the arrival times. UTOPIA uses loop detectors at key locations in the network which are just downstream of the previous junction (Gardner et al., 2009).

UTOPIA in Turin had a significant impact on journey time as it resulted in reductions of 20% for public transport vehicle journey times and 10 - 15% for other vehicles (Papageorgiou et al., 2006). UTOPIA appears to be more adaptive throughout the network, but the cost function has a lot of uncertainty associated with it, and requires regular updating to ensure sufficient efficiency. UTOPIA is fairly dependent on accurate journey time forecasting and detection technology so that priority can be given to public transport (Gardner et al., 2009).

Real-time Hierarchical Optimized Distributed and Effective System (RHODES)

Similar to UTOPIA, RHODES architecture is based on a three tiered hierarchy: the highest level assigns traffic to the network to determine base levels of traffic, this takes into account evolving traffic demand and network geometry. The level below is based on predicted platoon arrival patterns to determine signal timings. Thirdly, at the junction level the movements of individual movements are modelled.

RHODES responds to the natural stochastic behaviour of traffic (Mirchandani and Head, 2001). There are two significant processes: 'estimation and prediction' and the 'decision system' process. The first stage is based on actual upstream data collected, and the second stage is where the split and cycle times are selected to optimise the given objective (minimal queue length, delay per vehicle or number of stops) (Mirchandani and Head, 2001).

Method for the Optimization of Traffic signals In Online controlled Networks (MOTION)

MOTION has two main components, MOTION Central and MOTION Local. The central function creates plans which can then be adjusted by the local element (Gardner et al., 2009). MOTION operates on four different functional levels (Hounsell et al., 2001):

- Data acquisition – this is used for different functions: network incident detection and for Origin and Destination pairs.
- Dynamic traffic model – through estimation of the most important traffic streams and analysis of traffic by determination of current traffic status.
- Optimizing control variables – iterations of common cycle times and split times are carried out to determine the optimum green times. The platoon model is used to try and optimise the offset timings between junctions.
- Decision – the new signal programs are compared to the current signal program. If there are major improvements then the signals are changed, however, if only minor improvements then the current signals are not changed.

MOTION does consider both the local and network levels; however, it is unclear how much the local plans can change the more strategic network plan.

Worldwide UTC Systems

There are many UTC systems worldwide which are not widely discussed in the literature but are significant improvements over fixed time systems. The UTC system in Singapore is Green Link Determining (GLIDE), and it is a dynamic system which optimises green time for every approach. GLIDE has increased the average journey speeds by 8% in morning peak against fixed time systems (Keong, 1993).

The Japanese UTC system is Universal Traffic Management System (UTMS) and it uses infra-red technology to detect and communicate with vehicles. Therefore UTMS is able to re-route drivers if they have an infra-red device installed in the car, as was shown in the Nagano Winter Olympics where drivers with the infra-red device could arrive at the destination up to 11% faster than drivers without (Kitamura, 1998).

2.3.2 Discussion and Conclusion for UTC Systems

The most challenging problem of comparing UTC systems, both directly and in relation to their fit to policy drivers, is that there are very few field studies with two commercial systems directly compared. Each UTC system has different detector requirements for a junction and therefore it would be very expensive to carry out a real world trial of competing systems. Some UTC systems require sensors more than 100 metres from the junction whereas others require stop line sensors, so cost is always an important factor in deciding which UTC system should be used (as well as performance).

When looking at published statistics from the designer, there will always be an element of bias due to the commercial nature of the product. Every city is different and has different requirements due to varying (and evolving) policies within countries; for example, environmental policies in many countries encourage the use of public transport and bicycles over private motor vehicles, whereas this may not be the policy or culture in other countries. Therefore choosing a UTC system is a specialised task; Hounsell et al. (2001) highlights some of the reasons why a local authority may choose one UTC system over another:

- National standards or preferences
- Expertise or available support for the system
- Robust demonstrations of its effectiveness in similar operating situations
- Implementation, operating and maintenance costs
- Traffic characteristics (modal split, growth, variability, level of congestion)
- Issues surrounding detector dependent systems (cost of maintenance)
- Prospects for future development

As growth in a town or city occurs, typically fixed time signals have been replaced by some form of UTC system to improve the efficiency of the network. However as fixed time signals have been replaced, it was observed by Transportation Research Board (TRB) that UTC systems are considered much more operationally demanding than fixed time systems because of the additional technical expertise required to operate them (NCHRP, 2010). Therefore they have higher installation costs due to the required training and equipment.

A potential weakness of adaptive UTC systems was highlighted in a survey that was carried out by TRB: UTC operators appeared to believe that they were often not given sufficient time or training to learn how to fully operate the systems (NCHRP, 2010). Clearly UTC systems have substantial performance benefits over fixed time systems as seen throughout this section; but insufficient training can cause significant problems for the efficiency of UTC systems if the operators do not understand how they work. Therefore it is important for UTC operators to have the relevant training to achieve the full benefits of adaptive UTC systems.

Table 2 indicates the advantages and disadvantages of the three different types of control system and it also shows the requirements of detection and communication technologies. As there are no direct comparisons of UTC systems, it is not possible to state objectively which system is best; however using Table 2 it is possible to identify the strengths and weaknesses of different systems and select a system based on the requirements.

The UTC systems which have been described in this section have been shaped by the technology available. Currently UTC systems only have snapshots of the traffic state on the road due to the detection technologies used (inductive loops, infra-red, radar). For UTC systems to improve beyond current limitations a better understanding of the road state is required and this can only occur through advances in detection and communication technologies which provide improved spatial and temporal data sources.

Table 2: Summary of advantages and disadvantages of different types of UTC system (After: Papageorgiou et al., 2006)

Traffic Signal System	**Advantages**	**Disadvantages**	**Technology**
Fixed Time (e.g. TRANSYT)	1) Cheaper to install and maintain the infrastructure 2) Can be implemented using non centrally controlled equipment 3) Familiarity with settings for regular users 4) Green Waves more easily implemented	1) Large amount of data to be collected and updated 2) Signal plans require updating 3) Disruption caused when plans change 4) Operator needs to respond to incidents 5) Cannot deal with short term traffic fluctuations	*Sensing*: Offline *Communications*: None
Responsive plan selection (e.g. SCATS, MOVA)	1) Can deal with some day to day fluctuations 2) Could benefit arterial routes more 3) Cheaper than fully responsive systems	1) Require more data than fixed time 2) Detector failures can cause problems 3) Discussions are required on when to change a plan 4) The plan could change for a wrong reason if automated 5) Difficult to foresee all eventualities	*Sensing*: Current road state through static sensors (uses arrival profile) *Communications*: System Dependent
Fully responsive (e.g. SCOOT, UTOPIA)	1) Less data required in advance 2) Plan evolves with time so less updating required 3) Can deal with short and long term fluctuations (better at long) 4) Automatic reaction to incidents 5) Live traffic information available	1) Detector failure can cause significant loss of efficiency 2) More expensive to install, comparable for maintenance 3) Requires some central control 4) Maintenance is critical	*Sensing*: Current road state through static sensors (uses speed and arrival profile) *Communications*: Minimum of local level

2.3.3 PHASE 5 - Integrated UTC & Intelligent Transport Systems [1997 – present]

The most advanced urban traffic control systems are becoming more centrally integrated with other traffic management systems to reduce the workload of network operators and to improve the efficiency of the network. There are many different elements to consider when managing traffic control (see Figure 3), and through effective integration the operator involvement can be reduced. This has been enabled through a number of technological advances, most of which are either improvements in detection techniques or methods of communicating with drivers.

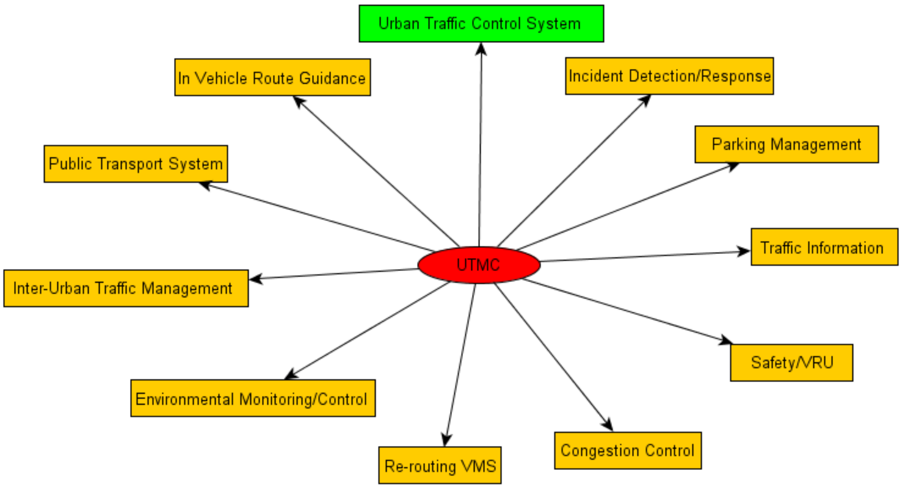

Figure 3: Schematic Illustration of a UTMC system (after DETR, 1999)

Urban Traffic Management and Control (UTMC) Systems

UTMC was a UK Department for Transport initiative to help local authorities obtain the most from their combined UTC system and Intelligent Transport Systems (ITS). UTMC systems are designed to allow different applications used within traffic management systems to communicate and share information with each other (DfT, 2009). This helps to build a more dynamic, intelligent and real-time information based traffic management system. Transport policy in the UK during the 1990's had targets of (Glaister, 2001):

- A safe and efficient transport system
- A better, more integrated public transport system
- A more environmentally sustainable transport system
- Better and more strategic integration of transport and land use planning

These targets were fairly generic but it is clear that integration was crucial to the policy of this era, and this was exactly the aim of UTMC.

Fundamentally UTMC systems are considered as modular, open systems which incorporate and build on existing functionalities of current signal control and other traffic management systems (Papageorgiou et al., 2006). The UTC system is at the heart of a UTMC system; however the other features add significant benefits by providing additional information about the network. Accurate and up to date information is critical for a successful UTMC system; for example the operators can inform road users of congestion or accidents in the network and re-route them accordingly, or inform motorists of available parking facilities in a city centre. UTMC systems are built-up of many Intelligent Transport Systems, see Figure 3.

UTMC has many advantages for the road user (UTMC, 2009):

- Advice – the system can advise motorists on journey times, for example, using Automatic Number Plate Recognition cameras, the average speed can be determined and journey time displayed on Variable Messaging Signs (VMS).
- Warn – motorists can be warned of dangers on the network using VMS. For example, 'Strong wind' messages can be displayed on bridges to warn motorists.
- Guide – motorists can be informed of delays on the road due to congestion or an accident using VMS. Also many cities use car park VMS upon entering city centre so that motorists can plan which car park to use.

A major benefit for the operators of UTMC is that national standards were created so that communication between ITS features would become easier. Standardisation was a policy led approach to deal with the issues of complex interactions between initially separate UTC and ITS systems, but this also enables a wider (and potentially cheaper) selection of products for local authorities (UTMC, 2009). A common language was developed to share information much faster and therefore the transport network can utilise other forms of communication without paying the high installation costs, for example, the cable TV network can be used to send information (UTMC, 2009). The cost of running individual ITS were higher as individual detectors and communication devices were required, whereas detectors can now be used for more than one purpose. A shift to an all-inclusive traffic control system has created a more competitive market, with a wider choice of systems and suppliers. The interoperability of data is now much easier due to a standard format within UTMC systems, which is essentially a common database, and now there are systems such as CUTLAS, Comet or Stratos which manage the data from various UTC and ITC sources to try to gain operational advantage (Envitia Plc., 2012)(Siemens, 2012).

2.3.4 Summary

Sections 2.2 and 2.3 have demonstrated that at any point in time the leading UTC systems were defined by the capabilities of the available technology, and hence UTC systems have historically had to wait for technological advances to facilitate step changes in performance. A new phase is beginning where technological advances are faster than the development rate of UTC systems, causing a rebalancing of the relationship between policy, technology and UTC systems.

2.4 The Future

The continued policy desire to enable sustainable mobility is unlikely to change in the near future, with the key drivers remaining lower costs and lower environmental impacts. This section will demonstrate that the near future of urban traffic control will be shaped by the advances in technology which are likely to be implemented relatively soon into the transport industry. However it is imperative for policy measures to maintain pace with technology or infiltration rates of technologies will be much slower as vehicle manufacturers are not forced into including new technologies. With improved integration of technology into traffic control:

"[For the commuter] intelligently connected transport networks mean better travel information, fewer delays and less stress; [for the environment] it means fewer emissions" (Siemens, 2010).

2.4.1 What technologies are likely to be used in the near future?

The future will depend on a very large number of variables ranging from technological breakthroughs, political decisions to public acceptance of the latest inventions. Therefore it is very challenging to accurately predict what the future will be like in 10 years or more; and this is why studies frequently consider multiple scenarios for what the future could look like so that the reader can understand what is likely to happen depending on circumstances. This section will highlight some technologies, which could be used in the future, with varying degrees of certainty depending on how the barriers to public acceptance and implementation are overcome.

Wolfgang Homburger (a transport engineer for more than 50 years) stated that:

> "*Knowledge is always expanding. Technological progress is inevitable and rapid, and will bring us tools and analysis methods that we might label as science fiction today. And the priorities of the public may well shift again, but in what direction?*
>
> *Opportunities for more automation of traffic control equipment, of entire highways and rail transit lines and of enforcement will abound. Environmental health will continue to be a major policy issue - carbon dioxide emissions are only the latest addition to the list of global concerns*." (Homburger, 2002)

The transport industry needs to be dynamic and fast moving to keep pace with the ever improving advances in technology. However there are always barriers and constraints which need to be overcome before any new technology can be implemented.

Smartphones and Satellite Navigation

It is generally accepted within the transport industry that there is an ever growing number of data sources which are unutilised to their maximum potential. More than half of the population in the UK and US have smartphones, which are capable of sharing data using Bluetooth and Wi-Fi (NewMedia, 2013 and Forbes, 2013). Researchers are only beginning to realise the potential that this data has for the transportation network. A smartphone creates an opportunity to not only detect the presence of a road user, but also can communicate with them using clear, concise and relevant messages for their individual transport needs. Foell et al. (2013) believes that a thorough investigation of how this data could be used effectively is missing in current literature.

This relatively new data source (smartphones were only released in 2007), creates an opportunity for monitoring people flow and informing road users like never before. It is now possible to data mine large amounts of origin and destination pairs with accurate journey times (data mining is looking for trends in current data to help predict future scenarios). Having access to historical data enables the system to determine an individual's "typical" route and therefore could advise them on the best route. There is the option of personalising the Key Performance Indicator (KPI) which is most important to the user – KPI's could be avoiding congestion, cheapest, quickest or shortest route or reducing emissions. This routing information could be used to determine the most suitable location of bus routes, train stations, cycle routes, pedestrian zones or home zones, speed cameras (the Dutch police used TomTom data to place speed cameras but it was not very popular amongst TomTom users and therefore was stopped (Engadget, 2011)), or it could even be used for advertising relevant local events, shops or restaurants.

Since it would be possible to accurately detect individual, yet anonymous, location data (where historical journeys could be accessed) then journeys could become much more predictable and potentially be used in signal control. The system could gather the vehicle's location, speed, predicted route and approximate arrival time of each person with a smartphone and therefore could generate a much richer data set which could be used in a novel signal control algorithm. Smartphone usage has other potential benefits within the transport industry, 'apps' also make live public transport timetables readily available and could be used to promote the use of greener modes of transport.

Data mining would not be the only source for predicting journeys; satellite navigation systems could also be used by uploading a user's intended journey and approximate timings to determine additional information for signal control and routing. Sat-navs could also provide a valuable method of communication with the network operator as messages could be pushed to sat-nav devices, informing the road user of congestion or potentially quicker routes.

Satellite navigation systems are currently used by approximately 28% of road vehicles (Oxford Economics, 2012). There are huge potential savings through the use of sat-navs, for example, a survey carried out to investigate the effects of sat-navs amongst drivers who were travelling to an unfamiliar destination reduced vehicle mileage by up to 16% and reduced time spent travelling by up to 18% (Oxford Economics, 2012).

Further research into the potential advantages of using smartphone and sat-nav data needs to be carried out and could realistically be trialled within the next decade. However, a major barrier to using smartphone data is public acceptance and dealing with their privacy concerns. A real benefit of this system is that the infrastructure is already in place to connect to smartphones and sat-navs. The major risk with implementing a control system based on smartphone or sat-nav data is that there is no control over how the public uses them and people could choose to boycott any control system or stop using the devices.

Vehicle to Vehicle and Vehicle to Infrastructure Systems

Currently any information which is passed to a driver is mainly through variable messaging signs, prior internet usage or social media. However there have been significant amounts of investment in Vehicle to Vehicle (V2V) and Vehicle to Infrastructure (V2I) communication systems which could be used to improve route choice, provide valuable information for drivers and improve signal coordination. A European funded project called Cooperative Vehicle-Infrastructure Systems (CVIS) has researched and developed a new communications architecture which enables vehicles to communicate with one another and the surrounding infrastructure. The medium of communicating is through WLAN, infrared, cellular (GPRS/UTMS) or digital broadcast communication (CVIS, 2010a), which means there is a high potential for infiltration as a large number of vehicles will be able to communicate by one of these methods. Trials using the CVIS architecture and traffic control system have suggested that vehicles could save approximately 15% on travel time, and minor road traffic could save up to five seconds per vehicle per junction (CVIS, 2010a). This system was based on vehicles communicating with the surrounding infrastructure so that vehicles would be informed of the downstream signal plan and a suitable speed so that they arrive during a green wave.

Also, if vehicles are able to communicate with one another and there is heavy congestion then this information can be passed upstream of the incident rapidly. The EU project COOPERS used a driving simulator to demonstrate that drivers change their driving behaviour when advanced warning is given of severe driving conditions, and the driver's average speed dropped by 14% (COOPERS, 2010). Therefore incoming vehicles could avoid joining queues or entering congested areas by using this information; hence improving the state of the network. A study carried out by the National Highway Traffic Safety Administration in 2010 says that V2V has the potential to reduce 79% of target vehicle crashes on the road because vehicles would be able to communicate with one another to avoid accidents occurring (Green Car Congress, 2011). As V2V and V2I is already in the trial phase with many major investors (Compass4D, 2013), then it is very probable that this will feature in various cities within the next decade as high end manufacturers begin to install more advanced systems in their vehicles.

Traffic View (Dashtinezhad et al., 2004) was an early research project which experimented with Vehicle Adhoc Networks (VANET), where vehicles had short ranged wireless communication devices installed and therefore vehicles could share information with one another. By using VANET's, vehicles transmitted location, identification number, speed, direction, state and a timestamp to the surrounding vehicles. Then UTC junctions were able to detect this information and determine appropriate signal timings based on the number of vehicles at each arm.

There has been a recent trial in Michigan with over 3000 vehicles that could communicate to one another (Funkhouser, 2012). These vehicles use dedicated short range communications (a wireless radio spectrum) which has a range of approximately 200m. The vehicles were able to share information regarding journey times, incidents on the road or weather conditions. This type of V2X technology enables vehicles to share additional data such as the vehicle's location, speed and destination.

One of the biggest barriers to implementing V2X (either V2V or V2I) technology for traffic control is the low levels of infiltration in vehicles, however, 12 major vehicle manufacturers have set a self-imposed target of including V2X hardware in all new vehicles from 2015 onwards (ITS, 2012). This will obviously take time to filter through, Green Car Congress (2013) have predicted that there will be a 10% infiltration of V2X by 2018 and ABI research (2013b) predicts up to 61.8% infiltration by 2027. Public acceptance of these systems is still very important to ensure the success of this technology but it will be helped by the fact that 12 major manufacturers are including the technology in all new vehicles.

Bluetooth

Bluetooth sensors are becoming more popular for journey time estimation and Transport for London (TfL) have carried out trials to find out if Bluetooth could be used to send information to drivers along key urban routes (TfL, 2006). One of the problems with Bluetooth sensors is that there is no certainty of the infiltration rate within vehicles which makes it inadequate for accurately determining flow, however it does provide good speed and presence detection data (ITS, 2011a).

Manchester (UK) has recently invested in Bluetooth technologies in order to determine average link-based journey times along a major route (TDC, 2013). This information is desirable so that it can be communicated to incoming drivers so that they will not add to the congestion by potentially seeking an alternative route. One of the significant benefits of Bluetooth is the cost of the equipment, very little infrastructure is required to detect Bluetooth enabled devices (mobile phones and vehicle stereos) and therefore it is a cheap data source for local authorities.

Floating Vehicle Data

Floating vehicle data is a detection technique likely to be used more in the near future as it has already been tested (e.g. by ITIS Holdings plc and OPTUS (PR Newswire, 2009)). This is where active mobile phones can be used as traffic sensors; the location and velocity of the vehicle can be inferred which informs the network operators of the state of the road. One of the most beneficial features of this technology is that no extra hardware is required through the network; however new system architecture would be required to incorporate the new source of information into the traffic controls, as the current systems use a single detector point as opposed to a continuous data stream. Currently it is quite difficult to calibrate and validate UTC systems, but when floating vehicle data is used, it could become easier due to the simplicity of data collection (CVIS, 2010b).

Communication Systems

Currently variable messaging signs are the main method of conveying network information to the driver. However as live traffic feeds for satellite navigation systems or smartphones becomes more commonplace then the operator could inform the motorist of any delays and re-route the vehicles through in-vehicle technologies. According to the CVIS project, the future ideal ITS needs a communication sub system which: (CVIS, 2010c)

- Is available wherever and whenever a vehicle is present in a traffic situation

- Can communicate vehicle to vehicle and vehicle to infrastructure in a transparent way
- Relieves the application from the need to know about communication setup and management
- Uses modern internet techniques and standards for global usability (IPv6)
- Provides a range of different possibilities related to data speeds, communication distance, cost and many other parameters

Augmented Reality Dashboards

In-vehicle technologies continue to expand so that vehicles can become not only safer, but have much greater functionality than a basic car. Augmented Reality (AR) dashboards could be used in the near future to highlight hazards or other important information to the driver.

> *"So if you're approaching a car too quickly, a red box may appear on the car you're approaching and arrows will appear showing you how to manoeuvre into the next lane before you collide with the other car. An augmented reality GPS system could highlight the actual lane you need to be in and show you where you need to turn down the road without you ever having to take your eyes off the road*" (HowStuffWorks, 2012).

This provides another method of communicating with road users which enables them to receive up-to-date routing information or information about potential delays. AR systems are designed to provide information safely to the driver without the need for them to take their eyes off the road. BMW are currently developing AR dashboards as they already have a windshield display which shows drivers some basic information (HowStuffWorks, 2012).

For this system to work, advances in car internet systems would need to be developed further. According to CarandDriver (2010), internet in cars is currently in its infancy, with only a few high end manufacturers experimenting with it in their latest models. They expect that most new cars will become Wi-Fi hot spots, either sharing an internet connection with a smartphone or with its own data plan. They predicted that in 2015, nearly 25% of cars will be connected to the internet, and Bracken (2013) predicts that every new car will be connected to the internet by 2025. If cars are connected to the internet in the near future then this makes communicating with them, and surrounding vehicles, much faster and easier than traditional VMS techniques. This will enable vehicles to emit a vehicle status containing vital information such as velocity, route and journey time, and the vehicle can be used as an active safety measure. If two cars are rapidly approaching a junction at the same time then they both could be warned before an accident takes place. In Japan, Nissan are testing an in-car system which can let drivers know where other cars have had accidents, preview hidden road hazards, and ‘sense’ the cell-phone signals of pedestrians to alert drivers of their presence (CarandDriver, 2010).

2.4.2 What systems are likely to be used in the near future?

Artificial Intelligence Signal Control Methods

Trends in data become even more difficult to spot to the human eye as data sets grow ever larger; and the transport industry will inevitably turn to Artificial Intelligence systems to aid them with data manipulation (Foresight Report 2006). Traffic flow patterns can be recognised easily and are well documented for all major cities, but this information could be used more within signal control plans. It may be used for the design of the junction, but UTC systems do not consider the likely impending flow upon the junction. Traffic operators currently use specific strategies (or plans) to accommodate individual scenarios, but what if these indicators could be automatically detected and the relevant plan put into action? For example, if there is a football match in city centre then there will be a sudden, large influx of traffic trying to use the arterial routes at the end of the match. Detectors on the roads surrounding the stadium could be used in an intelligent way to prioritise all arterial routes out of the city so that the duration of congestion is minimised; however the current practice of resolving this situation is for a network operator to pre-empt the influx of traffic and set the strategy for a particular time within the UTC system.

The University of Southampton have worked on new signal control algorithms which are able to pre-empt traffic flow using machine learning techniques, which are able to reduce the delay on vehicles compared to SCOOT and MOVA (Box and Waterson, 2012). However a major barrier to implementing a new traffic control system is the need for a new architecture to manage all the new data sources available throughout the network. Also, current systems such as SCOOT, SCATS or UTOPIA are thoroughly tested systems, whereas any new product has only simulated results and it could be very challenging to persuade a town or city to trial the new system.

However, there is no reason why a new traffic control system could not be implemented within the next decade, even with these barriers to implementation. The required detection and communication technology is already available to trial new systems but the inertia within the industry and the logical desire to defend one’s market share may prevent new systems from entering the market. The existing systems have been used for more than 30 years and a new system could help to bring UTC in line with the technology available today.

Machine Vision and Automated Vehicles

Globally, it has been estimated that there are 1.2 million people killed annually in road traffic accidents and a further 50 million seriously injured (Mohan, 2002 and WHO, 2010). This motivates many companies to try to improve safety standards through more automated processes within vehicles, especially as 90% of all accidents are due to human error (WHO, 2004). However there are many barriers to this, primarily the law need to be changed so that driverless vehicles can be legally used without the need for a person monitoring the car (ReadWrite, 2013). There are already many automatic systems in vehicles to reduce accidents, such as Collision Avoidance Systems, Automatic Parking, Lane Monitoring and Driver Monitoring to avoid a driver falling asleep at the wheel.

Advances in machine vision and semi-automated vehicles could have a significant impact on reducing accidents but also by smoothing traffic on the road network (Bose and Ioannou, 2003). Vehicles would be able travel closer together and at a more constant speed, therefore reducing the space on the road and improving fuel efficiency. As vehicles become more automated and have more sensors then the network operator will have a much richer data set which could be used for signal control, traffic monitoring and provide route choice information to the vehicles or drivers. Also there are many social benefits to using fully automated vehicles, especially for people who are unable to drive, the elderly, and it could eliminate drunk-driving accidents (DaVinci Institute, 2006).

The improvements in machine vision are not limited to automated vehicles; they could greatly improve roadside monitoring for traffic operators. Current traffic cameras could be used to help predict and monitor turning proportions, vehicle occupation and other road user statistics.

The biggest barrier to automated vehicles is liability concerns. Who is responsible if there is an accident in a driverless vehicle: the passenger, the manufacturer, the software developer or the maintenance garage? This is a serious issue which needs to be resolved before fully automated, commercially viable, vehicles could become a reality. The Google driverless vehicle is only legal when there are two passengers monitoring the vehicle at all times, however the only accidents in which the vehicle has had were two human error situations where a person was driving and another vehicle drove into the back of the vehicle (Wall Street Journal, 2013). The other potential barrier for the driverless car is: would people be willing to concede driving to an automated vehicle? According to Cisco (2013) 57% of people would be willing to use a driverless vehicle, and it is very likely that this will increase if there are no at fault accidents when the driverless vehicle is introduced.

Connected Vehicles

A connected vehicle is one which is connected to the internet through some means of communication, such as 3G, 4G or V2X. If all modes of transport were controlled by one authority then there are potential benefits for the local authority, road user and the environment. A road user could use a smartphone (or other connected device) at the start of their journey to determine the most suitable route to their destination. The decision could be based on cost, time, environmental impact or distance and the device could suggest the best route for that individual based on the current (or predicted) road conditions, public transport infrastructure, weather and user's willingness to walk or cycle. An integrated system could be used to pay for the entire journey so that travelling on different modes can become simpler and could be fairly compared. This 'future of transport' would have a number of barriers, similar to what the Oyster card in London faced, but could increase the use of public transport and enable people to make an informed choice about their route. The biggest barrier would be for different modes of transport to be controlled under one authority or willingness to use shared tickets which would remove a potential differentiator in the competitive mobility market.

Google Traffic

A recent example of how a non-government commercial innovation can be applied to a higher level transport system is Google Maps. Since 2007 Google Maps have displayed live traffic information for users who planned their route before travelling. This uses crowd-sourced data (where Google users share information) to gather anonymous location and velocity data to estimate the road conditions (Barth, 2009). Google then processes the information to output a visualisation of how congested or 'free flowing' the road is (although during the summer of 2011 the feature was briefly removed as Google themselves believed it to be "too inaccurate" (Schwartz, 2011)).

Feedback to Drivers

Wiering et al. (2004) stated that being able to predict traffic conditions is very important for optimal traffic control and emphasised that communication with drivers would be very beneficial to help reduce the effects of congestion. Levinson (2003) highlighted that by increasing the percentage of 'informed' drivers (i.e. choosing the best route) then the average journey time would reduce for both the informed and uninformed drivers. This highlights the benefit to having feedback to drivers within the network so that delay can be reduced for all users.

Internet of Things

The 'internet of things' is a methodology with which vehicles will be able to send and receive data. Individual vehicles have unique identities and act as messaging systems in which other vehicles, pedestrians and UTC operators will be able to read data sent from the vehicle. This could be where they have been, where they are going, what the weather was like in the previous road section and many other characteristics which may be of use (EPoSS, 2008).

Privacy Concerns

One of the largest problems with the location technologies described here are privacy issues regarding the information gathered from mobile phones or satellite navigation systems (Leduc, 2008). The data collected is made anonymous before being used to describe the road condition; however the general public may not believe this or understand the reasons behind collecting the information (Cruickshanks and Waterson, 2010). Many companies use vehicle tracking to locate all of their fleet at any given time, but employees must first be told that they are being tracked, but employers do not have the right to track company vehicles when they are being used outside of working hours (Expert Market, 2014).

Members of the public want to know what data is being collected, if it can be traced back to individuals, why the transport authorities need it, should it be constrained to law enforcement only and can fines be issued because of this data? These questions need to be addressed so that the public can feel reassured that their privacy is not breached in any way (ACLU, 2012).

Discussion of Future Technologies

There are a vast number of potential scenarios in the near future and it is very difficult to predict with any real accuracy. However with the rapidly increasing number of new data sources, then it is inevitable that more automated control processes and machine learning is essential for the future of transportation engineering. The technology used in vehicles and roads is rapidly improving and the control systems must keep up with the advances in technology.

Moriarty and Honnery (2008) stated that "*an examination of the history of transport technology shows that although genuine breakthroughs do occasionally occur, they are not as common as thought*". This is remark highlights the difficulty in predicting with any level of certainty when specific technologies will be fully implemented, but it is probable that crowd-sourced data will be used in near future as trials have already been carried out (PR Newswire, 2009, CVIS, 2010a).

2.4.3 PHASE 6 - Automated Urban Traffic Management & Control

As technology advances and policy drives toward continually reducing the need for human input into UTC systems, the likeliness of a future where UTC is based around more intuitive systems which run without human assistance become ever more probable. However the system will need to be able to highlight any issues within the network to the control centre. These automated systems should be able to manage the UTC system and ITS technologies efficiently to reduce human error during operation. An advantage of having a fully automated system would be the reduced costs, both labour costs and maintenance costs would be lower with less hardware in the road (inductive loops, infrared sensors) as network operators could use detection technologies such as floating vehicle data, smartphone and satellite navigation systems.

With an intelligent automated system, the system could learn over time how best to control the traffic signals if it were to monitor the average delay per vehicle. This type of control system has been developed and is based on logistic regression and neural networks. This automated method proved to outperform MOVA in simulation modelling but is yet to be tested on a real network (Box and Waterson, 2012).

While fully automated systems clearly have advantages, it is not anticipated that humans will be completely removed in the near future. As described previously, current UTC systems are unable to take a holistic view and pre-empt large traffic flows. Large city events, such as sporting events, can cause considerable trouble for the surrounding traffic control systems if strategies are not created to deal with the impending large flows. Due to the nature of sudden increases in traffic flow, UTC systems will require some human input to update the time of these events, unless a vehicle’s route choice is shared with the control system.

When a holistic view of traffic management is taken, individual junction efficiencies can suffer to improve the state of the network as a whole. This occurs within SCOOT regions so that a regional net benefit can be achieved. This is also used in the concept of gating, where minor roads are intentionally delayed to maintain higher flow rates and more reliable journey times on the major route; for example, gating was used at the 2012 London Olympics to improve journey time reliability along key corridor routes (SCOOT, 2008).

If the control system was automated then it may recognise flow breakdown much quicker than a human, so it could prioritise major roads to potentially reduce overall lost time. When road conditions are approaching saturated flow then it would most likely be beneficial to prioritise the major roads at junctions to maintain free flowing traffic for as long as possible. This could cause significant delays to a small number of motorists though (potential rat-running traffic), which might be perceived as unfair, even though it could improve the state of the road for the remainder of their journey.

2.4.4 Information Abundance

If new technologies, such as floating vehicle data and vehicle to vehicle communications, are used in the near future to help coordinate traffic control, then there will be a paradigm shift from an era where there was a lack of information available to the UTC operator, to an era with an abundance of data. Currently there is a limited amount of data available through traditional sensors (inductive loops, infra-red, radar) and operators would like to know more information about the network, whether it be journey time data through automatic number plate recognition cameras or more CCTV cameras. However, if all of the potential new technologies are utilised then an increase in operational resources would need to be allocated to interpret the data, or else the extra information could become a wasted, and expensive, resource. A big challenge is being able to filter the many new data sources into a result which is relevant and useful for the network operator.

The transport industry is beginning to consider how it could use technologies which were not specifically designed for it (ITS, 2011a); for example Wi-Fi has a dedicated bandwidth in Europe for transport but Wi-Fi was not designed with UTC in mind. Cellular data is now available for estimating journey times, and ‘apps’ have been developed, based on the very high infiltration rates of smartphones, which can display the current state of the network through crowd-sourced data. Also, satellite navigation systems were not developed with the intention of providing crowd-sourced data for traffic control. However, the fact that UTC is moving in the direction of using technology which was not specifically developed for it can be seen as a result of financial-style policies. By using existing technologies which do not require any additional infrastructure on the road, then perhaps policy could more strongly enforce these potentially cost effective methods.

Before new policies can be implemented, the technologies must be assessed using a cost benefit analysis tool (DfT, 2011c). Benefits are typically measured in the form of vehicle hours saved, willingness to pay and the reduced maintenance costs (if any), whereas some of the costs will be the initial outlay and operational costs. Throughout this chapter, policy has been shown to reduce costs through implementing new technology but money is not the only influencing factor. There is a real challenge involved with trying to quantify other benefits, for example, the ‘willingness to pay’ value is widely accepted within the industry (SafetyNet, 2009). However, as monetary valuations on issues such as road safety are subjective, then a sensitivity analysis needs to be carried out before deciding on whether a project is beneficial.

The dissemination of information is also changing within the transport industry; it's not only local authorities who have to collect and disseminate information now. Social networking is having an impact on the way in which people travel, and it is an easy way to share traffic information with the general public. Many local authorities have Twitter and Facebook accounts so that they can pass on useful information to the local residents and visitors. Also with the increase of smart phones, there are 'apps' available to update the user of congestion so that they can use other routes (ITS, 2011b). Although it is still in its infancy as an industry, commercial travel information dissemination (i.e. not directly from local authorities) is also increasing, especially through increasing development and use of real-time data feeds for in-vehicle navigation systems.

2.5 Conclusion

Urban traffic control has evolved significantly due to continually facilitating technological improvements which has been encouraged by the policies implemented. The current coordinated UTC systems however are still limited by the availability of data and there are many technologies which are likely to be introduced in the near future which could improve detection and communication techniques to shift the balance to an abundance of data. At present, UTC systems do not generate sufficient feedback from the data they have and therefore minimal attempts are made to continually improve the configuration (operator's discretion). A strategic view of the entire urban network, with improved detection and communication technologies, is required to enter the next evolution of urban traffic control.

The detection and communication technologies required (Wi-Fi, smartphone, Bluetooth, cellular data, vehicle to vehicle communications) to support this next phase are readily available now, but the infrastructure and architecture required to support them is not in place. Large investments are required to implement such systems (especially a move from infrastructure based to vehicle based detection) and this is the key block to achieving the next generation of UTC systems. Transport policy therefore needs to be changed to accommodate these new technologies into the transport network, but unfortunately there may be very long lead times (years or even decades) before the changes come into full effect (Eddington Report, 2006). This is the first time in UTC history where policy has not been the driver for the next stage; and until the environmental implications of the EU White paper are incorporated into policy, it will continue to be new technologies, which were not specifically designed for UTC, that is driving policy.

The challenge will then be how to create a more integrated, intuitive control system which requires minimal human input. New technologies will help to develop a better understanding of where vehicles are, and where they are going, however, the current UTC systems have no way of using or collating this new information. Innovative control algorithms will need to be developed to utilise new data sources and help us to take the next step of the UTC evolutionary chain.

2.6 Chapter 2 Key Points

1. Urban traffic control has changed significantly over the past century as policy has often led to advances in technology.
2. Current UTC systems are heavily reliant on infrastructure based detection but there are many opportunities to shift this to a vehicle based detection (Wi-Fi, Satellite navigation systems, Bluetooth, smartphones, cellular data).
3. However this will require significant investment as a system architecture change is required to decipher relevant data from these large data sources.
4. This information is likely to provide the operator with a much richer data set containing vehicle speed, location, origin, destination and potential route choice through the network.
5. Future systems are likely to use more integrated, automated processes in order to reduce human errors, both in network operation and vehicle control.
6. Need to understand how any new traffic control systems should be evaluated and therefore need to investigate key performance indicators.

Chapter 3: Key Performance Indicators

Key Performance Indicators (KPI's) are essential within UTC to understand what effect the traffic control system is having on the network. There are local, regional and entire network KPI's, all of which are required to develop a full understanding of how traffic is behaving and how people are moving across the city. Therefore this chapter will investigate what role KPI's have in traffic control and what are the most suitable indicators for evaluating any novel traffic control algorithms which are going to be developed during this research project.

A number of interviews were carried out to understand the priorities of different stakeholders within the traffic control industry. The interviews were carried out with people from three different roles and from three different cities so that different work cultures could be observed and each of them could share what factors they perceive as affecting overall network performance. This chapter will display the results of the interviews and a thorough literature review, which provides a good understanding of what metrics are most useful for UTC systems.

3.1 Interviews with Key Stakeholders

Interviews were carried out in 2012, with a UTC network operator in Bristol, a UTC signals engineer in Southampton and the Chief Transport Analyst at TfL. This section will highlight some of the key points made regarding network performance. Appendix 1 shows the interview questions which were asked to each of the interviewees.

3.1.1 Network Operator - Bristol

One of the network operator's main roles is 'firefighting' everyday problems within the network; to achieve this, network operators need to have good communication links with the local radio stations, bus companies, road works contractors and police services so that up to date information regarding the network can be disseminated.

One difficulty faced by Bristol control centre is that there are different councils controlling various parts of the network. There are some roads which are out of their control, which have a significant impact on the performance of their network. Therefore very good communication links are essential; however the preferred solution would be to have one control centre controlling the entire network.

Network operators will frequently override SCOOT to force stage skipping in rush hour periods to alleviate some of the traffic on major routes. This demonstrates the need for suitable training of network operators because they are making decisions based on observations from the network and are significantly affecting the performance (either positively or negatively, and it is hard to tell as the performance gains are humanly perceived by the operator). The KPI for network operators is therefore queue length as they will prioritise major roads if the queue length is too high.

The network operators are not involved in the annual reports which document the performance metrics, and they believe that the manager holds the holistic view of the network. However performance targets are discussed at daily and weekly team meetings, where there is an effort to create synergy within the control centre between the traffic signals, maintenance and ITS teams.

The network operator stated that there are key junctions within the network which can signpost if the entire network is operating well or is congested. The challenge for the network operator is to ensure that these key junctions are flowing smoothly. This emphasises the importance of understanding the network, and how difficulties could arise in automating the process as humans currently identify the critical junctions within the network.

The network operator believed that accurate journey time data from Automatic Number Plate Recognition (ANPR) cameras would be the best way to measure performance benefits from new schemes, because currently it is very difficult to justify any changes they make. Much of the justification is through observations in the network and witnessing a perceived improvement, which is not deemed as satisfactory rationalisation for annual reports. They believe that a way of improving the performance of the network is to have better VMS infrastructure in place, more ANPR cameras to observe the network and more methods of communicating with drivers through social media. This highlights the need for network operators to be able to communicate with drivers to observe a performance gain throughout the network.

3.1.2 Transport for London (TfL) Chief Transport Analyst - London

London is the largest city in the UK and provides a very different viewpoint to Bristol on the role of traffic control. TfL control the largest network in the UK where they manage 5% of London's roads but 30% of London's traffic volume. There are approximately 6000 signals and approximately 2000 of them are SCOOT controlled. After using a number of different performance metrics, it was determined that journey time reliability was the most suitable KPI for TfL to use, where a target of 89% of journeys must be considered as reliable. TfL stated that they discovered when journey time reliability improved then journey time was reduced, emphasising that there is a strong relationship between the two. Another reason for choosing journey time reliability is because the KPI must be public facing and easily understandable by Londoners. Reliability of journey time is defined by TfL as:

> *"The percentage of journeys completed within an 'allowable' excess of 5 minutes for a standard 30-minute journey during the weekday morning peak period"* (TfL, 2011).

TfL also believe that more ANPR cameras throughout the network would help them gain a better understanding of how the network operates. They receive over 14 million vehicle snapshots on ANPR cameras every day, of which approximately 1 – 1.25 million are considered as useful journeys. Therefore there is an abundance of data to manage within TfL and the perception is that there is excellent temporal data but very weak spatial data; hence why more ANPR cameras would help with understanding the network. TfL are investigating the possibility of using O2 cellular data to improve spatial awareness throughout the network and they are trialling Bluetooth data to improve granularity of data sources.

TfL try to optimise people movement as opposed to traffic movement, especially as they control the tube network as well as the traffic signals. Performance targets are carefully chosen so that one mode of transport will not negatively affect another; for example, when driver targets are set there is a corresponding pedestrian target to ensure that any improvements made for drivers are not at the expense of pedestrians.

TfL stated that there are core links in every corridor and they typically determine the performance of the whole corridor. This corresponds with what was described by the network operator at Bristol, and therefore gives further support to the validity of this statement.

TfL have a much larger team dedicated to traffic control than anywhere else in the UK, and there are many more resources available to investigate relationships in the data collected. Some research carried out by TfL investigated all of the causal effects on journey time reliability, where a list of over 200 variables was created. It was concluded that only 4% of the network can be controlled or influenced by them. Traffic volume has the biggest influence on network performance, of which there is no real control over. TfL expect large scale schemes to only have a reduction of approximately 1% in delay. This expectation seems to be substantially lower than the improvements described by many UTC systems in Section 2.3, and therefore should not be relied upon as an indication of potential gains from any new algorithms developed during this research.

3.1.3 UTC Signals Engineer – Southampton

Southampton was the smallest of the cities investigated with the fewest number of staff working at the traffic control centre. The UTC signals engineer considers the most important performance metric for controlling the network as the ‘maintenance of assets’, by attending all faults quickly, tracking the fix times and continuously assessing how the department is dealing with faults. This approach is vastly different to the other two control centres; the signals engineer stated that SCOOT is the best system available and that they do not challenge the ‘proven technology’.

Their biggest concern was budget constraints and how the budgets were allocated for transport. The issue is that the performance targets were set by ‘laymen’ and they had no knowledge of how the network would be affected by the targets, yet if the department did not meet them then they would lose funding. This problem emphasises how performance is not necessarily the ‘top priority’ of the traffic control centre, but maintaining the funding is obviously more important.

The signals engineer also emphasised the importance of good communication with bus operators, police, radio and contractors. They suggested that the state of the network would improve by moving towards mobile detector data as it is cheaper and provides better coverage of the network.

A holistic view of the city was taken as they wanted to ensure that a good experience occurs for every driver coming into and going out of the city. For example shoppers should have a smooth experience entering and leaving the city to ensure that they will return and boost the local economy. It was suggested that the traffic signals should be manipulated more in favour of improving the commuter and retail experiences in the city, which would improve its connectivity.

They stated that network operators make a lot of day to day decisions throughout the network and this has significant impacts on the performance, therefore training is essential for the staff. However there is no performance based, daily targets set for the operators, as they have confidence in SCOOT, and try to ensure that the variables are validated.

Section 2.3 demonstrated the considerable benefits of using vehicle actuated control systems over fixed time controllers; however TRB (NCHRP, 2010) suggested that UTC operators did not believe that they received enough training. After carrying out the interviews it became obvious that much of the network is operated by people who make decisions based on a perceived benefit. Therefore it is incredibly important that these people are trained sufficiently to ensure the maximum possible benefits are achieved.

3.1.4 Summary of Interviews

The three interviews provided an invaluable insight into how different stakeholders value different performance metrics for optimising their system. However, there were some common themes throughout all of the interviews:

- Excellent communication is essential for increasing the performance of the network, where it is important to communicate through a number of mediums, such as Twitter, radio and the police.
- All interviewees highlighted the importance of recognising ‘critical’ junctions within the network, so that they can be optimising to minimise the negative impacts on surrounding junctions.

When developing suitable key performance indicators for a whole network, these holistic views must be considered.

3.2 Key Performance Indicators for Individual Junctions or Regions

There are two types of performance targets which are of interest to traffic operators: local KPI's which can be used to assess a single junction, and holistic, network based KPI's. From the interviews described in Section 3.1, the network KPI's are the targets which must be met to secure funding from the government; however when considering their use in traffic control algorithms it becomes more difficult. This section will discuss the individual junction (or small region) KPI's and how they need to be managed.

3.2.1 Delay

Gradinescu et al. (2007) developed a signal control technique and emphasised how the performance metric needs to be considered before developing the model. Possibilities included minimising the average delay of vehicles, increasing progression of vehicles between neighbouring junctions by coordinating platoon travel, reducing the queue length of all approaches to a junction, reducing overall fuel consumption and reducing pollution emissions. They concluded that the most useful metric for signal control was minimising average delay to vehicles.

The implication of minimising delay at junction is that a cycle length should be as short as possible to produce less wasted time and dispersed queues. However there is a critical point where the percentage of inter green time is too high and causes additional delay (Gradinescu et al., 2007). At this point, the cycle length should be increased and can be slowly increased up to the junction constraint which is set by the governing body; for example, the DfT recommend that cycle times should not regularly exceed 120 seconds (DfT, 2007).

SCOOT aims to maintain the saturation level of junctions around 90 - 95% in order to minimise delay in the region (Chaudbury et al. (2002) also suggests the use of 95% saturation). SCOOT controls regions which typically contain six to eight junctions, and there is a critical junction which dictates the common cycle time for all of the other junctions within the region. However the problem is that not all of the junctions will be running under the same flow conditions and therefore the critical junction could be much more saturated than the others. This results in a much lower saturation level at non critical junctions, which inevitably results in longer delays to vehicles at those junctions. Gradinescu et al. (2007) states the selection of a cycle time needs to be as short as possible to minimise delays, but by forcing all junctions to run under the same cycle time in a region, it will reduce individual junction efficiency, but more importantly, by coordinating the junctions then the efficiency of the whole region can be improved.

When calculating delay manually (i.e. not using a simulation software package) then the typical free flow speeds are useful to determine what the journey time would be if there was free flowing traffic travelling through the network. These speeds, determined by DfT, can be seen in Table 3.

Table 3: Free flow speeds according to DfT (2013)

Speed Limit (mph)	Trunk 'A' Road, Single Carriageway	Trunk 'A' Road, Dual Carriageway	Motorway
30	22	25	-
40	32	30	-
50	40	37	50
60	45	57	60
70	-	62	67

Webster (1958) derived a formula which calculated average delay per vehicle:

$$d = \frac{c(1-\frac{g}{c})^2}{2(1-\frac{q}{s})} + \frac{x^2}{2q(1-x)} - 0.65\left(\frac{c}{q^2}\right)^{1/3} x^{2+5g/c}$$

Where:

d = average delay per vehicle

c = cycle length

g = length of effective green phase

q = arrival rate of vehicles

s = saturation flow

x = the traffic intensity (qc/sg)

Webster's equation has been accepted and used by many other authors (Udoh and Ekpenyong, 2012). One of the key assumptions regarding this method of calculating delay is that the signal control method is fixed time, which means that a cycle length will inherently exist. This assumption will be investigated further later in this research.

3.2.2 Safety

There is often a trade-off when deciding upon a performance metric. Salter and Hounsell (1996) highlight a common trade off in UTC systems which are trying to minimise delay over the network, as they prioritise major routes at the expense of the minor road users. Also there are allowances made to improve the safety of a junction, for example, there is a concession made for safety against junction efficiency when determining an appropriate inter-green time. The inter-green time is calculated depending on the size of the junction and there is a short amount of time where no vehicles are moving to ensure the junction will operate safely. Safety is used as a constraint on junction set-up and operation to meet KPI targets as opposed to a measurable value which influences signal timings (for example, queue length can be measured every second, whereas safety is measured over a much longer period of time).

Safety is the priority when designing a traffic control system for a junction, and sometimes the efficiency of the junction must suffer to improve the safety standard. Traffic lights were installed at a roundabout in Poole in 2011, and as a result the accident rate dropped from an average of 7 accidents per year to 2.68 accidents per year, however many local people complained about this as the delay was perceived to be larger (BBC, 2011). The traffic lights were estimated to save the local economy £300,000 each year and potentially lives of the local people, yet there were still requests to remove the traffic lights to improve flow. This example highlights that even with public opposition local authorities will try to prioritise safety over traffic flow.

3.2.3 Reliability of Journey Time

Some KPI's are not considered as public facing, for example, motorists may not appreciate seeing the average speed travelling through a city because it is much lower than what could be expected. The average Greater London traffic speed in 2010/11 was 28.6 kph (17.9 mph), which is considerably lower than the speed limit, however the journey times were very reliable (approximately 88 – 90% were deemed as reliable) (TfL, 2011). As can be seen in Section 3.1.2, TfL have concluded that reliability is what people want and when a journey becomes reliable then the journey times can drop; however a counter argument to this point is that a journey could be very reliable but also be very slow which is not what a commuter would want either.

In the UK, the Department for Transport (2013b) sets out guidelines for how journey time reliability should be calculated. The Highways Agency use 70,000 GPS equipped probe vehicles with data every 15 minutes to help them understand the delay caused to the network. This process is very specific to their situation and therefore it is not particularly relevant for the purpose of this research (see Table 4). A simple way of determining reliability is by investigating the average journey time, along with the standard deviation, maximum journey time and median values to determine how variable a scenario is. This technique will help to determine how equitable a control strategy has been to all arms of a junction.

The DfT define reliability of journey time through the percentage of ‘journeys’ on the specified roads which are ‘on time’ (DfT, 2013b), where:

- A ‘journey represents travel between adjacent junctions on the network
- An ‘on time journey’ is defined as one which is completed within a set reference time, drawn from historic data on that particular section of the road

Table 4: The DfT method of determining reliability (After: DfT, 2013b)

1.	For calculating the on time reliability measure, average journey times are estimated for each 15 minute time period throughout the day for each junction to junction link on the network. These journey time estimates are made using real data with a good temporal match.
2.	Journey time estimates are based on a minimum of two (real) vehicle observations per 15 minute period where available.
3.	Where two vehicles are not observed in a specified 15 minute period, vehicle observations from adjacent 15 minute periods (i.e. 15 minutes either side) are used (together with an observed vehicle in the central period if it exists) to estimate the average journey time for that central 15 minute period. Again, a minimum of two vehicles is required across the three time periods.
4.	Where less than two vehicles (in total) are observed within the specified 15 minute time period or 15 minutes either side, vehicle observations from two 15 time periods (i.e. 30 minutes) either side are used to estimate the average journey time for that central 15 minute period. As before, a minimum of two vehicles are required across the five time periods.
5.	Where less than two vehicles (in total) are observed within the specified 15 minute time period or 30 minutes either side for a particular section of road or time period, reliability performance is calculated using other methods.

3.2.4 Summary of common KPI's for Local Junctions or Regions

There are a number of possible local KPI's which could be used:

1. Average delay to vehicles – this metric is used by many systems, including MOVA and SCOOT (which is the most used UTC system in the world). Delay can be used to explain the state of the current road against free flowing traffic journey time. This metric is useful for both individual junctions and to explain the current state of the entire network. Delay is not affected by driver behaviour as the delay is measured against free flowing traffic.
2. Average stop time – This metric can be difficult to measure, and also it can be easily skewed by driver behaviour, depending on how quickly the driver approaches a junction.
3. Number of stops – This metric is used to demonstrate the progression of vehicles between junctions, however like average stop time it can be strongly affected by driver behaviour (which is difficult to predict or quantify).
4. Journey time – This information can be especially useful to local drivers, familiar motorway drivers and network operators to determine how congested the network is.
5. Reliability of journey time – TfL uses this metric and it provides an excellent illustration of the 'fairness' of the control system (one vehicle isn't benefitting at the detriment of another).
6. Emissions – This is especially important in places where there is an Air Quality Management Area (AQMA). There can be restrictions on vehicle types passing through AQMAs.
7. Cost function - UTOPIA tries to minimise a custom made cost function to prioritise public transport.
8. Safety – this is commonly used worldwide to describe how dangerous a junction is. Safety is a key priority in KPI targets as the public typically take a very strong interest in safety. Many countries use seat belt use, blood alcohol levels, speed management, road safety audits and vehicle crashworthiness as important KPI's (Meyer et al., 2004).

3.3 Wider Issues when Considering Key Performance Indicators

3.3.1 Funding

The use of performance targets is increasingly common within the public sector in recent years, however the transport sector has not been the department which led this change, it has merely followed suit with other sectors in the UK. The private sector has long used performance targets and is an integral part of the management philosophy (Marsden & Bonsall, 2005). Studies have shown that companies which use performance based targets consistently outperform companies which do not (Gates, 2001). The UK government recognised this and have tried to run the government more like a business (Marsden & Bonsall, 2005).

Funding for councils is only made available when targets are met and this has caused some concern within local councils, as discussed during the interview process with engineers in Southampton. In the UK, local authorities have to set performance targets for the next five years and the funding will depend on how they meet the targets (Marsden & Bonsall, 2005). The concern is that targets may be set to improve one mode of transport but it could negatively affect another; hence why TfL suggest that they always have multi modal targets to ensure the benefit in one mode is not at the detriment of another. These targets are usually focused on a higher level than individual junction efficiencies and are targeted towards improvements throughout the network.

3.3.2 Gating

Network efficiency can often be prioritised over individual junction efficiency (Gradinescu et al. 2007). For example, gating is used in many places to hold back traffic in areas where congestion does not block other roads, which enables free flowing traffic in more sensitive areas, such as city centres where congestion can block many junctions and bring the city to a standstill. However, gating policies could affect the emission targets set for the city as queuing cars will cause localised air pollution problems. As with some level crossings, there could be warning signs to turn off the engine to reduce air pollution as the vehicle could be waiting for a few minutes.

3.3.3 Communication

During a ‘UTC and SCOOT for managers’ course run by Siemens, a common problem was raised stating that there should only be one person dealing with the strategic vision in traffic control centres. The justification was: if a number of people set up the UTC timetables then others are less likely to challenge what is currently used as they presume someone else has set it up for a reason, which could result in sub-optimal or outdated timetables. This is a great example of how a lack of communication within a team and a lack of clear goals can strongly affect the performance of a network if systems are not regularly checked, updated and documented. Also during the training course, a number of reasons for poor performance at a junction were highlighted:

1. Poor validation
2. Incorrect Offsets
3. Too many vehicles
4. Road works
5. Vulnerable pedestrians and buses
6. Exit blocking

3.3.4 Stakeholders

There are a number of different areas within major cities, such as the Central Business District (CBD), arterial routes, suburban areas and motorways. Each of these regions will have different priorities, for example, the commuter and freight drivers will want to enter and leave the city with minimum delays on motorways and arterial roads. Whereas suburban areas may prioritise safety, and the CBD could strive for lowest carbon emissions due to the EU White Paper 2011 target of zero carbon city centres by 2050 (European Commission, 2011). Therefore it may be beneficial to select different KPI's depending on what zone of the city road users are in.

Varying priorities makes performance target setting very challenging, for example, New Zealand set a target of reducing road usage by 20% but this had significant impacts on the mobility and sustainability targets which had been set. Hence it can be very difficult to decide on meaningful targets. Public consultation and integration should be an important part of developing KPI targets for a local area (Meyer et al., 2004).

3.3.5 KPI Target Pairs

Network performance metrics can be manipulated and therefore any KPI target needs to be carefully selected, and often a 'paired target' needs to be set to ensure that the benefit is occurring for the intended purpose. For example, the 2000 Ten Year Plan (for the UK) had a target of increasing bus patronage by 10%, which has been achieved. However this target was only reached because London considerably outperformed the target and due to size of London, the statistics has been skewed. Most of the country has seen nowhere near this scale of increase and therefore the intended purpose of the KPI has not been achieved (Marsden & Bonsall, 2005). The target should have been split into two regions because London's public transport is very different to the rest of the UK, and therefore two separate targets should have been set. It is very challenging to understand all of the causal links when making these KPI targets, but as mentioned in Section 3.1.2, any benefit to the road network should not be at the cost of another more sustainable mode of transport.

3.4 KPI Conclusion

The results of interviewing three different stakeholders within the UTC industry proved an invaluable insight into how each stakeholder has different priorities. The network operator had to manage individual junctions to ensure that queue lengths did not get too long, whereas the signals engineer prioritised the maintenance of assets. The chief analyst at TfL stated that reliability of journey time is the most important KPI. However, all of the interviewees emphasised the importance of having good communication (with radio stations, social media, and police). The network operators have a significant influence on the performance of both the individual junction and entire network (as there are usually key junctions within the network which can define how the network is operating).

A problem with setting specific modal KPI targets is that one mode of transport may be disadvantaged as a result of it. For example, a target to reduce delay to all motorists could be achieved through reducing the number of pedestrian stages at traffic lights, but this would be an unsustainable consequence. Therefore network based KPI targets need to be carefully considered for cause and effect on all modes of transport.

The literature review suggested that the most important KPIs are average delay of vehicles and reliability of journey time to ensure fairness amongst road users. A number of existing UTC systems minimises delay (MOVA and SCOOT) and TfL strongly stated how beneficial reliability of journey time is. Therefore, for any experiments carried out in this research project, both metrics will be used to ensure that delay is minimised at the junction but also that reliable journey times are observed.

3.5 Chapter 3 Key Points

1. Network operators perceive queue length as an important KPI as it influences their decision making.
2. TfL use reliability of journey time as the KPI for London transport.
3. Southampton's traffic control centre perceives SCOOT to be the leading industry software and therefore their aim is to simply 'maintain the assets' and manage all faults.
4. Minimising delay is a very common KPI and often described as the most useful.
5. Reliability of journey time is highly desirable for road users.
6. Network KPI targets must have an understanding of both the cause and effects so that statistics cannot be manipulated. For example, a reduction in delay for motorists could be caused by the dis-benefit to sustainable forms of transport (walking, cycling).

Chapter 4: Can turning intention data be detected?

Chapter 2 has demonstrated the state of the art UTC systems and new data sources which could be used in the near future. This information has been essential in developing a good understanding of what data is available for controlling signalised junctions. This chapter will investigate some of the new data sources in greater detail with the intention of designing a novel traffic control algorithm which incorporates this data. Chapter 3 has justified which key performance indicators are most appropriate to evaluate any new traffic control algorithms.

With new data sources slowly filtering into the transport industry, three key pieces of data are becoming more available for traffic control: speed, location and vehicle routing. Smartphones can provide substantial amounts of this data (depending on the surrounding infrastructure) via Bluetooth, V2X communication through Wi-Fi, cellular location and satellite navigation communication. This information provides spatial and temporal data which has not been incorporated into major UTC systems yet. This is a substantial gap in knowledge and therefore needs to be investigated further to determine what can be done with this data (Foell et al., 2013).

As speed and location data are relatively easy to glean from new data sources, the prospect of knowing a vehicle's intended route through a network (or individual junction) is a new area of research. There have been very few studies carried out to determine a live update of a vehicle's turning intention at an upcoming junction. Previously, the idea of knowing a vehicle's route would have been a 'post event' exercise, for example, calculating the turning proportions for a junction (which does not require live data for each vehicle). Siemens expressed an interest in knowing what the possible benefits are of knowing a vehicle's route throughout a network.

Therefore as discussed in Chapter 1, when a new data source becomes available there are three key questions must be answered:

1. How can the data be detected?
2. How can the data be used?
3. Is there a benefit to using the data?

Each of these questions must be answered before any conclusion can be drawn regarding the quality and possible benefits of using the new data source. Hence, this chapter will investigate the first of the three questions: can a vehicle's turning intention (route choice through each junction) can be detected? Much of this chapter has been published in the TRB conference and Transportation Research Record (TRR) journal proceedings (Hamilton et al., 2015).

4.1 Introduction

4.1.1 Predicting Turning Intention

'Turning intention' is defined as how a driver is planning to travel through an upcoming junction, for example, are they intending to turn left, right or travel straight on at a typical crossroads. This section examines what previous research has been carried out on detecting live turning intention data.

Different technologies have been used in an attempt to predict turning movements due to their importance in: traffic signal control systems (improved turning proportion accuracy enables more efficient stage determination and calibration of junction signal timings), highway safety and design (designing roads to help pedestrians cross the road safely and to make it easier for merging traffic), and in-vehicle driver support systems (emergency breaking and crash avoidance). In general, turning intention can currently be determined through two key methods:

- Real time detection within vehicles (in-vehicle sensors)
- Pre-defined route choices (satellite navigation systems)

This section investigates both of these methods to develop a thorough understanding of existing research regarding prediction of turning intention. Also this literature review will be used to identify factors which could influence humans who are considering the same situation.

There have been a number of studies carried out to predict a driver's turning intention for the benefit of advanced driver assistance systems to improve safety on the road. This has primarily been for lane departure warning systems to determine if a driver's behaviour can help the system to predict which way they are intending to turn. Investigations have been carried out into the relationship between turning movements and the driver's eye movement, accelerator and brake usage, indicator activation, steering wheel angle, lane position and many other variables (Henning et al., 2007). The most obvious way for a driver to share their turning intention would be to use the indicators (a flashing amber/red light on the exterior of the vehicle), and a sensor could be placed in the vehicle to alert the surrounding infrastructure of the driver's intentions. However an issue with this technique is that it does not enable the system to know where the vehicle is intending to travel until a very short time (or distance) before the junction.

Lidstrom and Larsson (2008) investigated proactive vehicle alert systems which warn the driver about hazardous situations in the near future. The conclusion from this study was that passengers are often able to predict what drivers are intending to do because of their surrounding environment and how drivers follow a common set of conventions on the road. For example, the speed of a vehicle when approaching a junction, the gaze of the driver towards other roads and the positioning of the vehicle within the lane will help to indicate a driver's turning intention. Therefore by monitoring both in-vehicle movements, such as indicator usage, a driver turning their head, use of brakes and accelerator, and by observing a vehicle's speed and position within the lane, then it is possible to predict what a driver intends to do at the next junction.

Similar to Lidstrom and Larsson (2008), Liu and Pentland (1997) stated that most passengers in a car would be able to infer what a driver intends to do simply by watching them. The passenger would be able to determine what the driver intends to do through eye movements, posture change, speed of the vehicle and lane position; therefore it is not inconceivable that sensors in a car would also be able to make the same conclusions from the movements. They carried out an experiment to test if driver intention could be determined in real time, and the results showed that left turns could be recognized 60 - 70% of the time and right turns were recognized over 60% of the time; it should be noted that this was within three seconds of being given a command to turn left or right, which may not represent reality as drivers could take longer than three seconds to change their driving behaviour. However, Hidden Markov models were developed (Liu and Pentland, 1997, and Oliver and Pentland, 2000) to predict when a vehicle was going to change lane to the left based on in-vehicle data and driver gaze information, with varying degrees of success. However the problem was that the manoeuvre was predicted only a very short period of time before the event (Naito et al., 2008), and the accuracy was 50% at best. Also, these predictive algorithms were all based on small sample sizes and were carried out in simulators (Henning et al., 2007).

An instrumented vehicle was used in an experiment to recognize any patterns of when drivers are about to change lanes (Henning et al., 2007). This research identified a very strong correlation to when drivers look at the left mirror and indicate; which is understandable as this is the driving procedure taught in driving lessons. However, the problem is that during the experiment people tended to indicate more frequently than what other research has suggested. Olsen stated that only 64% of people actually use their turning signals and this has a significant effect on prediction accuracy (Olsen, 2003).

Alternatively, a study carried out by Ito et al. (2004) (aimed at developing a new navigation system which interacts with the driver and attempts to determine turning intention), showed that turning intention could be predicted up to 94% of the time by using in-vehicle data; this was also based on a driving simulator (Ito et al., 2004). The study attempted to determine a distance from the junction when turning intention could be predicted, stating that it could recognise a driver's intention at 80 metres away from the junction at 60 kilometres per hour (37 mph). While this prediction may be specific to the particular junction that was investigated, it suggests that there may be a cut-off threshold on approach to the junction before which turning intention may not be predictable.

Naito et al. (2008) highlights that there is a crucial stage in the driver's preparations on approach to a junction, when all the participants carried out very similar actions with the brakes, accelerator and velocity for a turning manoeuvre, which was around three seconds away from the junction (Naito et al., 2008). One important difference between Naito's experiment and the research in this chapter is that 'left' and 'right' movements need to be distinguished here.

Prediction models do not solely have to rely on in-vehicle data sources. Ziebart et al. (2008) states that future satellite navigation systems will likely learn drivers' preferences, habits and will be able to provide the driver with up to date information on the traffic network. With this additional data source, it could be fed into an algorithm which is attempting to predict the turning intention of an approaching vehicle with a relatively high confidence value for repeated journeys.

While most of the existing research for predicting a vehicle's turning intention has utilized direct vehicle or driver data such as accelerator and brake usage, steering angle and eye movements. It is clear that very little research has been completed on externally observing a vehicle when it is approaching a junction. It does however provide some insight into how external observers may perceive an approaching vehicle, especially the possible existence of an approach threshold (distance or time) before which predictions may be little more than an educated guess (for example, using overall turning proportions at the junction to make a prediction).

The overall high performance of these prediction algorithms is confirmation that the approach of vehicles to junctions is not merely a random process, instead that different turning intentions do lead to different approach characteristics. Critical for this chapter is that all the existing research relies on detailed monitoring of the driver to make predictions (e.g. head movements or eye glances) from inside the vehicle. This type of information would generally not be available to an external observer or network operator and is therefore of limited wider application. Further research needs to be carried out to determine if a vehicle's turning intention could be predicted from outside of a vehicle, for example, using a camera to detect intended movements.

4.1.2 Privacy

A significant concern regarding the detection of turning intention from in-vehicle or on-person technologies is the potential invasion of privacy. Some people may feel uncomfortable sharing location data or intended journeys through a network because they would feel 'tracked' (see accusations of living in a 'big brother' state (The Guardian, 2009)). According to The Guardian (2009), the UK is already subjected to the closest surveillance of any country in the world. This topic does divide opinion though, and if the benefits of using systems which require location data could be disseminated amongst more people then perhaps more of the population would be interested in using such a system.

There is a real benefit of investigating the possibility of being able to anonymously detect turning intention at junctions because this will reduce the need for people to willingly share information. If turning intention data could be externally detected then this helps to reduce any privacy concerns that the public may have about sharing their data.

4.1.3 Safety Improvements

Section 2.4.1 describes V2V and V2I technology which could enable the sharing of additional data, such as turning intention, from in-vehicle systems. By using V2X, it is possible to move from a reactive traffic control system to a pre-emptive system which could potentially provide many benefits to road efficiency but also safety. If vehicles were capable of sharing their intended turning movements then fewer collisions may take place because V2V communications would alert drivers of impending accidents (Green Car Congress, 2011).

4.1.4 Conclusion

This section has demonstrated that it is possible to predict a vehicle's turning intention using in-vehicle sensors on the accelerator, steering wheel and indicator. However, sharing such data could prove to be a privacy concern for drivers. Therefore, due to the lack of research in predicting turning intention without the use of in-vehicle technology and the existing privacy concerns, this chapter will investigate how accurately turning intention can be predicted from outside of the vehicle.

To do this, a number of areas need to be explored regarding the quality of data from observations outside of the vehicle:

- What level of accuracy can be predicted by external observations?
- How far away from the junction can a vehicle's turning intention be predicted?
- What are the explanatory variables which help make accurate predictions of turning intention?

Before any external observations could automatically predict turning intention, it is important to consider how capable humans are at predicting turning intention. Therefore the previous three questions can be applied to people:

- What level of accuracy can people predict turning intention from outside of the vehicle?
- How far away from the junction can a person predict a vehicle's turning intention?
- What are the explanatory variables which help people make accurate predictions of turning intention?

These questions will be investigated throughout the following sections.

4.2 Proof of Concept – Can humans determine turning intention?

Crossing the road safely is a part of most pedestrians' everyday routine which doesn't require too much conscious thought. Drivers also are (usually) able to safely merge into traffic through their perception of what other vehicles are intending to do. However while both crossing and merging behaviour are frequently studied, the idea of predicting a vehicle's turning intention (which is central to both these situations) is relatively un-researched as described in Section 4.1.

New technologies are still in the early stages of development and implementation for predicting a driver's intentions from within the vehicle (Henning et al. 2007), but these usually rely on accurate sensors being installed in the vehicle. For people to be able to perceive where vehicles are going when they are driving or crossing the road then they must be able to equivalently 'sense' what the vehicle is doing and extrapolate (or pattern match) this into an expected future behaviour. An understanding of the overall correctness of these predictions and the factors which influence the correctness will enable a better understanding of the impacts on signal control.

4.2.1 Introduction

As most people make predictions of traffic movements almost every day, the hypothesis for this section is that people have an inherent ability to 'predict' what an incoming vehicle is intending to do. A method of investigating this hypothesis is to film a number of vehicles approaching a junction and ask people to predict which way they believe the vehicle is intending to travel before the vehicle makes the movement. Therefore a proof of concept experiment has been developed to determine if there would be any benefit to creating a larger experiment with greater control measures and repeatability. If the proof of concept experiment demonstrates that people are reasonably good at predicting turning intention then a more thorough investigation will be executed.

4.2.2 Methodology

This section will explain the proof of concept experiment which was carried out to determine if people could reasonably predict a vehicle's turning intention. To do this a number of videos of incoming vehicles were displayed to the Transportation Research Group (TRG), who was provided with audience participation devices. The videos were paused when the highlighted vehicle was at a key decision point (stop line or split in the road) so that the audience could make a prediction based upon all of the information they had observed up until this point. By pausing the video, this ensured that all participants would have the same information and be able to make the decision at the same time. This was trialled on two different types of junction in this experiment, see Figure 4:

- A two lane approach T-junction where there is a dedicated lane for each turning movement (Burgess Road – labelled 'BR' in the Figures)
- A one lane approach crossroad where all three movements were possible from the single lane (Shirley High Street - labelled 'S' in the Figures)

There were a total of 30 videos shown to 15 people who took part in the experiment. Every answer was anonymous but it was possible to review individual scores from each device at the end of the test. To encourage active participation, everyone was informed that the best result would win a prize.

Figure 4: Burgess Road T-junction (Left), Shirley High Street (Right)

4.2.3 Results

Figure 5 is a histogram which shows how turning intention was correctly predicted by over 80% of the audience in the majority of videos (i.e. 19 vehicles - 63% were correctly predicted by over 80% of the audience). This histogram demonstrates how successful people were at predicting individual vehicle turning movements, where only 13% of vehicles failed to be correctly predicted by less than 50% of the audience.

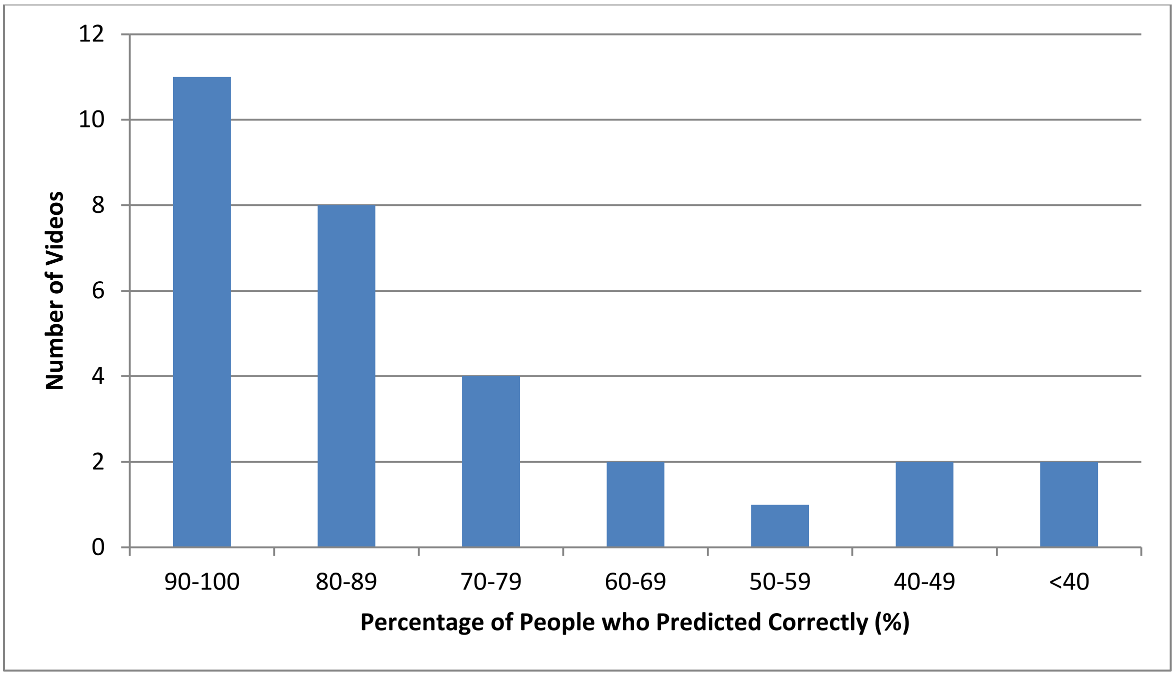

Figure 5: A histogram showing percentage results for each video

Figure 6 and Figure 7 demonstrates that participants were able to make a reasonable prediction regardless of whether the vehicle used an indicator or not. This can be observed as reasonable predictions of turning intention are still made when vehicles did not indicate when they should have (Figure 7). Therefore there must be additional explanatory variables other than indicator usage which provides observers with obvious information for predicting turning intention.

Participants did suggest explanatory variables which helped them to predict a vehicle's turning intention, such as a vehicle's position in the road and their speed of approach. It should also be noted that the video quality was not particularly high and therefore visibility of the vehicle's indicator was not always clear, which further emphasises that other factors are useful for predicting turning intention.

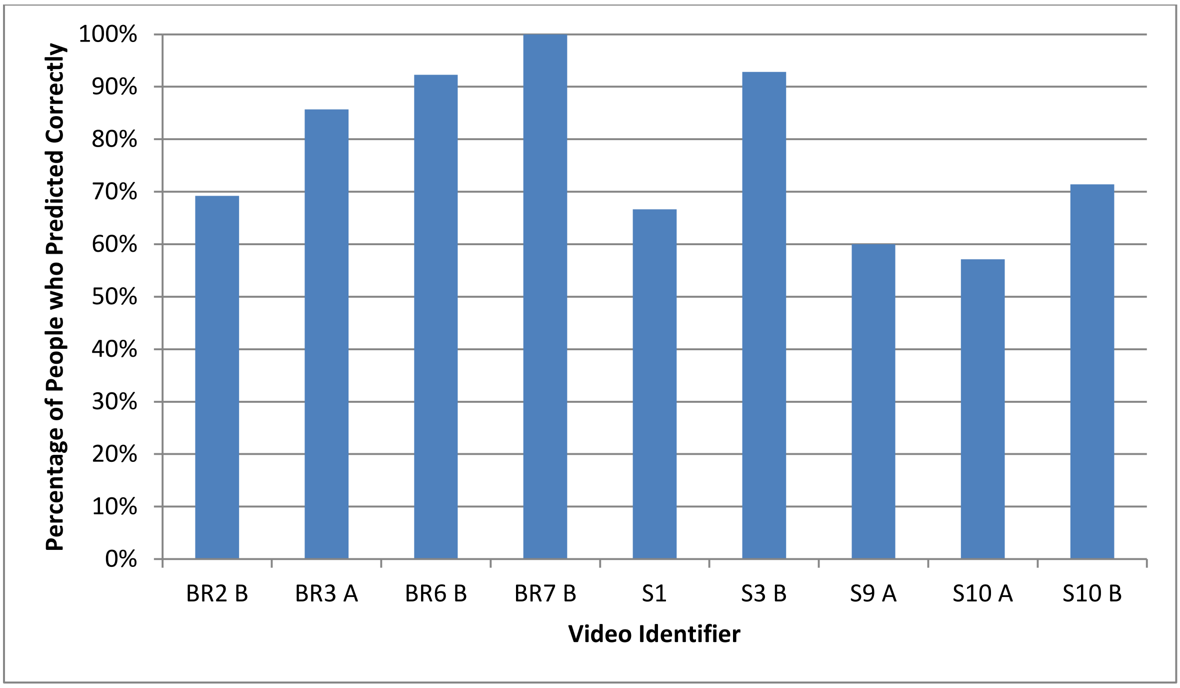

Figure 6: Results of videos when indicator had been used by the driver (in order of question)

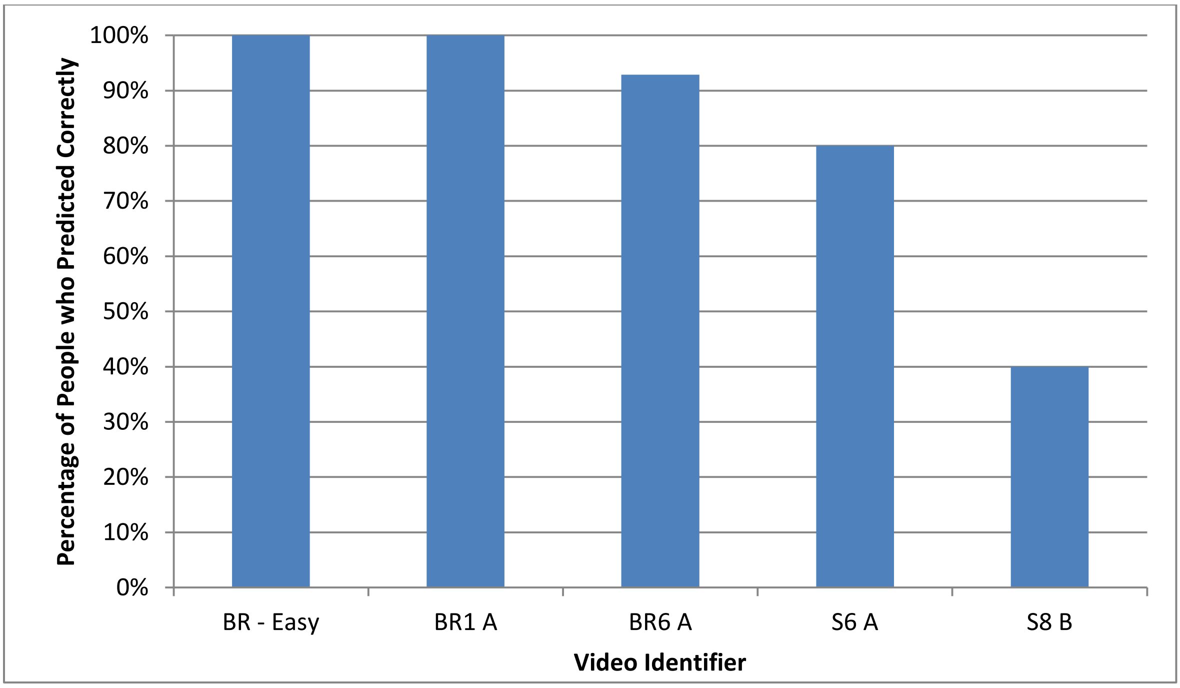

Figure 7: Results of videos where the vehicle did not indicate but should have (in order of question)

Figure 8 and Figure 9 show the complete results from both junctions. These figures are particularly useful to observe any learning effects, of which there does not appear to be any from observational analysis. Also it should be noted that Burgess Road only had two possible choices (left or straight) whereas Shirley High Street had three possibilities (left, straight or right) which was expected to be considerably harder to predict.

Some videos were particularly challenging for everyone, such as video 'BR4B' which no-one correctly predicted. This highlights that prediction of turning intention is unlikely to ever achieve 100% accuracy for all vehicles as some drivers will change the manoeuvre at the last moment. Therefore reliance on accurate predictions for traffic control needs to be flexible as the correct movements cannot always be predicted. Figure 8 also displays the result of the 'warm up' question which was named 'BR-Easy'; however this result was not included in the analysis.

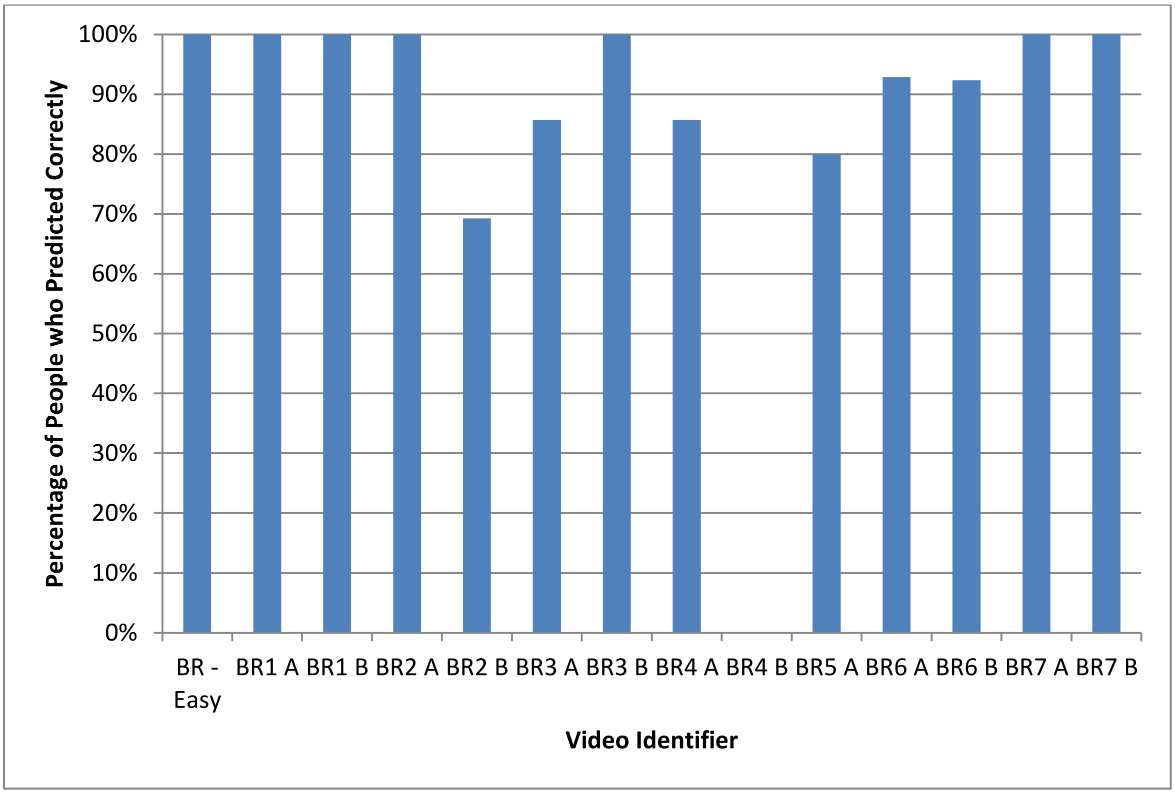

Figure 8: Burgess Road results (left or straight were available to choose)

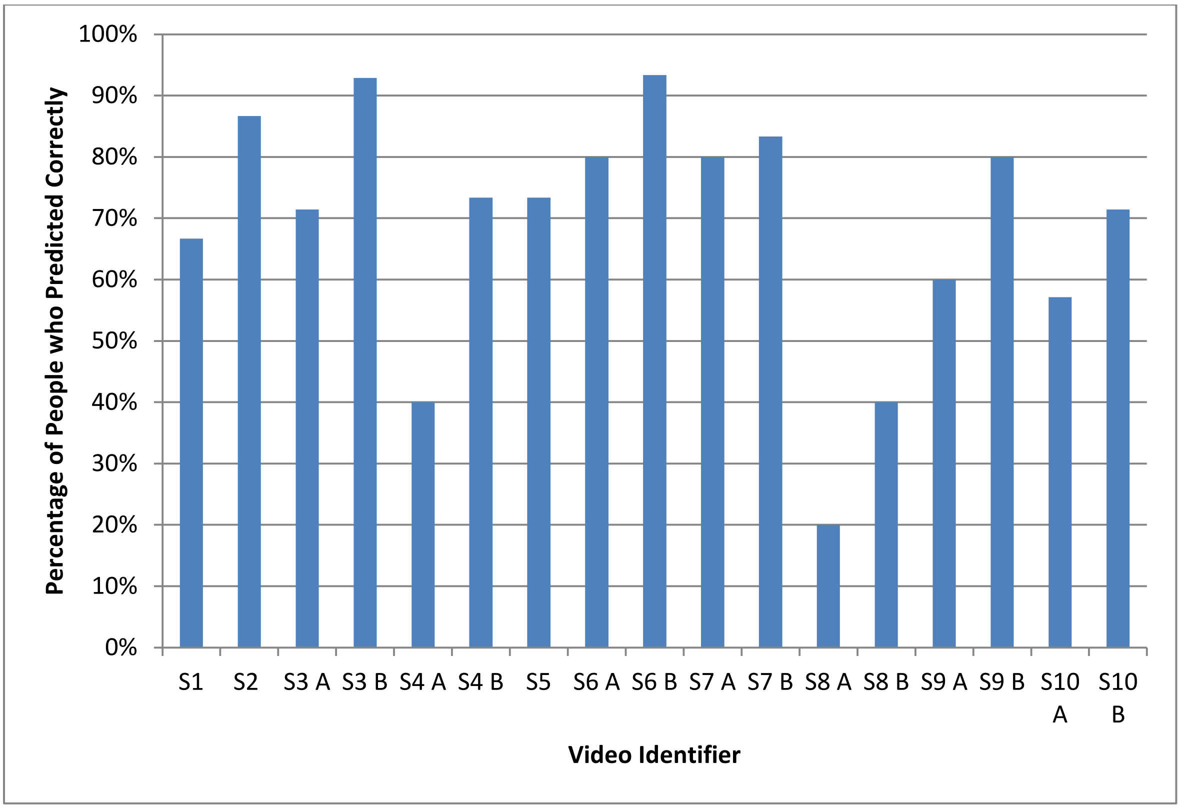

Figure 9: Shirley High Street results (left, straight or right were available to choose)

Figure 10 and Figure 11 highlights that most of the participants found the Burgess Road experiment easier to predict than the Shirley Road experiments, as most participants achieved a higher score in the Burgess Road experiment. However there was a vehicle on Burgess Road where no-one correctly predicted the movement (in this video, the vehicle had very poor road positioning on the approach to the junction and a changed their direction after the decision point – when the video was paused). Only one participant achieved a higher percentage of correct predictions in Shirley High Street; it should be noted that they achieved the average score on Burgess Road then they did exceptionally well at correctly predicting turning intention.

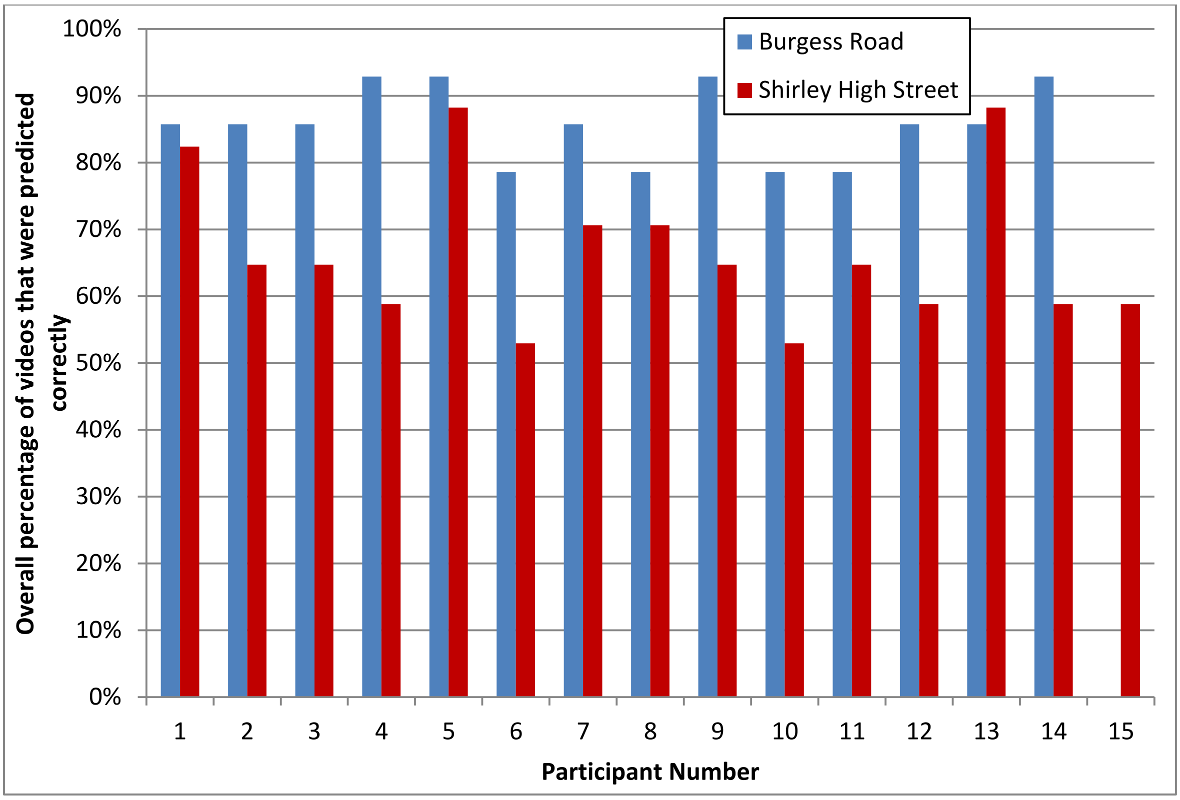

Figure 10: Comparing each participant's result with Burgess Road test and Shirley Test, Note Participant 15 did not take part in the BR experiment

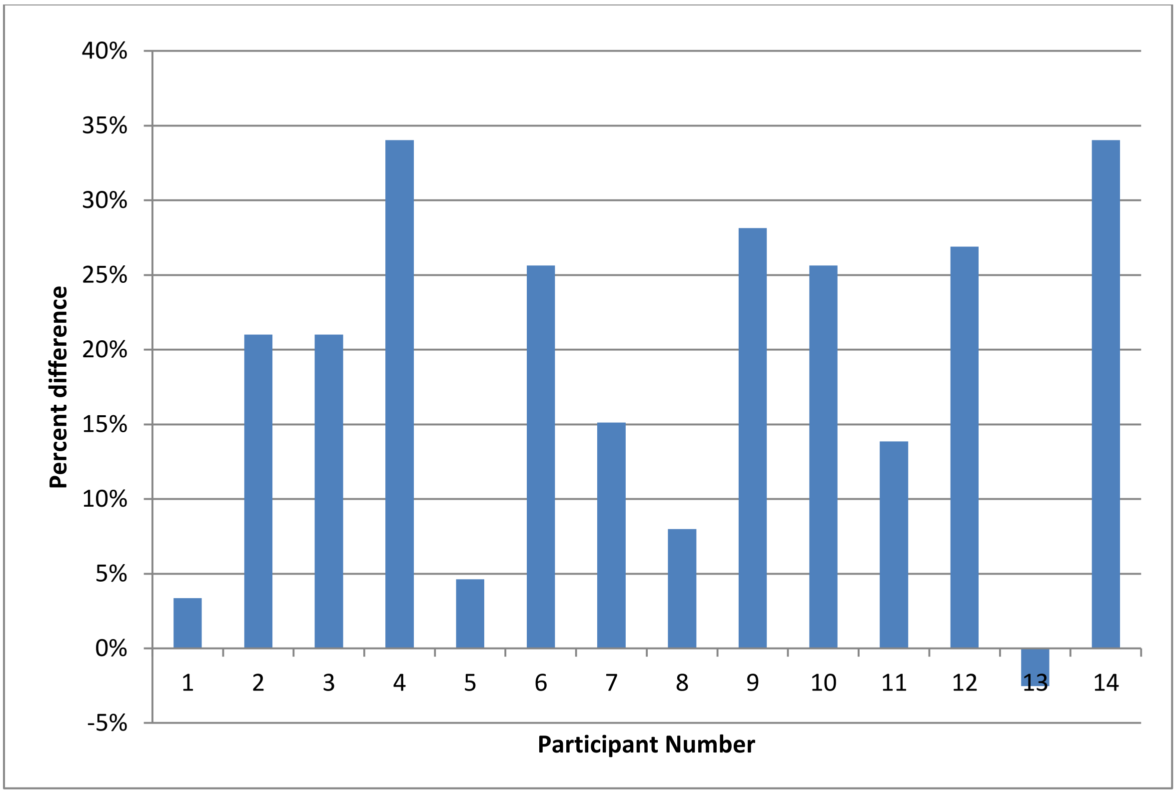

Figure 11: Percentage difference between Burgess Road and Shirley High Street tests, where a positive value indicates that the participant scored higher on the Burgess Road experiment. Note participant 15 has been excluded from this graph because they did not take part in Burgess Road experiments

Table 5 shows descriptive statistics for each junction and how successful the participants were at predicting turning intention. A random guess would have averaged 50% and 33% correct for Burgess Road and Shirley High Street respectively, but it is clear that the participants were not simply guessing but able to draw sufficient information from the videos to make an educated prediction. In the Burgess Road experiment, the participants achieved a 35.7% improvement over a random guess and a 33.3% improvement in the Shirley High Street experiment.

Table 5: Statistics from Experiment

	Burgess Road	Shirley High Street	Difference between Burgess Road and Shirley (BR – S)
Mean	85.7%	66.7%	18.5%
Median	85.7%	64.7%	21.0%
Standard Deviation	5.6%	11.5%	11.7%

4.2.4 Conclusion

This proof of concept experiment has shown that people can predict turning movements substantially better than a random prediction. The next stages of this experiment are:

- How accurately can people predict turning intention?
- What is the relationship between distance from the junction and correctness of predictions?
- What explanatory variables are useful for making the predictions?

Predictably, participants achieved a higher success rate in the T-junction compared with the single lane crossroads. A potential justification for this is that number of lanes and number of possible turning movements makes a difference in the correctness of people's predictions. Therefore further investigations need to be carried out to determine how different junction types will affect the prediction accuracy.

4.3 Experiment

4.3.1 Introduction

Continuing the research from the proof of concept experiment, this section aims to rigorously investigate how good people are at predicting turning intention of oncoming vehicles and the contextual variables which influence the correctness of those predictions. Key questions that need to be answered to advance research in this area include:

1. How well can people predict a vehicle's turning intention as it approaches a junction?
2. Is there a relationship between the distance the vehicle is from the junction and the predictions made about turning intention?
3. What are the most influential variables in predicting turning intention?
4. What role do demographic variables play in predicting turning intention?
5. What do people perceive as the most important variables which help them to predict a vehicle's turning intention?

4.3.2 Methodology

Section 4.1.1 makes it clear that there is little existing evidence on how well people can predict turning intention or on how contextual factors such as use of indicators influence these perceptions. To answer these challenging questions, an interactive touch screen experiment was developed to provide a dataset which can be used to determine how well a person can predict a vehicle's turning intention as it approaches a junction.

The experiment was designed to act in a standalone manner, i.e. making it self-contained without the need for anybody present to guide the participant through the experiment. This was done to remove the possibility of experimenter bias or influencing the participants' answers, and also this maximized both the number and variety of participants. Therefore the experiment was placed at various locations around the main campus of the University of Southampton, over a period of two weeks so that any passers-by (both staff and students of all subject areas, representing a wide demographic of people) could be reached.

In the experiment, participants were shown videos of ten different vehicles approaching a junction and they had to predict which way they thought the vehicle was intending to turn. Each video would pause when the vehicle was at different distances from the junction and then the participant could decide which direction they thought the vehicle was intending to turn; they had the option of 'Left', 'Straight', 'Right' or 'Don't Know'. As identified in Section 4.3.1, a key aspect of the research is how far away from the junction a vehicle's turning intention can be accurately predicted. Therefore during the design of the experiment, the videos were paused at specific locations (unknown to the participant) which were 0, 10, 20, 30, 40 or 50 metres from the junction. For usability purposes, it was decided to only pause the video twice each time so that the participant could make an initial guess when the vehicle was further away and then they would get the chance to make a second prediction when the vehicle was closer. Naito et al. (2008) stated that turning intention could be accurately predicted when a vehicle was approximately three seconds away from the junction (see Section 4.1.1). Therefore all of the videos were created with at least three seconds of viewing before the junction to ensure that participants could have sufficient time to observe the vehicle before making a decision.

Although the 'pause' approach is in some ways unrealistic as vehicles approaching a junction rarely stop in this way, this method was used to ensure that the participant (a) could only consider information up to that point in time and (b) did not miss visual information between the first and second pauses in each video while they made their selection for the first pause. However this does mean that the second decision will have been influenced by data from the first decision. In reality decision-making of turning intention is a continual process, with people prepared to reassess their prediction at any point if the vehicle appears to not be behaving as expected by their current prediction.

There were three different types of crossroad (Figure 12) used in the experiment to determine whether junction layout had any effect on a person's ability to predict turning intention. It was decided to only consider crossroads to reduce the chances of participants simply guessing the correct answer at a T-junction. The proof of concept experiment demonstrated that people were much better at predicting the correct turning movement for a T-junction over a crossroad.

1. Junction 1 was un-signalised with a single lane approach, very low traffic flow and clear visibility.
2. Junction 2 was signalised with high traffic flow, clear visibility and a two lane approach, where one was a dedicated right turn lane and the other lane was only for straight and left turning traffic.
3. Junction 3 was signalised with a two lane approach where the right lane was for right and straight turning traffic and the left lane was for left and straight turning traffic; there was a high traffic flow and only ground level visibility (see Figure 12).

For the signalised junctions, all the vehicles were approaching when the lights were green. All of the videos were filmed at 1080p quality, in the United Kingdom where vehicles drive on the left.

Figure 12: The three junction options

The selection of ten videos for each junction was chosen because they were representative examples of the observed traffic; however each turning movement was chosen at least three times for each junction. This ensured that all turning movements would have an equal opportunity of being predicted.

The participant was able to complete as many videos as they wanted to, however to improve the quality of the dataset being generated, all of the results which have been analysed only show completed junctions to reduce any potential bias of learning effects which may occur. For each junction selected by the participant, the videos were shown in a random order so that learning effects would be minimised over the entire dataset. Participants would potentially become better at the experiment as they attempted more videos; hence the video order was randomised to remove this effect.

At the end of each junction (a set of ten videos), the participant was then asked to select what they thought the most influential variables were that helped them determine a vehicle's turning intention. The participant was given 12 options and was able to choose as many (or as few) as they thought were applicable. Some of the possible answers were unlikely to be helpful, but these were included to (a) ensure that people would take the experiment seriously (i.e. if they chose 'vehicle colour' as a useful variable then it would be unlikely that their answers were serious) and (b) to prevent participants simply ticking all the options (in the mistaken impression that it was a list of things that the researchers thought was useful and therefore they would have been wrong if they had considered all of the options to be important). The 12 options that were available were:

1. Indicators
2. Speed
3. Position in the road
4. Lane choice
5. Trajectory
6. Vehicle type
7. Distance to other vehicles
8. Braking distance
9. Vehicle colour
10. Driver age
11. Size of engine
12. Don't know

The definitions for each of the potentially ambiguous terms are:

- Position in the road – the lateral positioning of the vehicle
- Trajectory – how the lateral positioning of the vehicle has changed over the previous few seconds
- Lane choice – which approach lane the vehicle is located in

In order to create a small competitive element to the experiment, a score screen was presented at the end of each junction (after ten videos). This displayed the participant's result, the overall average score for that junction and the highest score achieved by all participants. As each video paused twice, a point was awarded if the participant predicted the movement correctly, and therefore the maximum possible score was 20 for each junction. No prize or other incentive was offered to participants, either to participate at all or to reward a high score.

Although all participation in the experiment was anonymous, some basic demographic data was collected at the beginning of each experiment to enable demographic impacts on correctness of prediction to be investigated. The following questions were asked (all of which had an opt-out option for participants who did not want to give the information):

- Gender
- Age Range (17-22, 23-30, 31-50, 50+)
- Did they drive or cycle in a typical week (or both)?
- Were they a car passenger in a typical week?

While not directly considering turning intention, significant amounts of research have been carried out in the wider field of pedestrian safety when crossing a road. It is evident from this research that different age groups can have very different perceptions of a vehicle's speed of approach, which could correlate with predictions of vehicle turning intention. Child safety had been of particular interest for a number of decades, where studies have found that young children (5-9 years old) struggle with determining a vehicle's speed (Connelly, 1998). However there also are studies (Scialfa et al., 1987) on adults and elderly people which suggest that age and gender continue to have a significant impact on a pedestrian's perception of approaching vehicles.

The questions about driving/cycling and being a passenger were included to understand whether higher levels of experience relate to improved correctness of prediction. While it is expected that all participants would have experience of crossing roads and predicting turning intentions as a pedestrian, a larger amount of experience of predicting turning movements at a greater closing speeds, either as a driver or cyclist, may mean a higher level of accuracy in their predictions. As it is very difficult to quantify quickly and simply how much experience a participant has, these questions, along with age group are included as a possible proxy for an overall experience measure.

4.3.3 Results and Discussion

A total of 128 participants over a two week period at the University started the experiment, with the results presented here being from 106 participants who completed at least one junction. The demographics of participants is shown in Figure 13 and this confirms that a broad range of participants were included in the dataset.

As there were three junctions to choose from, and participants could attempt more than one junction (in any order), then there were varying numbers of participants for each junction. Junction 1 and 2 each had 65 participants and Junction 3 had 54 participants. Figure 14 shows the overall scores achieved by all participants for each junction, suggesting a high level of correctness in predictions (overall mean score 14.4/20 is substantially higher than the 6.7/20 which would have been achieved by a random guess – ignoring the effect of lane choice). There appears to be a negative skew (especially with Junction 2 and 3) and Shapiro-Wilk tests confirm that all three junctions deviate from normality (p= 0.037, 0.002 and 0.014 for junctions 1, 2 and 3 respectively).

The scores achieved in this experiment compare very similarly to the results of the proof of concept experiment (Section 4.2). The single approach lane crossroad in the proof of concept experiment achieved a 66.6% success rate of predictions, and Junction 1 (which is also a single approach lane crossroads) achieved a 64.5% success rate of predictions. Junctions 2 and 3 were higher with 77.5% and 74.5% respectively.

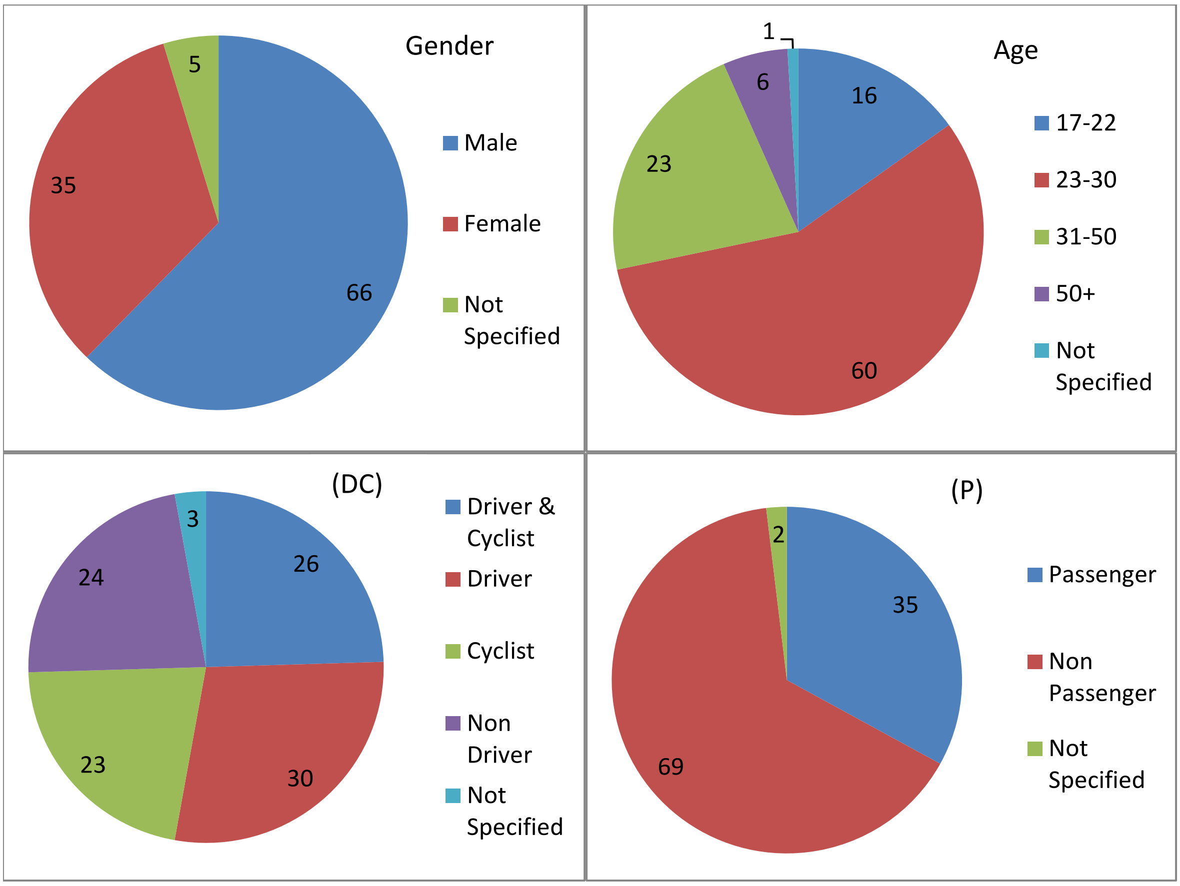

Figure 13: Summary demographic data (numbers of participants in each category are displayed)

Figure 14 clearly displays that Junction 1 was the most difficult junction to predict as it had a lower mean score and the distribution is considerably to the left of Junctions 2 and 3. However the scores for Junction 2 and 3 were very similar. One possible reason for this is that Junction 1 only has a single approach lane, and the vehicles started in the middle of the lane due to parked cars at either side of the road (see Figure 12). At Junction 1, all three manoeuvre choices were always possible, whereas in the other two junctions, a lane choice would mean that the vehicle would only have two turning options available (assuming rules of the road were obeyed).

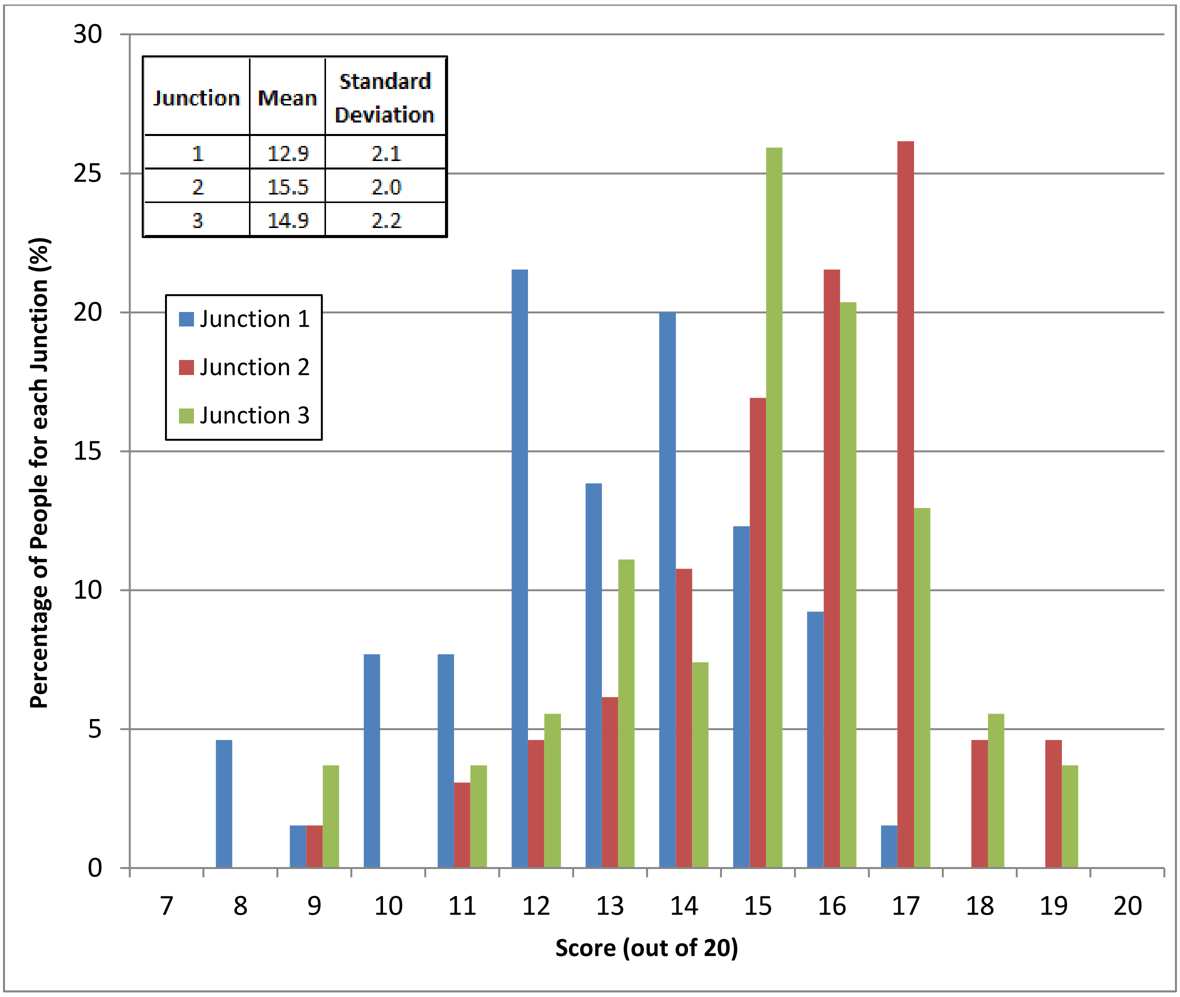

Figure 14: Correct predictions for each junction

4.3.4 Impact of Physical and Demographic Factors

The videos were paused when the highlighted vehicle was at a specific distance from the junction and Figure 15 displays a box plot of how accurately people predicted turning intention at different distances from all three junctions combined. The box plot shows a substantial step change between 20 - 30 metres with around a 20% reduction in prediction accuracy. At 0 metres from the junction, the median percentage of people that predicted correctly was 91.7% (falling slightly to 90% by 20m), whereas at 30m only 70% of people were able to predict correctly (falling slightly to 69.2% when distance is increased to 50 metres.

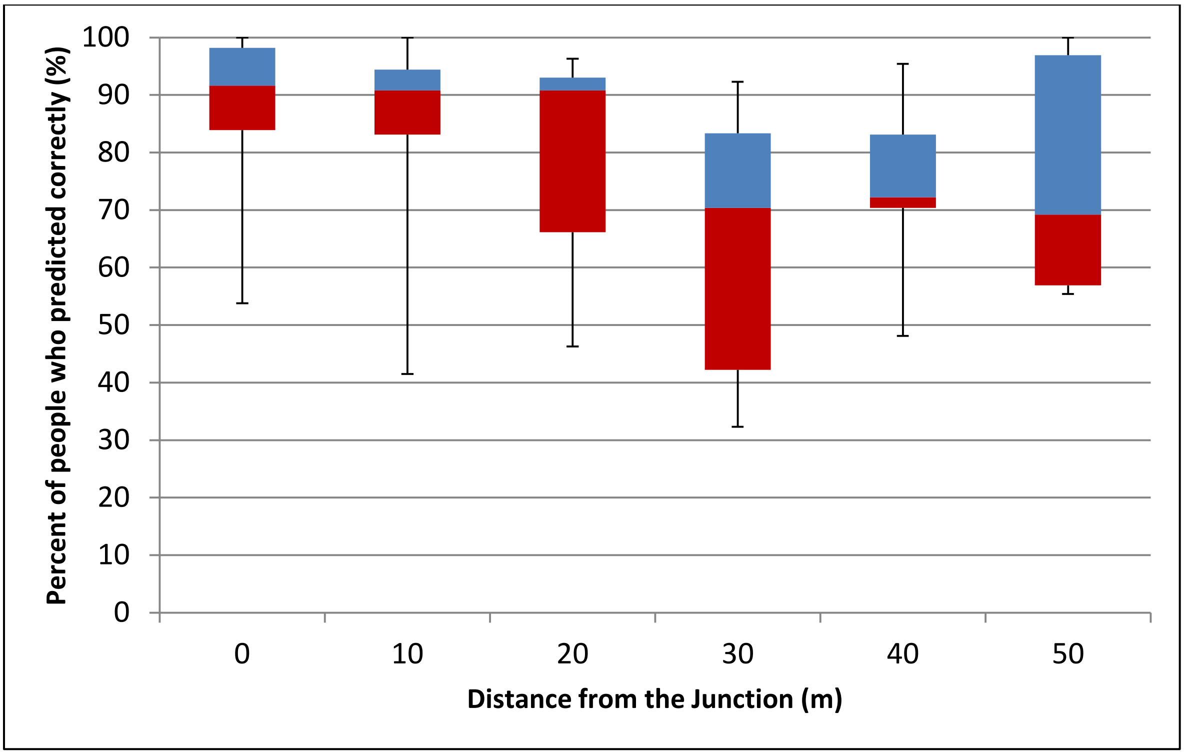

Figure 15: Percentage of people predicting correctly for varying distances

The speed limit for each junction is 30 miles per hour (mph) and using the free flow speed on an A road (from Table 3 in Section 3.2.1) then 22mph average speed can be assumed. However, the vehicles could be travelling slower than free flow conditions due to upcoming junction. This equates to approximately 9m/s and therefore the vehicle is roughly 27 metres away at three seconds before the junction. This agrees strongly with the findings of Naito et al. (2008) who concluded three seconds before a junction is when a vehicle's turning intention can be accurately predicted from in-vehicle monitoring. However, this is less than the value identified by Ito et al. (2004) who stated that they could predict a driver's turning intention, from inside the vehicle, when they were 4.8 seconds away from the junction.

This experiment did not consider further than 50 metres from the junction as the proximity of other junctions would have become an issue or visibility of approaching vehicles would have been too occluded. Nevertheless it does not appear that people are able to predict turning intention from outside of the vehicle as accurately as Ito achieved through in-vehicle technology. Ito managed to correctly predict 80 - 94% of vehicles during the experiment, whereas the median percentage of people predicting correctly at 50 metres here was only 69.2%. This implies that it is more challenging to predict turning intention without the help of in-vehicle data sources.

Figure 15 clearly demonstrates that people find it harder to predict turning intention when the vehicle is further away, but not included in Figure 15 are a small number of videos which people appeared to find very difficult to predict regardless of distance. These 'challenging' vehicles were included as part of a representative sample of vehicles from the video footage and included vehicles which straddled two lanes on approach and others which had poor observer visibility due to the presence of surrounding vehicles. Predicting turning intention is never going to be a perfect science and there will always be challenging drivers who change direction at the last moment. One of the intentions of this experiment was to determine what variables help people most in predicting turning intention, and the videos which people achieved the lowest scores were when the vehicles did not perform a 'text book' turn at the junction.

While distance has a clear impact on correctness of prediction, a logistic regression analysis was undertaken to assess how all the physical variables interact to impact the predictive capabilities of people. Variables (and two-factor interactions) were added sequentially in order of greatest improvement in log-likelihood, with the resulting sequence of models and their corresponding Nagelkerke R^2 values given in Table 6 (Appendix 2 gives further reasoning for focusing on the Predictive Accuracy in the analysis). Although the R^2 values may appear low in comparison to the overall level of correct predictions in Figure 14, it should be noted that this analysis is attempting to identify the important factors in variation in correctness, not the overall level of correct predictions. Therefore the analysis is attempting to model if the participant will make a correct prediction, if they have access to the variables used in the analysis. The following physical factors were considered in the logistic regression analysis:

- Indicator – whether the vehicle indicated before the video paused
- Turning_Direction – did the vehicle turn left, right or travel straight on
- Distance_Threshold – the vehicle is more than 25m from the junction
- Junction_Type – to allow for the variations in lane layouts

Unsurprisingly, the most important physical factor is the presence of an indicator. This was closely followed by the turning direction and junction type, which together can be seen as a partial proxy for lane choice. The clear non-linear relationship with distance in Figure 15 is then represented by the Distance_Threshold factor being included in the model rather than a linear effect of the actual distance (all effects of which are insignificant once the threshold factor has been included). This means that distance can be considered as a binary variable: either the vehicle was closer than 25m or further than 25m. Although the three physical factor interactions denoted # in Table 6 are formally significant due to the amount of data available, their inclusion in the model does not increase the predictive accuracy beyond the 79.5% of correct/incorrect predictions forecast (by the including Indicator, Turning_Direction, Junction_Type, Distance_Threshold and the Turning_Direction * Junction_Type interaction).

Table 6: Logistic Regression Analysis

Factor Type	Factor/Interaction	R^2	Predictive Accuracy
None	No Variable	0.000	71.4
Physical	Indicator	0.147	71.4
Physical	Turning_Direction	0.270	78.9
Physical	Junction_Type	0.307	78.9
Physical	Distance_Threshold	0.327	78.9
Physical	Turning_Direction * Junction_Type	0.348	79.5
Physical	Indicator * Junction_Type	0.359 #	79.5
Physical	Distance_Threshold * Turning_Direction	0.362 #	79.5
Physical	Distance_Threshold * Junction_Type	0.364 #	79.5
Demographic	Age	0.371	80.3
Demographic	Driver_Cyclist	0.373 #	80.3
Demographic	Age * Driver_Cyclist	0.377 #	80.3

The demographic data collected was also investigated in this analysis, by adding it to the final physical factors model, to determine if the characteristics of the participant had any additional influence on their ability to predict correctly. The following demographic factors were considered in the logistic regression analysis:

- Age – the age group
- Gender – the gender group
- Driver_Cyclist – Did they drive or cycle in a typical week?
- Passenger – Were they a car passenger in a typical week?

The inclusion of age group in the model in addition to the physical factors (Table 6) seems to be sufficient to represent a level of experience effect, increasing the predictive accuracy of the model slightly to 80.3% of correct/incorrect responses. Although the effect of regular driving/cycling did have additional significant effect on the fit of the model, as with the later interactions of the physical factors it does not contribute to an increase in the predictive ability. The impact of the age factor, while small, suggests that correctness of prediction may rise from the 17-22 group to the 23-30 group, before falling back slightly in the groups over 30 years of age.

Table 6 demonstrates that if no variables were provided to the logistic regression analysis, then the accuracy of predictions would be 71.4% (this is because 71.4% of all answers were correct).

Therefore if a model predicted that all participants would always get the answer correct, then the model would be correct 71.4% of the time. However, by providing additional information to the analysis then the model can correctly predict when 80.3% of the total participants will select a correct answer. This shows an improvement of 8.9% in predictive accuracy from providing the model with fairly basic variables.

Allowing for all two-way interactions within the physical and demographic factors produces an overall logistic regression model with a Nagelkerke R^2 value of around 0.4 (which is typical for a human behaviour experiment), already sufficient to predict the correctness of participants' decisions in over 80% of the data (see Appendix 2 for further explanation). This suggests that while more subtle explanatory factors such as approach speed profiles and precise lane positioning may be having an impact on perceptions in borderline cases (and may also be the reason why the overall correct rate of predictions by participants was 71.4%), the correctness of external observer predictions of turning intention can usually be forecast by the limited range of explanatory factors considered in this section.

An interesting finding from this study was that right turning traffic was easier to predict than straight on and left turning traffic. On average, 87% of participants predicted right turning movements correctly, whereas only 72% and 55% of straight and left turning traffic respectively were predicted correctly. One reason for this could be that Junction 2 had a dedicated right turning lane which would make right turning predictions somewhat easier than straight and left turning traffic because of lane choice and road positioning of vehicles.

4.3.5 Perceived Important Variables

While the preceding section investigated which physical and demographic variables were significant in determining the correctness of turning intention predictions, the counterpoint to this is to consider which variables were perceived to be useful by the participants. Figure 16 highlights the perceived important variables which influenced participants to predict turning intention at each junction. As expected given the actual result above, almost everybody selected 'indicators' for each of the three junctions, with lane choice, trajectory and position in the road also highly rated variables. It should be noted that nobody selected vehicle colour or size of engine which helps to demonstrate that even though no experimenter was present, participants were still selecting realistic answers.

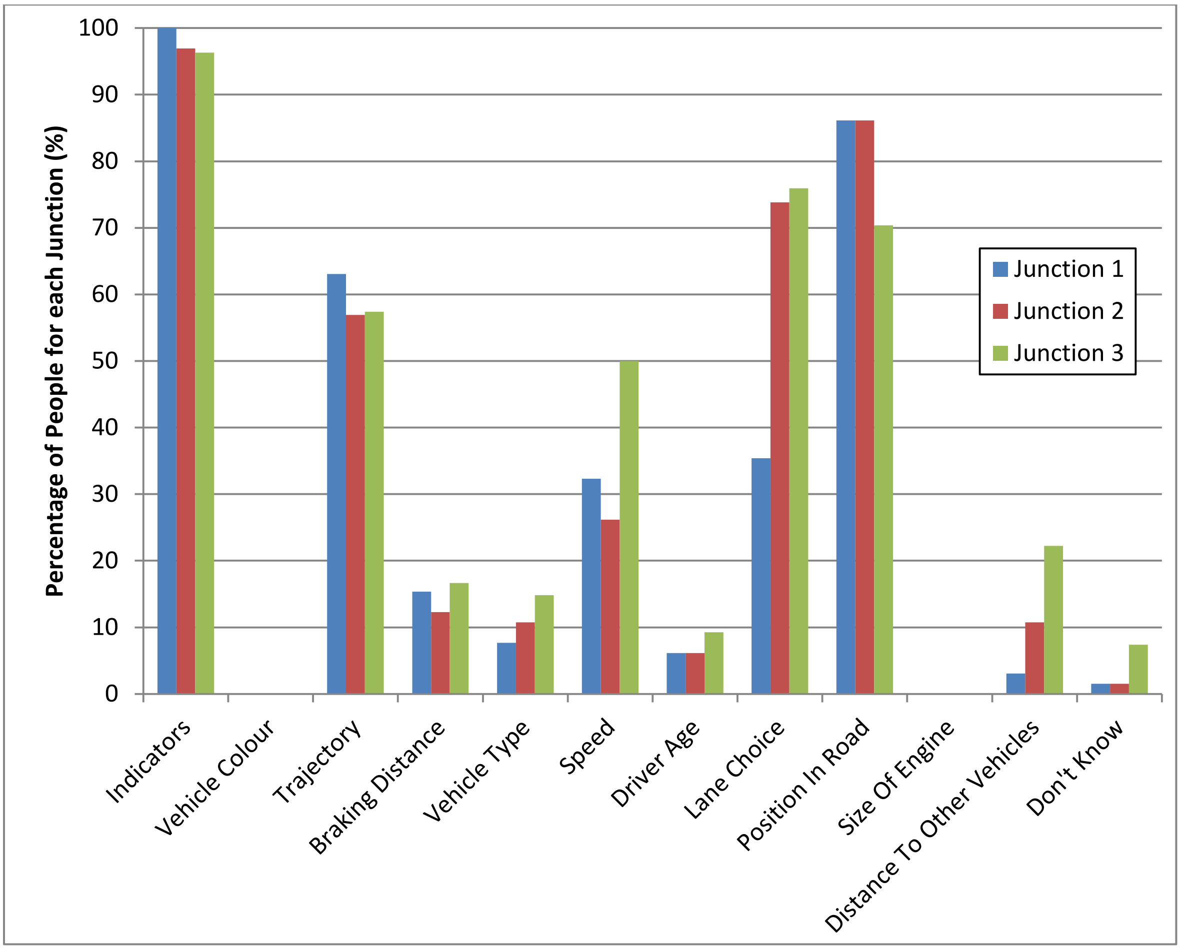

Figure 16: Participants perceptions of important factors

Figure 16 shows a strong degree of agreement between the junctions, even though in many cases different participants attempted different junctions. The exception to this is Junction 3 where speed of approach and distance to other vehicles was considered as comparatively more beneficial, with fewer participants suggesting they felt they used the vehicle's position in the road. This could be because the position in the road was much harder to see in Junction 3 due to the lower viewing angle and therefore participants were much more dependent on other variables.

A number of participants wanted to discuss the experiment further after they had completed it (contact details for the researchers were provided at the end of the experiment to facilitate this). A key aspect of participants' feedback was that they did not trust 'white van' drivers whereas they expected emergency service vehicles to obey the rules of the road. Even with this response, the vehicle type variable was seldom selected and this suggests that different participants may have been interpreting the 'vehicle type' option in different ways. This vehicle specific effect may also be represented by participants feeding back that local knowledge may have played some part in their decision making, especially when a local bus was included in the video, as participants may have been able to use the known trajectories as a guide to predicting the turning intention. If this experiment was to be repeated then a brief explanation of what each variable means would need to be included for the participants to read before selecting variables (as highlighted in Section 4.3.2). This may help to eliminate the 'vehicle type' problem but also 'lane choice' would possibly be selected less for Junction 1, where there is only one approach lane.

As mentioned in Section 4.3.3, there is a noticeable difference in participants scores between Junction 1 and Junctions 2 and 3. The logistic regression analysis has demonstrated that there is a statistically significant difference between the different types of junction. Participants also perceived different variables more useful depending on the type of junction, as demonstrated in Figure 16. Therefore junction layout is an important factor in considering the success rate of predicting turning intention.

4.3.6 Conclusions

Overall, it appears that people are very good at predicting turning intention of a vehicle as the average score overall was 14.4 out of 20. Previous research has considered the problem of predicting turning intention from within the vehicle, but this research shows that high levels of correctness can also be achieved when turning intention is being predicted from outside of the vehicle (which would be a 'passive', infrastructure based, approach as opposed to an 'active', vehicle based approach which relies on having specific technologies installed in vehicles). Considering that there were, effectively, three possible options for users to select (although "don't know" was included as an option, it was rarely selected), this demonstrates how good people really are at predicting turning intention and how they were significantly better than random guessing.

When considering how distance influences people's ability to predict turning intention, it was found that a substantial step change occurs between 20 - 30 metres away from the junction. There was a median value of approximately 90% success when the vehicle was between 0 - 20 metres; and 70% success when between 30 and 50 metres upstream. The sudden step change can be compared to research carried out by Naito et al. (2008), where people were able to predict the turning intention very accurately (over 90%) when the vehicle was only three seconds away from the junction (when observing variables from inside the vehicle); therefore the threshold value appears to be temporally fixed as opposed to spatially constrained.

Section 4.3.4 investigated the most influential variables in the correctness of predicted turning intentions through a logistic regression analysis. While physical factors dominate the relationships, demographics of the participant also appear to be affecting the prediction, with age group providing a significant and important effect. When asked to indicate the variables that participants perceived to be most useful for making their decisions, they were generally in agreement with the physical factors identified in the logistic model, but also perceived a number of other variables such as the position in the road and trajectory to be useful. The problem with including these into the model is that it is difficult to quantify what aspects of position and trajectory are being used and how these might vary between participants. One key aspect of this research is that unlike a computer algorithm, human brains cannot be interrogated to understand precisely how all the factors are combined to produce the end result, nor are participants likely to be able to consistently explain exactly what it is about each variable that is important to them. While these additional variables are potentially important in borderline cases, the overall success rate of participants was 72% correct predictions and success rate of 80% for the logistic regression model in forecasting whether the participants would predict correctly; which suggests that their effect is less important than simpler factors such as overall lane choice and indicator use.

Very little previous work has been carried out on the correctness of predicted turning intention from outside of the vehicle. Therefore this research shows for the first time that while external predictions by people are generally correct, the physical variables related to the junction design and vehicle operation can influence how well turning intention can be predicted. Understanding these influences is the first step to accurately predicting turning intention data for use within signal control algorithms.

4.4 Conclusion

Many new data sources, which were described in Section 2.4, can provide additional information for signal control algorithms, such as vehicle location, speed and routing data for individual road users. Smartphones are capable of easily transmitting vehicle location and speed, however, little research has been carried out on how routing information could be used by network operators. As described at the start of Chapter 4, new data sources must be investigated in three ways:

1. How can the data be detected?
2. How can the data be used?
3. Is there a benefit to using the data?

This chapter has demonstrated the availability of turning intention as a new data source, which is a novel area of research. This topic was published in a TRB conference and TRR journal paper which investigated how well a person could predict a vehicle's turning intention as the vehicle approached a junction.

The key findings of this study are that people are very good at predicting turning intention with approximately a 90% median success rate when vehicles are between 0 and 20 metres away from the junction, but with a substantial fall to approximately a 70% median success rate when the vehicle is between 30 and 50 metres away. Other key explanatory variables include vehicle specific factors (use of indicators), junction layout and which direction the vehicle is intending to turn (right turns were predicted more accurately).

The experiment carried out in Section 4.3 has shown that a vehicle's turning intention could be detected with a high success rate up to 50 metres away on a 30 mph road (the experiment did not test further distances due to camera visibility and proximity of other junctions). This research could form the foundations of machine vision technology which could use the explanatory variables discovered in this research to predict turning intention. However, an investigation into if 50 metres from the junction is far enough for controlling the traffic lights needs to be considered before any further work is completed.

Also, previous research (see Section 4.1) suggested a number of methods from inside the vehicle which could detect turning intention. If available, and there are no privacy concerns, then the simplest technique would be sharing a satellite navigation system's data with the surrounding infrastructure so that route choice throughout the network could be known. This would enable turning intention data to be shared much sooner than detecting it at the junction.

However it is very unlikely that all road users will suddenly use a technology which uploads route choice, unless there is a significant change in manufacturing guidelines or political influences. Therefore this research could provide an intermediate stage on detection which can be carried out until infiltration is at a higher rate (if required). Therefore two key questions remain, what can turning intention data be used for and what are the benefits?

4.5 Chapter 4 Key Points

1. Many new data sources could provide live routing information for vehicles travelling through a network, and potentially their intended route through individual junctions (i.e. their turning intention).
2. Any new data source must be investigated in three different ways: can the data be detected, what can it be used for and what are the benefits of using it? This chapter has focused on how the data can be detected.
3. Previous research on turning intention has been carried out using in-vehicle technology to monitor the driver's accelerator, brake, and indicator usage and eye movements. No research has studied the detection of turning intention from outside of the vehicle.
4. This section describes two experiments which were carried out to determine if turning intention could be detected through a passive, infrastructure based technique rather than requiring detector equipped vehicles. Therefore experiments focused on the ability of humans to predict turning intention, how far from the junction that it could be predicted and what influencing variables were used to make a prediction (for example, indicator, position in road).
5. The main experiment had over 100 participants and the average correctness of predictions was 72% for all junction types.
6. There was a significant drop in median values when the vehicles were more than 25 metres away from the junction (which is approximately 3 seconds away), which strongly correlates with experiments carried out by Naito et al. (2008) which used in vehicle technology to predict turning intentions.
7. Statistically significant variables for predicting the correctness of turning intention predictions were use of indicators, which turning movement was being carried out, the junction layout, distance from the junction and participant's age.
8. An investigation into how turning intention data can be used and if there are any benefits now needs to be carried out.

Chapter 5: Turning intention data – what can it be used for?

As described in Chapter 4, turning intention data could be detected externally or transmitted using in-vehicle technologies as vehicles approach a junction. However, as described in Section 1.2.4, if turning intention data is available then what can a traffic control system use it for and what are the potential benefits of using such data (given the detection constraints described in Chapter 4)? This chapter will consider these key questions relating to turning intention data.

Other traffic control algorithms which use additional data sources will be considered in this chapter alongside how micro-simulation modelling can be used to represent the effects of having a new data source. Micro-simulation models are frequently used to demonstrate the effects of using new algorithms before carrying out expensive real world trials.

A methodology for using turning intention data for traffic control is developed and explained throughout this chapter along with some preliminary results for a theoretical junction. The new algorithm is adapted from the Highbid algorithm which was developed at the University of Southampton (Box and Waterson, 2010). Any results from the adapted Highbid algorithm are compared against its predecessor using the key performance indicators of average delay and reliability of journey time.

5.1 Introduction

5.1.1 How is turning intention data currently used?

As Section 2.3 described, current UTC systems use sensors in the road (inductive loops, infra-red, and radar) to detect the presence of vehicles. When a signalised junction has a dedicated turning lane then these sensors can be strategically placed to detect vehicles which are intending to travel in that specified direction. For example, MOVA stipulates the requirement of 'OUT' loops and a stop-line detector for dedicated right turning traffic. This is stated to ensure that a vehicle will not become trapped at a junction if the stage is not compulsory within the cycle (Highways Agency, 2005). This method of garnering turning intention data is not infallible and only works for specific junction layouts, but the prediction of turning intention (or anticipation using satellite navigation systems) is not perfect either. Therefore using inductive loops in dedicated turning lanes provides a good estimate of turning intention without requiring additional information.

It is important to define the terminology used within this thesis and therefore the following definitions have been adapted from the British Standard descriptions (DfT, 2006):

- A **phase** is a single turning movement on one approach arm to a junction (for example, there would be 12 phases at a crossroads with left, straight or right as a movement on each arm of the junction).
- A **stage** is a collection of phases which are allowed to be released simultaneously.
- A **cycle** is a predetermined, sequential ordering of stages such that all phases are released at least once.

5.1.2 How can it be used?

The definition of turning intention (see Section 4.1.1) is the knowledge of how drivers are planning to travel through an upcoming junction, for example, are they intending to turn left, right or travel straight on at a typical crossroads? Therefore raw turning intention data would be a series of turning directions as vehicles approach a junction, these movements are representative of the junction's phases.

If every vehicle's intended route throughout the network was known then this would enable UTC systems to move from the reactive systems which they currently are (see Section 2.3) to pre-emptive systems which have a much better understanding of where vehicles are going within the network. This would ensure that optimal stage selections can be made to guide traffic through the network (since the required turning movements are known).

There are two key methods in which turning intention could be used for traffic control:

1. Stage manipulation – vehicles can be categorised into individual phases. This gives greater resolution of the traffic at the junction and phase control could be used instead of traditional stage control methods.
2. Co-ordination of neighbouring junctions – as the route through the network is known, downstream junctions can be informed sooner of the impending traffic.

For the purpose of this research, stage manipulation will be considered first as this requires the comparison of isolated junctions which removes additional variables in the analysis (for example, ensuring that the offset times are correct). Siemens were more interested in comparing the isolated junction control systems (e.g. MOVA) than the regional UTC systems (e.g. PC SCOOT – which is Siemens version of the SCOOT algorithm).

The next section will consider novel traffic control algorithms which include additional data sources such as vehicle location and speed. By investigating how other algorithms use new data sources, then possible ways of incorporating turning intention data through stage manipulation can be explored as well.

5.2 Signal Control Algorithms

This section will investigate a number of other UTC algorithms which have been developed to include additional data sources. Many different signal control algorithms have been hypothesised but only a select few have ever become widely commercially available as discussed in Section 2.3. As the major UTC systems (see Table 1, in Section 2.3.1) use traditional data sources such as inductive loops, infra-red and radar, then this section will consider some 'theoretical' control systems which were found during a literature review.

TRG have developed some unique control algorithms in the past few years (Box and Waterson 2010, Box and Waterson 2012, Box et al. in press). The Highbid algorithm is based on a bidding process which uses the incoming vehicles' speed and distance from the junction, and the signal control assumes a fixed time auctioning rate which assesses the road state every ten seconds. This is a relatively straight forward signal control algorithm and therefore it can be used as the foundation level for this research by incorporating turning intention into the bidding process. Box and Waterson (2010) demonstrated that the Highbid algorithm could outperform MOVA in simulation studies; and therefore with additional information, it is possible that by adding turning intention data it can be improved further.

Box, Snell and Waterson (in press) developed two UTC algorithms that were based on machine learning: one was trained by a human expert and the other was trained by temporal difference learning. These algorithms were able to outperform SCOOT by 49% and 41% respectively. These significant improvements in performance demonstrate the potential benefits of using additional data sources for traffic control.

A study carried out by Gradinescu et al. (2007) highlights the advantages of using VANET systems over fixed location detectors to improve the understanding of where vehicles are within the network. The study developed a signal control algorithm to utilise this additional information which resulted in a reduction in delay of 28%, shorter congested periods and a 6.5% reduction in fuel consumption.

Blip Systems (2013) are a company which develop sensors on the road to detect Bluetooth and Wi-Fi devices so that historical data can be generated for use in signal control strategies, this system is used in more than 30 cities worldwide (Blip Systems, 2014). This method is based on average journey times for the monitored section of road and is able to provide real time feedback of vehicle location data. The system optimises signals using traffic volumes but there are limitations of using this as volume counts do not reflect actual demand due to penetration rates

(Olesen, 2014). One of the issues surrounding this method of signal control is that 95% penetration is required and currently only 20 - 30% of vehicles are being detected (Olesen, 2014).

These signal control algorithms demonstrate the potential benefits of using probe data (Bluetooth, Wi-Fi, Smart phones) against static sensors (inductive loops, infra-red, radar). This additional data provides greater data resolution for use within signal control algorithms and enables the system to pre-empt impending traffic flow sooner than traditional methods. These new technologies are slowly filtering into the transport industry as the sensors become more commonplace. Therefore further research is required to understand what the benefits are of using turning intention knowledge within traffic control algorithms.

5.3 Simulation Modelling

Micro-simulation software is incredibly useful for imitating real world scenarios without the expense of carrying out physical experiments. It provides researchers with an opportunity to experiment with real world situations by manipulating the junction layout, drivers' route choice and traffic signal control methods to optimise the junction.

SIAS Paramics (Paramics) software has been frequently used within TRG for simulating new signal control techniques (Box and Waterson, 2010, Box and Waterson, 2012) and it is also used within Siemens for customer network models. Siemens and the University of Southampton have a long history of working together and they each often develop models using Paramics, hence why Paramics is the software choice for this research project. However, it is imperative that turning intention data can be extracted from the software or else it would not be suitable for use within this project.

Paramics software outputs snapshot files, at user specified time intervals, which display many vehicle characteristics such as speed, link location and the next two link turning intentions. Appendix 3 explains how the snapshot file provides every vehicle's next two link turning movements. By extracting the required information it is possible to know exactly where every vehicle intends to go, which makes using turning intention data possible in simulations. This information can be stored in a database (such as MySQL) so that it is readily available for any control algorithms which require it.

Paramics is therefore suitable for use within this research as it can simulate turning intention knowledge and it is currently used by Siemens.

5.4 Methodology

5.4.1 Introduction

This section will explain how an existing algorithm which was developed by TRG can be adapted to incorporate turning intention. The Highbid algorithm already uses speed and location data to calculate a bid for a stage at the junction, and therefore this algorithm can be altered to include turning intention through stage manipulation, as described in Section 5.1.2. This new algorithm will be compared against the existing Highbid algorithm which was shown to outperform MOVA (Box and Waterson, 2010).

5.4.2 Highbid

Box and Waterson (2010) developed a simple signal control algorithm called 'Highbid' which is a bidding algorithm based on the number of vehicles in each arm, the average speed and average distance from the junction's stop-line:

$$Bid = Vehicle\ Count \times [1 - 0.01 \times (Average\ Speed) - 0.001 \times (Average\ Distance\ to\ the\ Stopline)]$$

Every stage associated with a junction would have a bid calculated using the above formula. Each bid is calculated every ten simulated seconds and the highest bid would 'win' control of the junction and therefore the stage would receive a green light (see Figure 17). Ten seconds is used to represent a simplistic version of real world constraints such as minimum green time and the inter-green period. This algorithm is not constrained by a cyclic order or stage length (the same stage could be continually selected if the same bid continued to be the highest). The coefficients determined for Highbid simply provide the relationship between speed and distance (speed is ten times more important than distance in the calculation (Box and Waterson, 2010)).

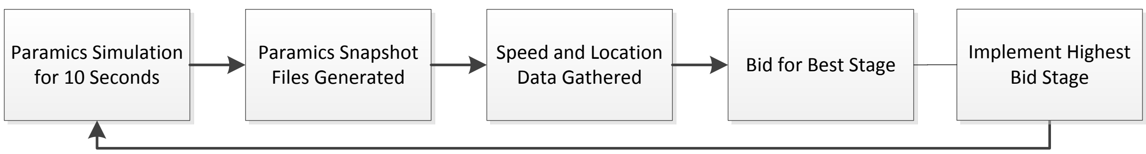

Figure 17: Flow diagram of Highbid controller logic

A limitation of the Highbid algorithm is that it provides no override feature to stop a vehicle being stuck on a minor road while the major road continually receives a green light. This means that the control system is very unfair against low flow traffic arms, however this is inherent from what is essentially a greedy algorithm (i.e. it takes the best option at that moment without any consideration of the long term effect).

The Highbid algorithm was trialled using Paramics which provided the control algorithm with perfect data of every vehicle's location and speed. Experiments were carried out using degraded data but this still proved to be better than MOVA (for up to 8 metres standard deviation in distance) (Waterson and Box, 2010).

5.4.3 Turning Intention Algorithm (TIA)

Highbid was based on a freedom of stage selection. However it is restricted to a very limited number of stages because all vehicles on the same approach road would be considered as part of the same stage. This means that there could not be any distinction in turning movements which restricts stages to either: releasing each road individually or opposite roads simultaneously.

As Appendix 3 describes, Paramics can also inform the user of each vehicle's turning intention for the next two links, and therefore Highbid can be adapted to include turning intention as well. By incorporating turning intention, vehicles would no longer bid for a stage but they would bid for their specific turning movement (phase) which shifts the control strategy from stage based to phase based. This enables the system to select the best combination of phases rather than selecting a stage from limited options (there will be many more combinations of possible phases as opposed to pre-defined 'whole arm' stages).

The turning intention algorithm will follow the same logic as the Highbid algorithm except that a bid will be made for an individual phase as opposed to the overall stage:

$$\begin{gathered} Bid\ for\ phase\ = Vehicle\ count\ requiring\ this\ phase\ \times \\ [1 - \ 0.01\ \times (Average\ speed\ of\ vehicles\ requiring\ this\ phase) \\ - 0.001\ \times (Average\ Distance\ to\ the\ Stopline\ of\ vehicles\ requiring\ this\ phase)] \end{gathered}$$

Figure 18 displays the logical sequence of decisions for the Turning Intention Algorithm. This highlights the need for an additional step where the bids for each phase are determined, followed by a stage selection step.

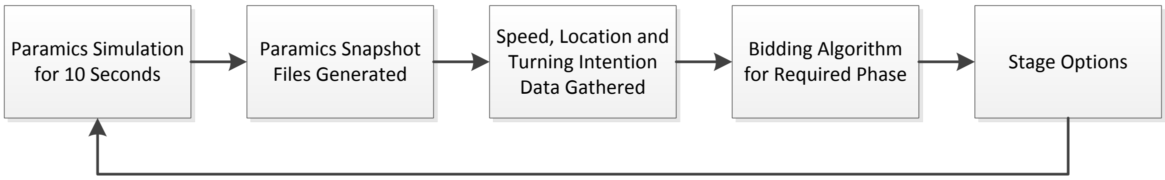

Figure 18: Flow diagram for Turning Intention Algorithm

Stage Options

This section will consider how stages are selected using the Turning Intention Algorithm. There are two parts to the stage selection process:

1. Generating all possible stage combinations (pre-determined)
2. Choosing the 'optimal' stage (real time)

A conflict matrix must be developed for the junction to understand what phase combinations are allowed to occur on the grounds of safety. A computer program was developed to generate every possible stage which could legally be released at the junction to ensure that: conflicted movements were never released in the same stage and if additional phases could be released at the same time then they were also included.

Once all of the possible stages were determined (prior to running any simulations), then a decision had to be made to determine which stage was 'optimal'. When selecting the 'optimal' stage there were a number of options which needed to be considered:

1. Highest combination of allowable phases (highest bid wins)
2. 'X' percent better than the current stage (for example, the new stage must be at least 10% better than the current stage)

The easiest solution to this problem is to release the stage with the highest possible bid (a sum of each phase within the stage). However, if the highest combination was used, then the algorithm completely negates the lost time during any inter-green period. Whereas by incorporating 'percentage improvement' logic then the new stage would need to be at least an improvement on the current stage before winning the bid. This solution has been used so that a fixed decision point (i.e. every 10 seconds) can be used as opposed to calculating stage duration as well, which would significantly increase the complexity of the algorithm.

5.5 Case Study – Theoretical Three Lane Approach Crossroads

5.5.1 Junction Layout

A theoretical junction was developed to evaluate Highbid against the Turning Intention Algorithm (TIA). In order to provide maximum flexibility with the stage options, each arm of the crossroads has three approach lanes, each with a dedicated turning movement (left, straight and right). This ensured that the turning movements had minimal interference with one another and would provide an optimal scenario to demonstrate the effects of using turning intention data. All of the approach roads are straight with 500 metres of storage capacity for the junction. It is very unlikely that there are many junctions (if any) similar to this design; however the freedom of movement enables complete control of all turning movements at the junction.

Figure 19 displays the junction layout with all approach roads stretching back 500 metres. There are also three lane exit arms so that vehicles have a dedicated approach and exit lane to use. By doing this, the junction is inherently simple as all vehicles will move to a specific lane for a unique turning movement and can exit into a dedicated lane to reduce as many environmental influences as possible. By having an approach road of 500 metres, then the default 'detection distance' of vehicles is 500 metres for this experiment. The speed limit on this junction is 30 mph from all directions.

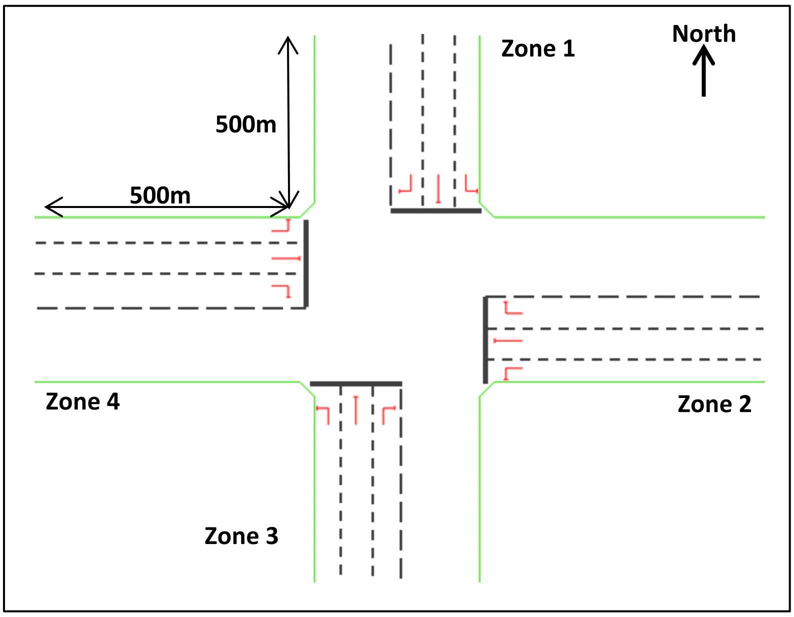

Figure 19: Theoretical crossroads with three dedicated turning lanes on each arm

5.5.2 Demand Scenarios

A number of demand scenarios were set up to compare control algorithms under different demand levels. Two demand profiles were used, a flat demand profile (uniform) and a 'typical day' profile which was developed as seen in Figure 20. Three demand scenarios were created to evaluate the algorithms under a low, medium and high level of demand:

1. A flat demand profile of 200 vehicles in every direction (total demand level of 2400 vehicles for the entire simulation)
2. A typical day profile of 10,000 vehicles split evenly between each turning movement (834 vehicles for each movement for the entire simulation)
3. A typical day profile but the flow was unevenly distributed, with the North arm carrying significantly more traffic, see Table 7 (total demand level was 8500 vehicles for the entire simulation).

Table 7: Demand for Scenario 3 for the entire simulation

	North	**East**	**South**	**West**
North	-	1000	2000	1000
East	500	-	500	500
South	500	500	-	500
West	500	500	500	-

For this case study, a typical day demand profile was generated by having two surges in demand to represent morning and lunchtime or evening rush hours. However the time period was reduced from a whole day profile to a four hour test so that the simulations would not take too long (which helps with repeatability validations). This was because the simulation would take approximately a quarter of the simulated time to complete if the junction could run in free flow conditions, whereas if it was congested then the actual time was close to the simulated time.

Therefore a number of tests were carried out to determine how long the simulation should last to provide sufficient information to make a conclusion. Four hour simulated tests provided enough information instead of simulating an entire day as was concluded by Box and Waterson (2010), also see Appendix 4. The 'typical day' profile can be seen in Figure 20; there was a low demand period introduced in the 'typical day' profile to ensure that any congestion which had built up from the morning rush hour would have a chance to be dissipated before the lunchtime or evening rush hour began.

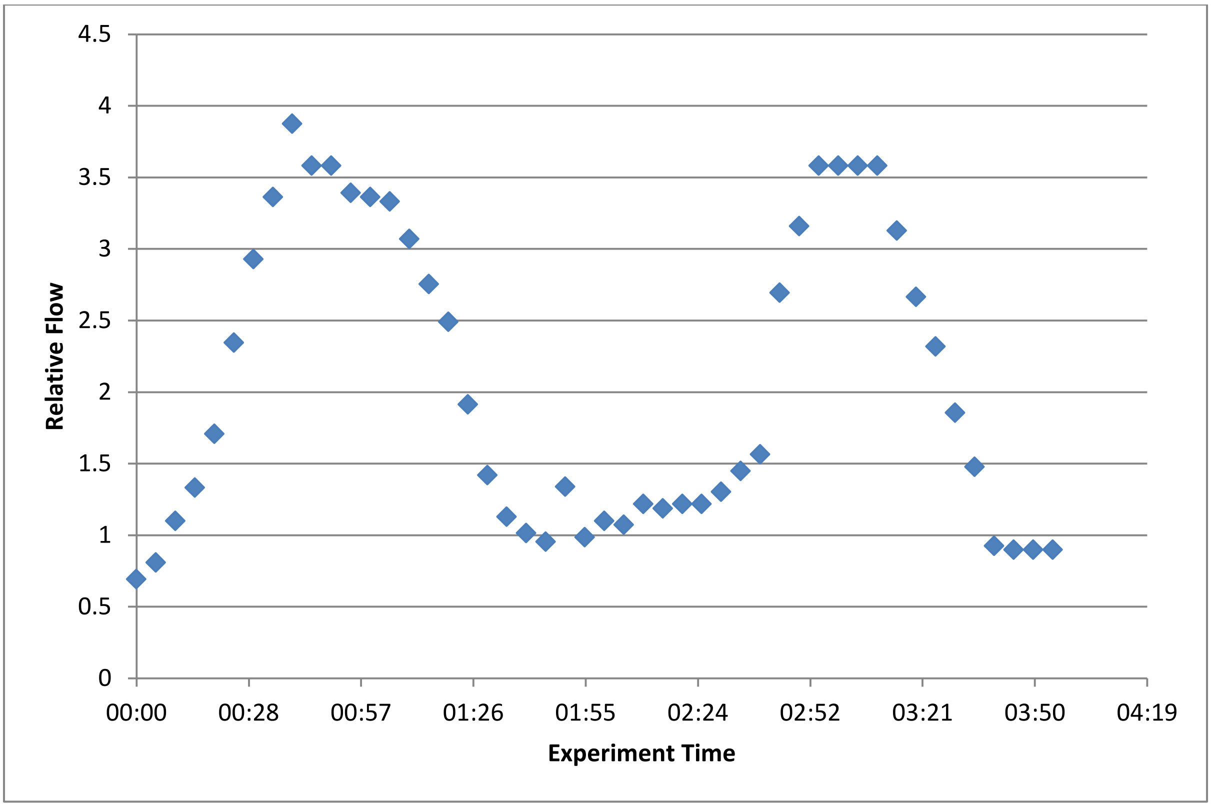

Figure 20: The demand profile used to represent a typical day – two rush hour scenarios

In order to calculate the average delay for the theoretical three lane approach crossroads then the free flow journey times must be determined for each of the origin destination pairs. The zone numbers are numbered from the Northern arm in a clockwise direction. The free flow journey times in Table 8 are determined from when each traffic movement receives a green light prior to arrival at the junction with no opposing traffic. As the demand scenario can be observed in Table 7, then an overall average free flow journey time can be calculated through a weighting method; by multiplying the demand for each movement by the corresponding free flow journey time and dividing by the total demand. Therefore the average free flow journey time for:

- Demand scenario 1 is 72 seconds
- Demand scenario 2 is 72 seconds
- Demand scenario 3 is 72 seconds

These values will be subtracted from the mean journey time to represent the mean delay for each simulated scenario. The reason that the weighted average free flow journey times are the same in each of the three scenarios is because all approach arms are the exact same length and only the right turn movements require a marginally longer journey time; therefore even with the three different demand profiles, the weighted average remains the same.

Table 8: Free flow journey time for each origin destination pair (from simulated values)

Free Flow Journey Time (seconds)		Destination Zone			
		1	**2**	**3**	**4**
Origin Zone	**1**	-	71	71	73
	2	73	-	71	71
	3	71	73	-	71
	4	71	71	73	-

5.5.3 Stage Manipulation

Highbid

Under Highbid control, the stage diagrams can be one of two main options, see Figure 21 and Figure 22. The algorithm can only release an entire arm and therefore these two options have been considered: a four stage solution or a two stage solution. A three stage solution (one stage releases two arms, and the other two arms are released separately) could be used but the way in which the algorithm bids for control, then the individual arms would struggle to outbid two arms combined.

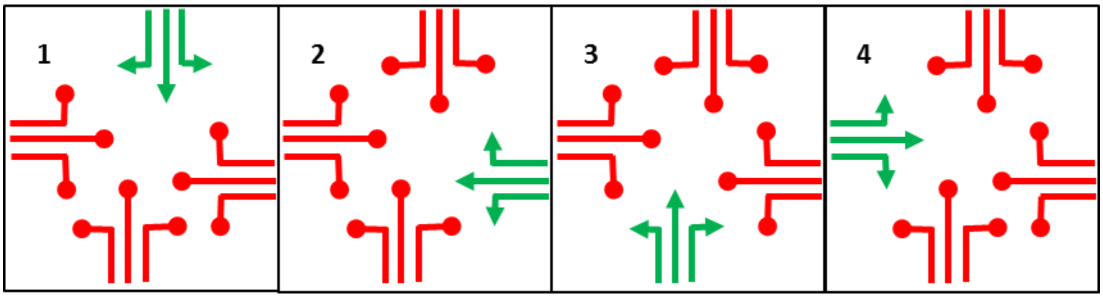

Figure 21: Highbid - 4 Stage Control

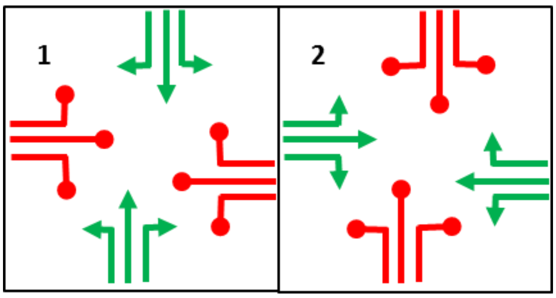

Figure 22: Highbid - 2 Stage Control

Turning Intention Algorithm

Note that the hypothesis for this part of the research is that there are potential benefits by selecting the most suitable, allowable phase combination (i.e. a stage) so that delay can be reduced. Therefore all allowable phase combinations need to be determined and this section will explain how this process was carried out.

Initially each phase was assigned a number (as observed in Figure 23) to quickly identify each phase and to make a simple naming system for coding the problem in C#. Each phase can be separately controlled due to the junction layout and therefore no phases need to be released in the same stage as any other.

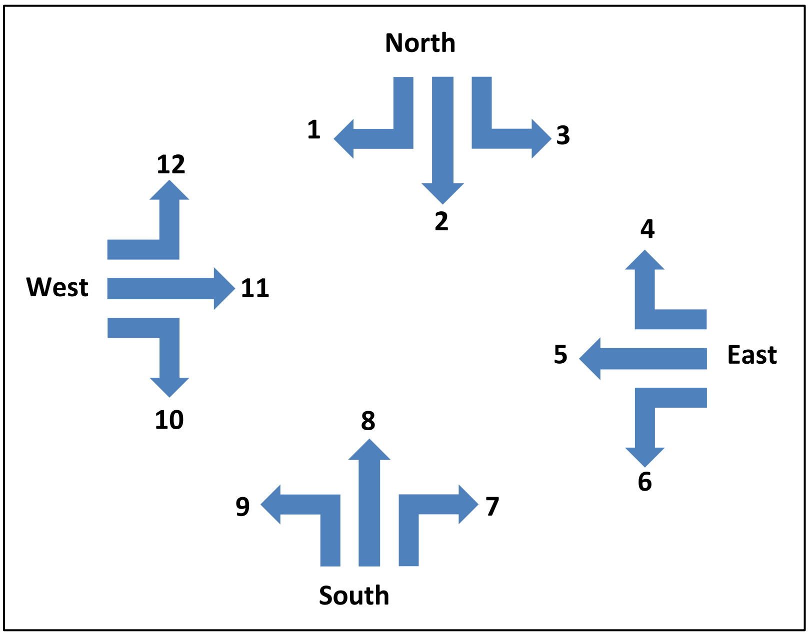

Figure 23: Numbering system for phase identifier

Then a matrix diagram was developed, as seen in Figure 24, to demonstrate if a turning movement was allowable along with another turning movement. For example, a vehicle travelling from North to South is not in conflict with a vehicle travelling from South to North, therefore check matrix (2, 8) in Figure 24 to see that the turning movements are allowed to take place simultaneously. However if a vehicle is travelling North to South and another vehicle is travelling South to East (2, 7), then this is an allowable conflict because the vehicles can see each other straight ahead and the South to East vehicle would wait for an appropriate gap to turn right across the traffic. For the purposes of this research, an unallowable conflict was where a vehicle would cross the path of a vehicle travelling on a perpendicular road. For example, a vehicle travelling from East to West would not be allowed to cross the junction at the same time as a vehicle travelling from North to South (5, 2).

		Phase Movement											
		N - W	N - S	N - E	E - N	E - W	E - S	S - E	S - N	S - W	W - S	W - E	W - N
		1	2	3	4	5	6	7	8	9	10	11	12
N - W	1		2	2	0	0	2	2	1	1	0	0	2
N - S	2	2		2	0	0	0	1	2	2	0	0	2
N - E	3	2	2		2	2	2	1	2	2	2	0	2
E - N	4	0	0	2		2	2	0	0	2	2	1	1
E - W	5	0	0	2	2		2	0	0	0	1	2	2
E - S	6	2	0	2	2	2		2	2	2	1	2	2
S - E	7	2	1	1	0	0	2		2	2	0	0	2
S - N	8	1	2	2	0	0	2	2		2	0	0	0
S - W	9	1	2	2	2	0	2	2	2		2	2	2
W - S	10	0	0	2	2	1	1	0	0	2		2	2
W - E	11	0	0	0	1	2	2	0	0	2	2		2
W - N	12	2	2	2	1	2	2	2	0	2	2	2	

Key	
0	Conflict
1	Managed Conflict
2	No Conflict

Figure 24: Matrix diagram showing if a turning movement is permissible

Using this matrix, all possible stages could be determined through some simple computer coding which considered every allowable phase combination and attempted to add an additional, allowable phase. If adding an additional phase was not possible, then the current combination would represent a final stage. This iterative process was carried out through two scenarios:

1. Managed conflicts were allowed
2. Managed conflicts were not allowed

This generated two sets of stages: when managed conflicts were allowed then there were 8 possible stages and when they were not allowed then there were 17 possible stages (see Figure 25 and Figure 26 respectively). The limitation of the 8 stage solution is that right turning traffic would never be released unopposed (as a no conflict) and therefore would be unlikely to work effectively under heavy right turn conditions.

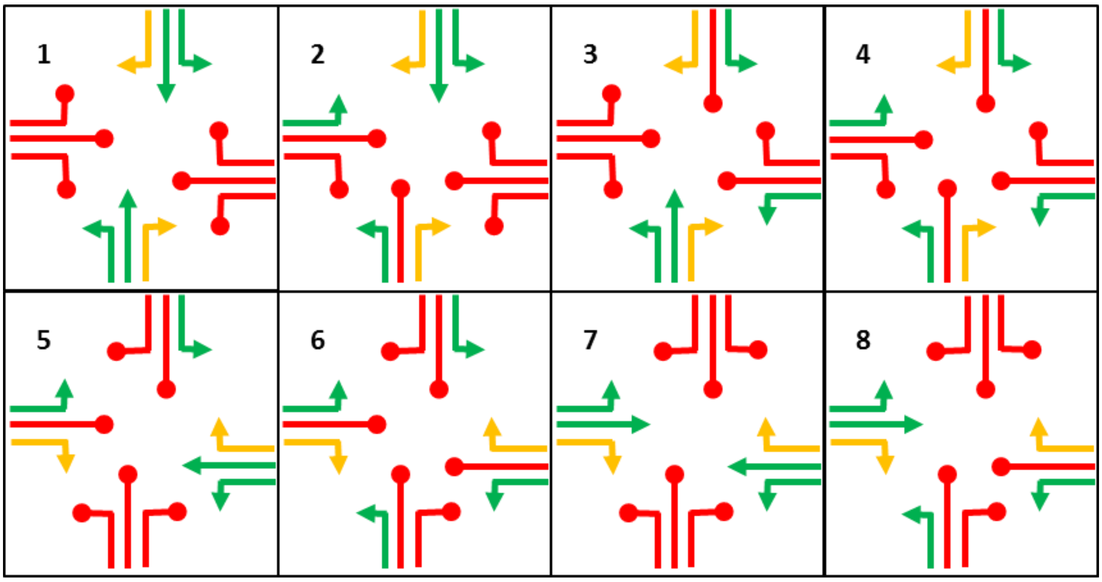

Figure 25: An 8 stage solution where managed conflicts are allowed

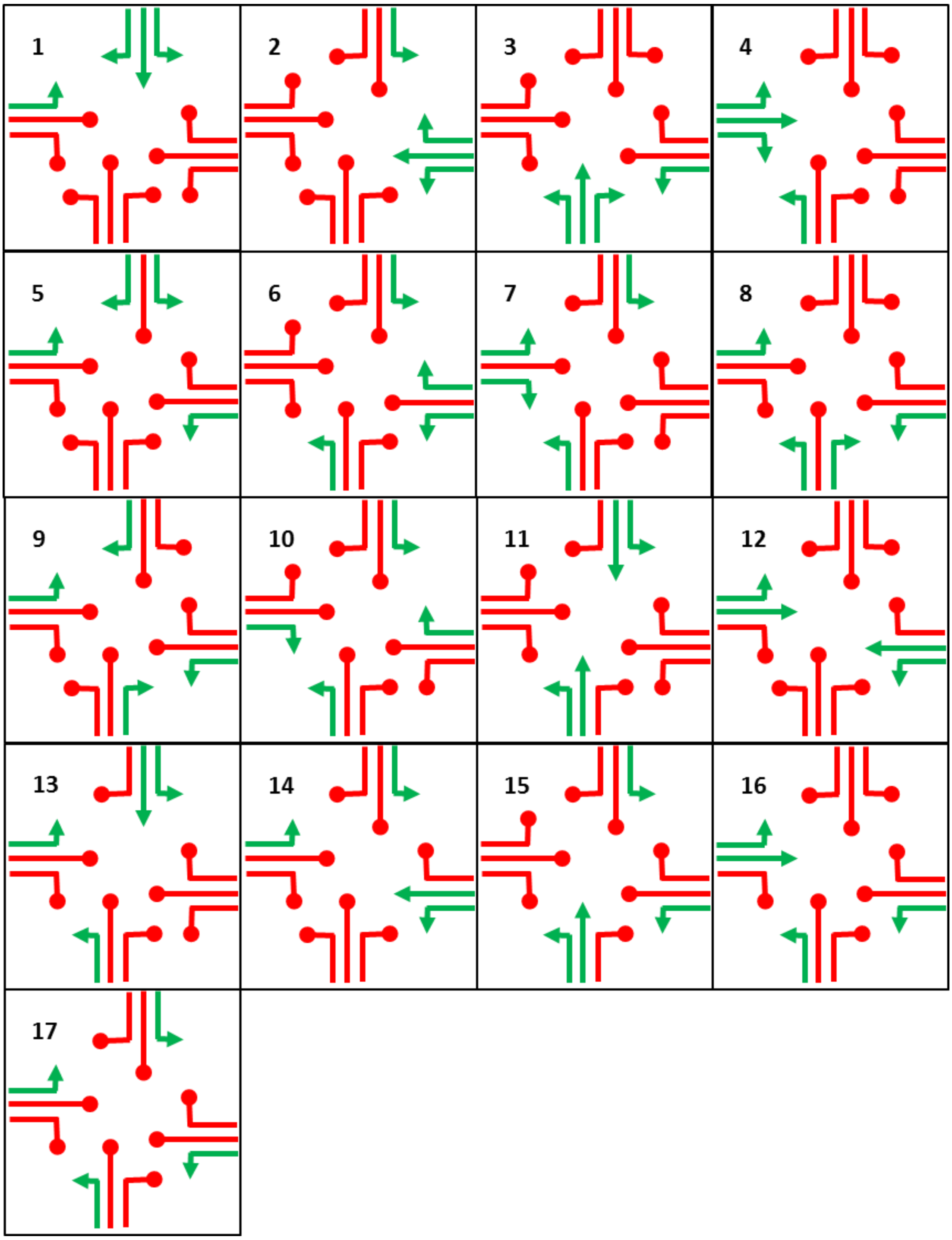

Figure 26: A 17 stage solution where all movements are unopposed

5.5.4 Example Calculation

The stage diagram shown in Figure 25 will be used for this illustrative example. As described in Section 5.4.3, the following equation was used to calculate the bid for each phase (see Table 9 – Left):

$$\begin{aligned} Bid\ for\ phase\ &= Vehicle\ count\ requiring\ this\ phase\ \times [1 - 0.01 \\ &\times (Average\ speed\ of\ vehicles\ requiring\ this\ phase) - 0.001 \\ &\times (Average\ Distance\ of\ vehicle\ requiring\ this\ phase)] \end{aligned}$$

Therefore 12 bids were created to accommodate each of the 12 turning movements. Then the total stage bid was generated from the sum of each of the phases in that stage (see Figure 25 for a reminder of what phases are in each stage). If the method of the 'highest bid wins' then – in this example, stage 5 would be selected regardless of the current stage.

However if the other method of 'X percent better than the current stage' was used, where if the current stage was stage 7 and the next stage had to be 10% better than the current stage, then stage 7 would remain as the best available stage because no stage was 10% higher than it. This ensures that lost time through inter-green time is factored into the decision process.

Table 9: Example Calculation of Turning Intention Algorithm (Left = Phase Bids, Right = Stage Total)

Phase	Bid
1	50
2	50
3	150
4	40
5	123
6	15
7	55
8	50
9	50
10	110
11	120
12	130

Stage	Total Bid
1	405
2	485
3	370
4	450
5	568
6	495
7	538
8	465

5.6 Results

This section will present results from the case study experiment as described in Section 5.5. A number of comparisons were carried out:

- 2 stage Highbid against 8 stage TIA
- Stage selection comparison – 'highest bid' against 'X percent better' method
- What effect does the detection distance have on the performance of the algorithm?
- 2 Stage vs 4 Stage Highbid and 8 Stage vs 17 Stage TIA

The TIA is inherently very similar to the Highbid algorithm where the only significant difference is turning intention data and therefore this section will help to demonstrate how turning intention data can be used as a new source.

The 2 stage Highbid and 8 stage TIA are most similar in terms of stage configuration, each of the stages have six phases released with two 'managed conflicting' right turns. Whereas the 4 stage Highbid and 17 stage TIA are more similar as no managed conflicts are allowed and only three phases or four phases are released per stage respectively. Therefore the results section will show comparisons of the two solutions for each algorithm in this manner.

5.6.1 2 Stage Highbid vs 8 Stage TIA

This experiment was carried out to determine which algorithm provided the lowest delay and reliability of journey times. Table 10 and Figure 27 display how TIA outperforms Highbid under all three demand scenarios, especially in the higher demand scenarios where TIA has a lower mean delay than Highbid algorithm. During the low flow scenario (200 Flow), the Highbid algorithm and TIA are very similar in terms of journey time, except that the TIA has more variability than Highbid (which is undesirable). TIA has a higher standard deviation and maximum journey time which suggests the higher variability in journey time, for the low flow scenario but this is not the case in the other two scenarios.

The TIA sees a reduction of 5% in mean delay (200 Flow) but it should be noted that there is minimal delay and therefore the absolute values are very similar. However in the other two scenarios, TIA outperforms Highbid by 24% and 5% for average delay and 15% and 3% for average journey time (for 10000 Flow and North Weighted scenarios respectively). In both scenarios, the TIA has a lower standard deviation and maximum journey time than Highbid and therefore has less variation in journey time. This demonstrates that turning intention data could prove to be beneficial in reducing average delay and improving reliability of journey time.

Table 10: 2 stage Highbid against 8 stage TIA under the three demand scenarios

Demand and Control Method	Delay			Journey Time (seconds)			
	Mean Delay (sec)	Mean Speed (mph)	Mean Queue Time (sec)	Maximum	Mean	Standard Dev.	Median
200 Flow - Highbid	10.9	27.4	4.7	139	82.9	8	81
200 Flow - TIA	10.3	27.6	4.3	153	82.3	10	79
10000 Flow - Highbid	116.5	14.8	80.7	902	188.5	145	111
10000 Flow - TIA	88.1	16.0	64.0	643	160.1	116	104
North Weighted Flow - Highbid	59.0	18.6	41.9	1243	131.0	125	91
North Weighted Flow - TIA	56.1	19.5	36.1	1044	128.1	112	90

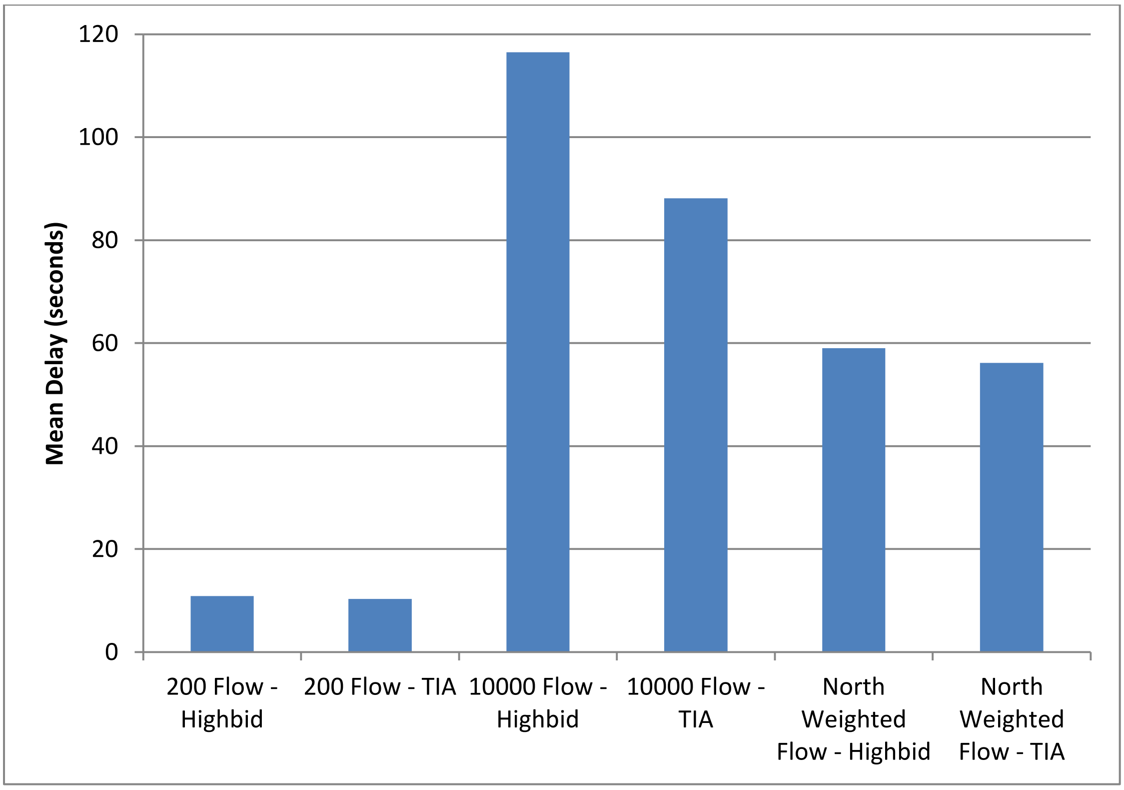

Figure 27: A bar chart comparing the mean delay for each of the control algorithms under the three demand scenarios

5.6.2 North Weighted – X Percent Stage selection

This section details the difference in how stages are chosen once the bids have been generated. Both the 'highest combination of allowable phases' and 'X percent better than the current stage' techniques were tested to determine if there was any difference between the selection methods. The North Weighted demand scenario was used.

It became clear that a reduction in delay could be achieved by changing the current stage when the new stage could generate a bid which was greater than 'X' percent of the current stage. Table 11 and Figure 28 demonstrate that the lowest average delay and journey time were when the new stage's bid was 25% higher than the current stage. This resulted in a reduction of 31% and 14% in average delay and journey time respectively, where the standard deviation in journey time was significantly reduced along with the maximum journey time. This means that the '25% better' approach was fairer to traffic than the 'highest bid' approach and improved the flow of traffic.

This approach was considered because of the ten second decision-making constraint which has been imposed on the system. This constraint was used because it reduced the complexity of the algorithm as a stage length (which could require additional data or potentially a different approach) did not have to be calculated.

Table 11: A comparison of various values for the 'X' percent better than previous stage method

X Percent Better Approach	Delay			Journey Time (seconds)			
	Mean Delay (sec)	Mean Speed (mph)	Mean Queue Time (sec)	Maximum	Mean	Standard Dev.	Median
0%	55.6	19.3	36.4	831	127.6	105	91
5%	45.6	20.3	30.4	684	117.6	89	88
10%	45.9	20.2	31.2	896	117.9	93	89
15%	41.7	21.1	25.9	745	113.7	80	88
20%	39.5	21.1	26.2	733	111.5	73	89
25%	38.3	21.4	23.4	534	110.3	62	89
30%	40.2	20.8	27.0	692	112.2	72	89

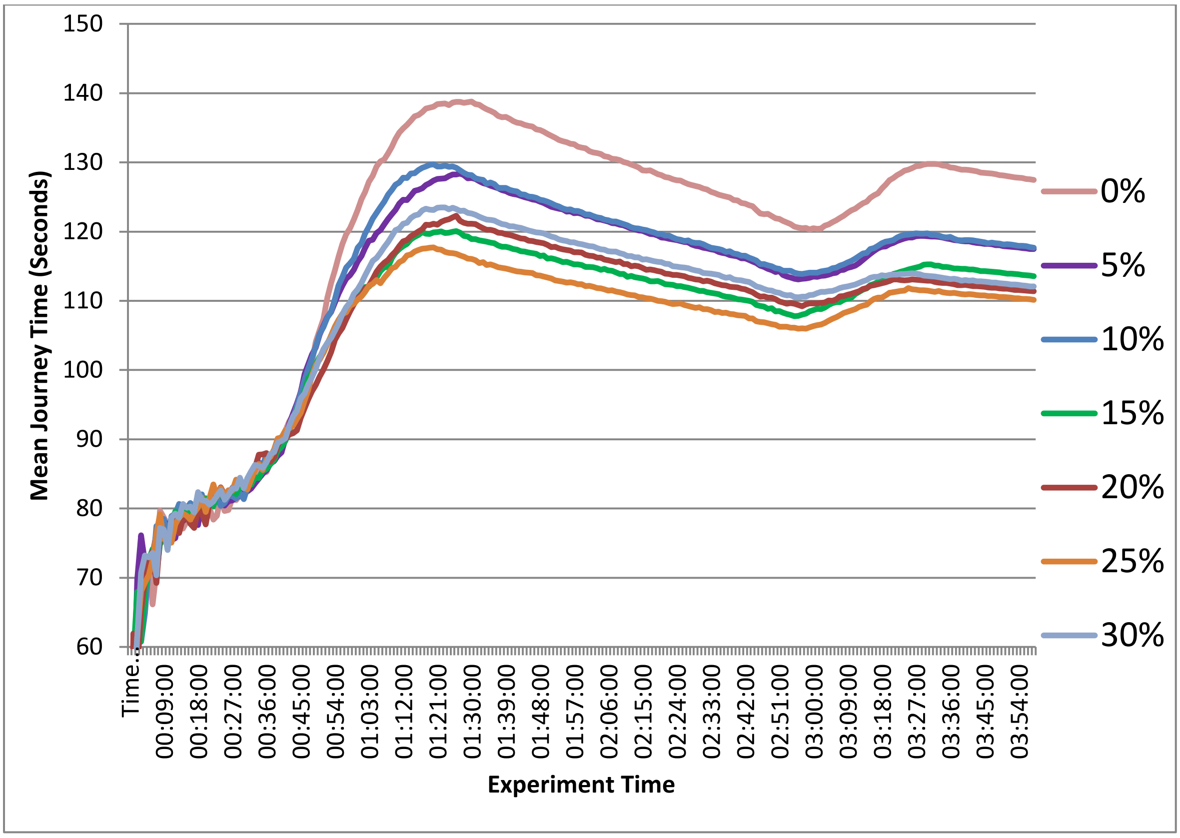

Figure 28: Comparison of how mean journey time evolved throughout the experiment for the 'X percent better than previous stage' method

5.6.3 Length of Approach for Detection

As described in Section 5.5.1, the default detection distance is 500 metres as this is the length of the approach road to the junction. However, it would be beneficial to determine what effect the detection distance has on the performance of the algorithm. Table 12 and Figure 29 display how the detection distance has little effect until the vehicles are within 200 metres, where the performance of TIA improves to approximately 150 metres after which the performance decreases.

The considerable drop in performance under 100 metres could be attributed to the fact that the control algorithm does not have sufficient time to change the signals by the time the vehicles arrive and therefore vehicles inevitably queue longer. This constraint is because of the ten second decision making variable which means that a decision could be made just before vehicles enter the detection zone, and by the time the next decision occurs then the vehicles could be queuing. This highlights the need to remove the ten second constraint for any future control algorithms developed in this research.

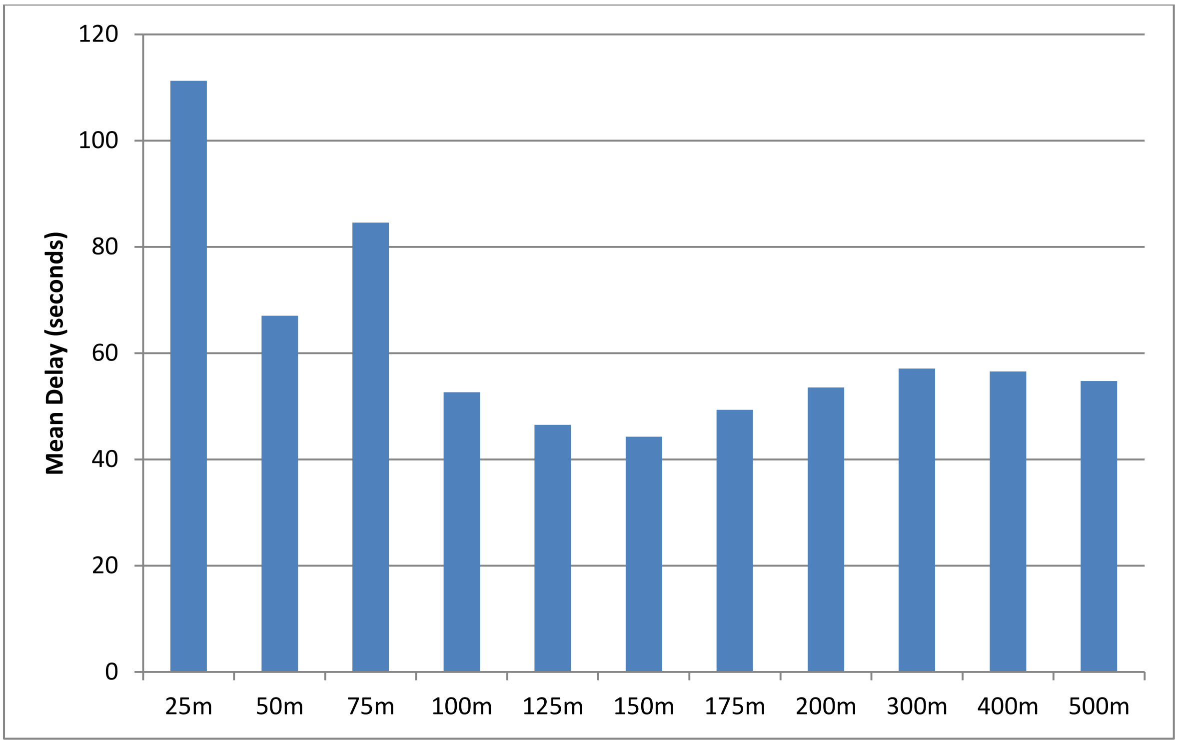

Figure 29: A bar chart showing the mean delay from variation of detection distance from the junction

Table 12: A table showing the variation of detection distance from the junction

Distance from the Junction	Delay			Journey Time (seconds)			
	Mean Delay (sec)	Mean Speed (mph)	Mean Queue Time (sec)	Maximum	Mean	Standard Dev.	Median
25m	111.2	14.3	76.3	1770	183.2	181	98
50m	67.0	17.7	47.6	1108	139.0	132	93
75m	84.5	16.1	65.6	2005	156.5	207	92
100m	52.7	19.6	34.6	1211	124.7	114	89
125m	46.5	20.7	27.6	976	118.5	97	88
150m	44.3	20.7	28.0	800	116.3	90	88
175m	49.4	19.9	33.1	794	121.4	97	88
200m	53.5	19.7	35.1	1228	125.5	117	88
300m	57.1	19.1	38.7	978	129.1	119	89
400m	56.5	19.0	39.3	1230	128.5	121	89
500m	54.7	19.3	37.4	978	126.7	108	90

5.6.4 2 Stage vs 4 Stage Highbid and 8 Stage vs 17 Stage TIA

This section describes the experiment of how different stage configurations affect the performance of either Highbid or TIA. There are advantages and disadvantages of using either stage configuration (allowing managed conflicts or not); vehicles will either be opposed and more streams of traffic can be released at the same time, or all streams of traffic will have unopposed movements and obviously less phases can be released at the same time. Table 13 and Figure 30 demonstrate how the 2 stage Highbid significantly outperforms the 4 stage Highbid approach, and how 8 stage TIA significantly outperforms the 17 stage approach. It should be noted that the TIA approach outperforms Highbid under either opposed or unopposed scenarios.

The problem with the 17 stage TIA approach is that there are so many options during congested periods. As a decision is being made every ten seconds then only a small amount of cars are being released before the stage is changed (enough cars are being released so that the bid is reduced sufficiently so that a different stage wins the next bid). This results in large amounts of time being lost through inter-green periods. The 17 stage solution is not viable when there is a ten second constraint on the decision making time. During congested periods, this algorithm could be improved to forcibly select the same stage for a longer period of time so that lost time is reduced. However, further research is required to determine how a suitable stage length can be calculated and therefore remove the ten second decision making problem.

It should be noted that this experiment demonstrates how the TIA consistently reduces mean delay compared to the Highbid algorithm. This emphasises how turning intention data can be used in signal control algorithms and there is potential to see a benefit from using this additional data source.

Table 13: Comparison of different control strategies on north weighted demand scenario

Control Method	Delay			Journey Time (seconds)			
	Mean Delay (sec)	Mean Speed (mph)	Mean Queue Time (sec)	Maximum	Mean	Standard Dev.	Median
2 Stage Highbid	60.5	18.4	43.3	1291	132.5	123	91
4 Stage Highbid	225.5	10.5	166.4	1374	297.5	237	198
8 Stage TIA	56.6	19.2	38.4	1218	128.6	118	89
17 Stage TIA	174.8	11.9	137.7	1866	246.8	265	137

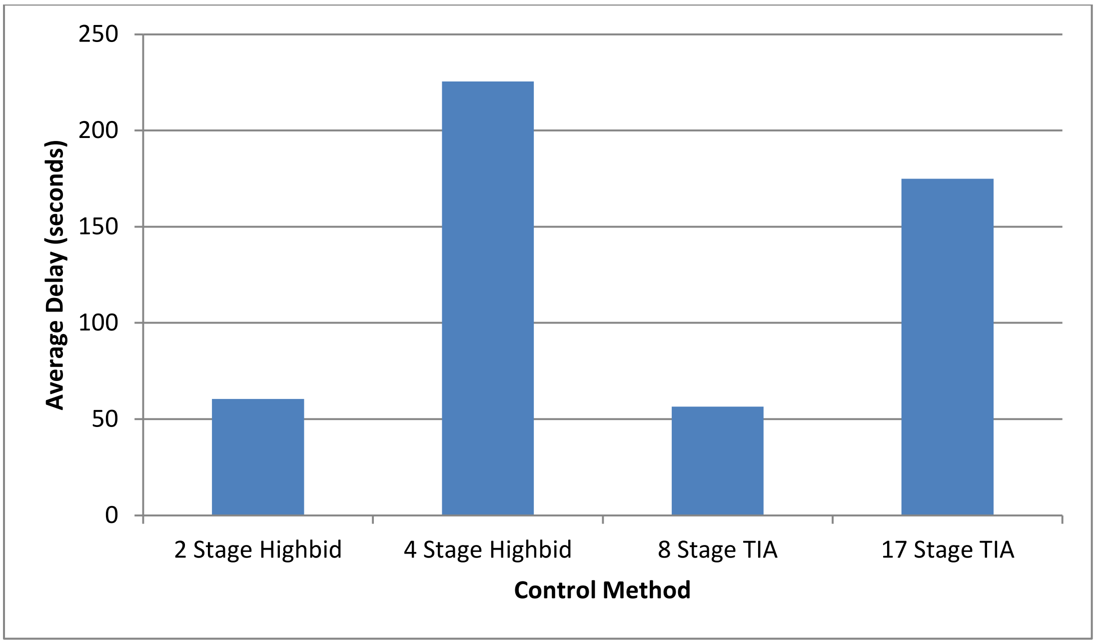

Figure 30: Comparison of different control methods

5.7 Limitations

The assumption was made that the right turning traffic could always be released as a managed conflict when generating the 8 stage diagram; therefore it means that right turning traffic never has an unopposed turn in this solution. This needs to be considered in future work to ensure that right turning traffic would be able to gap accept sufficiently and safely.

As mentioned throughout Section 5.6, the decision making frequency of ten seconds is a big constraint on the system as a large amount of time is lost through inter-green time if a new stage is selected at every decision point. Any future algorithms which will be developed during this research needs to consider a method of ensuring that a stage duration is calculated as well as considering the most appropriate stage.

Chapter 3 emphasised the importance of average delay and reliability of journey time for evaluating any signal control algorithms. Although both of these KPI's have been used in this chapter, a potential problem with this algorithm is the concept of fairness to low flow traffic. Using Highbid or TIA, a single car waiting on a side road would never be able to 'outbid' the major roads if there were always vehicles on the major road and therefore a 'maximum waiting time' needs to be considered within the signal control logic or else vehicles could wait indefinitely.

Pedestrians have not been included in this chapter and need to be considered during stage generation. In real junctions, stage diagrams often have a pedestrian phase (if the junction layout allows it) where the pedestrian crossing can be manipulated around the vehicle phases so that pedestrians can cross safely during a vehicle stage as well. For example pedestrians could cross to a pedestrian refuge during one stage and then cross the other half during the next stage.

There is an inherent assumption in this simple network model that every turning movement has a dedicated lane and filter light associated with it. This may not be case for many junctions and therefore more complex, real world scenarios need to be modelled where turning movements are perhaps shared in a lane (for example, straight and left in the left lane and right only in the right). If there is simply a one lane approach to the junction then there would be no potential benefits from knowing the turning intention data for that junction, but the information could still be useful for neighbouring junctions for estimating arrival times.

Due to the TIA and Highbid algorithms' simplicity, they could not be used on real junctions because they do not consider real junction constraints (such as minimum green time, maximum cycle time, inter-green time, etc.). Therefore any future work must consider how these real world constraints would affect the traffic control algorithm.

5.8 Conclusion

This chapter has provided an invaluable insight on how turning intention data can be used in a control algorithm. This has been shown using a theoretical junction as the TIA was compared against a theoretical control algorithm (Highbid), which was developed by the University of Southampton, and TIA outperformed Highbid across three demand scenarios by up to 24% and 15% in average delay and average journey time respectively. Both Highbid and TIA use additional data sources which include vehicle location and speed and the algorithms operate in very similar ways, the only difference was the inclusion of turning intention data in TIA.

The Turning Intention Algorithm is a theoretical algorithm which was used to highlight how turning intention data could be used in signal control. However, both the TIA and Highbid algorithms could not be used in reality (in their current forms) due to their many limitations. The next stage of this research will be to develop an algorithm which considers more real world constraints and could potentially be used as a control system. Elements of this system must calculate how long a stage should be selected for as opposed to using a fixed time period to reassess the road conditions (i.e. Highbid and TIA made a decision every ten simulated seconds). To make definitive comments on the benefits of using turning intention data, any new algorithm must be compared to an existing UTC system (see Sections 2.2 and 2.3 for examples) and preferably on real world junctions with actual demand profiles.

Taking a holistic view of what has been learnt from this research so far is that turning intention data can be detected/transmitted using in-vehicle technology but also can be fairly accurately predicted from outside of the vehicle, as observed in Chapter 4. Turning intention data can be used to manipulate current stage diagrams through novel methods by including every possible phase combination into the stage list and selecting the most beneficial stage at any given time. However the question of what are the real benefits of using turning intention data needs to be answered before a conclusion can be properly drawn on the usefulness of turning intention data.

5.9 Chapter 5 Key Points

1. Turning intention data can be used to manipulate stage diagrams by considering all possible phase combinations.
2. This enables the control algorithm to select the best phase combination at any decision point which provides additional flexibility over existing control algorithms.
3. There were up to 24% and 15% reductions in average delay and journey times respectively by including turning intention data into the control algorithm, on a theoretical junction.
4. The TIA uses a fixed decision point of every 10 seconds due to the complexity of calculating stage duration, but this significantly constrains the algorithm and the next part of the research must calculate suitable stage durations.
5. Real world constraints must be incorporated into any novel control algorithms, such as inter-green time, maximum cycle time, minimum green time and a stage configuration which enables unopposed right turns if required.
6. Now the question of 'what are the benefits of using turning intention data' must be answered by comparing turning intention algorithms against real world systems as opposed to theoretical systems.

Chapter 6: Novel signal control algorithms using new data sources

This chapter will seek to answer the question of 'what are the benefits of using turning intention data'. To do this, a novel control algorithm must be developed which considers real world constraints so that it can be compared against state of the art control systems such as MOVA (for isolated junctions). A list of constraints will be developed within this chapter so that any new algorithm could be used in a real world scenario, unlike the Turning Intention Algorithm (TIA) as described in Chapter 5. The TIA did demonstrate how turning intention data can be used and therefore the stage manipulation concept will be used within the development of new algorithms in this chapter.

A key problem which was highlighted in Chapter 5 was that stage duration needs to be calculated to potentially provide improved results. The TIA was constrained by a ten second decision making time which did not consider lost time during the inter-green period. A method of determining the best stage duration must be developed and to do that, the TIA case study will be used as it is well understood. This will enable a novel algorithm to have the best possible way of calculating stage duration.

6.1 Real World Junction Constraints

The Department for Transport provides a range of useful documents to develop an understanding of what constraints are needed for signal controlled junctions to ensure that safety standards are met. This section will investigate what junction constraints need to be adhered to and also describe any impact that they might have on the design of a novel control algorithm.

Minimum Green Time

A minimum green time is set to ensure that vehicles are able to have sufficient time to clear the junction and is typically set at seven seconds (DfT, 2006). This value would be extended if there are a high proportion of heavy goods vehicles or a steep gradient at the junction.

Inter-green Time

The British Standard definition of Inter-green time is:

> "*The period between the end of the green signal giving right of way for one phase, and the beginning of the green signal giving right of way for the next phase".* (DfT, 2006)

Inter-green time plays an important safety role in a signalised junction where there is a period of amber for the stopping traffic, followed by a period of red and amber for the starting traffic. The minimum time for an inter-green period is five seconds (three seconds for stopping traffic and two seconds for starting traffic) (DfT, 2006). This time is essential for minimising the possibility of having a conflict at the junction. Unfortunately drivers occasionally pass through a red light which is when a conflict could occur, but the inter-green period should provide sufficient time to account for the aggressive drivers who drive through red lights and the drivers who are starting their green period. The distance between starting and stopping phases is critical for calculation of this time as can be seen in Table 14. The distance 'x' can be determined by measuring the distance travelled to the probable collision points by vehicles losing right of way compared with those gaining right of way (DfT, 2006) – i.e. subtract the shorter distance to the collision point from the longer distance to the collision point.

Table 14: Determining inter-green time (DfT, 2006)

Distance 'x' metres	9	10-18	19-27	28-37	38-46	47-55	56-64	65-73
Inter-green (seconds)	5	6	7	8	9	10	11	12

Filter Lights

Department for Transport (2006) stated that a filter light should not be used unless the movement has unopposed or non-conflicting movements. This coincides with the practical inability to release isolated, opposed turning movements through the normal traffic light system. For example, an opposed right turn could not be given a green light or a green filter light without releasing the straight and or left turning traffic from the same road at the same time. In order to do this, a new type of signal head would be required to release the movement into an opposed traffic stream.

This constraint is critically important for this research because some of the stage diagrams shown in Figure 25 (in Section 5.5.3) would not be possible with this constraint. Right turning traffic cannot be released by itself without having complete priority. It is possible to simulate this scenario as demonstrated in Chapter 5 but it is not possible to implement this solution in reality, without a change to highway policy.

Gap Acceptance

There are constraints on allowing gap acceptance to take place when the 85th percentile approach speed is greater than 45 mph. Under these circumstances, right turning traffic must be separately signal controlled (unopposed) because there is a higher risk of accidents between right turning vehicles seeking gaps and on-coming vehicles (DMRB, 2004). Therefore any case study involving high speed roads must include a stage which provides an unopposed right turning stage.

Safety for High Speed Junction

MOVA controlled junctions monitor the arrival profile of vehicles as they cross the detection loops to ensure that there is a sufficient amount of inter-green time between stages. MOVA is able to add one or two seconds to the inter-green period so that high speed vehicles will be able to pass through the junction without an accident (Crabtree and Kennedy, 2005). For example (illustrative purposes only), if a vehicle is detected rapidly across sensors when they are close to the junction and the signals have turned amber then the inter-green period will be extended. This process will add more red time to the junction but has the potential to improve the safety record if there are a large number of drivers who run the red light. This concept could be incorporated into any novel control algorithms to ensure that there is a high safety standard to the junction.

Vehicle Type Impact

The discharge rate at a junction is heavily affected by the vehicle types using the junction. Kockelman and Shabih (2000) demonstrated that vehicle types have an impact on the capacity of the junction and therefore the discharge rate from it. For example, a van could be considered as 1.34 passenger car equivalents when determining junction capacity. Therefore if this data becomes available then it could be incorporated into signal control algorithms through a weighting method.

Maximum Cycle Time

For UK junctions, it is recommended that the maximum cycle time should be no longer than 120 seconds (DfT, 2006). This is a safety constraint to ensure that drivers do not become frustrated by waiting too long at the lights and potentially run a red light. This constraint has been re-interpreted as "*all phases which have a demand must receive a green light within a 120 second period*".

As mentioned in Chapter 5, phase control is required (as opposed to stage control) to use turning intention in signal control algorithms. Hence why this real world constraint has been re-interpreted to consider individual phases rather than assume that there is a sequential stage order which will release each stage that has a demand. Both the TIA and Highbid algorithms were unconstrained by a cycle order or cycle time and this impact needs to be explored further to understand what effect it could have on performance or safety at junctions.

6.2 Cycle Order

Historically, traffic signal control algorithms have been constrained by the limited granularity of real time data availability. However as the industry is moving into an era of an abundance of data sources (see Section 2.4.1 – smartphones, Wi-Fi, satellite navigation and Bluetooth) then control systems may require more flexibility to take advantage of significantly higher granularity. This section will investigate the possibility of having no pre-defined stage order but will instead select the most beneficial stage at any given time. Existing control algorithms such as MOVA operate on a predefined order of green signals, often referred to as the 'cycle'.

Typically cycle based controllers consider phase based demands (Further and Muller, 1999) and adjust the durations of the predefined stages to release phases in an optimum manner (DfT, 2006). As control systems are heavily constrained by the cyclic order, then more focus is placed on the stages than the phases as there is minimal flexibility (Butler, 2010). However, if the system is not constrained by stage order, then phases become the priority because the best combination of phases can be released instead of being restricted to those that form part of the next stage in the cycle order.

Simulation packages such as LinSig are often used to determine the best stage configuration and cycle order for isolated junctions (TfL, 2010). Through discussions with experts in the industry, it was apparent that these configurations are rarely challenged after initial setup due to the cost and time required to update them. Traffic flow is constantly evolving and hence why reactive systems such as SCOOT are used to manage these changes (Papageorgiou et al., 2006), but what if more flexibility could be given to the system so that junction calibration and validation does not need to occur quite so often? The Traffic Advisory Leaflet 1/06 suggests that stages should follow a cyclic order and only omit stages (known as 'stage skipping') when there is no demand for the stage (DfT, 2006 and Furth and Muller, 1999). Could additional stages be programmed into the control systems which are only used when needed, without the need for network operators to set up complex plans or strategies?

There is often a safety argument against stage skipping which suggests that local road users will not expect the perceived change in sequence order and could potentially cross the junction without due care and attention (whether pedestrian or motorist). However, from worldwide trials of stage skipping, there has been no evidence to suggest that stage skipping increases accident rates (Bretherton, 2003). However there have been more complaints of excessive waiting where traffic has not received a green light within five minutes (Bretherton, 2003), which exceeds the advice of DfT (2006) and therefore should not be used in any new control algorithm (i.e. 120 seconds should be the maximum cycle time).

The Transport Research Laboratory (TRL) trialled stage skipping logic in an attempt to improve bus priority systems and they observed no increase in accident rates (Bretherton, 2003). However there were some heavy constraints on the system, including that the main road stage was never skipped and pedestrian stages were never skipped unless there were multiple pedestrian stages in the cycle.

A number of European countries use phase based control to ensure safety performance targets are achieved (Furth and Muller, 1999). However even though the Netherlands use phase based control, it still has a fixed stage to ensure a definitive start of the cycle, regardless of the demand, which somewhat negates the benefits of using phase based control. The Netherlands uses a first in – first out logic for phase control which works well in light demand scenarios, however when there is high demand, then the system becomes locked into a cyclic order which may not be optimal (Furth and Muller, 1999).

This chapter is focused on developing a novel control algorithm which has more flexibility due to additional data sources and therefore any new algorithms will be able to select any allowable stage at any given time depending on the road conditions. This will create a more flexible system which can respond faster to the arrival of incoming vehicles. However the constraints mentioned in Section 6.1 must be adhered to as well and then a comparison can be made against a state of the art control algorithm (such as MOVA if considering an isolated junction) to ensure that there is a benefit to using additional data.

6.3 Methodology for Delay Minimisation Algorithm (DEMA)

Considering the KPI's described in Chapter 3, then the novel signal control algorithm must aim to minimise average delay across the junction while incorporating the real world constraints that are described in Section 6.1. To do that, a method of calculating delay based on the current road state must be developed; this section will describe how DEMA (a novel traffic control algorithm) has been created.

6.3.1 Quantifying Delay

When calculating mean delay, the traditional methods tend to use the cycle time of the system in the formula (for example Webster, 1958) but this does not work when stages can be selected in any order. To calculate delay for a phase based system, delay has been defined from first principles as the summation of queue lengths per second (so for every second that a vehicle is stopped in a queue then this would represent one second of delay). By using this method, the free flow journey time through the network does not need to be determined for the algorithm to calculate delay. This results in less set-up time for any traffic control algorithms which use this technique of calculating delay.

The disadvantage of calculating delay in this manner however is that it ignores the acceleration and deceleration part of delay (see Figure 31), but this is typically much smaller than the stationary period. The equations for calculating queue length per second are based on arithmetic sequences as it has been assumed here that the junction has a constant discharge and arrival rate for the period which is being investigated.

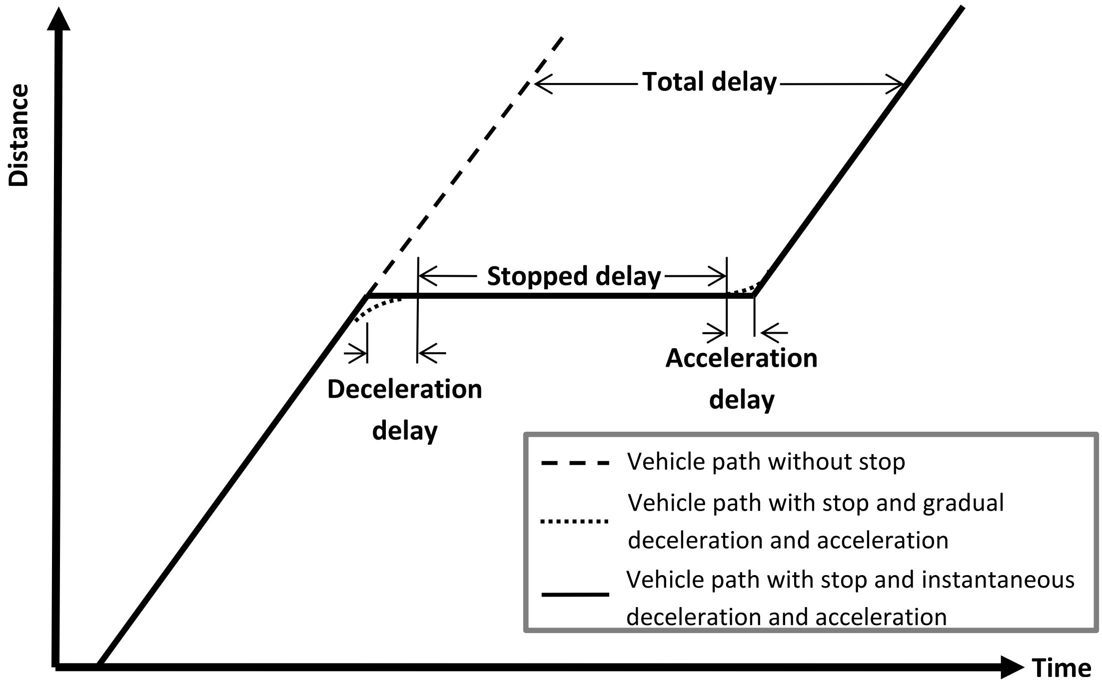

Figure 31: Graphical representation of vehicle delay as it passes through a junction (after Dion et al., 2004)

As this research can manipulate stages in any order, then the individual phase delay needs to be calculated. The following logic describes which equations should be used to calculate the sum of the queue lengths per second for phases which are currently active (receiving a green light) dependent on the duration of the specified stage ('t' seconds), initial queue length at the start of the stage ('n' vehicles) and arrival and discharge rates ('A' and 'D' vehicles per second respectively) (see Figure 32 for an illustrative diagram).

The delay depends on whether the initial queue can be fully discharged or not; and if it can, then the delay depends on whether the additional 'arrivals' queue, which builds up during the discharge of the initial queue, can also be cleared. This is also presented graphically in Figure 33 and a detailed explanation of the development of these equations can be seen in Appendix 5.

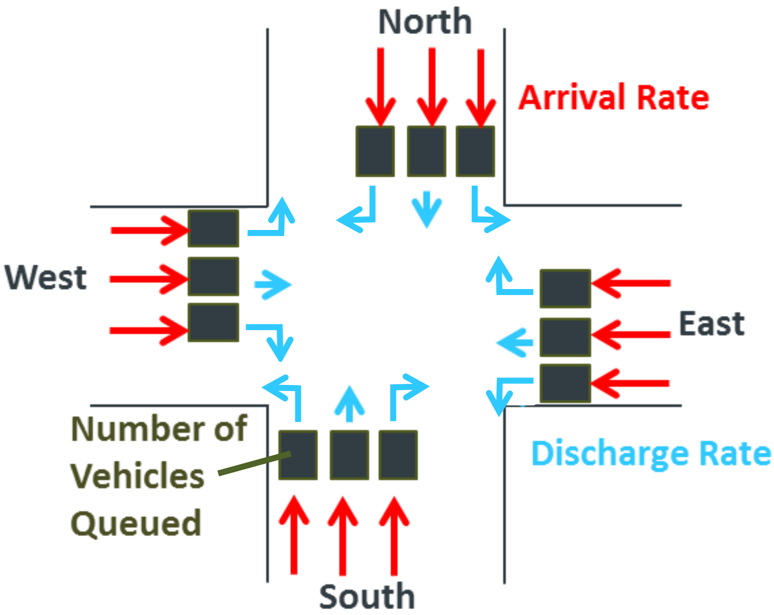

Figure 32: An illustrative diagram showing how each phase would have its own queue length, arrival rate and discharge rate

If the initial queue cannot be fully discharged:

$$\text{If}\frac{n}{D} > t\text{: UseEquation⍰}$$

If the initial queue can be fully discharged:

$$\text{If}\frac{n}{D} \leq t\text{: UseEquation⍰}$$

However if Equation 2 is used, then additional constraints apply:

If the arrivals queue can be fully discharged and the arrival rate is less than discharge rate:

$$\text{IfA} < \text{DandIf}\left(\frac{n}{D} - \frac{An}{D(A\text{-}D)}\right) \leq t\text{: AddEquation⍰}$$

If the arrivals queue cannot be fully discharged and the arrival rate is less than discharge rate:

$$\text{IfA} < \text{DandIf}\left(\frac{n}{D} - \frac{An}{D(A\text{-}D)}\right) > t\text{: AddEquation}(4)$$

If the arrival rate is greater than or equal to the discharge rate:

$$If \quad A \geq D: \quad \text{Add Equation 4}$$

Equation 5 can be used to determine the delay caused to a phase which has not been selected in the current stage.

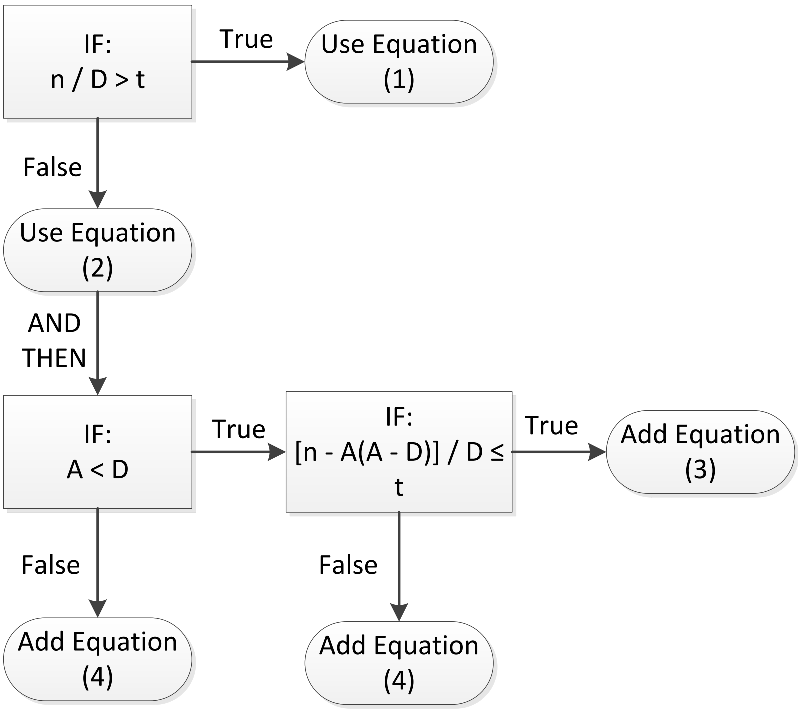

Figure 33: Flow diagram for equation selection

$$\frac{t}{2}\left[2n + (A - D)(t + 1)\right] \qquad \textbf{Equation 1}$$

$$\frac{n}{2D}\left[(n - D) + A\left(1 + \frac{n}{D}\right)\right] \qquad \textbf{Equation 2}$$

$$\frac{An}{2D\,(D-A)}\left[\frac{An}{D} + (A - D)\right] \qquad \textbf{Equation 3}$$

$$\frac{tD-n}{2D}\left[\frac{2An}{D} + (A - D)\left(1 + t - \frac{n}{D}\right)\right] \qquad \textbf{Equation 4}$$

$$\frac{t}{2}\left[2n + A(t + 1)\right] \qquad \textbf{Equation 5}$$

6.3.2 The DEMA Algorithm

With Equations 1 – 5 enabling calculation of the phase delays, then the basic operation of the proposed Delay Minimisation Algorithm (DEMA) is simply to determine the minimum delay from the list of possible stages. DEMA incorporates minimum and maximum stage durations, and the algorithm uses the current road state in the form of current queue length, arrival rate and discharge rate for each phase, see Figure 34 for an illustrative flow chart.

In relation to the current road state, it is worth considering what the difference in data resolution is between MOVA and DEMA. MOVA typically uses three inductance loops on each approach arm and therefore is able to estimate the queue length and arrival times (DfT, 2003). The furthest loop which could be used is 205 metres from the stop line, but 30mph to 40mph roads would typically be 80 – 120 metres (DfT, 2005). A MOVA loop should never be further than ten seconds from the stop line when a vehicle is at cruise speed (DfT, 2005).

DEMA uses additional information over MOVA; the algorithm considers if the vehicle is within 50 metres of the junction (equivalent of an inductance loop), and what speed the vehicle is doing. If the vehicle is travelling less than or equal to three miles per hour then it is considered to be part of the queue. The default setting for DEMA is if the vehicle is within 500 metres of the junction (similar to Highbid and TIA in Chapter 5) then it will be considered as part of the queue or as an arrival vehicle, depending on the speed of the vehicle, but this value will be thoroughly tested in the sensitivity analysis in Section 6.7.

The 500m vehicle location sensor is equivalent to either an inductance loop (which would be challenging and expensive for communication cabling) or more likely a Bluetooth detector or Vehicle to Infrastructure sensor. This additional information helps the algorithm to pre-empt a vehicle's arrival time more accurately than MOVA and therefore has more time to respond to approaching vehicles.

DEMA calculates the delay for all possible stages and their allowed durations (one second resolution); and the stage with the least delay (per second of stage duration) is selected. The approach taken is therefore equivalent to a 'Greedy Algorithm' which always selects the best stage at that decision point (Russell and Norvig, 2010). The problem with this approach is that it does not consider the long term effect on the junction. For example, releasing stage one followed by stage two may not be better overall compared with releasing stage two followed by stage one if there is a sudden increase in vehicles requiring stage one. However the alternative to this method is selecting a number of stages at each decision point and evaluating many more stage combinations (increasing exponentially). To be able to do this requires much more processing power and a more accurate prediction of arrival rate; therefore needing an even higher resolution of data. A detailed analysis of a greedy algorithm versus a multiple stage selecting algorithm is required and therefore will be carried out in Section 6.4 to determine which solution provides the better performance.

Beyond the core issue of determining the theoretically best stage, there are many constraints on real traffic control systems and a key part of DEMA is to ensure that all guidelines and best practice techniques (for example, safety constraints, inter-green, minimum greens) are adhered to. This enables the algorithm to be used in real junctions and not simply be a theoretical study.

A constraint which is very challenging for a flexible control algorithm such as DEMA to meet is the maximum cycle time of 120 seconds (DfT, 2006). As there is no cycle time within DEMA then a method of forcing the algorithm to select an unreleased phase needs to be implemented or else DEMA may never select the phase (because it does not have the lowest impact on delay). To do this a weighting factor was introduced to ensure that any phase, which had not received a green light within the previous 120 seconds and had vehicles waiting to be released, would have its delay value artificially reduced. This forcibly makes the phase more desirable and therefore would be selected at the next decision point. There remains is a risk with this method that even with the weighting factor, the phase would struggle to get released; but a lower weighting factor can be used if the junction has an arm with very low demand. The reason for not setting the weighting factor to zero is because the stage duration would then not be calculated properly and hence the weighting factor needs to be calibrated for the junction.

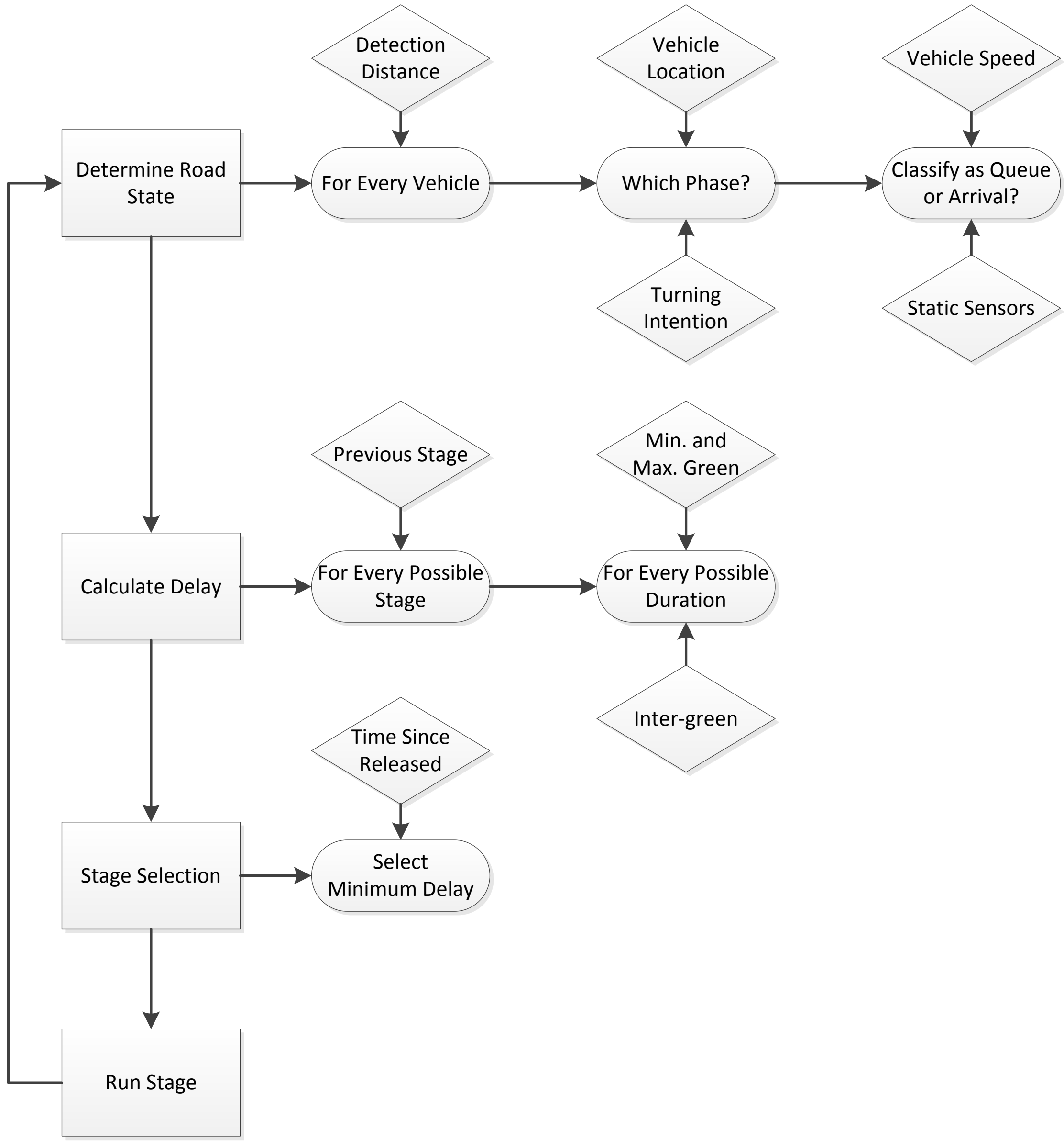

Figure 34: DEMA algorithm data flow

6.3.3 Determining Stages

Similar to the stage generation process described in Section 5.5.3, a matrix of allowable movements must be created so that a list of all possible stages can be determined. The constraints mentioned in Section 6.1 need to be considered during stage creation; this will ensure that right turning traffic has an unopposed turning movement if a filter light is used and that gap acceptance constraints can be applied depending on the speed profile of the vehicles.

If a case study uses a real world junction, then the current set up of the signal heads and junction layout must be considered to develop the stages. This process was split into two areas:

1. What stages would work under the current signal head arrangement?
2. What stages could work if the signal heads and minor junction alterations were allowed?

6.3.4 Discharge Rates

The discharge rate at the intersection was dependent on whether the phase was opposed or unopposed (see Table 15). The Traffic Advisory Leaflet suggests values of 1900pcu/hour (passenger car units) for straight ahead traffic and 1650pcu/hour for turning unopposed traffic (DfT, 2006). Opposed turning traffic will vary from as low as 120pcu/hour (two vehicles released at the end of each stage for a two minute cycle time) up to the unopposed flow rate, dependent on opposing flow.

Table 15: Discharge Rates

Turning Movement	Pcu per hour	Pcu per second
Unopposed Straight	1900	0.528
Unopposed Turning	1650	0.458
Opposed Turning	120	0.033

6.3.5 Determining Queue Length and Arrival Rate (Road State)

As Paramics provides the turning movements for the next two links, then all vehicles within two links can be classified into a phase road state using the following logic sequence.

1. If the vehicle is within 50m of the junction then it is considered as part of the stationary queue
2. Else if, the vehicle is travelling less than or equal to 3 mph AND if the vehicle has a tracking device fitted (i.e. was it randomly given a device which can transmit location and speed – this is controlled through an 'infiltration' variable) then it is added to the stationary queue

3. Else,
    a. If the vehicle is fitted with a tracking device, then it is added to the arrivals queue.
    b. Else if, the vehicle is within 100m then it is detected via the inductive loop at 100m then it is added to the arrivals queue.
    c. Else, the vehicle will not be detected (i.e. if there is no tracking device fitted and it is not within 100m of the junction then it will not be added to stationary or arrivals queue.

This logic sequence will classify every vehicle on the approach links and represents a scenario where additional data (more than inductive loops or equivalent) can be used to provide a richer picture of the road state. The infiltration variable enables the experimenter to vary how many vehicles are 'equipped' with devices that can transmit location and speed data.

To calculate an arrival rate then the number of observed vehicles must be divided by the duration of the observations. Traditional arrival rates have been calculated using the cycle time (Udoh and Ekpenyoug, 2012), however this will not work for this research as there are no cycle times. This means that average journey time from the 'detection distance' to the junction is the most appropriate value to use for calculating the arrival rate.

Therefore after every vehicle was categorised using the aforementioned logic, the 'arrival queue' was divided by the average journey time from the specified distance. The average journey time was calculated based on an examination of arrival time graphs, for example, the average journey time for a vehicle travelling from 500m away was 45 seconds for the three lane approach junction (in Section 5.5) and therefore the arrival rate would be calculated using the following equation:

$$\frac{Number\ of\ Vehicles\ Arriving}{Average\ Time\ taken\ to\ Travel\ 500m} = 'X'\ vehicles\ per\ second$$

The average time taken will be junction specific dependent on what the average speed of vehicles is through the junction.

6.4 Stage Selection – Hill Climber vs Single Stage

As mentioned in Section 6.3.2, a comparison of a greedy algorithm which selects a single 'best' stage against a multiple stage selection algorithm will be carried out in this section. A multiple stage selection algorithm is in response to the 120 second maximum cycle time constraint, which a greedy algorithm could never guarantee. There are advantages and disadvantages to using either approach as the following section demonstrates.

6.4.1 Single Stage Selector

A single stage selector algorithm is a greedy algorithm which selects the lowest possible delay per second out of all the possible stages and durations. The following list highlights the positive and negative aspects of using a single stage selector:

+ Makes a decision which will only affect the junction for a maximum duration of one stage
+ Requires less data for understanding the future arrival of vehicles
– Does not consider the knock on effects on other stages
– Cannot guarantee that all stages are released within a 120 second period (but it can make it very probable by using a weighting factor)

A weighting factor must be included after a phase has waited for 'X' seconds without being released ('X' can be set by the network operator). If this was not the case, then a low demand phase may never be released as the other phases provide a lower amount of delay.

Figure 35 demonstrates the logical order of how a single stage selector algorithm would operate when controlling a Paramics model. The reason that the KPI of minimum delay per second must be considered instead of minimum delay is that all the stage durations are being compared against one another. Therefore it would not be fair to compare a stage which only had duration of 15 seconds against a stage of 30 seconds, but looking for the lowest delay per second provides a fair comparison.

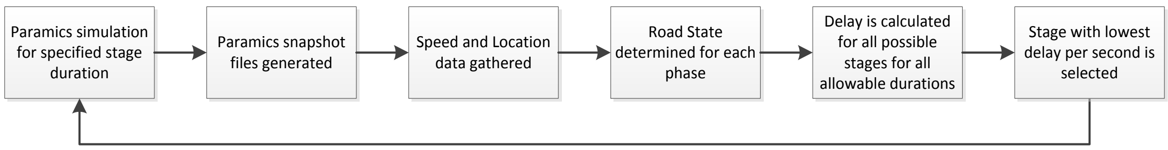

Figure 35: Single stage selector algorithm flow diagram

6.4.2 Multiple Stage Selector

A multiple stage selector would calculate a suitable cycle plan for the next 120 seconds and aims to minimise the total delay throughout that period. A cycle plan is defined as a series of stages of various durations for a specified amount of time (i.e. 120 seconds). The following list highlights the positive and negative aspects of using a multiple stage selector:

+ Ensures that every phase will be selected within a 120 second period
+ Considers the effects of selecting a stage on other streams of traffic by calculating a total delay for a specified period of time (i.e. not a greedy approach but considers the knock on effects of a decision)
– Requires much more detailed knowledge on the arrival rate of vehicles for the next 120 seconds which could be more challenging to obtain accurate data
– Much more processing time required which means that the road state will be more outdated by the time that the stages are selected

In an ideal situation, perfect knowledge of arrival rates would be known and therefore a cycle plan for the next 120 seconds could be developed which would minimise delay and release all phases which have a demand. However, unless there is a very long approach road then the arrival rate can typically be estimated for perhaps one minute away (500 metre approach for 30mph road), but this situation is unlikely as there could be other entry or exit roads before the signalised junction. Therefore if an arrival rate can only be predicted for up to one minute in advance, then the algorithm must forecast the arrival rate to predict arrival rate over the next 120 seconds.

In order to determine the best possible cycle plan for the next 120 seconds, then an excellent understanding of the current road state is required because any decision made will impact the junction for 120 seconds. Therefore all possible cycle plans should be considered with the appropriate constraints (minimum green, inter-green, etc.) applied. For a four stage model with a maximum green time (for each stage) of 25 seconds, then this would result in 33.5 trillion plausible combinations when considering a second by second approach. This is computationally not possible (for a typical desktop) every 120 seconds and therefore heuristic approaches are required. To put this number into perspective, a reasonably good specification of desktop could calculate delay for approximately 40,000 cycle plans every second (therefore requiring over 26 years to complete the entire combination list).

It should be noted that the single stage selector does not require a heuristic approach because it is able to calculate the delay for all stage configurations very quickly as it is only considering one stage in advance. For example, if there are four stages to choose from and each stage could run for up to 50 seconds then this is a quick calculation of less than 200 cycle plans.

The main priority of a heuristic algorithm for this research is the speed of calculation to consistently achieve a cycle plan with an acceptable performance level. The maximum amount of time the algorithm will have to find an acceptable solution is 120 seconds; however, if it requires this length of time then it will need to rely on road data which is 120 seconds old. Therefore, the algorithm will have more reliable data if it can perform quicker. Ideally the algorithm would be able to find a solution in less than the inter-green time so that old data does not need to be used for determining the road state.

6.4.3 Hill Climber Algorithm

Selecting a heuristic method is a complex task and large volumes of research are carried out on this topic. Therefore, this section will seek to select a heuristic method which can provide an acceptable solution in a short amount of time; the performance of the algorithm will be compared against the single stage selector. A simple heuristic algorithm which iterates over a problem until it finds a local optimum is a hill climber algorithm (Russell and Norvig, 2010). The idea is that sufficient search time is given so that the local optimum is as close as possible to the global optimum. A hill climber algorithm continually moves in the direction of increasing value (i.e. lowest delay for this problem), and can become 'stuck' in the search-space as it finds a local optimum. To counter this, a random starting point is selected and the process is repeated and compared against the previous best solution, this can be repeated as many times as the time constraint allows (Russell and Norvig, 2010).

Figure 36 demonstrates how a hill climber algorithm could be used to output a possible cycle plan for use in this research. It is clear that the hill climber process is very iterative and requires a large amount of processing power (compared to a single stage selector), to find a suitable solution in the large search space. Some definitions are needed:

- A **seed** is the initial starting point for a cycle plan which is randomly generated
- A **mutation** is a small change to the cycle plan by altering one second in stage length or by changing the stage number
- A **step** is the number of times the algorithm will repeat the whole mutation process and therefore 'climbing the hill'

The following logic described how the hill climber algorithm operates:

1. Initially a random cycle plan is generated with constraints such as the minimum and maximum green time along with inter-green time between stages.
2. The cycle plan would be mutated by adding or subtracting one second from a random stage and adding it to another stage (provided that the constraints were not exceeded). Or the stage number could be changed to any of the other stage numbers available.
3. This would be repeated by the number of mutations selected, and then the best performing cycle plan would be chosen.
4. With the mutated cycle plan, stages 2 and 3 would be repeated by the number of 'steps' selected, with the best performing cycle plan selected as the best cycle plan for that seed.
5. Stages 1 – 4 would be repeated by the number of seeds selected.
6. The best cycle plan from all seeds would be selected as the chosen cycle plan to be implemented in the simulation.

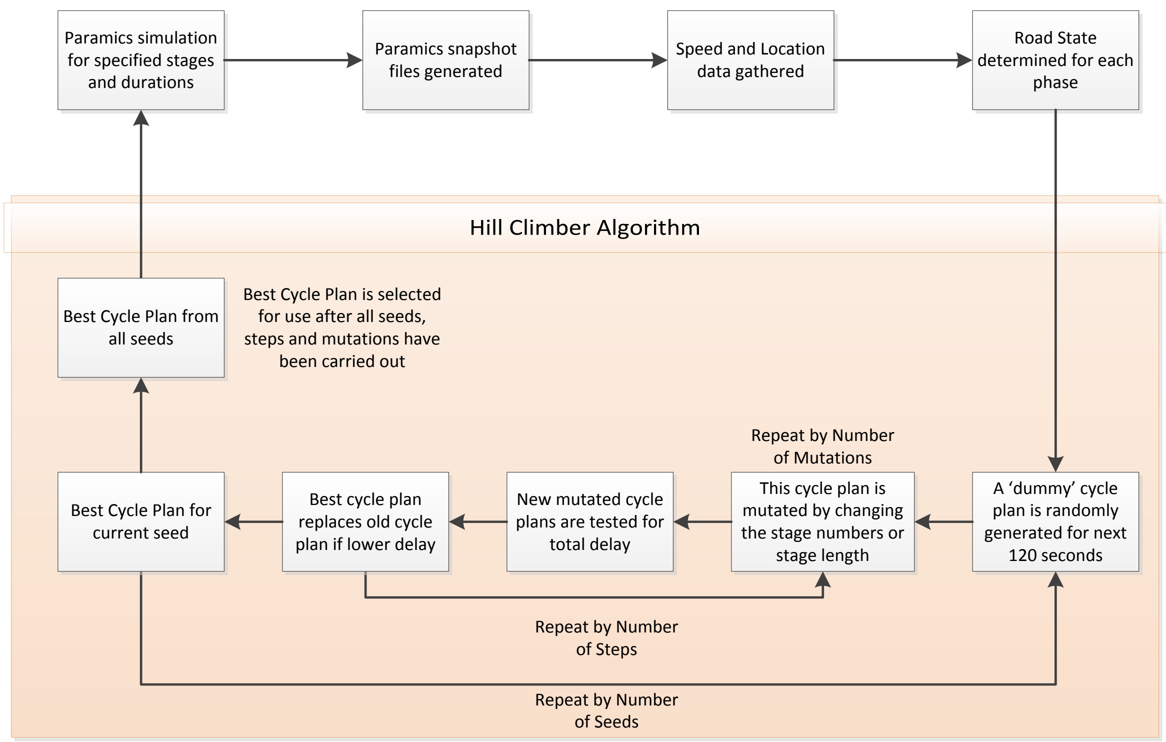

Figure 36: Hill climber algorithm flow diagram

6.4.4 Case Study

In order to compare the Hill Climber algorithm against the Single Stage selector algorithm then the case study junction from Section 5.5 was used (the three lane approach, theoretical junction). This also enables a brief comparison between the Highbid, Turning Intention Algorithm and the new algorithms since the same demand scenarios can be used. The North weighted demand scenario (see Section 5.5.2 for more detail) was selected for use and previously the 8 stage TIA algorithm proved to be the best solution to the problem. Now some further constraints are needed for the Hill Climber and Single Stage selector to operate:

- The maximum green time for each stage is 25 seconds (previously unconstrained)
- The inter-green time is inputted into the model at 7 seconds (same as before but previously not considered in the algorithm)
- The minimum green time is set at 7 seconds (previously a decision was made every 10 seconds, which meant that the minimum green could be as short as 3 seconds as the inter-green was 7 seconds)

Trials were carried out to determine how long the PC would take to calculate a cycle plan which could be reasonably adapted from the random cycle plan. As mentioned previously, a PC could calculate approximately 40,000 cycle plans per second, and therefore two scenarios were run where a short time plan would complete in approximately 2.5 seconds and a longer plan which would take approximately 25 seconds to calculate. However in this experiment, the longer plan was not provided with 25 second old data but it also received 'perfect' data in terms of vehicle location, speed and turning intention. The two Hill Climber plans were:

- 20 seeds, 50 steps and 100 mutations
- 100 seeds, 100 steps and 100 mutations

These values were determined from theoretical scenarios developed during the construction of the Hill Climber algorithm and cannot be considered as optimal. However, this research is not focused on optimising heuristic algorithms and therefore these solutions provide a reasonable representation of the Hill Climber algorithm.

Table 16, Table 17 and Figure 37 displays the results of this simple case study. The Hill Climber algorithm has a worse performance against the Single Stage selector, ranging from 12 - 20% reduction in average delay and a reduction of 4 - 8% in average journey time depending on the number of stages used in the solution. Based on these results, the Single Stage selector algorithm has a better performance than the Hill Climber as it reduces average delay and provides a more reliable journey times for vehicles. Therefore the Single Stage selector will be used for future experiments carried out in this research.

It should be noted that there is a significant improvement of using either the Hill Climber algorithm or Single Stage selector over the Turning Intention Algorithm or Highbid as shown in Table 13 (in Section 5.6.4). This observation would begin to suggest that DEMA's approach is considerably better than TIA as real world constraints are imposed and delay can be calculated for each phase of traffic. There is a large improvement of how the 4 stage or 17 stage solutions perform (82% and 77% reduction in mean delay for 4 stage and 17 stage solution respectively); this is because DEMA considers the effects of lost inter-green time, whereas the simplistic approaches of Highbid and TIA simply make a decision every ten seconds, regardless of lost time.

Table 16: Hill climber results

Stage Configuration and Hill Climber	Delay			Journey Time (seconds)			
	Mean Delay (sec)	Mean Speed (mph)	Mean Queue Time (sec)	Maximum	Mean	Standard Dev.	Median
4 Stage - 20 Seeds, 50 Steps, 100 Mutations	45.45	19.62	27.78	311	117.45	36.93	109
4 Stage - 100 Seeds, 100 Steps, 100 Mutations	44.95	20.02	26.04	356	116.95	38.27	108
8 Stage - 20 Seeds, 50 Steps, 100 Mutations	44.03	20.07	30.94	979	116.03	90.97	91
8 Stage - 100 Seeds, 100 Steps, 100 Mutations	41.17	20.83	26.70	1125	113.17	87.63	90
17 Stage - 20 Seeds, 50 Steps, 100 Mutations	51.01	18.84	33.83	713	123.01	62.42	106
17 Stage - 100 Seeds, 100 Steps, 100 Mutations	51.00	19.08	32.09	704	123.00	58.94	108

Table 17: Single stage selector results

Number of Stages in Solution	Delay			Journey Time (seconds)			
	Mean Delay (sec)	Mean Speed (mph)	Mean Queue Time (sec)	Maximum	Mean	Standard Dev.	Median
2 Stage	63.63	18.08	44.84	1699	135.63	149.60	92
4 Stage	39.81	20.68	23.89	317	111.81	35.50	100
8 Stage	34.84	21.86	21.60	783	106.84	64.77	88
17 Stage	40.65	21.25	22.38	673	112.65	49.90	96

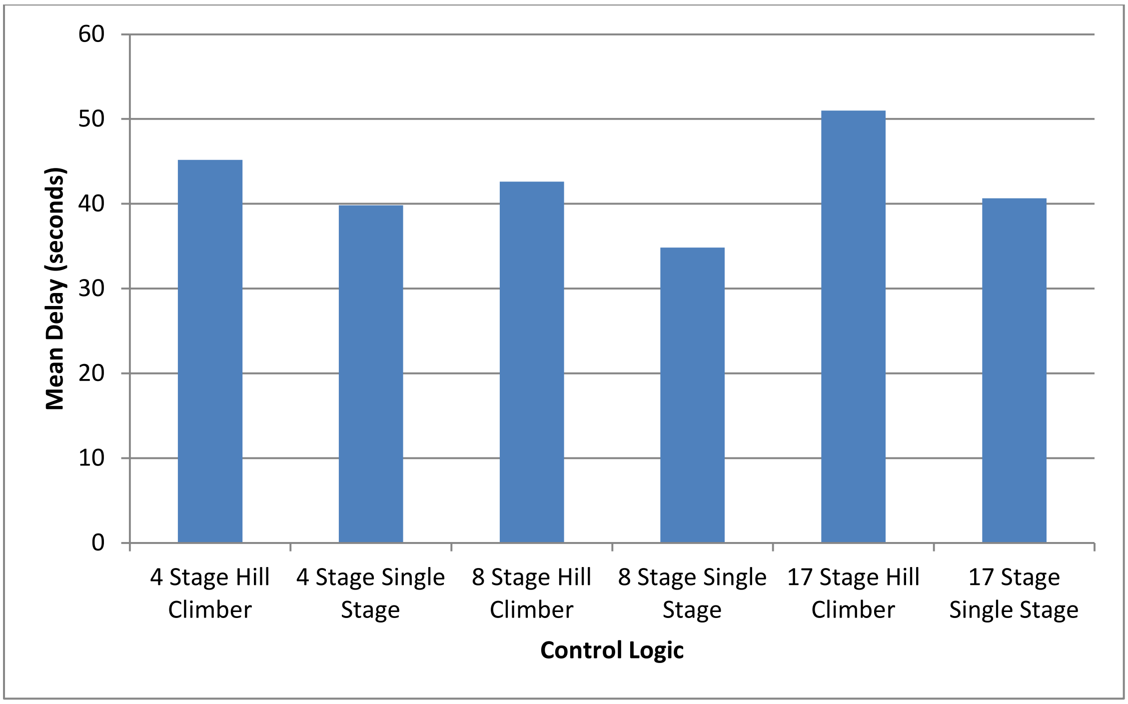

Figure 37: A comparison of the Hill Climber control logic against the Single Stage selector

6.4.5 Conclusion

The Hill Climber algorithm guarantees that all phases, which have a demand, will be released within a 120 second period. The Single Stage selector does force DEMA to meet this constraint by applying a weighting factor, but some vehicles may inevitably wait longer than 120 seconds by using this technique if the weighting factor is not applied soon enough. The performance of the Single Stage approach is up to a 20% reduction in average delay and 8% reduction in journey time against the Hill Climber algorithm. As the Hill Climber algorithm requires much longer processing time, then the algorithm would make use of older data in order to calculate the best cycle plan by the time it is needed. The problem with this is that at a low demand scenario then it would be difficult for the Hill Climber to accurately predict arrival rates. Therefore the Single Stage selector will be used to determine the most appropriate stage using the DEMA algorithm.

6.5 Case Study – Sopers Lane (T-Junction)

Siemens were able to provide data for two junctions which are located in Poole (United Kingdom). The first of these is a T-junction on Sopers Lane which is currently controlled by MOVA (see Section 2.2.3 for more information). The reason why a T-junction is being considered first is because stage manipulation is severely limited as there are only six possible phases at a T-junction. This will provide a suitable comparison for how DEMA compares with MOVA on a real junction, under the same constraints. Then in Section 6.6 a comparison can be made at a crossroads in Poole which will allow some stage manipulation to take place.

6.5.1 Junction Layout

Sopers Lane junction consists of a three lane approach from the North where there is a dedicated right turn lane, a two lane approach from the South where the left lane allows both straight and left turning movements, and a Western single lane road which allows both left and right movements (see Figure 38). Figure 39 displays the current stage diagram for the junction, where stage 2 is only selected when there is a pedestrian demand (which is not required in this experiment). The maximum stage lengths of Stages 1, 3 and 4 are 60 seconds, 22 seconds and 40 seconds respectively and the minimum green times are all 7 seconds. The speed limit is 40 mph on the dual carriageway section and 30 mph on the minor road.

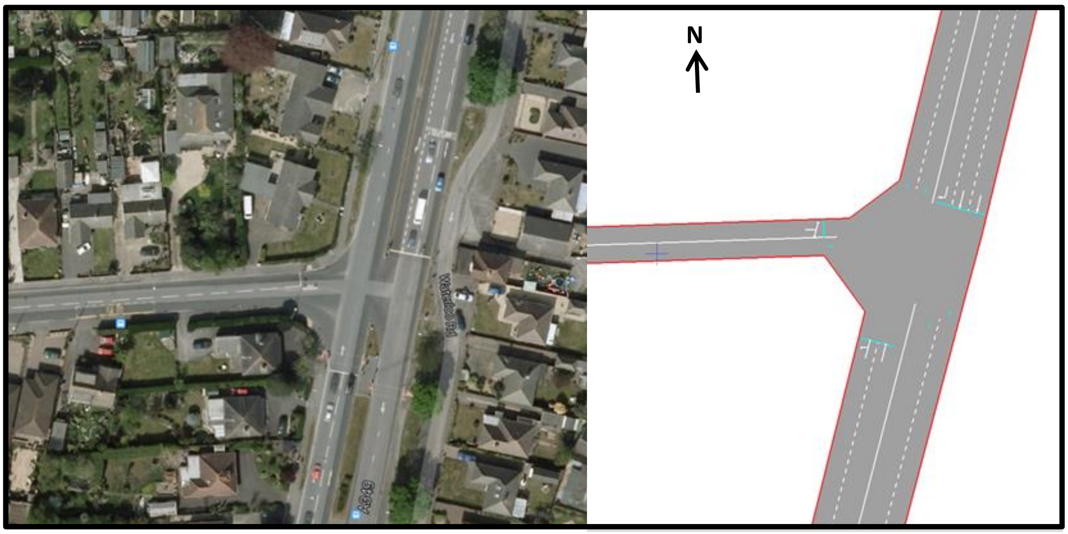

Figure 38: Sopers Lane junction layout (Paramics junction on right) (Image from: Google Maps, 2014a)

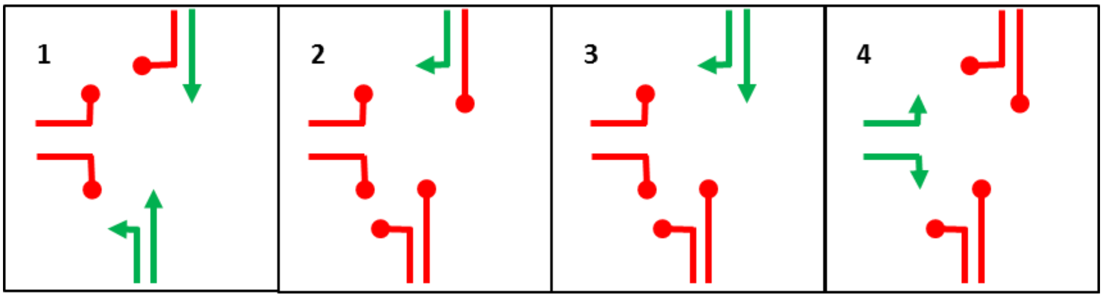

Figure 39: Stage diagram Sopers Lane junction

6.5.2 Demand Scenario

The demand scenario for Sopers Lane was determined from actual loop data for a typical weekday morning at the junction. Siemens provided the data shown in Table 18 and Figure 40. The experiments in this case study will only run for one hour as this is the volume of data given. To provide further insight into how the two algorithms will perform, then the demand scenarios will be varied from 20% up to 150% of the current typical weekday flow levels.

Table 18: Demand matrix for Sopers Lane for a one hour period

	North	South	West
North	-	980	76
South	793	-	244
West	122	122	-

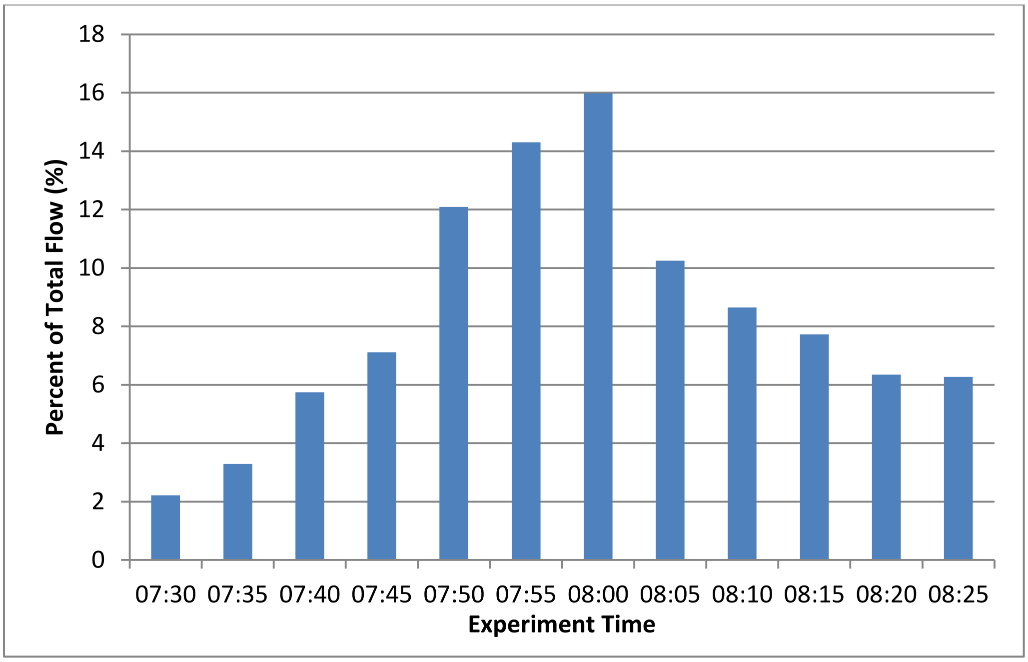

Figure 40: Demand profile for Sopers Lane

In order to calculate the average delay for Sopers Lane junction then the free flow journey times must be determined for each of the origin destination pairs. The zone numbers are numbered from the Northern arm in a clockwise direction. The free flow journey times in Table 19 are determined from when each traffic movement receives a green light prior to arrival at the junction with no opposing traffic. As the demand matrix can be observed in Table 18, then an overall average free flow journey time can be calculated through a weighting method; by multiplying the demand for each movement by the corresponding free flow journey time and dividing by the total demand. Therefore the average free flow journey time for Sopers Lane junction is 41 seconds; this value will be subtracted from the mean journey time to represent the mean delay for each simulated scenario.

Table 19: Free flow journey time for each origin destination pair

Free Flow Journey Time (seconds)		Destination Zone		
		1	2	3
Origin Zone	1	-	39	50
	2	37	-	52
	3	47	50	-

6.5.3 Results

This section shows a comparison of MOVA control against DEMA control (using Single Stage selection – see Section 6.4 for more information) under the typical weekday morning rush hour period. Table 20, Figure 41 and Figure 42 displays the reduction in average delay and journey time when under DEMA control compared to MOVA. DEMA is much fairer to vehicles in terms of distribution of journey times as the standard deviation is much lower than MOVA control. MOVA has a much higher maximum journey time which could potentially be attributed to a ‘settling in’ period before MOVA is able to optimise the junction.

The exception to this is at 150% demand scenario, this is where MOVA and DEMA are very comparable in terms of mean delay and journey time. Upon analysis of the journey time distribution at 150%, the average journey for vehicles travelling from the North was 57 seconds, from the South 61 seconds and from the West 280 seconds. This demonstrates how DEMA should be calibrated differently in congested scenarios because vehicles travelling on the minor road from the West will be forced to wait considerably longer than the main road (unless this is what network operators want). This is a consequence of the single stage choice which was decided in Section 6.4; however the weighting factor could be adjusted if the waiting time becomes unacceptable.

Table 20: Important statistics from the comparison of MOVA aganst DEMA

Control Method and Demand		Delay			Journey Time (seconds)			
		Mean Delay (sec)	Mean Speed (mph)	Mean Queue Time (sec)	Maximum	Mean	Standard Dev.	Median
MOVA	20%	8.44	22.9	29.4	491	49.44	37.8	40
DEMA		5.12	32.7	1.6	119	46.12	10.1	41
MOVA	40%	9.29	23.1	24.4	527	50.29	33.3	42
DEMA		6.33	32.1	2.0	139	47.33	11.7	42
MOVA	60%	11.01	22.1	26.9	554	52.01	36.1	44
DEMA		7.41	31.6	2.3	144	48.41	12.9	43
MOVA	80%	13.45	21.4	28.1	557	54.45	37.2	47
DEMA		9.60	30.5	3.2	169	50.60	16.4	45
MOVA	100%	15.53	21.0	27.5	555	56.53	36.0	49
DEMA		12.98	29.6	4.5	227	53.98	23.9	46
MOVA	150%	43.79	16.7	37.7	566	84.79	58.0	63
DEMA		43.26	25.1	13.3	640	84.26	97.5	54

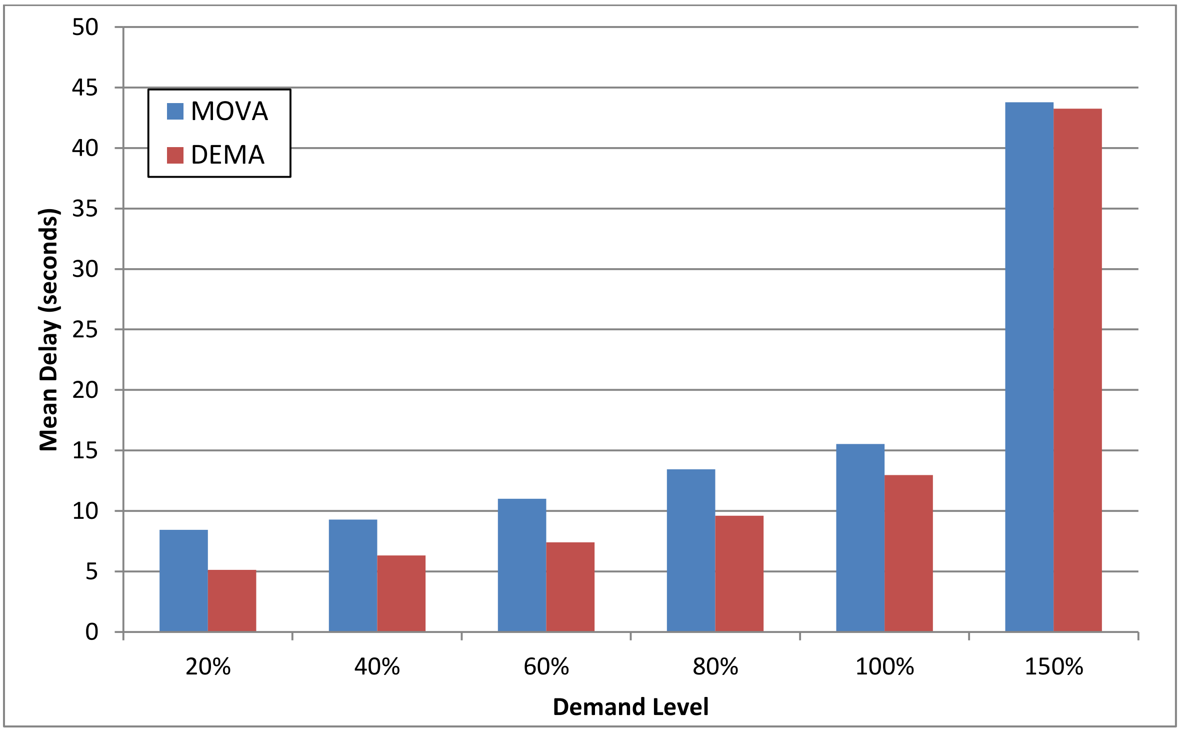

Figure 41: Comparison of average delay for MOVA and DEMA control at Sopers Lane

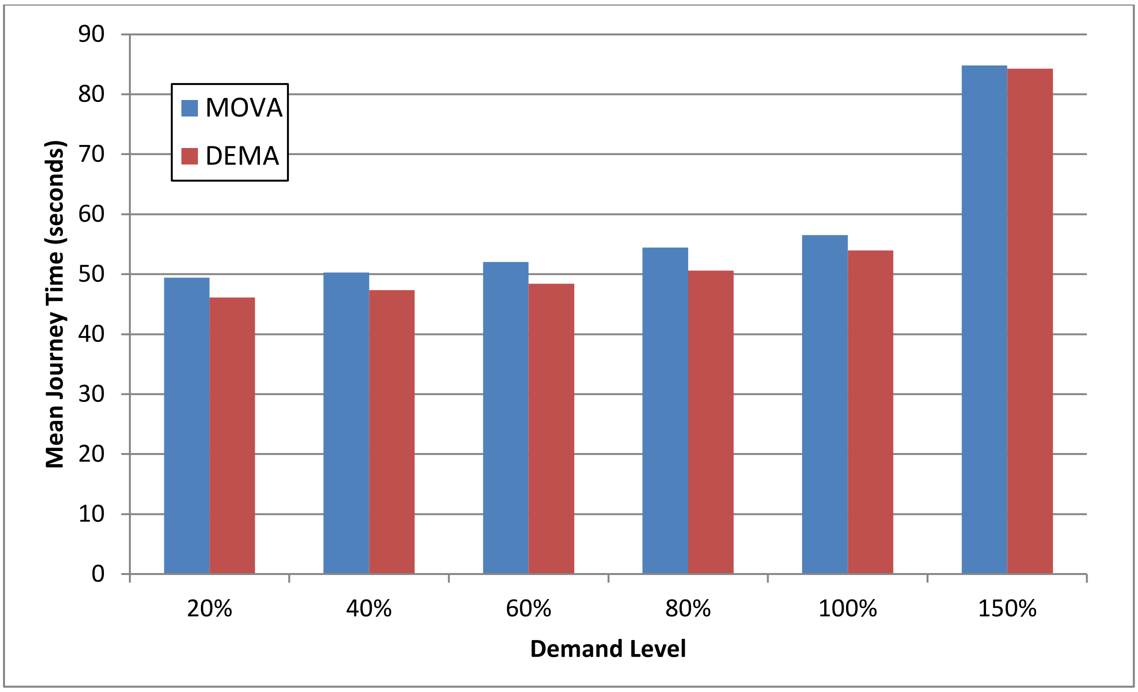

Figure 42: Comparison of average journey time for MOVA and DEMA control at Sopers Lane

Table 21 shows how much DEMA outperforms MOVA by for average delay and journey times. DEMA reduces average delay by a considerable margin over MOVA, ranging from 16% in the current demand scenario (100%) to as much as 39% in the lowest demand scenario. Whereas, the average journey time achieves a more modest reduction throughout the demand scenarios of approximately 4 - 7% (except 150% demand scenario). In the 150% demand scenario, MOVA and DEMA are virtually identical as the junction becomes oversaturated. In this situation, it is very difficult to achieve a reduction in delay or journey time as all stages are demanding the green light at all times (Shepherd, 1994).

Table 21: Percentage reduction of DEMA over MOVA

Demand	Percentage Reduction over MOVA (%)	
	Mean Delay	Mean Journey Time
20%	39.4	6.7
40%	31.9	5.9
60%	32.7	6.9
80%	28.7	7.1
100%	16.4	4.5
150%	1.2	0.6

Table 22 shows that there is a statistically significant difference of means for both average delay and journey time (except for the 150% demand scenario). It is important to highlight that there is no possibility of the means being equal to one another as the p-values are less than 0.05 which shows a 95% confidence value. Whereas in the 150% demand scenario, the null hypothesis (the means are equal to one another) must not be rejected.

Table 22: Independent sample T-test results of comparing means of delay and journey time

Demand	p Value	
	Mean Delay	Mean Journey Time
20%	0.000	0.000
40%	0.000	0.000
60%	0.000	0.000
80%	0.000	0.000
100%	0.000	0.000
150%	0.899	0.899

6.5.4 Conclusion

The Sopers Lane case study demonstrates that the DEMA algorithm can outperform MOVA by a statistically significant amount; however there are concerns of its fairness at excessive demand levels. This case study does not require the use of turning intention as there is no possible stage manipulation with only six phases and therefore provides a good foundation for testing DEMA against a state of the art control algorithm. However the next part of this research will investigate DEMA on a junction where turning intention can be used which may provide additional benefits.

The absolute average journey time reduction is approximately three to four seconds per vehicle at the junction. Over an entire network, this reduction can become fairly sizeable. To put this value in perspective, SCOOT bus priority systems achieve approximately 3 - 5 second reductions in journey times but this is only for buses (Bowen, 1997); i.e. there is a disadvantage to other road users. This demonstrates how desirable this system would be if it can deliver a 3 – 4 second reduction in journey time for all vehicles and therefore more scenarios need to be tested using the DEMA algorithm to determine its suitability in a real world test.

6.6 Case Study – Cabot Lane (Crossroads)

As Section 6.5 has demonstrated the benefits of using DEMA over MOVA at a T-junction, this section will investigate how DEMA performs when controlling a more complex junction. One of the benefits of using this junction for a case study is that Siemens use it as their 'test site' and therefore the junction is regularly updated and any comparisons of DEMA will be against an expertly configured MOVA junction. MOVA junctions have been selected because MOVA is also a delay minimisation algorithm for isolated junctions (DfT, 2006) and therefore it is a fair comparison against DEMA.

6.6.1 Junction Layout

Figure 43 and Figure 44 show the junction layout for Cabot Lane, where the speed limit is 50 mph and therefore it is a high speed signalised junction. There are two approach lanes from the North, both of which can travel straight ahead and vehicles can turn left or right from their respective lanes. From the East there are three approach lanes, all of which have an individual turning movement. From the South there are two approach lanes, with an additional left turn lane near the junction (it is a give way movement and is not controlled by the traffic signals); the other two lanes are dedicated straight and right lanes respectively. From the West there are two approach lanes, one is a dedicated right turn lane and the other is a straight and left lane.

The stages which MOVA currently use will also be used by DEMA in this section and can be seen in Figure 45. MOVA is allowed to skip any stages which do not have any demand and DEMA will be allowed to select any stage at any time provided that the 120 second release constraint has not been breached. The storage capacity on each approach lane is relatively low (approximately five vehicles) and therefore the phases on each arm are currently released as a stage to ensure that vehicle blocking is not an issue and that safety standards are met on a high speed junction (DfT, 2003). There is an all pedestrian stage (stage 5) but it has been omitted and is never selected in the simulation due to the focus on vehicular movements in this study, so there is no pedestrian demand.

Section 6.3.5 described how an arrival rate should be calculated; the average travel time for a vehicle travelling from 500m away in the Sopers Lane junction was 30 seconds due to the higher approach speeds. This was determined by adding a zone in the Paramics model which covered the junction itself and then observed the average journey time from all input zones.

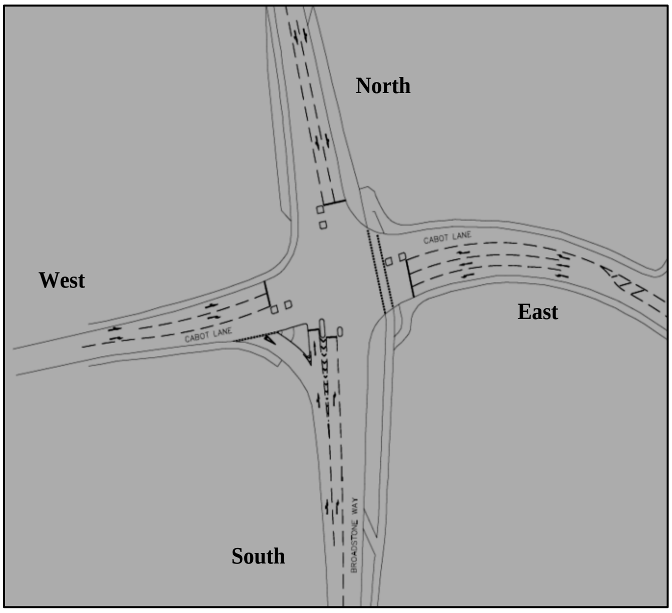

Figure 43: Cabot Lane junction layout and stage diagram, Poole (UK)

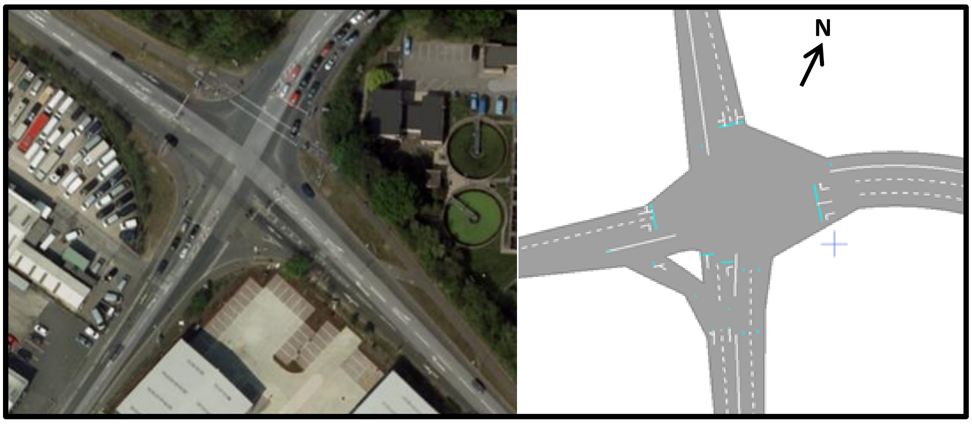

Figure 44: Cabot Lane junction layout (Paramics junction on the right) (Image from: Google Maps, 2014b)

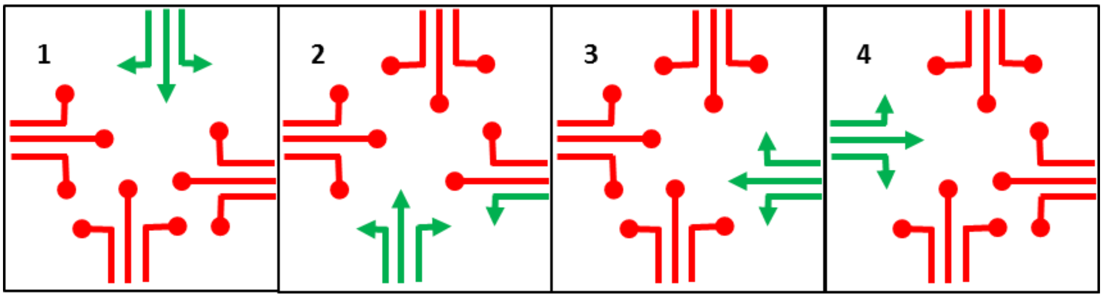

Figure 45: Cabot Lane current stage diagram for MOVA control

6.6.2 Paramics

As the Southern approach has three links before the junction, then Paramics could only see turning intention for less than 100m away (i.e. the nearest two links to the junction). Therefore an assumption was made for all vehicles that were on the third link at that moment in time - any vehicle which could be detected would be split evenly into the three possible turning movements (i.e. one third of a vehicle was assigned to the left, straight and right turning movements). This assumption was made because the junction would have been heavily weighted towards the other three approach roads as they could see turning intention over 500m away and the Southern approach would only be able to see 100m away.

A simulated environment enables a fair comparison of the two control algorithms because the demand profile can be accurately replicated. However, as there are stochastic variations in the release of vehicles, all demand scenarios will be simulated five times so that the average statistics can be fairly compared.

6.6.3 Demand Scenario

The demand scenario for Cabot Lane was provided by Siemens and represented a typical weekday, morning rush hour demand rate; the data is shown in Table 23 and Figure 46. Similar to the case study in Section 6.5, the demand rate will be varied from 20% to 100% as observations from the junction already suggest that it is oversaturated.

Table 23: Demand matrix for Cabot Lane for the two hour period

		Destination			
		West	**South**	**East**	**North**
Origin	**West**	-	150	300	100
	South	50	-	100	800
	East	300	100	-	100
	North	75	800	75	-

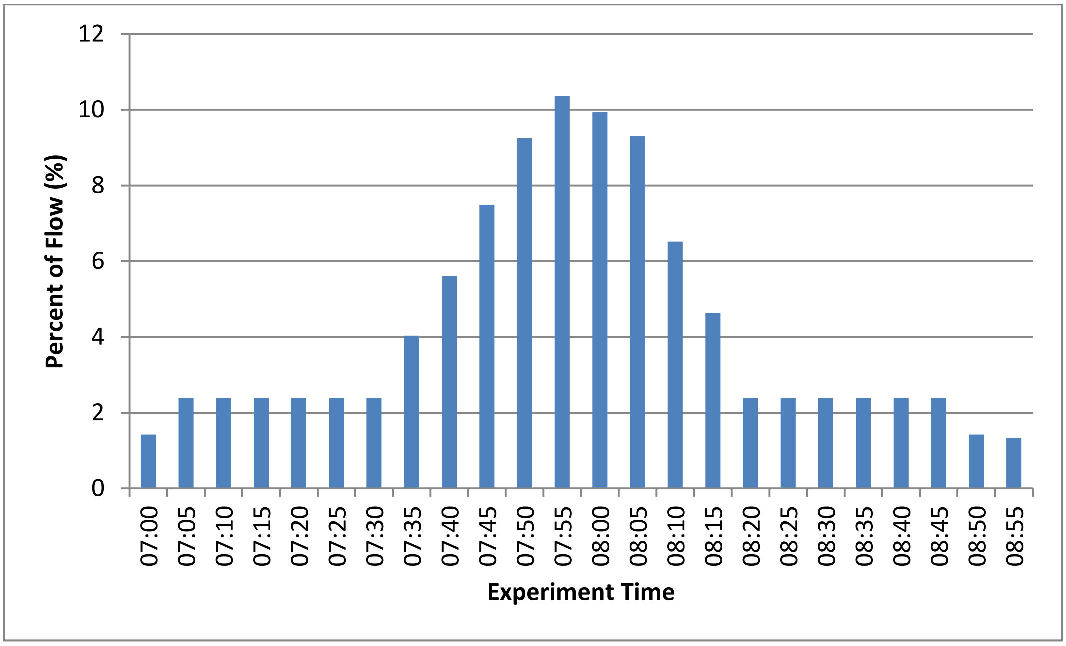

Figure 46: Demand profile for Cabot Lane

In order to calculate the average delay for Cabot Lane junction then the free flow journey times must be determined for each of the origin destination pairs. The zone numbers are numbered from the Western arm in an anticlockwise direction. The free flow journey times in Table 24 are determined from when each traffic movement receives a green light prior to arrival at the junction with no opposing traffic. As the demand matrix can be observed in Table 23, then an overall average free flow journey time can be calculated through a weighting method; by multiplying the demand for each movement by the corresponding free flow journey time and dividing by the total demand. Therefore the average free flow journey time for Cabot Lane junction is 56 seconds; this value will be subtracted from the mean journey time to represent the mean delay for each simulated scenario.

Table 24: Free flow journey time for each origin destination pair

Free Flow Journey Time (seconds)		Destination Zone			
		1	2	3	4
Origin Zone	1	-	68	81	68
	2	64	-	61	44
	3	80	65	-	65
	4	61	41	61	-

6.6.4 Constraints

All of the constraints placed on MOVA were also placed on DEMA control apart from stage order. The minimum green time was set to seven seconds per stage, and the minimum inter-green period was set at five seconds (three seconds of amber after a stage and two seconds before the next). The maximum stage lengths used in DEMA were taken directly from the MOVA configuration as seen in Table 25. The discharge rate at the junction was dependent on whether the phase was opposed or unopposed, using recommended values of 1900 pcu/hour for straight ahead traffic and 1650 pcu/hour for turning unopposed traffic (DfT, 2006).

Table 25: Maximum stage lengths for Cabot Lane

	Max Length (Minutes : Seconds)			
	Stage 1	**Stage 2**	**Stage 3**	**Stage 4**
Morning	1:13	1:11	0:37	0:32
Afternoon	0:47	0:35	0:22	0:32
Evening	0:52	0:24	0:25	0:24

6.6.5 Results

Figure 47, Figure 48, Figure 49 and Table 26 compares the performance of DEMA against the existing control strategy of MOVA. Under every demand scenario there is a considerable reduction in delay by using DEMA over MOVA. There is a substantial reduction in mean delay from 20% demand to 80%; during which, there were not large queues of traffic on every approach arm of the junction. However from observations during the experiments at 100% demand, all arms of the junction were completely congested under both control algorithms. This means that it is very difficult to achieve a sizeable performance improvement within the system because the demand is so high. At 100% demand, there is less opportunity to skip stages because all stages need to be released. This is demonstrated in the substantial drop of performance difference between 80% demand and 100% demand, as can be observed in Table 27.

DEMA produces a lower mean journey time through the junction but also provides a more reliable journey time as the standard deviation and maximum journey times are lower than MOVA simulations. This means that DEMA is fairer to vehicles and does not constrict the minor arms of the junction in an attempt to reduce the mean delay (i.e. the minor roads are given equal priority over the major roads, but this could be altered if desirable by the network operator). This can also be confirmed by lower maximum journey times across all levels of demand, hence minor roads are not being held back. If the network operator’s aim was to reduce ‘rat runs’ through a network, then these results suggest that the minor roads could be held back even more using DEMA (this is true if the maximum journey time during MOVA control is acceptable).

An independent sample T-test was carried out for each demand scenario to determine if there is a statistical significance between the means of the two control algorithms, with a confidence interval of 95%. For demand values 40 - 80%, the p-value was less than 0.01 which suggests a very significant difference in mean delay and journey time of each control algorithm. However the p-value in the 20% and 100% demand scenario were 0.27 and 0.06 respectively; which means that they are not statistically significant.

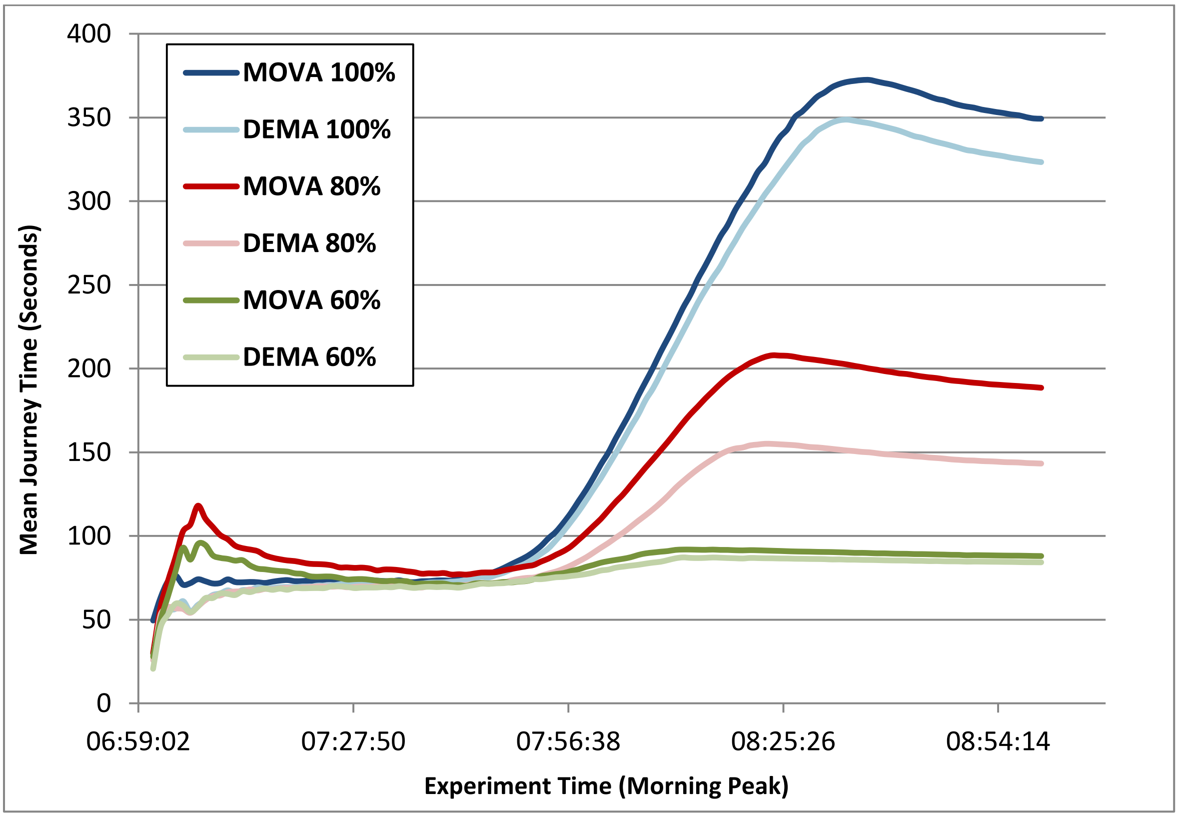

Figure 47: Mean journey time for the morning peak under varying demand scenarios (from 60% demand to 100% demand)

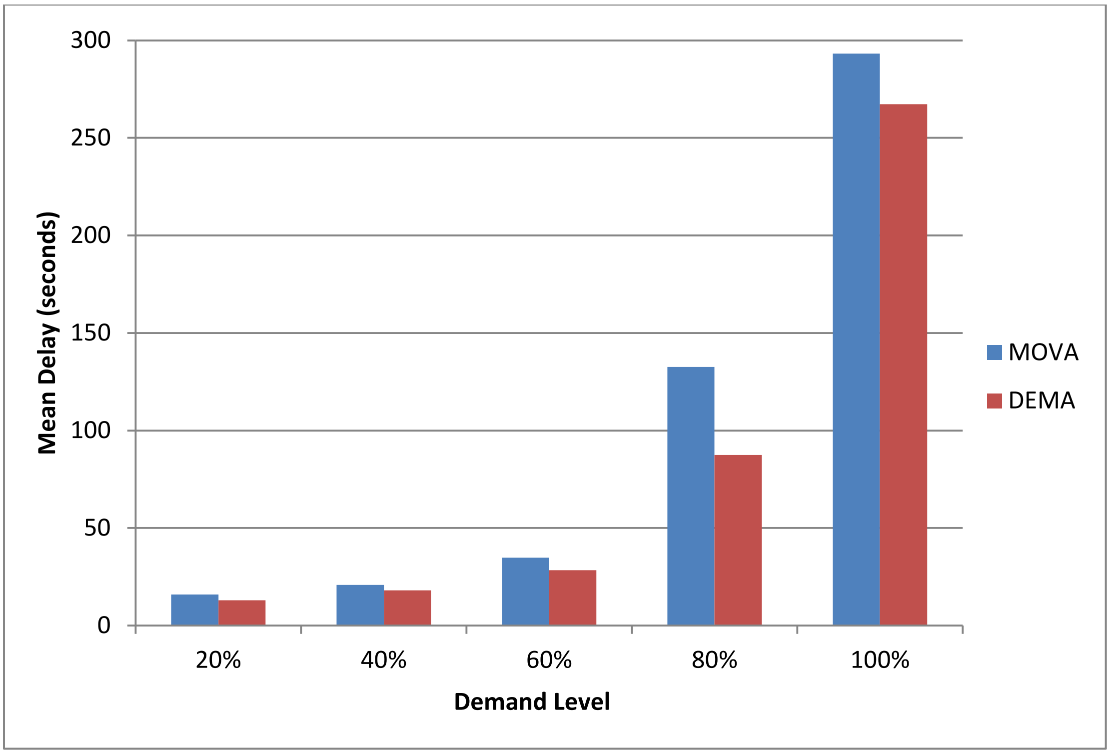

Figure 48: Comparison of average delay for MOVA and DEMA control at Cabot Lane

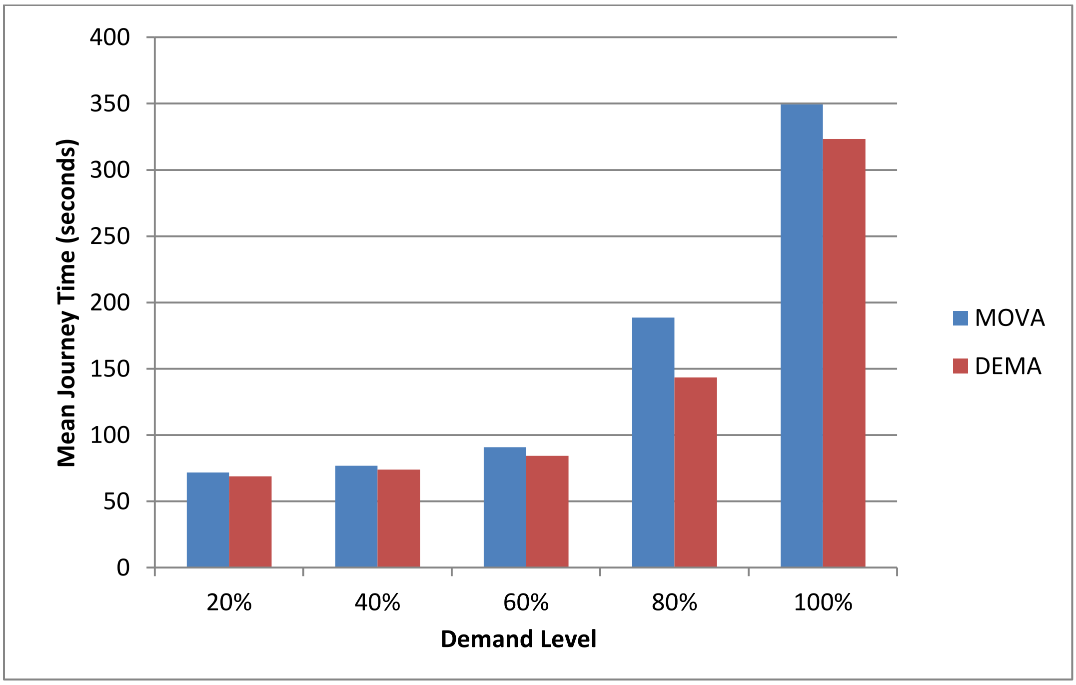

Figure 49: Comparison of average journey time for MOVA and DEMA control at Cabot Lane

Table 26: Results of different demand levels and method of controlling the junction

Control Method and Demand		Delay			Journey Time (seconds)			
		Mean Delay (sec)	Mean Speed (mph)	Mean Queue Time (sec)	Maximum	Mean	Standard Dev.	Median
MOVA	20%	15.9	35.4	10.6	268	71.9	25	67
DEMA		12.9	38.5	5.5	174	68.9	20	65
MOVA	40%	20.8	32.9	13.2	254	76.8	23	73
DEMA		18.1	35.9	8.4	190	74.1	23	69
MOVA	60%	34.8	29.1	20.8	295	90.8	36	83
DEMA		28.4	32.9	12.7	233	84.4	30	78
MOVA	80%	132.7	21.1	58.2	616	188.7	145	121
DEMA		87.4	26.9	35.5	489	143.4	100	104
MOVA	100%	293.3	19.8	78.2	1183	349.3	318	210
DEMA		267.4	20.9	72.3	1145	323.4	301	203

Table 27: Percentage improvement of DEMA over MOVA for various demand levels

Demand (%)	Percentage Reduction over MOVA (%)	
	Mean Delay	Mean Journey Time
20	18.4	4.1
40	13.1	3.5
60	18.5	7.1
80	34.1	24.0
100	8.8	7.4

6.6.6 Discussion

As noted in Section 6.4, a problem with greedy algorithms are that DEMA may never calculate a benefit in releasing the minor stages. Therefore a weighting factor is essential to ensuring that all stages would eventually become desirable. Occasionally during peak traffic the cycle time could exceed 120 seconds and last up to 175 seconds, whereas MOVA did not typically exceed 160 seconds waiting time in peak traffic. The reason for DEMA exceeding MOVA's maximum cycle time is because the weighting factor was only applied if the phase had not been released for more than 120 seconds. For example, if the decision point was at time 119 seconds since a particular phase was released, then the weighting factor would not yet be applied until the next stage was completed (which could be up to 73 seconds as explained in Section 6.6.4). If the network operator determined that the maximum waiting time needed to be less than 175 seconds, then the weighting factor could be applied sooner (for example at 100 seconds) and therefore the phase would be selected sooner.

Under low flow conditions, there is a greater benefit in knowing that vehicles are approaching from far away as the junction can 'prepare' for their arrival by setting the traffic light to green. However when the junction is totally congested and all stages need to be released, then it is unlikely that there will be much benefit in knowing that there are incoming vehicles 500 metres away from the junction. Hence this is one of the potential explanations for the considerable drop in performance at 100% demand. As a result of this, the 8.8% reduction in mean delay is more likely to be influenced by the flexibility in stage selection as opposed to the combined benefits of stage selection and improved data resolution in lower demand scenarios.

6.6.7 Oversaturation Observation

When the results of both Sopers Lane (T-junction) and Cabot Lane (crossroads) were analysed, it appeared that Cabot Lane was frequently oversaturated with queue lengths approaching the model boundaries; whereas Sopers Lane rarely was oversaturated. Both junctions were able to observe significant improvements over MOVA but Cabot Lane struggled to achieve as large a reduction in delay across all demand scenarios.

One interpretation of why this could be is that Cabot Lane was oversaturated at the 100% demand scenario whereas Sopers Lane was not. Oversaturation for a phase can be defined as:

> "*When the traffic demand exceeds the green time capacity such that a queue that exists at the beginning of the green time is not fully dissipated at the end of the green time for that movement*" (NCHRP, 2012)

In order to classify a junction as being oversaturated then two or more opposing phases must be classified as oversaturated (NCHRP, 2012). By this definition, Cabot Lane was oversaturated on the 100% demand scenario typically between 7:45am and 8:25am, whereas Sopers Lane rarely could be classified as oversaturated, only occasionally on the minor road. As both DEMA and MOVA have the same maximum stage lengths, then during oversaturated periods (when the maximum cycle time is used) the only difference between the two algorithms is DEMA's ability to freely choose the next stage. This highlights the benefits of using a flexible stage selection process over a predefined stage order.

6.6.8 Conclusion for the Case Study

This section has demonstrated that there are significant benefits to using additional data sources but it is also important to allow control systems to select any possible next stage. The results show that the novel Delay Minimisation Algorithm (DEMA) outperformed MOVA in every demand scenario at Cabot Lane (which has been expertly configured for MOVA control). The maximum reduction in mean delay was 34.1% and the minimum reduction was 8.8% under more congested scenarios. It should be noted that the 100% demand scenario did not achieve a statistically significant result, where one of the contributing factors is that the junction was oversaturated.

This study has shown the potential for improvement when using DEMA over MOVA, however all studies so far have used 'perfect data' and therefore the next section will investigate how DEMA is affected when imperfect data is provided to the control algorithm. Also this study has equipped all vehicles as data providers (this is unlikely to be the case in reality) and hence why a sensitivity analysis will compare MOVA against DEMA when there are various infiltration rates for vehicles that can provide additional data.

6.7 Sensitivity Analysis for Cabot Lane

Prior to this section, all of the results displayed for Cabot Lane, Sopers Lane and the three lane crossroads have used ‘perfect data’ to determine the best cycle plans. This is inherent of micro-simulation and therefore some variation of perfect data should be investigated because real data is rarely perfect. This also applies to the simulated results for MOVA but inductance loops are very reliable and hence the results for MOVA shall remain unaltered. This section will simulate different scenarios in order to understand how DEMA would operate using imperfect data sources and some variation in the ‘default’ parameters assumed in DEMA. The key areas which will be investigated in this section are:

1. Variation in the length of the detection zone (default was 500 metres)
2. Infiltration rate of vehicles which are equipped to provide additional data (speed and location)
3. Accuracy of location and speed data (through variation of the standard deviation)
4. Future scenarios which provide an insight to a combination of these variables

These four areas will be tested in the Cabot Lane case study as described in Section 6.6 and each scenario will be simulated at least ten times to ensure that the average results display a true reflection of the situation.

6.7.1 Length of Detection Zone

This section will investigate how detection distance affects the performance of DEMA. In order to do that, the simulation was altered so that vehicles were not detected until they were within a specified distance of the junction (in 50 metres increments). In a real junction, the cost of installing cabling to 500 metres away from the junction would be high and therefore it would be ideal to determine the shortest distance possible which can deliver the best performance. The demand level was set at 100% for Cabot Lane junction and MOVA was tested again (hence the subtle difference to MOVA results in Section 6.6.5).

Figure 50, Figure 51 and Table 28 display how the length of detection zone varies with distance. There is not a statistically significant difference in distances between any of the simulations for 200 to 500 metres even though the mean delay varies from 254 seconds to 268 seconds. The critical distance is at 150 metres when the average journey time becomes equivalent to MOVA and also the reliability of journey time decreases. Since the median and standard deviation of journey time increases when there is less data, then a fair conclusion is that DEMA struggles to know which stage to prioritise as it does not know how long the queue lengths are.

DEMA has been designed with the assumption that it will know the stationary queue length; but during the 50 metres detection distance experiment, the calculation will begin to break down in congested scenarios as all arms are likely to be queued in excess of 50 metres (and often much further than that). In congested scenarios with very short detection lengths, DEMA will not be able to determine any benefit to releasing one stage over another and therefore DEMA will inevitably act like a fixed time controller using the maximum stage lengths. The important factor in this situation is the weighting factor to ensure that DEMA will forcibly release all phases within the specified limit (120 seconds).

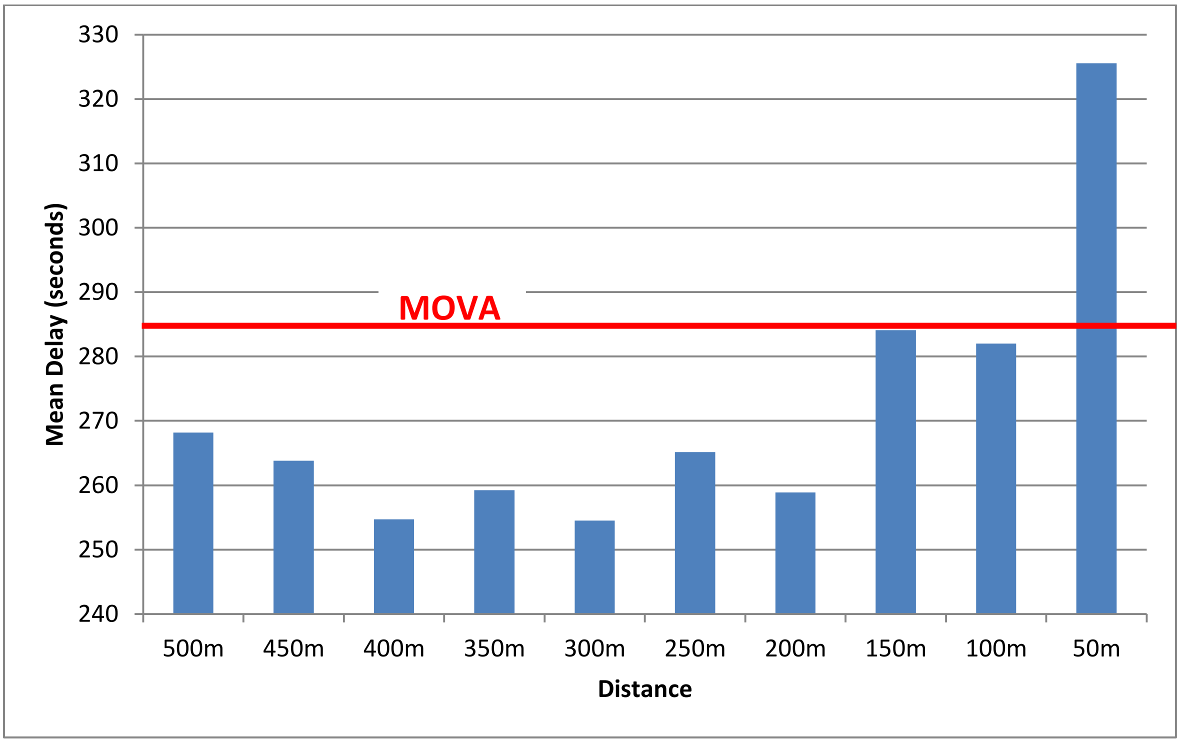

Figure 50: Comparison of mean delay for a range of detection distances against MOVA

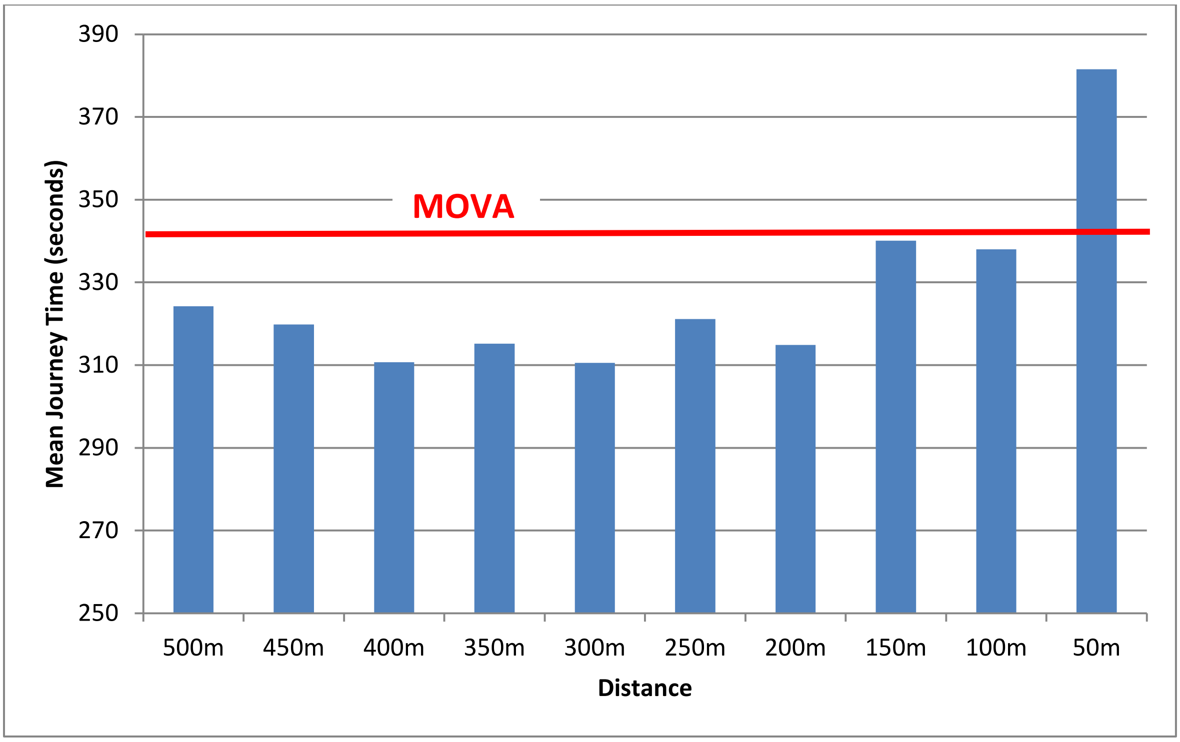

Figure 51: Comparison of mean journey times for a range of detection distance against MOVA

Table 28: Results of different detection distances compared against MOVA

Detection Distance for DEMA	Delay			Journey Time (seconds)			
	Mean Delay (sec)	Mean Speed (mph)	Mean Queue Time (sec)	Maximum	Mean	Standard Dev.	Median
MOVA	285.6	19.5	75.7	1189	341.6	299.8	196.8
500m	268.2	21.1	72.8	1209	324.2	309.0	194.6
450m	263.8	21.0	73.3	1155	319.8	299.7	190.9
400m	254.7	20.9	75.0	1025	310.7	269.6	198.3
350m	259.2	21.0	70.2	1036	315.2	276.2	200.6
300m	254.5	20.9	72.8	1030	310.5	270.1	202.4
250m	265.1	20.3	72.7	1050	321.1	281.7	199.3
200m	258.9	20.2	71.7	1081	314.9	285.6	182.6
150m	284.1	19.6	71.9	1152	340.1	304.0	209.8
100m	282.0	18.9	74.3	1125	338.0	301.4	211.7
50m	325.5	18.4	64.5	1493	381.5	405.6	169.8

Figure 52 displays a box plot of the range in mean delay values for all ten simulations for each of the distances. An interesting point to observe from this graph is how little MOVA varies in comparison with all of the DEMA scenarios, however the mean delay is statistically, significantly lower in DEMA for all scenarios between 200 and 500 metres detection distance (see Table 29). At 50 metres, DEMA does not operate favourably and has wide ranging effects on mean delay.

In conclusion for the results presented in this section, a minimum detection distance of 200 metres would be required as this scenario has a statistically significant reduction in mean delay and journey time. Importantly, there is no additional improvement in providing a detection distance greater than 200 metres as the greater detection distance scenarios present similar results to 200 metres. Therefore if there is an additional cost to detecting vehicles further away then it should not be installed as there is no performance benefit from the expenditure.

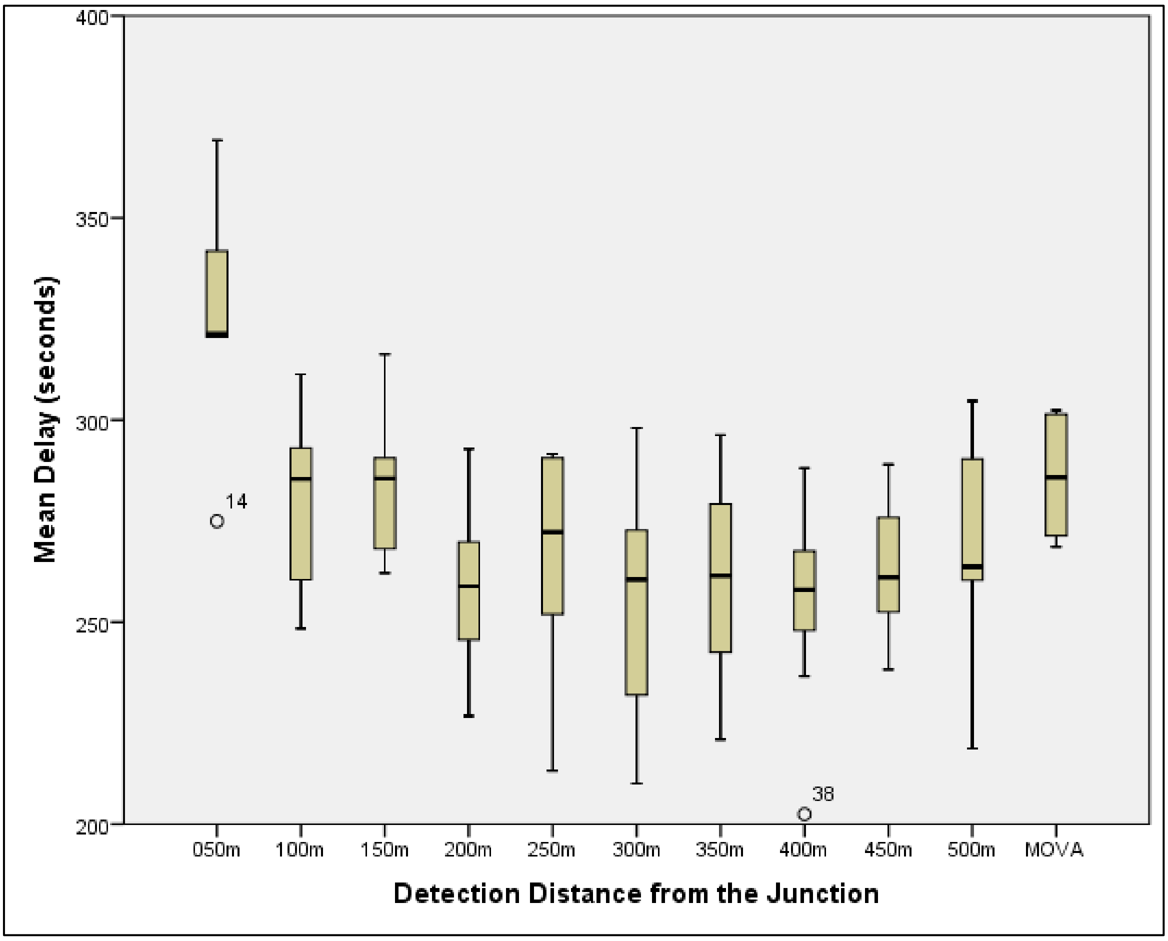

Figure 52: Box plot showing the range in results for a range of detection distances

Table 29: P-values in comparison for MOVA and DEMA at various detection distances

	P-values	
	Mean Delay	Mean Journey Time
500m	0.024	0.024
450m	0.004	0.004
400m	0.008	0.008
350m	0.001	0.001
300m	0.003	0.003
250m	0.040	0.040
200m	0.002	0.002
150m	0.110	0.110
100m	0.501	0.501
50m	0.007	0.007

6.7.2 Infiltration Rate

It is important to recognise that all vehicles cannot currently provide additional data sources and therefore an infiltration rate needs to be considered before evaluating if DEMA can outperform MOVA on a real junction. This section will vary the percentage of vehicles which can transmit additional data sources (location and speed), which helps to develop an understanding of when it is feasible to introduce DEMA in place of MOVA. Without knowing the effects of a low infiltration rate, then it is not possible to carry out a real world trial of DEMA.

As this research is focused on additional data sources, inductive loops are still used in the simulation to ensure that DEMA has some data available to it (as described in Section 6.3.5). The inductive loops are located at 50 and 100 metres from the junction on all arms (same as MOVA). This means that it is possible to simulate no additional data to compare DEMA against MOVA (otherwise DEMA would represent a fixed time system with no live data).

Figure 53, Figure 54 and Table 30 can be used to observe that DEMA outperforms MOVA when there are 30% to 100% of vehicles transmitting their location and speed. However in terms of a statistically significant difference in the two means, then the required infiltration rate is 100% to ensure it outperforms MOVA (see Table 31). The maximum journey time for DEMA outputs are worse than MOVA for every scenario which suggests that DEMA is less fair to all drivers and this is supported by the fact that the standard deviation is typically higher than MOVA's (which means that there are more drivers being held back for the benefit of others).

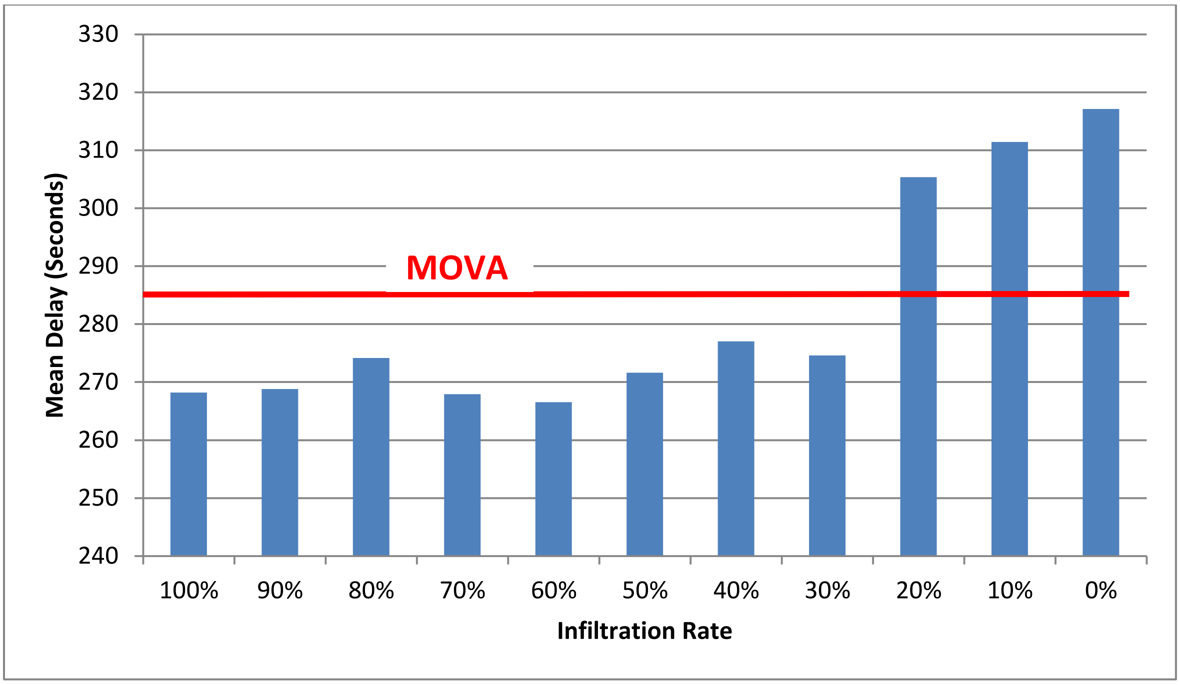

Figure 53: Comparison of mean delay for a range of infiltration rates against MOVA

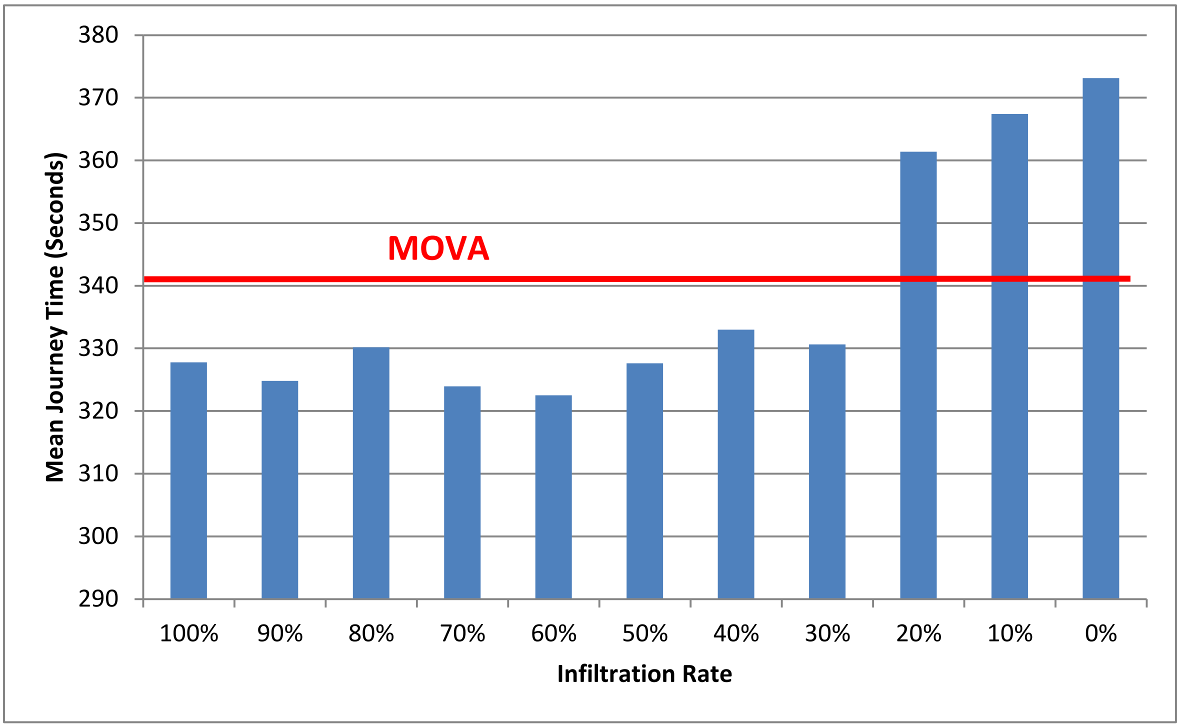

Figure 54: Comparison of mean journey times for a range of infiltration rates against MOVA

Table 30: Results of different infiltration rates compared against MOVA

Infiltration Rate for DEMA Detection	Delay			Journey Time (seconds)			
	Mean Delay (sec)	Mean Speed (mph)	Mean Queue Time (sec)	Maximum	Mean	Standard Dev.	Median
MOVA	285.6	19.5	75.7	1189	341.6	299.8	196.8
100%	271.8	20.6	75.6	1208	327.8	303.1	205.1
90%	268.8	21.0	73.2	1194	324.8	311.0	187.4
80%	274.2	20.8	73.0	1237	330.2	327.5	191.5
70%	267.9	20.8	71.2	1262	323.9	317.0	199.2
60%	266.5	20.9	71.0	1234	322.5	312.3	195.7
50%	271.6	20.4	71.7	1224	327.6	317.3	199.1
40%	277.0	20.2	69.8	1302	333.0	334.8	198.7
30%	274.6	19.9	71.9	1271	330.6	316.2	209.7
20%	305.4	19.4	72.4	1265	361.4	336.2	233.7
10%	311.4	19.1	73.5	1263	367.4	345.8	210.5
0%	317.1	18.9	65.1	1363	373.1	386.7	172.2

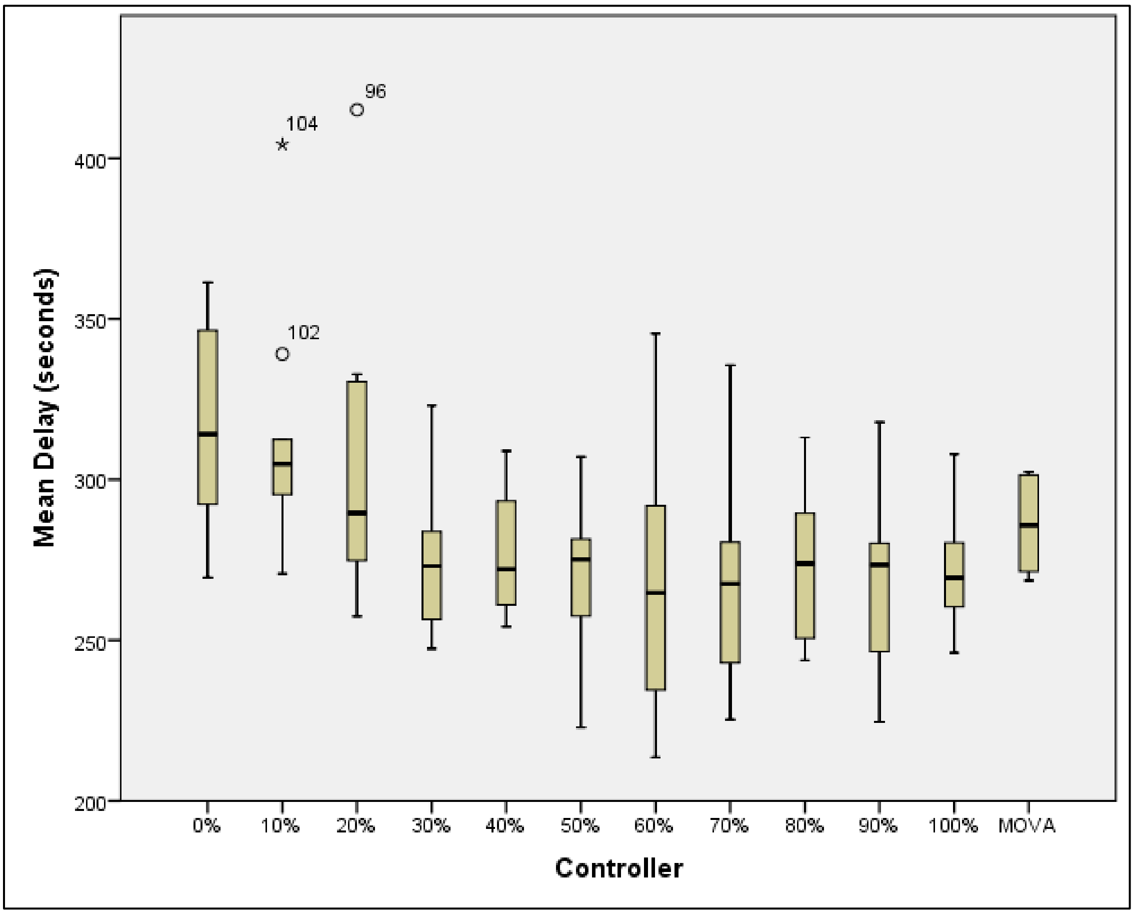

Figure 55: Box plot showing the mean delay for various infiltration rates

Table 31: P-values of each infiltration rate compared against MOVA

	P-values	
	Mean Delay	**Mean Journey Time**
100%	0.024	0.024
90%	0.095	0.095
80%	0.203	0.203
70%	0.146	0.146
60%	0.168	0.168
50%	0.134	0.134
40%	0.282	0.282
30%	0.205	0.205
20%	0.227	0.227
10%	0.060	0.060
0%	0.007	0.007

The results shown in Figure 55 and Table 31 demonstrate that when the infiltration rate is reduced then the reliability of the performance of DEMA reduces. The box plot highlights that the mean delay is considerably lower than MOVA from 30% to 100% infiltration, but there is a lot more variation in the potential performance.

These results show that it is important to achieve a high infiltration rate to attain the full benefits of DEMA or else the reliability of journey time and fairness for drivers appears to deteriorate. It should be noted that within the next 10 – 15 years, vehicles are expected to become much more connected to the internet and their surrounding environment. As stated in Section 2.4.1, it is anticipated that 70% of vehicles will be connected to the internet by 2027 (ABI research, 2013b) which provides an invaluable method of sharing information with other road users and the network operators. Also over 50% of the UK's population have smartphones now (NewMedia, 2013) which are capable of sharing a road user's location and speed. Hence why this research provides a valuable insight to how data can be used in the near future for traffic control purposes.

Further investigations are required to determine the real world potential of DEMA compared to MOVA as this section has demonstrated how a reduction of mean delay can occur with only 30% infiltration, but with considerably more unreliable journey times. The accuracy of data received needs to be considered but also one potential reason for DEMA's unreliable journey time in this experiment is that DEMA obtains too much irrelevant information as the detection distance is 500 metres. Section 6.7.1 has highlighted that only a 200m detection distance can achieve the same performance level as a 500m detection zone. Therefore further studies are required to determine how accurate the data needs to be but also how a combination of variables will affect DEMA compared to MOVA.

6.7.3 Accuracy of Location and Speed Data

This section will investigate what effect the accuracy of location and speed data has on the performance on DEMA on the Cabot Lane junction. As previously explained, this study is carried out in a simulated environment which provides perfect data whereas in the real world, it would be very unlikely to achieve perfect location and speed data through GPS or V2X communication devices. Waterson and Box (2010) investigated what effect location accuracy had on their traffic control algorithm, where they assumed a normal distribution with a pre-defined standard deviation to reduce the accuracy of the input data before using it in the control algorithm. Waterson and Box (2010) defined the following standard deviations:

- 1 - 2m is representative of very good differential GPS in open areas
- 4 - 8m is representative of accuracies from current standard GPS units
- 16 - 32m is representative of GPS systems operating in urban canyon environments

However, as speed is also an important factor for calculating delay in the DEMA algorithm (it is used to classify vehicles as part of the queue) then this section will also vary the speed by standard deviations of 1, 2, 3 and 4 miles per hour.

In order to alter the perfect data by a standard deviation, an equation is required to randomly generate a new location and speed. The Box-Muller Transform (Box and Muller, 1958) can be used to randomly select a value between zero and one which would represent a normal distribution:

$$X = \sqrt{-2\ln(U)}\,.\cos(2\pi V)$$
$$Y = \sqrt{-2\ln(U)}\,.\sin(2\pi V)$$

Where U and V are uniformly distributed between zero and one (i.e. they are random numbers between zero and one). Then to get the random Gaussian values (A, B) which fits on the normal distribution with mean (μ) and standard deviation (σ). Where A and B are independent variables:

$$A = \mu + \sigma X$$
$$B = \mu + \sigma Y$$

The perfect data which is generated from Paramics can be used as the mean value (μ) and the standard deviation will be constant throughout each experiment scenario.

Figure 56, Figure 57 and Table 33 show the results of various standard deviation experiments compared against MOVA. It is clear that an accurate speed reading is very important for DEMA to operate correctly because a standard deviation of 1 mph increases the average delay by 33 seconds (approximately a 9% increase in total delay). This highlights that speed data has a big impact on determining the length of the stationary queue and when there is less than perfect data then DEMA cannot estimate the queue length sufficiently. It should be noted that the speed limit on the approach roads are 50 mph but the overall average speed is only 20 mph. When there are low speeds involved then this large standard deviation has a significant impact on the range of potential speeds, see Figure 58.

The following example demonstrates the variation:

Mean speed = 10 mph and Standard deviation = 4 mph

- 38.2% of values will vary from 8 – 12 mph
- 30% of values will vary from 6 – 8 and 12 - 14 mph
- 18.4% of values will vary from 4 – 6 and 14 – 16 mph
- 8.8% of values will vary from 2 – 4 and 16 - 18 mph
- 3.4% of values will vary from 0 – 2 and 18 – 20 mph

This variation highlights how much the speed varies when using a standard deviation as high as 4 mph. A vehicle travelling 5 mph has approximately a 30% chance of being classified as part of the queue when it should not be.

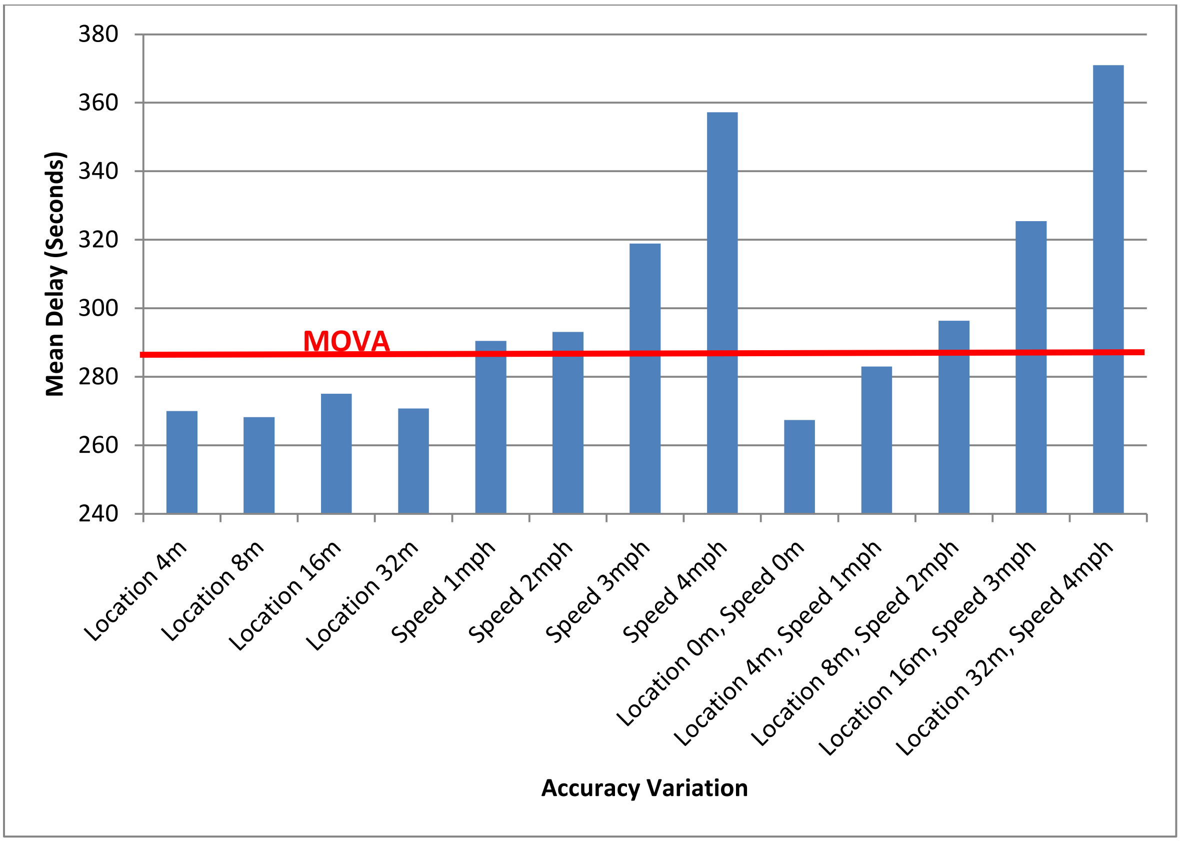

Figure 56: A comparison of mean delay for MOVA against varying standard deviations of both vehicle location and speed

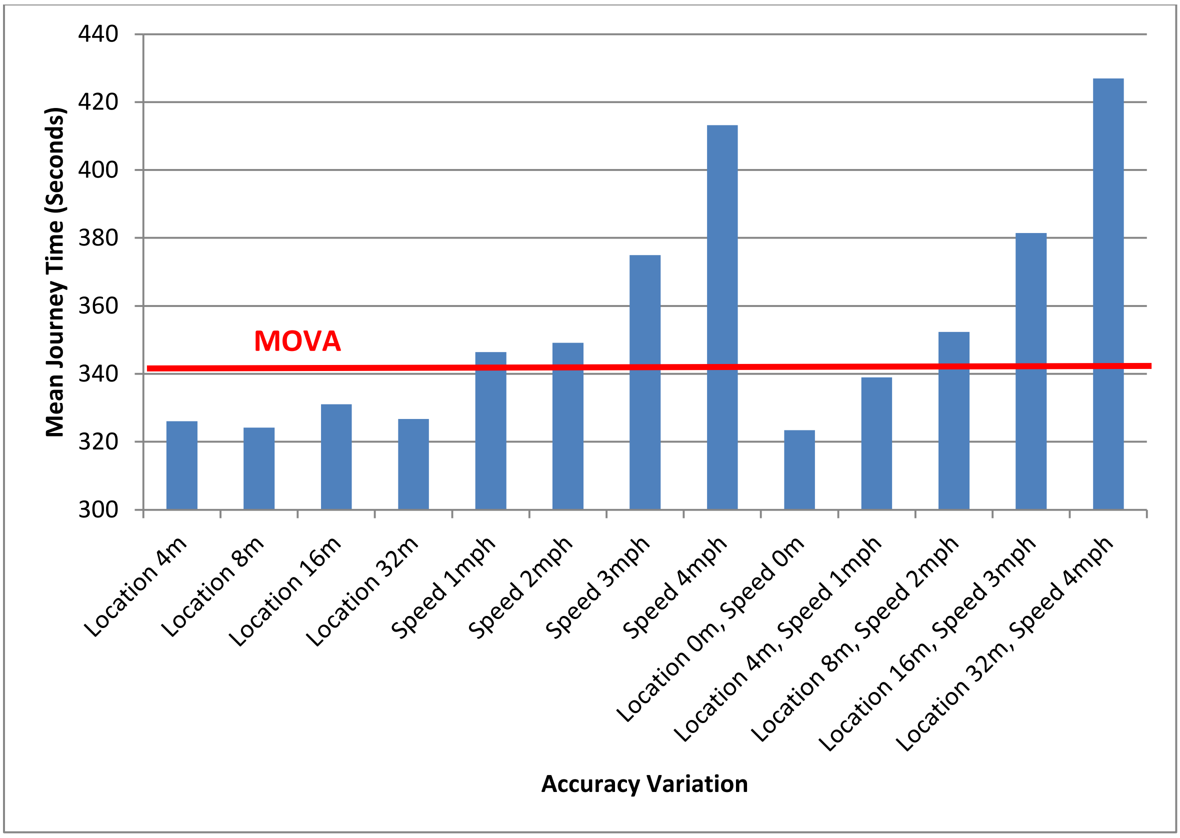

Figure 57: A comparison of mean journey time for MOVA against varying standard deviations of both vehicle location and speed

Table 32: Results of different standard deviations for location and speed data compared against MOVA

Standard Deviation (metres, miles per hour)	Delay			Journey Time (seconds)			
	Mean Delay (sec)	Mean Speed (mph)	Mean Queue Time (sec)	Max.	Mean	Standard Dev.	Median
MOVA	285.6	19.5	75.7	1189	341.6	299.8	196.8
Location 4m	270.0	20.9	75.8	1161	326.0	300.1	202.5
Location 8m	268.2	21.1	73.7	1193	324.2	313.1	190.7
Location 16m	275.0	20.8	76.3	1130	331.0	301.3	206.0
Location 32m	270.7	20.9	73.1	1207	326.7	322.2	181.6
Speed 1mph	290.4	20.6	72.6	1353	346.4	364.3	178.4
Speed 2mph	293.1	20.8	74.8	1301	349.1	354.3	180.4
Speed 3mph	318.9	20.4	80.8	1341	374.9	385.0	173.1
Speed 4mph	357.2	20.2	85.4	1529	413.2	423.7	225.3
Location 4m, Speed 1mph	283.0	20.6	71.5	1290	339.0	347.6	189.3
Location 8m, Speed 2mph	296.4	20.6	75.8	1286	352.4	358.4	175.7
Location 16m, Speed 3mph	325.4	20.5	80.5	1424	381.4	396.5	181.3
Location 32m, Speed 4mph	371.0	19.9	90.2	1714	427.0	449.5	244.6

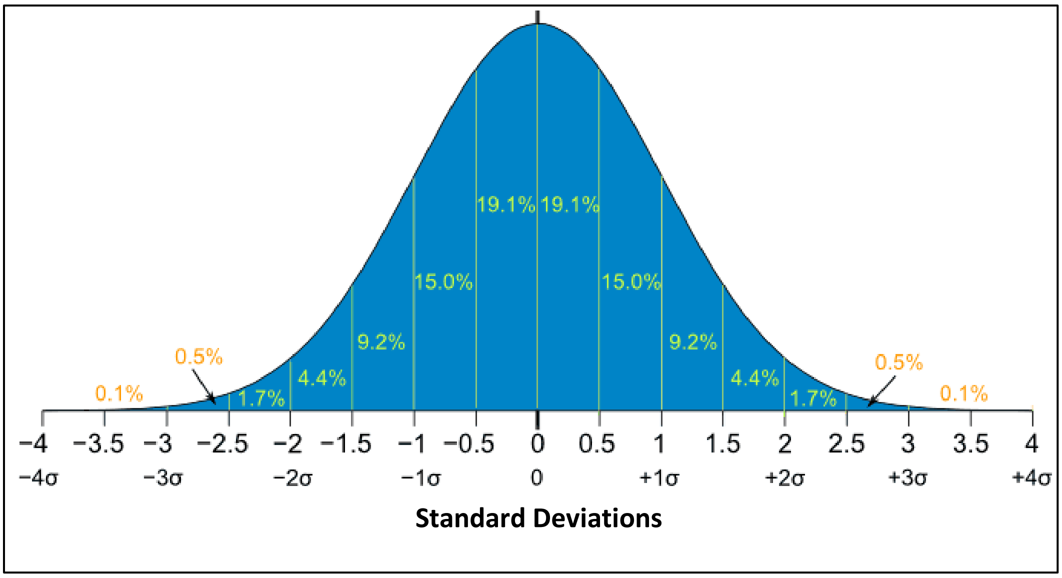

Figure 58: Percentage of variation through standard deviation (after Pierce, 2014)

Location data is significantly less affected by imperfect data in comparison to speed data. The standard deviations of 4 – 32 metres have little effect on how DEMA performs. Table 33 and Figure 59 highlight how none of the permutations are statistically significantly better than MOVA (however some of the scenarios are statistically significantly worse than MOVA).

Table 33: P-values in comparison against MOVA for various standard deviations

Standard Deviation (metres, miles per hour)	P-values	
	Mean Delay	Mean Journey Time
Location 4m	0.127	0.127
Location 8m	0.078	0.078
Location 16m	0.435	0.435
Location 32m	0.214	0.214
Speed 1mph	0.700	0.700
Speed 2mph	0.363	0.363
Speed 3mph	0.005	0.005
Speed 4mph	0.000	0.000
Location 0m, Speed 0m	0.060	0.060
Location 4m, Speed 1mph	0.711	0.711
Location 8m, Speed 2mph	0.253	0.253
Location 16m, Speed 3mph	0.071	0.071
Location 32m, Speed 4mph	0.000	0.000

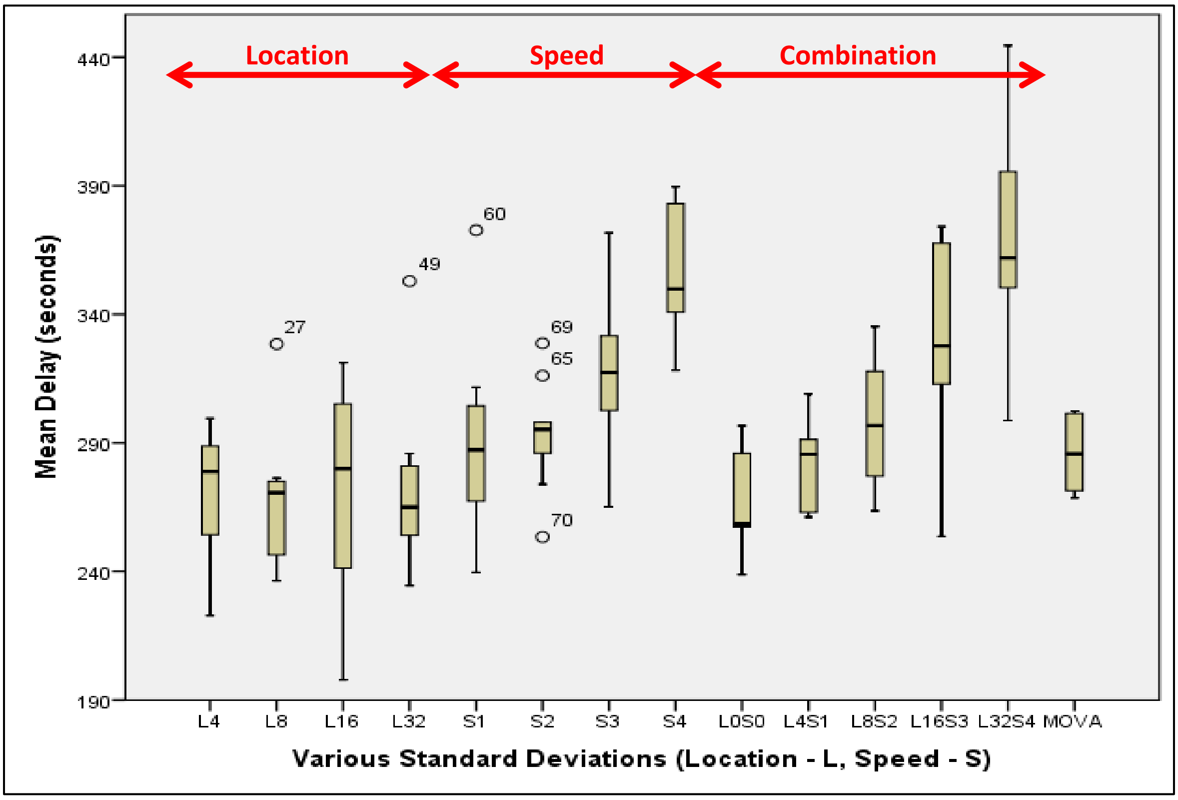

Figure 59: Box plot showing the variation in standard deviations compared against MOVA

This experiment has highlighted the importance of having fairly accurate speed data or else the classification of queue length cannot operate efficiently within DEMA. Whereas, imperfect location has little impact on the performance of the DEMA algorithm, which strongly suggests it is not used as much for classifying vehicles as part of the 'stationary' queue. The sensitivity analysis so far has shown that reducing the quality of data does have an impact on DEMA's performance but it is important to gain an understanding of how DEMA can operate under a combination of detection distances, infiltration rates and accuracy of data.

6.7.4 Combination of Variables

This section will investigate how DEMA performs in a number of scenarios which range in detection distances, infiltration rates and accuracy of location and speed data. It is not possible to simulate all of the possible combinations and therefore this section will demonstrate a small sample of plausible future scenarios where some vehicles are equipped to provide additional data, of varying quality and detection distances.

There are three scenarios tested in this section:

1. 200 metre detection distance (DD), varying infiltration (I)
2. 400 metre detection distance, varying infiltration
3. 200 metre detection distance, 4 metres location (L) and 1 miles per hour speed (S) standard deviation, varying infiltration

Figure 60, Figure 61 and Table 34 display the results from the three difference scenarios. Scenario one produces surprising results where 50% infiltration produces worse results than 20% infiltration (it should be noted that all of these simulations were run ten times). However, Figure 62 shows how there are more variance in the 20% scenario even though it achieves a lower mean delay and journey time (the results do not have statistically significant differences in means). Scenario two produces anticipated results when comparing the 20% and 50% infiltration rates, but it should be noted that both the 20% and 50% scenarios are worse than when the detection distance is only 200m.

The third scenario (where variation of location and speed accuracy were introduced) produced expected results that show a loss in performance as infiltration rate is reduced. However, it is important to highlight the significant improvement in performance compared to Section 6.7.3 where varying the speed accuracy had large reductions in performance. When imperfect data is used over a shorter detection distance of 200m (compared to 500m previously), then DEMA appears to be able to outperform MOVA. Also, unlike any of the P-values produced in Table 33 (where various accuracies were tested), there are statistically significant differences in means between DEMA and MOVA, as can be observed in Table 35. When only 50% of vehicles provide additional data, a detection distance of 200m and imperfect location and speed data, DEMA can still extract a significant improvement in average delay, with a reduction of 5.2%; and if 75% of vehicles provide additional data then a reduction of 8.0% can be achieved.

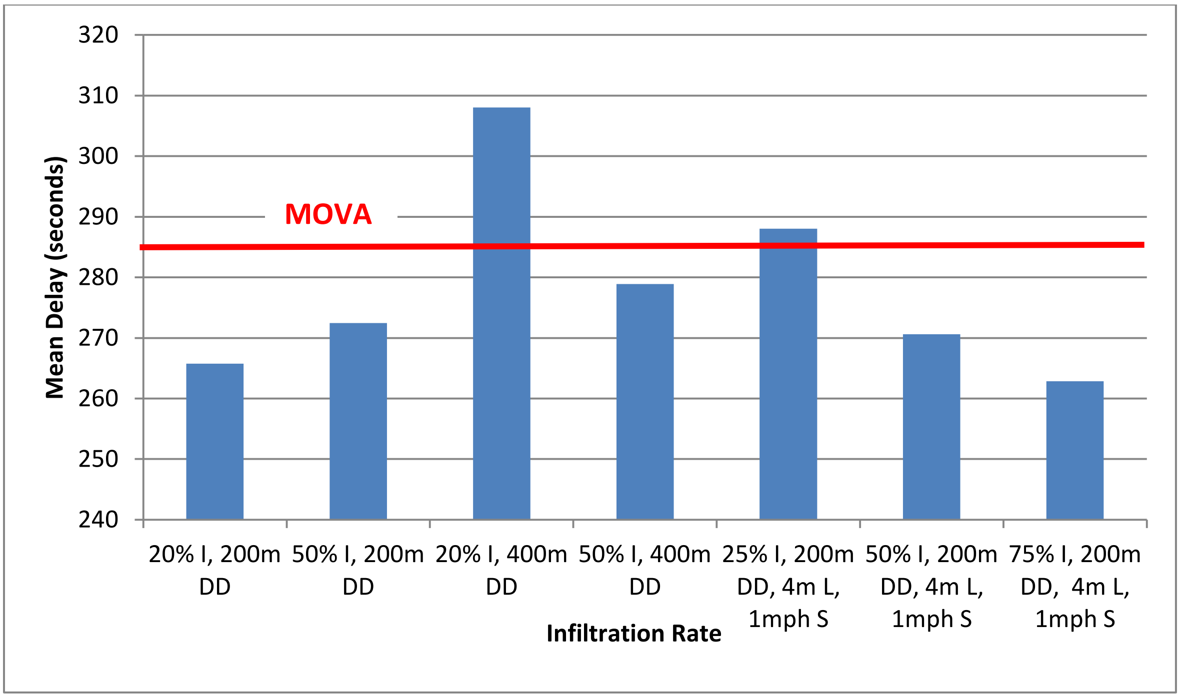

Figure 60: A comparison of mean delay for MOVA against combinations of variables

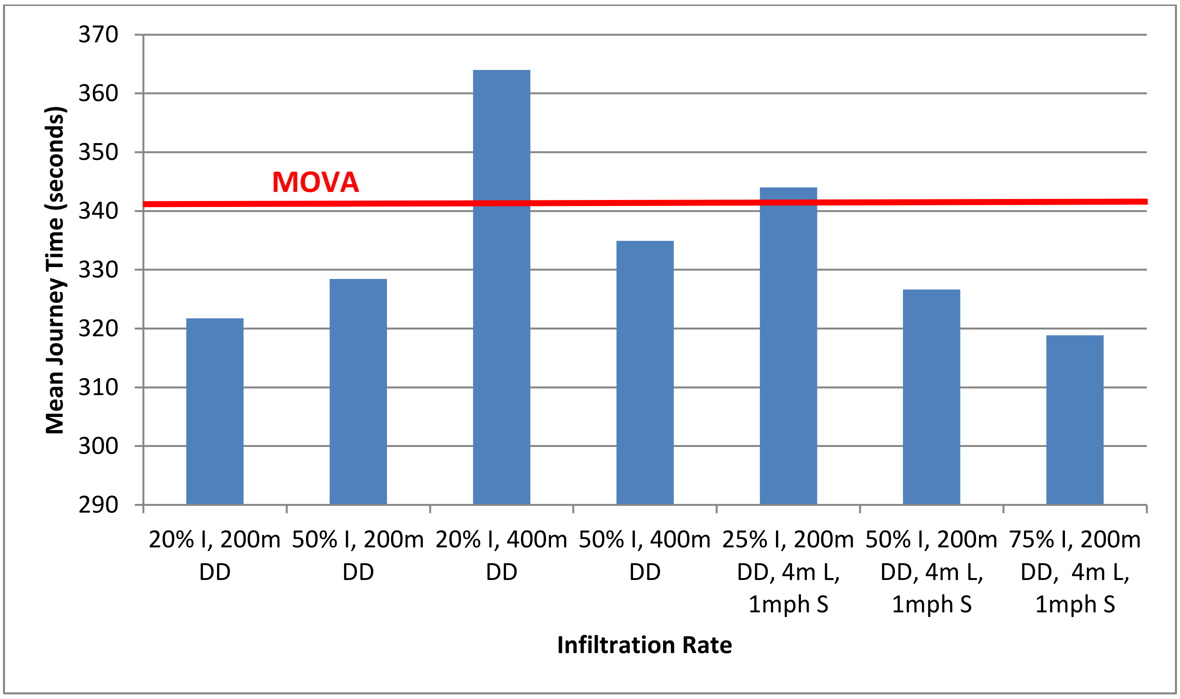

Figure 61: A comparison of mean journey time for MOVA against combinations of variables

Table 34: Results of combinations of variables compared against MOVA

Combinations	Delay			Journey Time (seconds)			
	Mean Delay (sec)	Mean Speed (mph)	Mean Queue Time (sec)	Max.	Mean	Standard Dev.	Median
MOVA	285.6	19.5	75.7	1189	341.6	299.8	196.8
20% Infiltration, 200m Detection Distance	265.7	19.7	58.7	1133	321.7	317.7	163.5
50% Infiltration, 200m Detection Distance	272.4	19.6	67.5	1070	328.4	298.4	193.1
20% Infiltration, 400m Detection Distance	308.0	19.6	72.5	1246	364.0	337.9	221.1
50% Infiltration, 400m Detection Distance	278.9	20.5	72.9	1236	334.9	309.9	212.5
25% Infiltration, 200m Detection Distance, 4m Location, 1mph Speed	288.0	19.3	63.0	1149	344.0	327.9	181.9
50% Infiltration, 200m Detection Distance, 4m Location, 1mph Speed	270.6	19.8	64.8	1119	326.6	304.1	189.4
75% Infiltration, 200m Detection Distance, 4m Location, 1mph Speed	262.8	19.9	69.9	1097	318.8	284.0	198.9

Table 35: P-values in comparison against MOVA for combinations of variables

Combinations	P-values	
	Mean Delay	Mean Journey Time
20% Infiltration, 200m Detection Distance	0.042	0.042
50% Infiltration, 200m Detection Distance	0.179	0.179
20% Infiltration, 400m Detection Distance	0.113	0.113
50% Infiltration, 400m Detection Distance	0.561	0.561
25% Infiltration, 200m Detection Distance, 4m Location, 1mph Speed	0.758	0.758
50% Infiltration, 200m Detection Distance, 4m Location, 1mph Speed	0.044	0.044
75% Infiltration, 200m Detection Distance, 4m Location, 1mph Speed	0.026	0.026

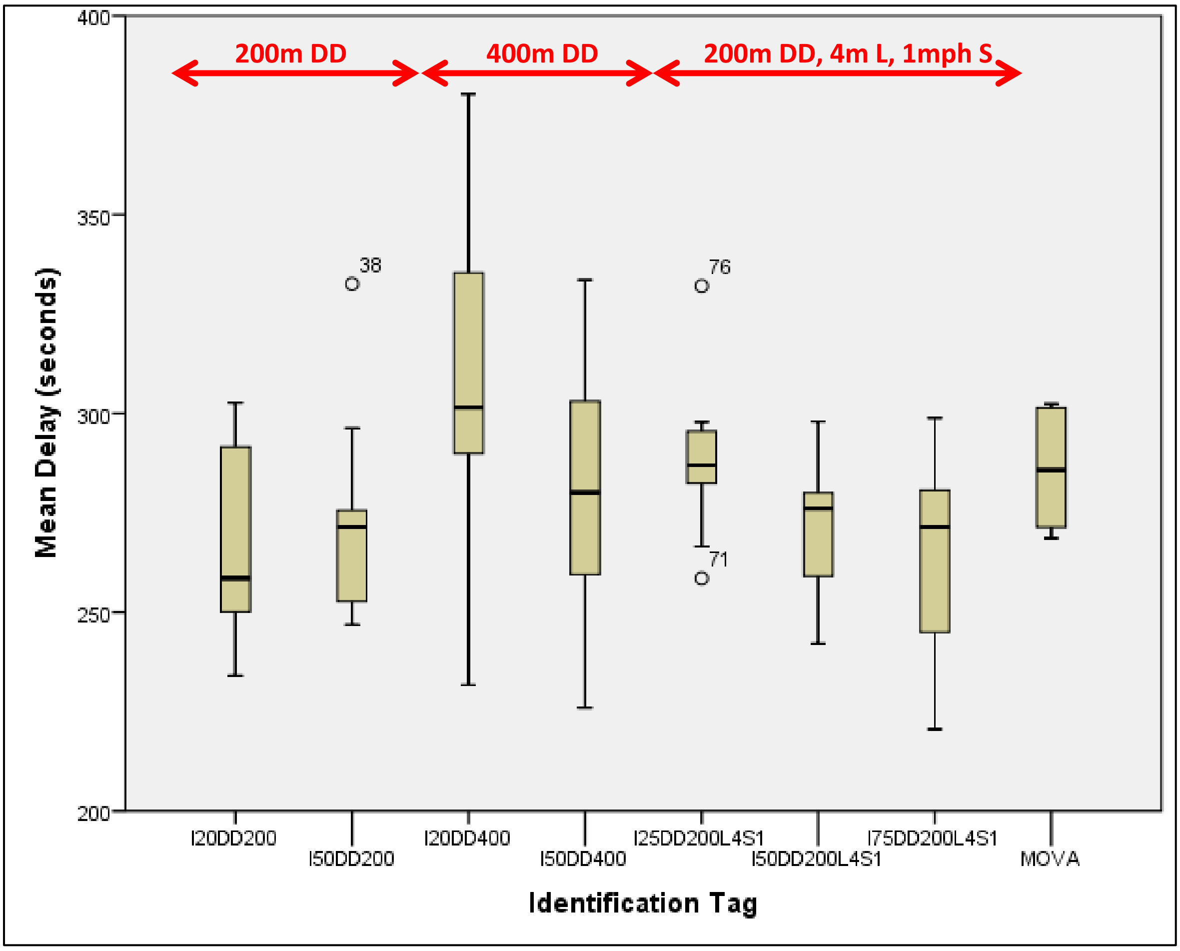

Figure 62: Box plot showing the combination of variables compared against MOVA

Although this section only provided a sample of the possible combinations, some interesting results were produced. For example, Section 6.7.1 suggested that there was little difference between detection distances of 200 – 500m, but when the infiltration rate is also varied then a shorter detection distance appears to be very important. This can be observed through the results in Section 6.7.2 where the detection distance is 500m, but none of the infiltration rates were statistically significantly better than MOVA. However when the detection distance was reduced to 200m then infiltrations of 20%, 50% and 75%, produced results which statistically outperformed MOVA.

6.7.5 Conclusion

The sensitivity analysis provided a valuable insight into how DEMA can perform when perfect data is degraded and detection distances are varied. The detection distance can be anywhere from 200 metres to 500 metres when perfect data is provided to DEMA, however through combination trials, the 200 metre detection zone appears to outperform the 500 metre zone (it achieves statistically significant reductions in mean delay). This has a positive impact on reducing any infrastructure costs that would be required at the roadside as the detection zone would only be 200 metres as opposed to 500 metres.

The infiltration rate is important so that DEMA is able to detect queue lengths accurately and it requires at least 30% of vehicles to provide additional data (for a 500 metres detection zone). However this will result in less reliable journey times, even if the average journey time is reduced, therefore DEMA becomes unfair to minor roads at this infiltration level. Interestingly, when the detection distance is reduced, then the infiltration rate required to statistically outperform MOVA is also reduced. DEMA was able to statistically outperform MOVA with only 20% of vehicles providing additional data with a detection distance of 200 metres.

One of the key conclusions from this section is that the detection distance should be reduced to only 200 metres from the junction. Also, by having a higher infiltration of data providers, then the journey time becomes more reliable and can generate a statistically significant difference in the means between DEMA and MOVA. When imperfect data is provided to DEMA, speed data has a much more significant impact on performance compared to location data and therefore accurate speed detection should be focused on when implementing DEMA in reality. However speed data is only used in DEMA for determining the queue length, consequentially, if there is an alternative method which can accurately measure the queue length without using speed, then it could be used instead.

6.8 Case Study – Cabot Lane (Crossroads) – With Alterations

Sections 6.5 and 6.6 both investigated how DEMA performed against MOVA control when DEMA used the existing stage diagrams. These experiments demonstrated how DEMA is able to outperform MOVA without the use of turning intention data. This thesis has investigated how turning intention data could be used and why it could be beneficial (through Chapter 5). Therefore this section will consider if turning intention data provides any additional benefits for DEMA in the Cabot Lane junction. The hypothesis is that with turning intention data, there will be more freedom in stage selection and therefore improved performance as DEMA is not constrained to MOVA's stage choices.

In Chapter 5, a method was proposed for using turning intention data by manipulating the current stage diagram. Cabot Lane is significantly more constrained than the theoretical three lane approach crossroads, however there are additional stages which could be created if turning intention data was known. The constraints placed upon real world junctions still apply (Section 6.1), but the current signal heads need to be considered when generating the stage diagram for Cabot Lane (as Section 6.3.3 explained). By analysing the current signal heads, it is then possible to determine what changes would need to be made for a junction to use turning intention data.

6.8.1 Current Signal Heads

Figure 63 and Figure 64 show the existing location and configuration of Cabot Lane's signal heads. If the signal head is represented by a blank circle then all traffic movements are allowed from that arm, and if there is a directional arrow then only that traffic movement is allowed to move. The current signal head configuration is:

- North: an all travel green light and a right turn filter (right turning traffic cannot be controlled separately)
- East: filter lights for all movements, each can be controlled separately
- South: both straight and right turns have dedicated filter lights (left turn is give way priority)
- West: an all travel green light

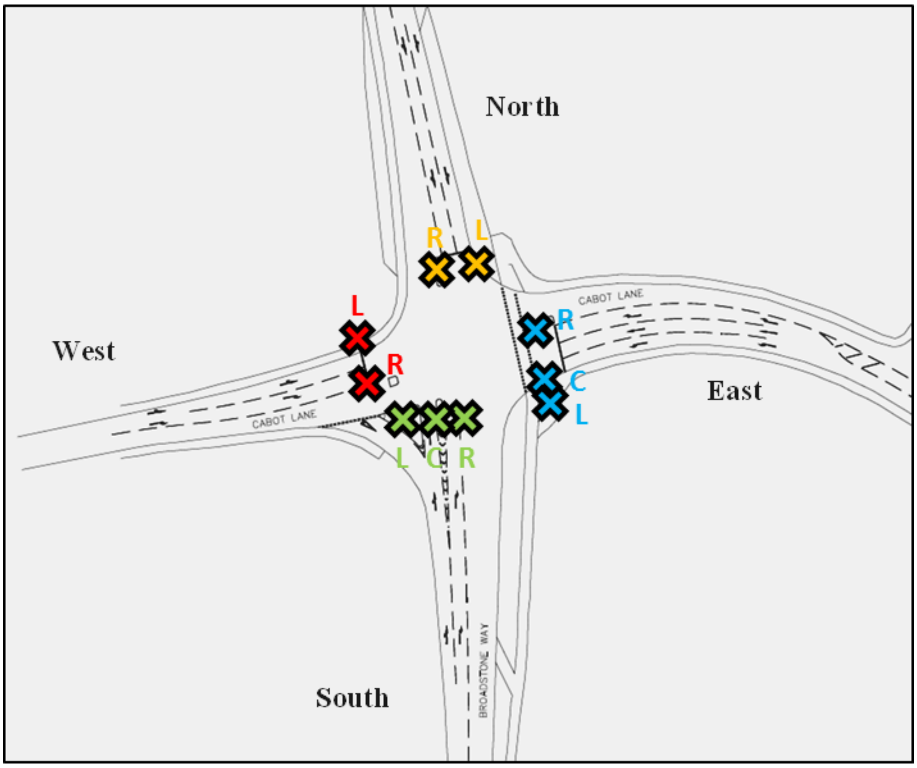

Figure 63: Location of signal heads

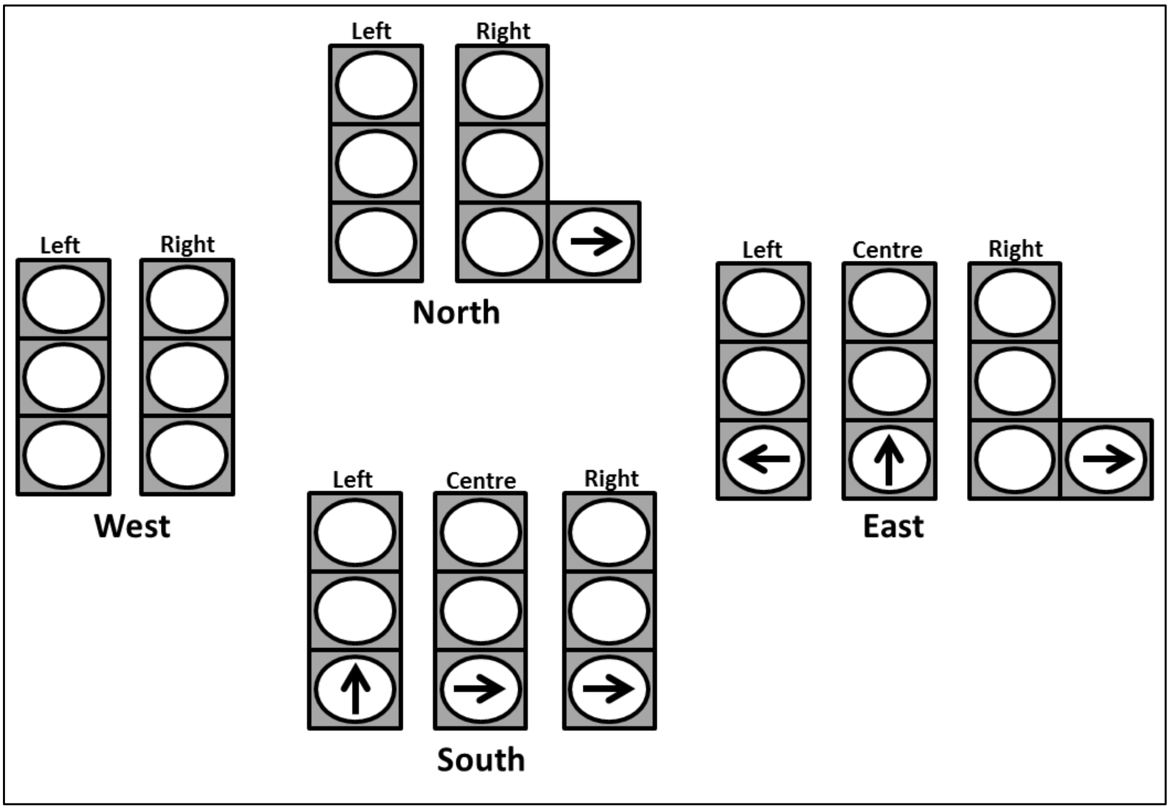

Figure 64: Configuration of current of signal heads

6.8.2 Stage Configuration

With turning intention knowledge, there are additional stages which could be used with minor changes to the signal head configuration. One of the most influential constraints on the new stage configuration is that right turning traffic cannot choose to gap accept when the 85th percentile approach speed is greater than 45 mph (which is true at Cabot Lane) and therefore all right turning traffic must have unopposed turning movements for safety improvements.

With the additional three stages (stages 5, 6 and 7 in Figure 65) included then the signal head configuration must be altered on the Northern and Western approaches, as can be observed in Figure 66. These changes would incur a one off additional expenditure but this section will investigate if there would be any performance benefits from the alteration. It should be noted that the two lane approach from the Northern arm can no longer allow both lanes to serve straight ahead traffic and been changed to have a dedicated right turn lane with a straight and left turn lane. This will result in a loss of capacity for the straight ahead movements but enables stage 7 to be used and ensures that safety constraints are adhered to.

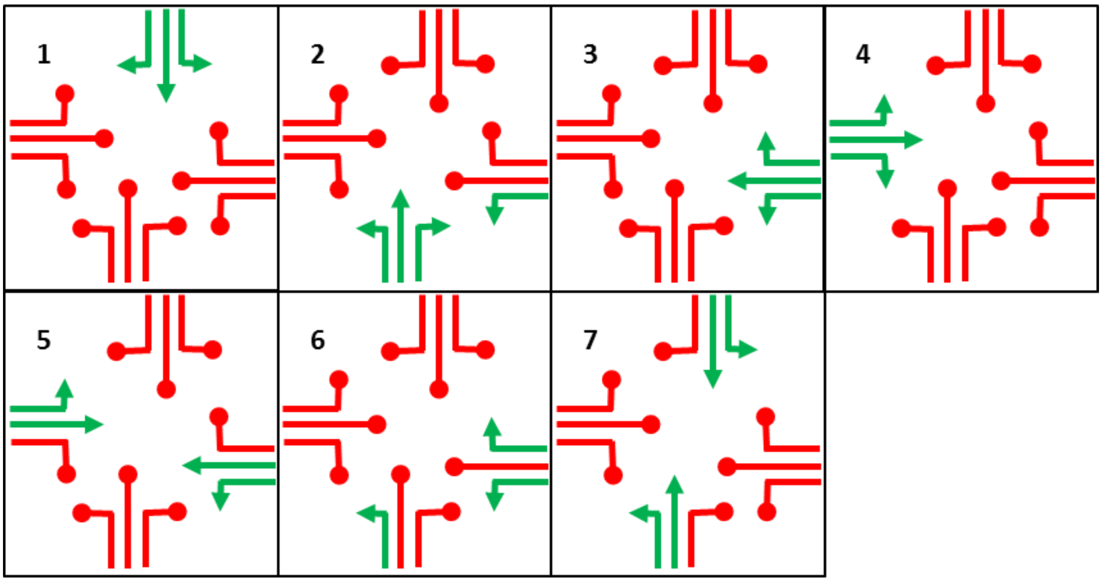

Figure 65: Stage configuration for Cabot Lane when turning intention data is used

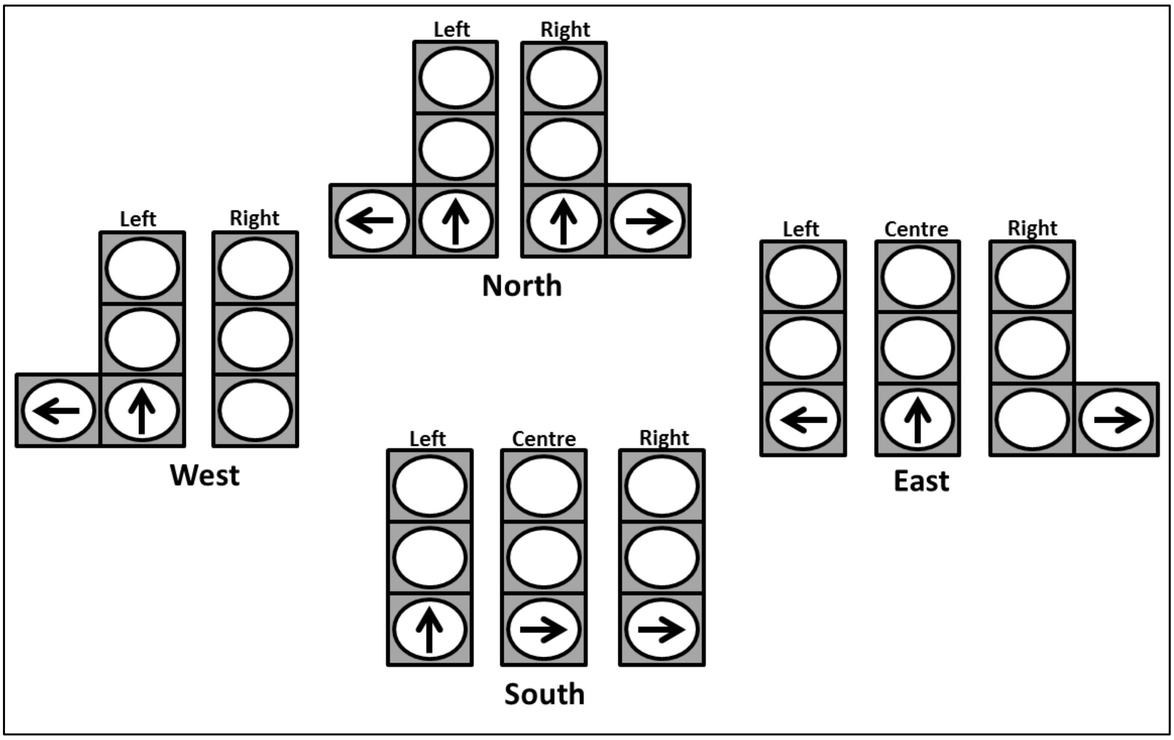

Figure 66: New configuration of signal heads when turning intention is used

6.8.3 Variation in Demand

This section will investigate the effect of changing demand levels compared to the base flow (100%), where all the demand profiles still apply from Section 6.6. Again five scenarios will be compared against MOVA control at 20%, 40%, 60%, 80% and 100% demand.

Figure 67, Figure 68 and Table 36 shows the very significant reduction in mean delay and journey time when turning intention data is used within DEMA. Turning intention data enables the use of additional stages which would not be possible under normal circumstances and therefore provides a significant benefit to the road users at Cabot Lane. The variation in journey time significantly reduces as well with DEMA able to be much fairer to all road users compared with MOVA control. The improvement has such a large effect that the junction only suffers with oversaturation for approximately 15 minutes from 8:00 to 8:15, which is when 30% of the two hour demand level is trying to pass through the junction.

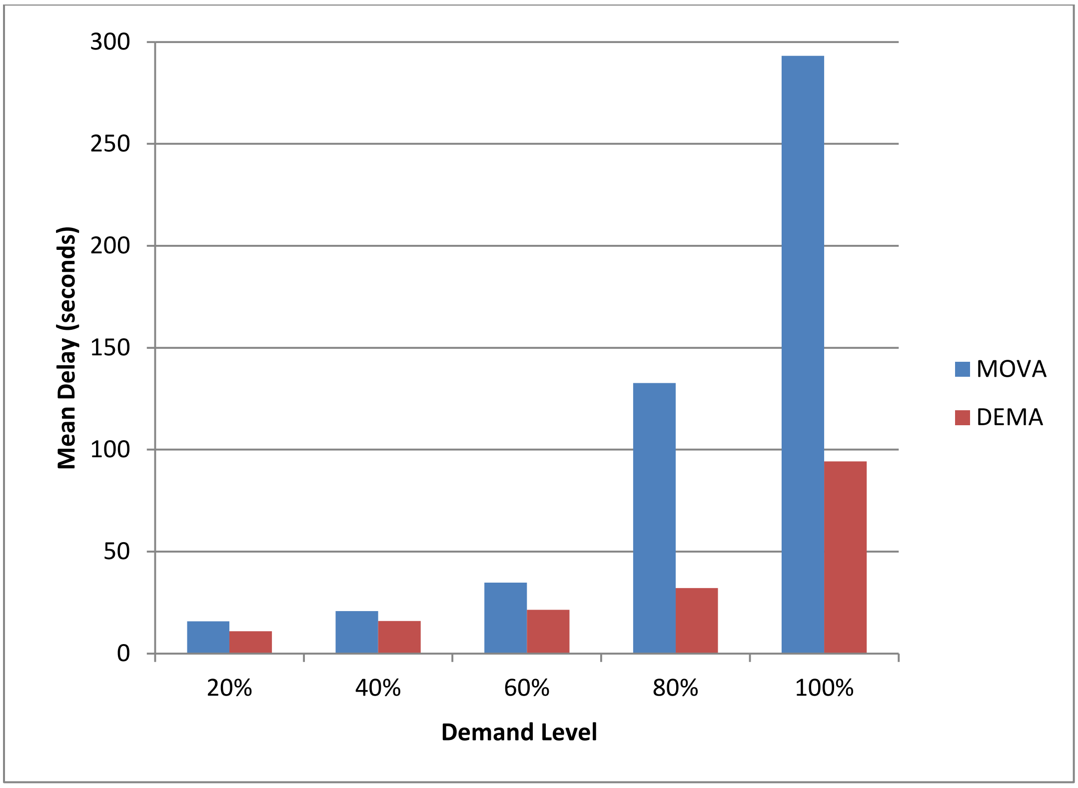

Figure 67: Comparison of average delay for MOVA and DEMA control at various demand levels

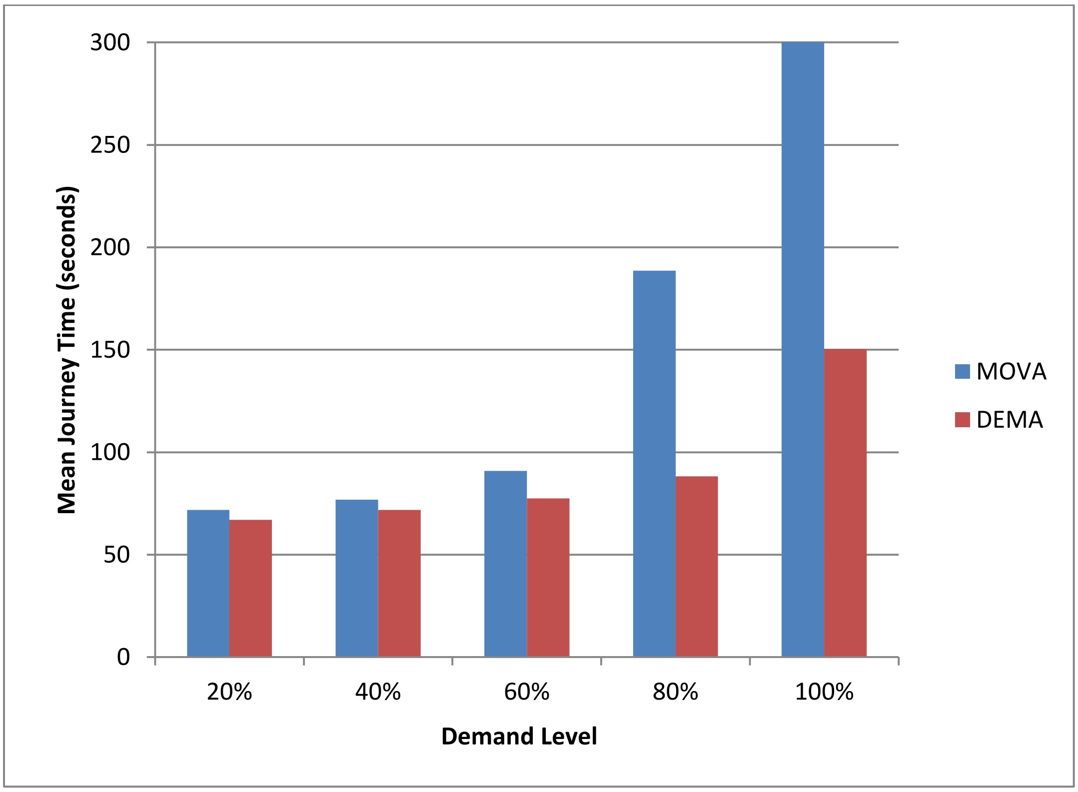

Figure 68: Comparison of average journey time for MOVA and DEMA control at various demand levels

Table 36: Results of various demand levels at Cabot Lane

Control Method and Demand		Delay			Journey Time (seconds)			
		Mean Delay (sec)	Mean Speed (mph)	Mean Queue Time (sec)	Maximum	Mean	Standard Dev.	Median
MOVA	20%	15.9	35.4	10.6	268	71.9	25	67
DEMA		11.0	39.4	4.8	158	67.0	19	64
MOVA	40%	20.8	32.9	13.2	254	76.8	23	73
DEMA		15.9	37.0	7.1	198	71.9	22	67
MOVA	60%	34.8	29.1	20.8	295	90.8	36	83
DEMA		21.4	34.9	9.5	214	77.4	27	71
MOVA	80%	132.7	21.1	58.2	616	188.7	145	121
DEMA		32.2	32.5	14.2	335	88.2	38	79
MOVA	100%	293.3	19.8	78.2	1183	349.3	318	210
DEMA		94.3	26.2	36.0	605	150.3	112	103

Table 37 highlights the considerable improvements which DEMA can make over MOVA when turning intention data is used; DEMA is able to reduce delay by up to 75%. One of the major reasons for this is DEMA's ability to allow simultaneous straight on movement (i.e. stages 5 and 7) but constraining the right turning traffic until there is a demand for it. This would not be possible without the use of turning intention data.

Table 37: Percentage improvement of DEMA over MOVA for various demand levels

Demand	Percentage Reduction over MOVA (%)	
	Mean Delay	Mean Journey Time
20%	30.6	6.8
40%	23.6	6.4
60%	38.5	14.8
80%	75.7	53.3
100%	67.8	57.0

Table 38 and Figure 69 show that DEMA has a statistically significant difference in means from MOVA control where the p-values are all below 0.05 (95% confidence). The box plot is heavily influenced by the 80% and 100% demand levels where MOVA has a considerably larger average delay compared with DEMA. Not only does DEMA (with turning intention data) outperform MOVA, but it also considerably outperforms the DEMA algorithm which is constrained to use MOVA's stage configuration.

Table 38: P-values in comparison against MOVA for various demand levels

Demand	P-values	
	Mean Delay	Mean Journey Time
100%	0.000	0.000
80%	0.000	0.000
60%	0.000	0.000
40%	0.000	0.000
20%	0.013	0.013

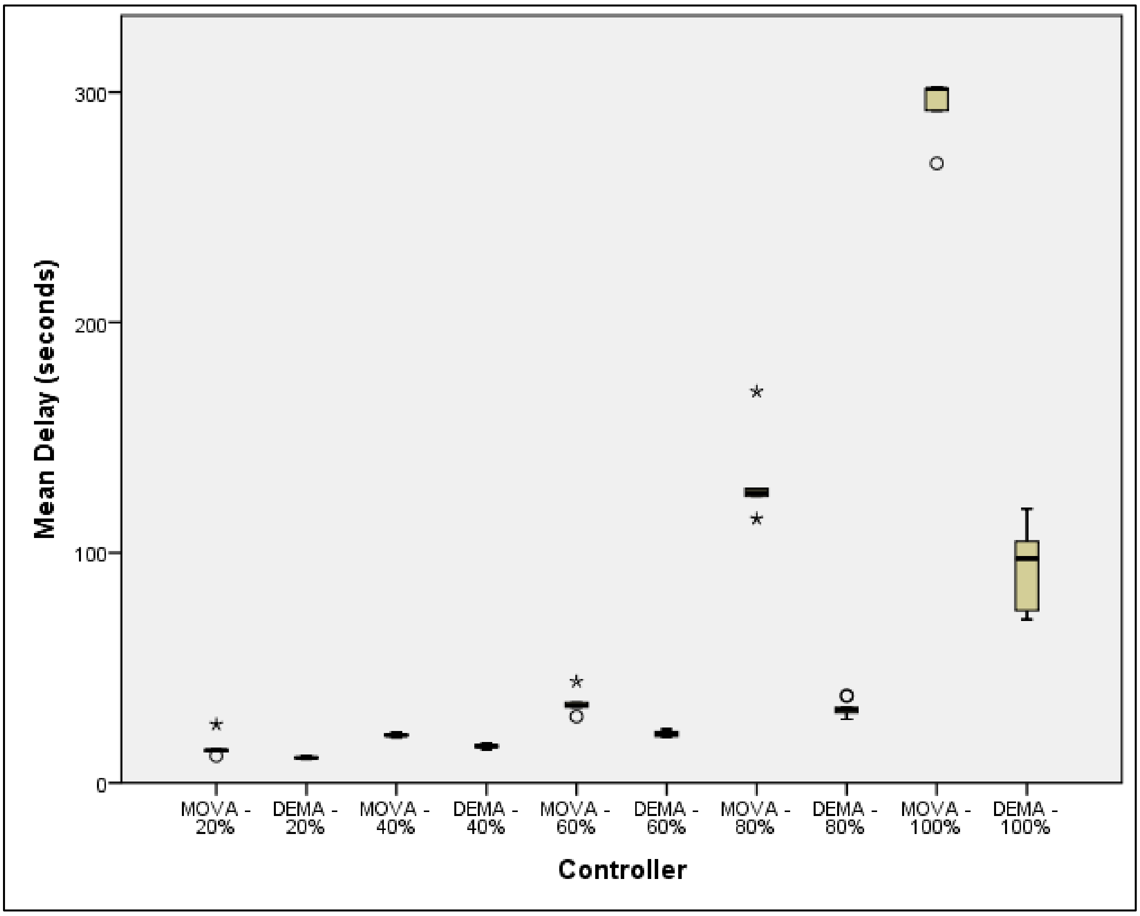

Figure 69: Box plot showing the variation in demand compared against MOVA

This section has demonstrated how DEMA is able to use additional data effectively to significantly reduce the average delay and improve reliability of journey time. However, this section has assumed that all vehicles are providing data and therefore an investigation into how many vehicles need to be equipped to achieve an acceptable performance will be carried out in the next section.

6.8.4 Infiltration Rate

This experiment will investigate how DEMA performs when it does not receive data from all of the vehicles in the network. The same principles have been applied which were used in Section 6.7.2 so that vehicles can still be detected using inductive loops if they do not provide additional data from further afield.

Figure 70, Figure 71 and Table 39 show that under every infiltration rate, DEMA still outperforms MOVA. The interesting conclusion which can be drawn from these results is that even at 0% infiltration, the new stage configuration can statistically outperform MOVA. This implies that stage flexibility and importantly, a different stage configuration would help to improve the current performance at Cabot Lane. However, it is clear from the results that there is a significant reduction in performance when no data is provided to DEMA. At 20% infiltration and below, the journey times become much more variable as the standard deviation and median journey times increase considerably compared to results with greater than 20% infiltration.

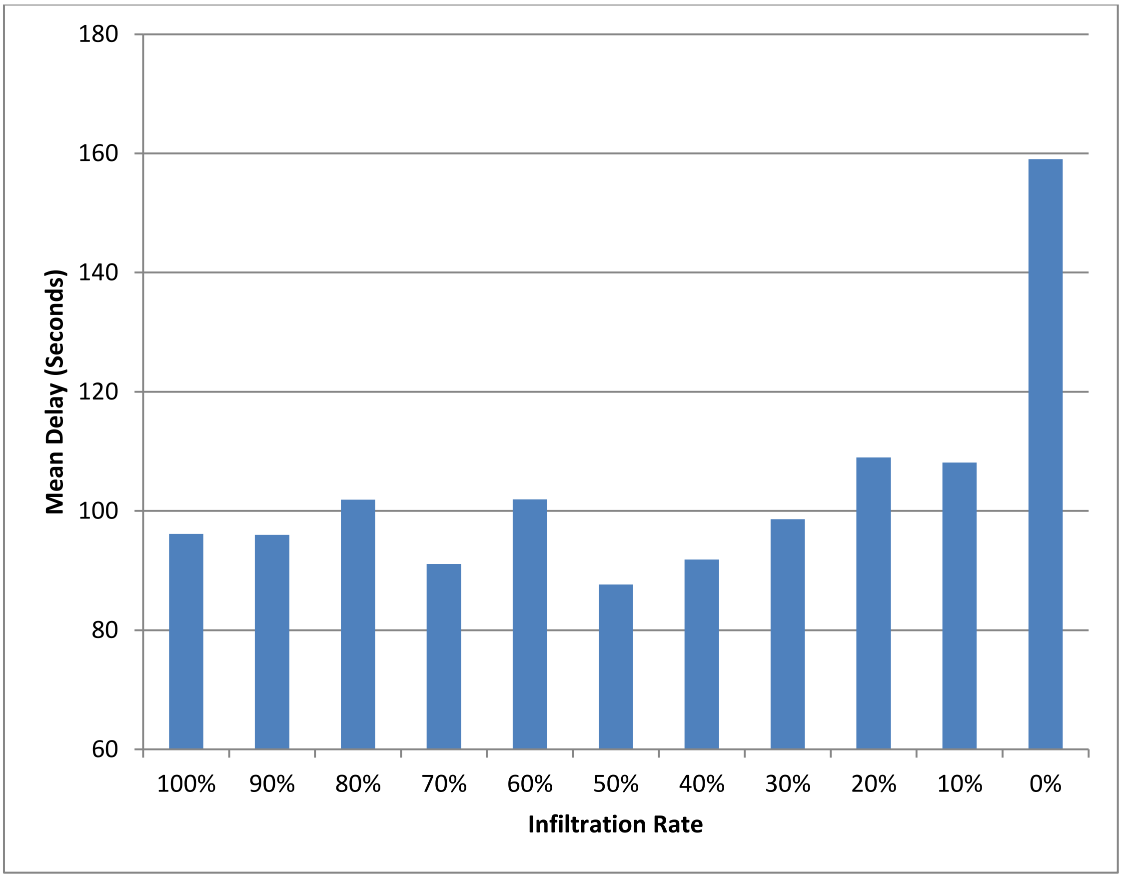

Figure 70: Comparison of average delay for DEMA control at various infiltration rates

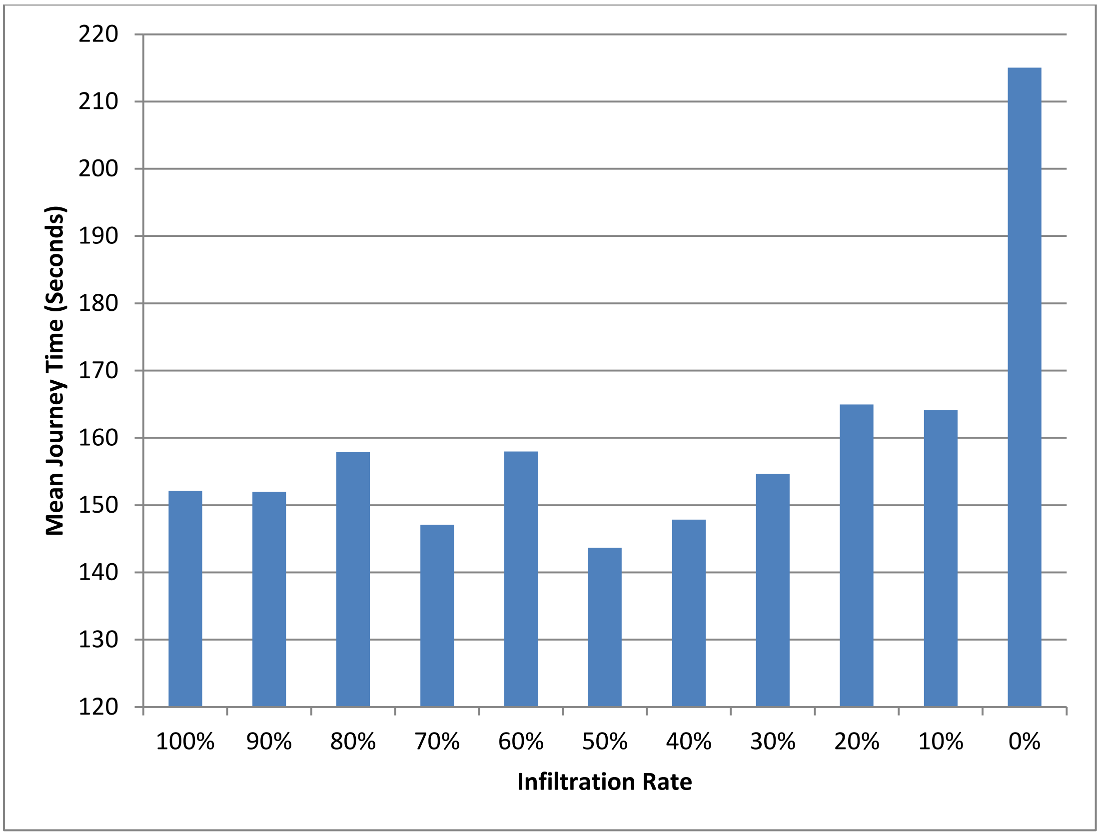

Figure 71: Comparison of average journey time for DEMA control at various infiltration rates

Table 39: Results of various infiltration rates at Cabot Lane

Infiltration Rate for DEMA Detection	Delay			Journey Time (seconds)			
	Mean Delay (sec)	Mean Speed (mph)	Mean Queue Time (sec)	Maximum	Mean	Standard Dev.	Median
MOVA	285.6	19.5	75.7	1189	341.6	299.8	196.8
100%	96.1	26.1	36.4	612	152.1	113.0	103.9
90%	96.0	26.2	36.7	602	152.0	111.3	104.6
80%	101.9	25.7	38.0	606	157.9	120.5	107.0
70%	91.1	26.2	36.2	568	147.1	103.5	105.5
60%	102.0	25.4	38.0	595	158.0	114.3	111.5
50%	87.7	26.0	33.6	532	143.7	96.2	105.7
40%	91.8	25.8	35.2	540	147.8	101.9	106.9
30%	98.6	25.2	36.6	576	154.6	108.3	109.4
20%	109.0	24.3	39.9	612	165.0	119.6	116.6
10%	108.1	24.0	37.4	592	164.1	116.5	118.8
0%	159.0	22.1	43.9	820	215.0	188.0	124.3

Table 40 and Figure 72 show that there is a statistically significant difference in the means between MOVA and DEMA for all infiltration levels. The box plot shows that there is a similar amount of variation between DEMA and MOVA except at the 20% infiltration level where there is step change in performance. There are no statistical differences in means between each of the infiltration rates (except for the 0% scenario where all of the remaining scenarios are statistically different from it).

Table 40: P-values in comparison against MOVA for various infiltration rates

	P-values	
	Mean Delay	**Mean Journey Time**
100%	0.000	0.000
90%	0.000	0.000
80%	0.000	0.000
70%	0.000	0.000
60%	0.000	0.000
50%	0.000	0.000
40%	0.000	0.000
30%	0.000	0.000
20%	0.000	0.000
10%	0.000	0.000
0%	0.000	0.000

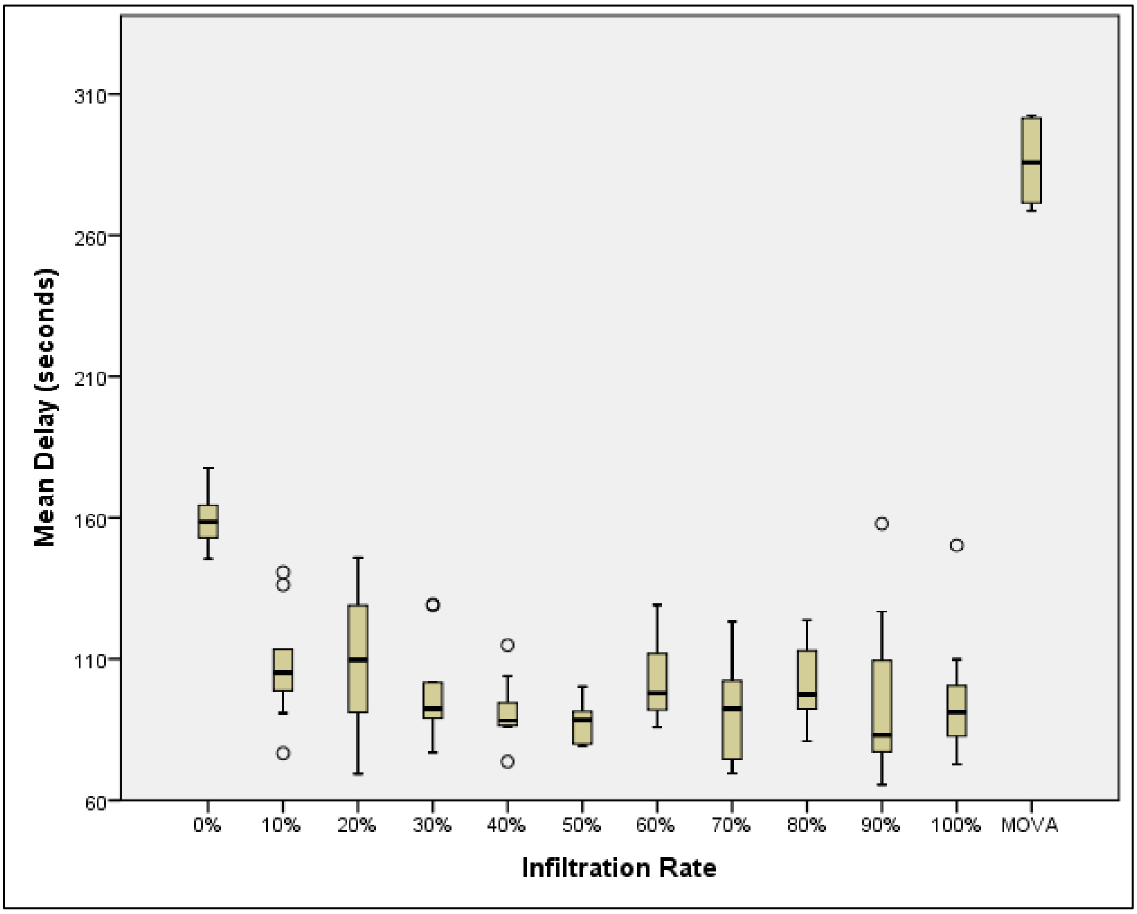

Figure 72: Box plot showing the various infiltration rates compared against MOVA

6.8.5 Chapter 4: Comparison

Chapter 4 investigated how accurately turning intention data could be detected and the results demonstrated that humans could predict turning intention from 50 metres away, with a success rate of approximately 70%. Section 6.7 has demonstrated that 200 metres is the ideal detection distance when using DEMA, but this section will investigate if the accuracy levels described in Chapter 4 are sufficient to outperform MOVA. Therefore an experiment was carried out where DEMA received turning intention data at 50 metres and from only 70% of vehicles.

Table 41 shows the results of the experiment where DEMA reduces average delay by 21.6% compared to MOVA. It should be noted that this is far from the ideal conditions for DEMA to operate as can be observed in Section 6.8.4, where DEMA achieves a mean delay of approximately 100 seconds. The performance of DEMA under these conditions is greatly reduced and therefore the results shown in Chapter 4 would not be practical for use in reality as the detection distance should be further afield. However it is not yet known how well humans can predict turning intention at 200 metres from the junction.

Table 41: Results of 50m detection distance and 70% infiltration at Cabot Lane

	Delay			Journey Time (seconds)			
	Mean Delay (sec)	Mean Speed (mph)	Mean Queue Time (sec)	Max.	Mean	Standard Dev.	Median
MOVA	285.6	19.5	75.7	1189	341.6	299.8	196.8
70% Infiltration, 50m Detection Distance	223.7	20.1	49.3	1057	279.7	278.1	133.0

6.8.6 Conclusion

This case study has demonstrated the substantial benefits of using turning intention data for traffic control as the mean delay can be reduced by up to 75% over the existing control strategy. To achieve this reduction and a more reliable journey time then an infiltration rate of at least 30% was required and a few changes were made to the junction configuration. These changes included more stage options for DEMA to use and the reduction of the northern arm to only one lane travelling straight on as opposed to two in the base example.

6.9 Conclusion

This chapter has presented clear results to show the benefits of using additional data sources to control traffic lights. A novel traffic control algorithm called the Delay Minimisation Algorithm (DEMA) was developed using real world constraints, for example, minimum green time and maximum cycle time. This algorithm was developed with the objective of using additional data sources such as vehicle location, speed and turning intention information. An important outcome from the development of DEMA was that it is difficult to guarantee that every phase will be released within the maximum cycle time if there is no pre-defined stage order. However after trials of using a hill climber algorithm versus a weighting factor method, the weighting factor method proved to achieve a higher performance because less accurate predictions of the arrival rate were required for controlling the traffic lights. Therefore DEMA has been allowed the freedom of selecting any stage in any order, provided that minor phases are not held back for an indefinite period of time.

A number of case studies were used in this chapter to test DEMA against the existing traffic controller, which was MOVA for both Sopers Lane and Cabot Lane. DEMA was able to reduce average delay by approximately 20 – 30% over MOVA in under-saturated scenarios, by using the same stage configuration. Whereas, DEMA could reduce average delay approximately 8% in over-saturated scenarios compared with MOVA. These values were based on perfect input data for DEMA and therefore a sensitivity analysis was carried out to determine what effect the detection distance, infiltration rate and accuracy of data had on DEMA.

A scenario where vehicles were detected 200 metres from the junction, 50% of vehicles provided additional data, and vehicles provided data similar to GPS devices (4m location standard deviation and 1 mph speed data), resulted in a statistically lower average delay compared to MOVA (a reduction of 5%). This scenario was not using turning intention but only vehicle location and speed information and yet a reduction in delay was still achieved.

When turning intention data was used along with location and speed information then DEMA was able to drastically reduce the mean delay and provide a much more reliable journey time. The additional data enabled a different stage configuration and more freedom in stage selection. This case study reduced mean delay by a minimum of 23% and maximum of 75% because of the new stages added to the junction. Therefore this chapter has demonstrated how valuable additional data sources are to the future of traffic control because significant reductions in delay and improvements in journey time reliability can be achieved.

6.10 Chapter 6 Key Points

1. Real world constraints were used in the development of a novel control algorithm called DEMA (Delay Minimisation Algorithm), for example, minimum green time, maximum cycle time and inter-green time.
2. DEMA is not constrained to a pre-defined cycle order but has the complete flexibility to choose the next stage.
3. DEMA calculates the anticipated delay for every possible stage combination through estimating the queue length, discharge rate and predicted arrival rate.
4. To ensure that DEMA would adhere to the maximum cycle time, two methods were tested – a hill climber algorithm (which guaranteed every stage would be selected within the maximum cycle time and was very computationally heavy) and a single stage selector which used a weighting factor to make the less frequently selected phases more desirable when they approached the maximum cycle time. The weighting factor method proved to achieve a higher performance over the hill climber method.
5. A T-junction case study was carried out where no turning intention data could be used to determine how DEMA would perform against the existing controller (MOVA). The results showed that DEMA consistently reduced average delay by 3 – 4 seconds per vehicle. This reduction demonstrated that additional data (vehicle location and speed) could provide improvements in traffic control.
6. An over-saturated crossroads case study provided more depth into how DEMA performed against MOVA by reducing average delay by approximately 8% in real world conditions. When there were lower demand levels then DEMA was able to reduce average delay by a larger proportion, up to 34%.
7. A sensitivity analysis was carried out to determine how DEMA would perform with imperfect data and a variation of detection distances. The outcome was that DEMA performed best when vehicles were detected from 200 metres away and approximately 50% of vehicles should provide additional data to achieve a statistically significant reduced delay and more reliable journey times.
8. Turning intention data was then included for the over-saturated crossroads which made a major reduction in average delay and journey time because of improved stage configurations. With the knowledge of vehicle's turning intention, then new stages could be utilised which reduced delay by as much as 75% over the existing MOVA control method.
9. This chapter has strongly demonstrated the potential benefits of using additional data to reduce average delay and improve reliability of journey time.

Chapter 7: Contributions of the Research and Conclusions

The transport industry is constantly evolving, both pre-empting and reacting to the arrival of new technologies and control techniques. When new generations of traffic control occur, there are some fundamental shifts in the way of thinking, for example moving from fixed time systems to vehicle actuated added a new dimension as traffic lights could respond to vehicle demand. Consequentially, when developing novel control methods some of the previous principles will inevitably be challenged, such as moving from static sensors (inductive loops, infra-red, radar) to multi-mobile data sources (Wi-Fi, smart phone, Bluetooth, GPS).

This research has sought to incorporate additional data sources into a new traffic control system by determining what data is available, how it can be used and what the potential benefits are. It is essential to recognise what impact this research will have within the transport industry and therefore this chapter will seek to investigate what the limitations are but also what opportunities have been created from this work (this is in response to Objective 5). Also, the key conclusions from all facets of this thesis will be summarised to emphasise how additional data sources can help to improve the performance of UTC systems in the near future.

The thesis has focused on additional data in three key areas:

1. How can the data be detected?
2. How can the data be used?
3. Is there a benefit to using the data?

Chapter 4 investigated how turning intention can be detected, where the results demonstrated that turning intention information can be detected from outside of the vehicle with a median success of 70% when a vehicle is 50 metres from the junction, rising to 90% when less than 30 metres. Chapter 5 investigated how turning intention can be used by adapting an existing (theoretical) control algorithm called Highbid. The adapted algorithm (Turning Intention Algorithm) was able to outperform Highbid by reducing average delay by 24% and overall journey time by 15%. This chapter successfully demonstrated how turning intention data could be used.

Chapter 6 developed a novel control algorithm (DEMA) which incorporated real world constraints to ensure that it could be used in reality. Two case studies were carried out to determine if DEMA could outperform MOVA (current state of the art system) using additional information. The results showed that DEMA could reduce average delay by up to 34% and potentially much greater savings if minor alterations are allowed to the junction.

7.1 Points to Consider before Commercialisation

7.1.1 Stage Flexibility

A key aspect of this research is the fundamental change from using a fixed stage order and cycle time, to a more flexible control system which can choose the most beneficial stage order. The results from Sections 6.5 and 6.6 highlight the substantial improvement in performance when DEMA controls the same stage configuration as MOVA, but has the flexibility to select any possible stage at the decision point.

Bretherton (2003) stated that there were no observed safety implications from skipping stages, however this was under strict conditions of never skipping the major road stages or pedestrian stages (unless there were multiple stages within the cycle). Therefore further real-world trials need to be carried out to determine what impact there is on safety when a control system has complete flexibility over stage order.

7.1.2 Privacy

As the industry moves into an era of data abundance, then protocols will need to be developed to ensure that anonymous data is provided to the control algorithm so that personal data is not used for unintended purposes. With strict standards in place, then dissemination of the benefits needs to be promoted to the public so that a willingness and understanding can be developed between individuals and operators. If this was in place, then travellers may be more willing to share their data so that they can receive a potential improvement to their journey.

7.1.3 Pedestrians and Cyclists

This research has focused on how additional data sources could reduce average delay and journey time for vehicles, and therefore less focus has been on pedestrian or bicycle movements. With ever changing stage orders, then pedestrians would find it more challenging to cross the road unless a green man was displayed. Consequently, further research is required to determine what impact this would have on the safety of pedestrians who are willing to jaywalk.

Cyclists are notoriously difficult to detect on the roads; however this research would encourage cyclists to share their data (through a smart phone or equivalent) to provide additional information on their location so that they can be included in the decision making process in DEMA. The research in Chapter 4 did not focus on cyclists who were mixed with other vehicles and therefore cannot make a conclusion on the prediction of turning intention for bicycle movements.

7.1.4 Safety

One of the reasons for MOVA being promoted as the industry standard within the UK is because of its ability to increase the inter-green time when approaching vehicles are travelling quickly towards the end of a stage. As a vehicle travels across MOVA detection loops (the assumed journey time is used) and if the vehicle is likely to travel through an amber or red light then MOVA can increase the 'all red' time by one or two seconds if necessary to ensure that conflicting vehicles do not cross paths (DMRB, 2004).

If DEMA was incorporated into a real traffic controller, then this capability would need to be included in the design to alleviate the safety concern. As this research was carried out in a simulated environment then there was no need to include this control system into the algorithm because vehicles would never run a red light or collide in Paramics.

7.2 Benefits to Siemens

MOVA is a multi-million pound, annual revenue stream to Siemens and therefore this novel algorithm provides Siemens with the opportunity to match and outperform MOVA in the future using additional data sources. If this research was incorporated into the isolated junction solution, then this would remove the licence costs of MOVA and potentially increase sales of roadside equipment which is required for some forms of the additional data sources being collected.

One of the motivations for this research (see Section 1.2.5) was that Zhao and Tian (2012) highlighted how only 6% of all signalised junctions in the US are adaptive. Therefore there is a large potential for growth in this market as many benefits can be observed from using additional data sources. Key to growing this market is disseminating the large reductions in delay and journey times when using novel traffic control algorithms.

As this research is 'future focused' then it has provided Siemens with an insight into how the market is likely to shift in the near future as more data sources become available. Therefore with Siemens' large market share and influence, they are strategically placed to help shape the next generation of UTC systems. Siemens are currently in discussions with the University of Southampton into how this research could be trialled in a safe location where the potential benefits can be observed on a real junction.

7.3 Limitations

7.3.1 Detection Distance

If DEMA can only detect vehicles a short distance away from the junction then the delay calculation will make little or no distinction between the phases under congested conditions. For example, if DEMA can only detect vehicles that are 50 metres away and all four stages have vehicles queueing in excess of this detection distance, then DEMA will not be able to determine any benefit to releasing one stage over another. Therefore it would be beneficial for DEMA to be able to detect the maximum queue length, which will be junction specific, so that the delay calculations are based on representative data. However in reality this must be balanced against cost of detection as it will increase with a larger detection distance.

7.3.2 Hardware

As mentioned in Section 6.2, junction controllers are typically set up to recognise the stages within the junction. Stage based hardware and control systems dominate markets in the United States (Furth and Muller, 1999). This means that a limitation of this work could be that some current hardware cannot recognise individual phases and therefore would struggle with the concept of flexible stage selection. If there was no flexibility in stage selection then DEMA would not be able to perform as effectively as it could.

7.3.3 Feedback to DEMA

Currently there is no feedback mechanism into DEMA during a selected stage to determine if it has made a bad decision. If there is a low infiltration rate (which is impossible to know within DEMA) then DEMA may make a decision based on poor spatial awareness and potentially give longer/shorter green time than is necessary. It would be useful to develop a feedback process which could monitor the static detectors (assumed 'ground truth') to determine if the data being gathered during the stage represents what DEMA previously predicted. However this would require micro-simulation software to be paused even more frequently (as a C# external interface decides on the most suitable stage, not Paramics), which would make the experiments last longer; but with better computing power then this would be less of a problem, or a different software could be used.

7.3.4 Communication from Mobile Devices

A limitation which could have a large impact on the viability of exploiting this research is the availability and accessibility of mobile data sources. Currently, smart phone, Bluetooth, Wi-Fi and satellite navigation devices do not communicate to a centralised location which stores all device data, and therefore trying to access this data source presents a political, commercial and privacy problem.

Data is very valuable and trying to encourage mobile phone and satellite navigation operators to share their data would be an expensive process. There would need to be a guarantee of anonymity for the device users, but also a benefit to the operators themselves. Also, data provided from the operators would need to be processed in a standardised method to ensure consistency of data.

Siemens have been working with Newcastle City Council and Newcastle University on the Compass4D project (Compass4D, 2013), which has ensured that suitable data protocols have been developed to communicate with equipped vehicles. By using a V2X approach, this can help to remove the commercial problems of using mobile phone or sat-nav data as there is a standardised, voluntary message being shared between the road user and the surrounding infrastructure.

Another method of sharing data could be through smart phone applications. If road users choose to use the application then they could willingly share additional data if they could receive a benefit when travelling through the network. However, it would be important to suitably advertise the application so that sufficient numbers of road users would use it.

7.3.5 Pedestrian Crossings

Signalised pedestrian crossings can enable pedestrians to cross a road during a single stage or by using a central reserve so that they can cross during two separate stages. By splitting the pedestrian movement into two stages, this allows additional vehicular movements to occur during the pedestrian stage and can potentially have performance benefits for road users. However when turning intention data is used to manipulate stage diagrams, then more phases are often incorporated which reduces the opportunities for pedestrians to cross during a vehicular phase. This is a junction specific problem, but if one stage pedestrian crossings were difficult to achieve then more central reserves would be required to split the pedestrian movements. Further research is required to fully understand the impact that this would have on pedestrians.

7.3.6 Junction Layout

If there is only one approach lane to a junction then there are no possible stage manipulations which could make use of turning intention data. Therefore if DEMA was used in its current form, then it could not derive an additional benefit of having turning intention knowledge. However, as described in Section 5.1.2, turning intention data could also be used for coordinating neighbouring junctions so that arrival rates could be more accurately predicted for the downstream junctions. However, further research is required to understand the benefits of coordinating neighbouring junctions using turning intention data.

7.3.7 Signal Timings

In order to better understand how DEMA made such significant savings over MOVA in the case study examples, then it would be very beneficial to record the signal timings during any simulations. This would enable the experimenter to directly compare how DEMA controlled the junction differently to MOVA so that a benefit was achieved, this should be considered in any future work. The difficulty in evaluating signal timing plans is that when there are large numbers of simulations being carried out then it can be challenging to determine a clear pattern between the control algorithms.

Signal timing plans would have helped to explain the discrepancies between MOVA's and TIA or DEMA's maximum journey time under low flow conditions. MOVA can occasionally have maximum journey times of over 500 seconds, whereas DEMA (or TIA) only have maximum journey times of 100-200 seconds in low flow conditions. This could be attributed to a 'settling in' period for MOVA where the system takes slightly longer than DEMA to understand the current road state within Paramics. This can further highlight the advantages of having additional data for improving performance.

7.4 Future Work

This research has answered the objectives set out in Section 1.3.2, but additional questions have arisen as a result of this work. Therefore this section will describe future areas of research which were deemed as out of scope for this thesis.

7.4.1 Neighbouring Junctions

Turning intention knowledge could be used to inform downstream junctions of impending arrival flows and potentially improve the predicted arrival rates. Further research is required to develop an understanding of how the data could be used for coordinating neighbouring junctions. An algorithm which could coordinate neighbouring junctions would need to be compared with a UTC system such as SCOOT because MOVA was not originally designed for coordinating nearby junctions.

7.4.2 Feedback to DEMA

As described in Section 7.3.3, DEMA does not receive any feedback of how the current stage is performing. Further research would help to understand if the predicted arrival rate was forecasted correctly in reality. Static detection methods which are closer to the junction (i.e. inductive loops, infra-red or radar) could be used to evaluate the forecasts. If the arrival rate was over or under predicted (especially when there is a low infiltration rate amongst vehicles), then providing feedback to DEMA could help to adjust the length of the selected stage accordingly.

This proposal may require a different micro-simulation tool because Paramics does not allow the user to develop novel algorithms within the software and therefore it would require a long time to continuously re-evaluate how the predicted arrival rate was performing. This thesis used a C# interface to communicate with Paramics, and during any decision making calculations, then the Paramics simulation was paused until a decision was made. Therefore a micro-simulator which could run the code simultaneously would be much more suitable for providing feedback to DEMA (provided that the calculations do not take any significant amount to time to be computed).

7.4.3 People Movement

If additional data sources become widely available and vehicle occupancy is known, then DEMA could easily be adapted to incorporate the movement of people rather than vehicles. Or if a network operator wanted to use vehicle type as a differentiator then this could also be included into DEMA by multiplying the detected vehicle by the corresponding pcu value. By considering vehicle occupancy or type then this could be used to provide public transport priority calls at traffic signals as the movement of people is prioritised through the network. This concept was deemed to be outside the scope of this thesis.

7.4.4 Refining DEMA

DEMA was developed in such a way that minimised the number of user inputs during the setup of the algorithm. This is a desirable trait so that less information needs to be pre-determined and calibrated by installation engineers, thereby reducing their workload. The limitation of this method is that the delay calculation only considered stationary delay (see Figure 31, in Section 6.3.1) and ignored both the acceleration and deceleration delay. This could be included into the delay calculation through observations of vehicle behaviour at the junction but it would be a time consuming process. Also the start lag and end lag could be incorporated into DEMA's delay calculations but this would again increase the amount of time required to setup and calibrate the algorithm at every junction.

7.4.5 Safety Considerations of Stage Skipping

An investigation into the effect of having complete flexibility of stage choice needs to be considered so that the impacts can be properly understood. Bretherton (2003) suggested that there were no negative safety impacts from stage skipping (under strict conditions) but further trials and user feedback need to be carried out (with more flexibility than Bretherton's trials). If stage skipping trials were carried out then DEMA could be used as the control algorithm to also determine what effect on safety and performance it has.

7.4.6 Real World Trials of DEMA

Micro-simulation can be an incredibly powerful tool to help understand what impacts could occur when using a new control algorithm. However there are always limitations to micro-simulation models as vehicles behave in a predictable and replicable manner, whereas if a real world test was carried out (with appropriate signage and legal implications managed), then the true performance benefits could be greater understood. Therefore this study recommends that DEMA is tested on a real junction, using probe vehicles to provide additional data within the vehicle mix.

7.5 Conclusion

This section will demonstrate how this thesis has achieved the following objectives, which were stated in Chapter 1, and highlight the key conclusions which can be made as a result of this research:

1. To understand 'state of the art' and future Urban Traffic Control systems, therefore highlighting any opportunities for improvement
2. To better understand how and why new technologies would be used in future UTC systems
3. Develop novel control algorithms which are able to incorporate modern data sources
4. Evaluate novel control algorithms against existing UTC systems and carry out a sensitivity analysis.
5. Provide recommendations based on the findings of any results from this research.

In response to Objective 1, this thesis investigated the current capabilities of urban traffic control systems through a thorough literature review in Chapter 2, but importantly exploring what technologies are likely to be available in the near future (which helps to satisfy Objective 2). This research highlighted that there will be much richer data sets available for network operators but unfortunately existing control systems do not appear to make full use of the greater quantity and quality of data inputs.

In order to investigate how a novel control algorithm could make use of the additional data sources, it was important to understand what key performance metrics would be used to evaluate existing and new control methods. Chapter 3 explains how stakeholders value different performance metrics depending on their role within the industry. These interviews, combined with a literature review, concluded that average delay and reliability of journey times were the most important KPI's when developing a control algorithm.

There were three key questions which then needed to be answered to fully understand how additional data sources could be used for urban traffic control systems:

1. How can the data be detected?
2. How can the data be used?
3. Is there a benefit to using the data?

Chapter 4 considered the first question by exploring how intended route choice can be currently detected through in-vehicle technologies and external methods. There appeared to be a lack of research and understanding of how turning intention data could be detected from outside of a vehicle, which helps to avoid any privacy concerns of road users who do not want information being shared from in-vehicle devices. Therefore Chapter 4 describes two novel experiments which investigated how accurately humans can predict turning intention as a vehicle approaches a junction. These experiments presented very interesting results as people were very good at correctly predicting turning intention and they achieved an overall correct prediction rate of 71.4%. However, there was a noticeable step change when predicting vehicles which were more than 25 metres from the junction. If a vehicle was closer than 25 metres then the median average success of predicting was over 90%, but if the vehicle was further than 25 metres then the accuracy fell to approximately 70%.

Chapter 5 investigated how turning intention could practically be used within a traffic control algorithm, therefore focusing on Objective 2 and 3. This chapter adapted a theoretical control algorithm, which was created by Box and Waterson (2010), to include turning intention knowledge through a manipulation of the possible stages. Their algorithm used vehicle location and speed data to create a ‘bid’ for the most beneficial stage every ten simulated seconds. However the Turning Intention Algorithm incorporated turning intention data and was able to observe additional reductions in average delay and journey time of 25% and 15% respectively on a theoretical, three lane approach crossroads. Chapter 5 demonstrated that turning intention data could be used within a control algorithm and potentially provide additional benefits. Nevertheless, both the Highbid and TIA algorithms would not be suitable for controlling a real junction due to the assumptions made which ignored real world constraints such as inter-green time, maximum cycle times and gap acceptance rules.

Consequently Chapter 6 developed a novel control algorithm which incorporated real junction constraints and was called the Delay Minimisation Algorithm, which satisfied Objective 4. One constraint which posed a particular problem was the maximum cycle time of 120 seconds, and therefore two methods were proposed to mitigate this issue: a single stage selector (which selected the best available stage at every decision point, i.e. end of each stage) and a heuristic approach that ensured all phases (with a demand) were released within a 120 second cycle. Upon comparison of both methods (on the test junction from Chapter 5), the single stage method had a greater reduction in average delay and improved reliability of junction time. However, a weighting factor was required to ensure that low flow phases would still be released within the given time constraint.

Siemens provided data for two real junctions in Poole, along with an expertly configured MOVA algorithm for both junctions. One of the junctions was a T-junction which could not make use of turning intention data; however this was a valuable case study that provided a comparison of how DEMA performed against MOVA without this data. DEMA was able to reduce average delay by approximately 3 – 4 seconds per vehicle (which represented up to a 39% reduction) and it improved the reliability of journey time.

The second junction was a more complex crossroads which suffered from oversaturation. DEMA was able to reduce average delay by approximately 8% for the existing demand profile, but under lower demand scenarios, DEMA outperformed MOVA by up to 34%. When the junction was oversaturated, then it was very difficult to achieve any significant improvements as all phases required a green light and queues could not be dissipated during their green stage.

Perfect data was used up to this point in the research and therefore it was essential to reduce the quality and quantity of data to develop a full understanding of how DEMA would perform in a real world scenario (in line with Objective 4). The conclusion of the sensitivity analysis was that vehicles should be detected when they are 200 metres from the junction, but also a 50% infiltration rate is required to ensure that there will be a reduction in average delay and improvement in the reliability of journey time. Accurate speed data had much more effect on the performance of DEMA as opposed to location data, which emphasises how important vehicle speed information is for classifying the queue length.

When turning intention data was introduced to the second junction, there was a drastic improvement in the performance of DEMA. Turning intention data allowed additional stages and therefore more flexibility in selecting the most appropriate stage for controlling the junction. Average delay was reduced by as much as 75% and reliability of journey time was significantly improved. Turning intention data enabled the two highest demand phases to be released simultaneously (which was previously not possible), and hence why such a substantial drop was observed.

In summary, this thesis has provided novel outputs for predicting turning intention from outside of a vehicle, which helps not only with improving signal control but has wide safety implications as well. A novel traffic control algorithm, which can utilise additional data sources, has been developed throughout this research. DEMA has consistently outperformed MOVA, which is the industry leader for isolated junctions. Therefore this research has demonstrated how turning intention data can be detected, how it can be used in a control algorithm and the substantial benefits that it brings when incorporated into a UTC system.

Appendices

Appendix 1

This appendix shows the questions which were asked during the KPI survey to Bristol, Southampton and London operators.

Interview Questions:

1. What performance metrics do you use to determine how the system is behaving?
2. How do you differentiate between network wide performance and individual junctions?
3. Do you publish 'network' performance? If so, how do you define the boundary of the network?
4. Who do you prioritise: buses, cars, freight, pedestrians and or people?
5. Who do you have to report to? And what information do you have to provide?
6. Is there a 'passenger user group' where people can provide feedback on the network?
7. What would you like to be able to do within the system to improve performance?
8. How do you implement your performance targets?
9. How do you integrate all of the different aspects within the traffic control centre?
10. Do you believe that your communication methods have a significant impact on the network (VMS, website, Facebook, twitter, etc.)? Do you observe people altering their route choice?
11. How do you use all the data you collect each day to improve the network? Is any research carried out to determine trends in the flow?
12. Do you ever challenge the industry standard pieces of software?
13. What environmental performance measures do you put in place and how do you implement them?

Appendix 1

Appendix 2

In Section 4.3.4, a logistic regression analysis is carried out to analyse which variables are most beneficial for anticipating whether a participant selected the correct answer or not? As this is a binary choice, the actual answer can either be represented by a zero (incorrect) or a one (correct). This appendix will provide an illustrative example of why predictive accuracy is more important than Nagelkerke's R-squared value. This example shows the results of ten participants, five people selected the correct answer and five people selected the incorrect answer.

If a logistic regression model calculates a participant's result to be greater than 0.5, then it will be assumed to be that the participant made a 'correct' decision. Whereas, if the participant's result is less than 0.5, then it will be assumed that the participant made an 'incorrect' decision.

Actual Answer

Figure 73 displays ten participants' results, five were correct and five were incorrect. To visually display this, all of the incorrect values are in line with zero and all the correct values are in line with one. In the actual answer, there are no decimal point representations because the participants were either correct (1) or incorrect (0). This figure would represent a perfect logistic regression model where there is 100% predictive accuracy and a Nagelkerke R-squared value of 1.

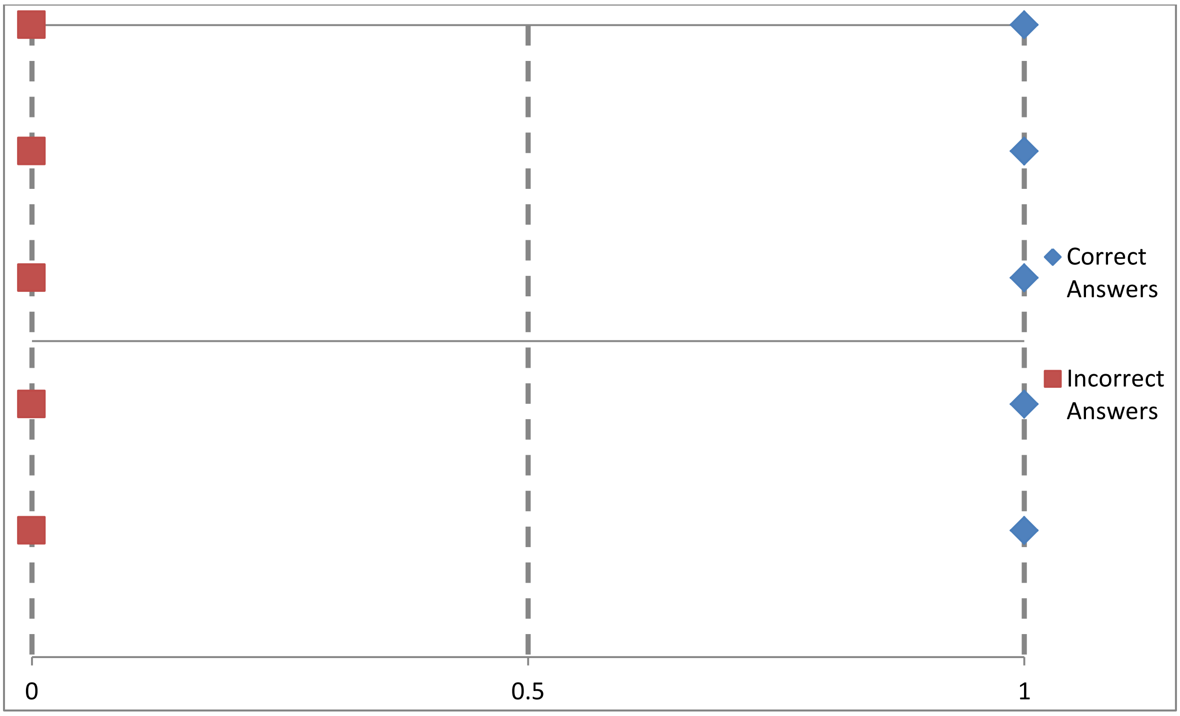

Figure 73: Distribution of Actual Answers

Poor Accuracy, Poor Nagelkerke R-Squared Value

Figure 74 demonstrates the illustrative results from a logistic regression analysis where there is a low Nagelkerke R-squared value and a low predictive accuracy as half of the expected values from the model are wrong. There is a low Nagelkerke R-squared value because there is a large variation from the correct answer.

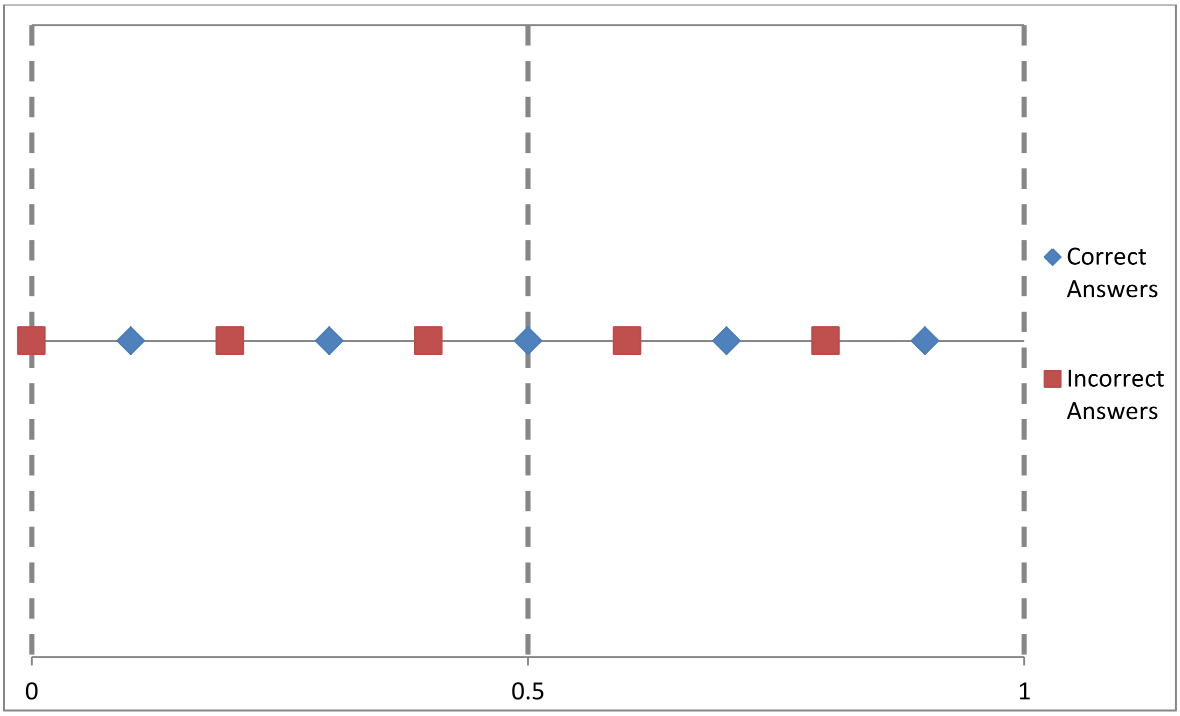

Figure 74: This represents a model where there is poor accuracy and a poor Nagelkerke R-squared value

Perfect Accuracy, Poor Nagelkerke R-Squared Value

Figure 75 represents a model where there is 100% accuracy, i.e. all of the expected values are on the sides which they should be on (all five correct answers are greater than 0.5 and all five incorrect answers are less than 0.5). However there is a poor Nagelkerke R-squared value for this result because many of the answers are significantly varied from where they should be (directly over zero and one).

This model is very useful because it has perfect predictions, therefore given the variables provided to the model, the model will always make the right prediction of how a participant will do. So there would be no additional benefit from adding more variables into the model, which could be more time consuming and costly.

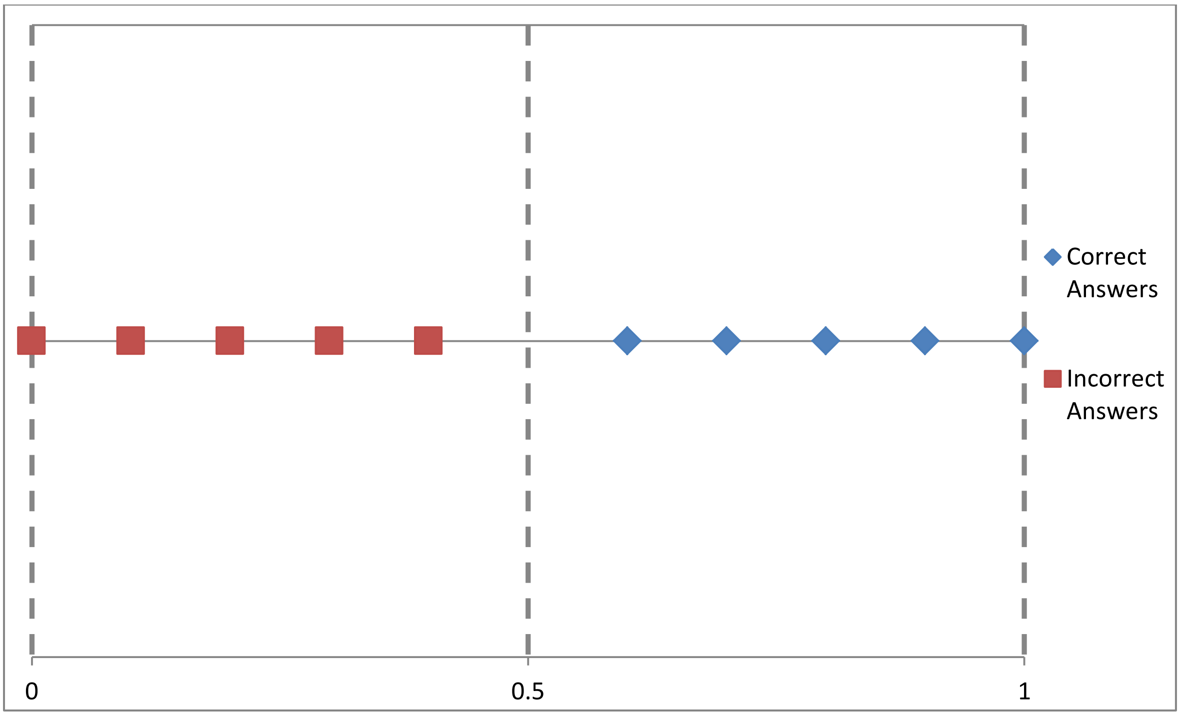

Figure 75: This represents a model where there is perfect accuracy but poor Nagelkerke R-squared value

Perfect Accuracy, Good Nagelkerke R-Squared Value but No Improvement in Performance

Figure 76 represents a model with perfect predictive accuracy (like Figure 75) but with a very high Nagelkerke R-squared value. Both of these models provide perfect predictive accuracy but Figure 76 will require additional variables and potentially cost more to develop.

Therefore, in Section 4.3.4, the important value is the predictive accuracy and not the Nagelkerke R-squared value. If the predictive accuracy is higher than the 'no variable' outcome, then the variables are beneficial in predicting the outcome of participants.

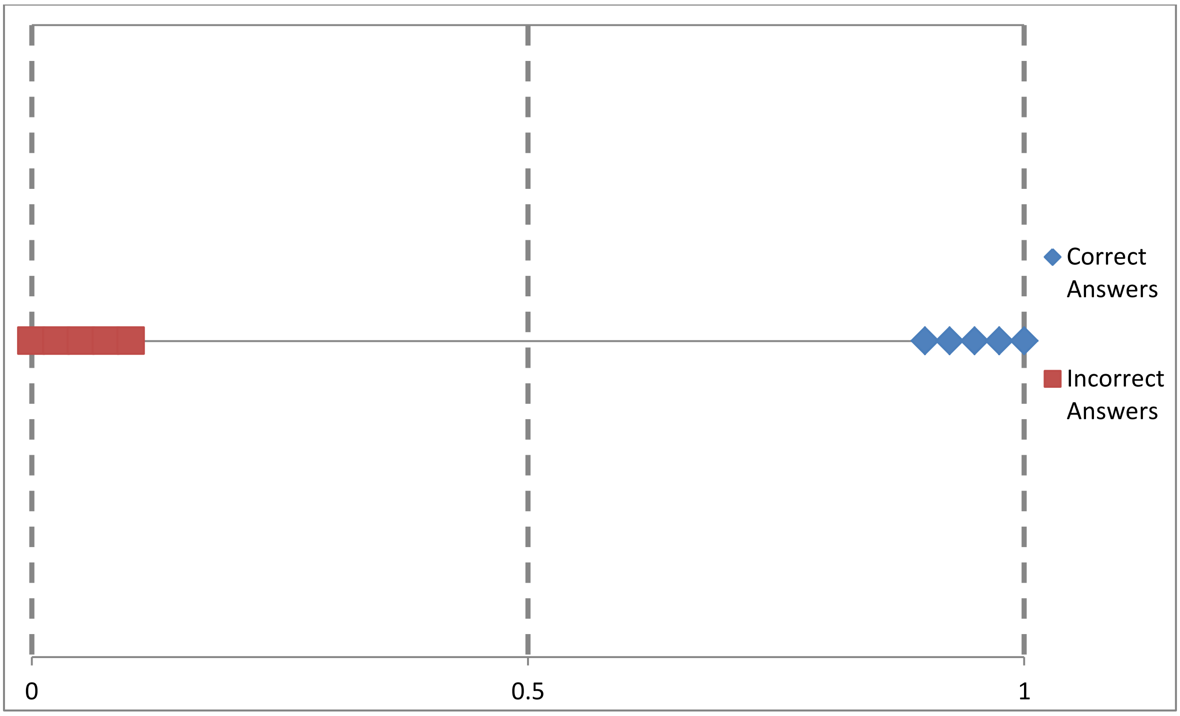

Figure 76: This represents a model with perfect predictive accuracy and high Nagelkerke R-squared value

Nagelkerke R-Squared

As a logistic regression R-squared value is distributed differently to a linear regression R-squared value (which many people are more familiar with), then a corrected R-squared can be used through Nagelkerke's technique. This approach can typically be understood by more people as the values are more similar to a linear regression model. SPSS also provides the Cox and Snell method which has not been used because it has a skewed upper bound which is less than one (Nagelkerke, 1991). Nagelkerke's method simply divides Cox and Snell's approach by the upper bound value to distribute the R-squared value between zero and one. However, this can result in a misleadingly high value compared to a linear probability model (Allison, 2013). For the purposes of this research though, the predictive accuracy is the most important feature rather than the R-squared value.

Appendix 2

Appendix 3

This section shows an example snapshot file from Paramics micro-simulation software which can be generated at a user specified time scale. Figure 77 shows a snapshot file from Paramics, and through email consultation with Paramics Support, the various characteristics of each vehicle were explained (Figure 78), however the support team emphasised that this file's intended purpose was never for traffic control. Reference number 11 and 12 (in Figure 78) are the important values for determining turning intention, if the value is represented by a zero, then this means that the vehicle is intending to take the first available turn in a clockwise direction (i.e. if there is a left turn then the vehicle will turn left). If the value is a one, then the vehicle will take the second available turning movement in a clockwise direction (i.e. the vehicle will not turn left but take the second exit – straight on).

Vehicle on Link 0:4

```
snapshot at time 150.00
on link 0:4
type 0 3 98 m 2 0 0 3 mps 3 2 137 0 0 3 7 0 0 1 0 0 0 0 0 0 0 0 0 0
on link 7:2
type 11 3 11 m 1 0 0 6 mps 3 1 147 0 2 3 3 1 0 1 0 0 0 0 0 0 0 0 0 0
Zone 0
Zone 1
Zone 2
Zone 3
D 0 0 2 3 0.00
D 0 0 1 2 0.00
D 0 0 0 0 0.00
```

Figure 77: Paramics snapshot file

Snapshot data	type 0	3	98m	2	0	0	3 mps	3	2	137	0	0	3	7	0	0	1	0	0	0	0	0
Reference Number	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22

Figure 78: Reference numbers for each of the vehicle characteristics shown in Figure 77

Reference Number - Vehicle Characteristic Key

1 - Vehicle type index

2 - From zone

3 - Distance to end of link (metres)

4 - Destination zone

5 - Routeing table

Appendix 3

6 - Lane

7 - Speed (metres per second)

8 - From zone (internal index)

9 - Destination zone (internal index)

10 - Start time of journey

11 - The index of the next link the vehicle intends to move to (clockwise turn index)

12 - The index of the next, next link the vehicle intends to move to (clockwise turn index)

13 - The vehicles aggression

14 - The vehicles awareness

15 - Has lane range been set next lane

16 - Is next out set (validity of index of the next link above)

17 - Highest lane range index

18 - Lowest lane range index

19 - Is the vehicle queued (not for signals)

20 - Was the vehicle previously queues (not for signals)

21 - Is the vehicle queued (for signals)

22 - Was the vehicle previously queues (for signals)

Appendix 4

For the case study in Section 5.5 it was desirable to determine what a 'typical day' flow profile would look like. Therefore an average weekday profile was calculated from inductive loop data from a major arterial route in Southampton throughout September 2010, this profile can be seen in Figure 79. This profile was from 5am to 10pm and shows a morning rush hour, followed by a period of lower demand and a small lunch-time peak, followed by a slow decline throughout the rest of the day. This demand scenario was simulated in Paramics but took a long time to complete as there was 17 hours of data to simulate; therefore a shorter demand scenario was proposed in line with research from Box and Waterson (2010) where a four hour simulation was carried out.

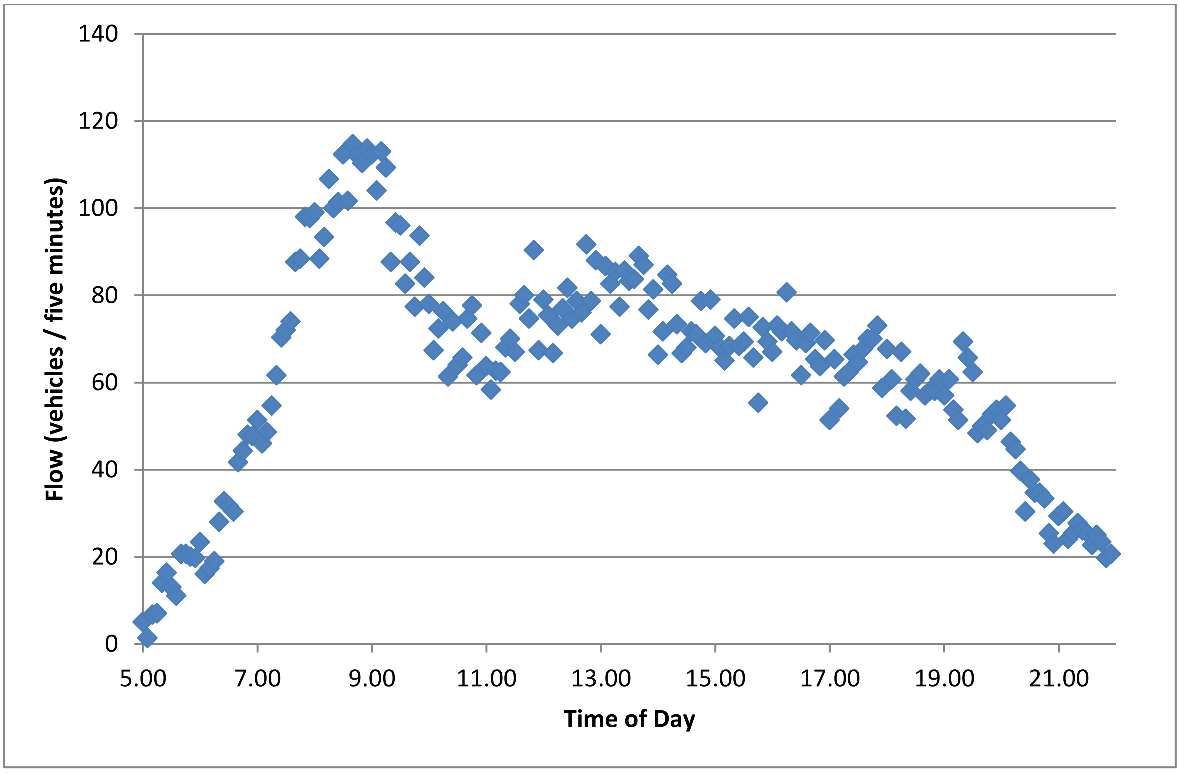

Figure 79: Average flow from Inductive loop data in Southampton during weekdays in September 2010

Appendix 4

Appendix 5

This appendix provides the mathematical proof for the delay calculations shown in Section 6.3. All of these equations are based on the standard equation for calculating the sum of arithmetic series:

$$Sum = \frac{x}{2}[2a + (x - 1)d]$$

Where:

x = Number of terms in the series

a = Initial term of the series

d = Common difference between successive values in the series

The following proofs will provide the starting values for each of the equations and a brief explanation. The following notation and terminology are used as can be seen in Section 6.3:

n = Stationary queue length (vehicles)

A = Arrival rate (vehicles per second)

D = Discharge rate (vehicles per second)

t = Time period considered (seconds)

Initial queue: is the number of vehicles which were stationary or very slow moving (less than 3mph) at the beginning of the time period.

Arrivals queue: is the number of vehicles which have arrived during the discharge of the initial queue from the beginning of the time period.

Starting values are calculated from one second after the start of the time period so that delay is not calculated twice. For example, a queue length is ten vehicles long, with no arrivals and a discharge rate of two vehicles per second; at time step zero there has been zero seconds of delay. Therefore the starting value of delay would be eight seconds at time step one second. It should be noted that the definition of delay for this calculation is the sum of the queue length at the end of each time step, hence why the value at time step zero is ignored.

When considering all of the starting values, the difference must be multiplied by '1 second' (t_1) to ensure that dimensionality is correct. However, when using the equations, then t_1 equals one and therefore makes no difference to the numerical outcome.

Appendix 5

The following pseudo-code logic is used to describe which equation should be used when a phase is being released:

If:	$n/D > t$	Use Equation 1
Else:		Use Equation 2
→ If:	$A < D$	
→ If:	$n/D - An/D(A-D) \leq t$	Add Equation 3
→ Else:		Add Equation 4
→ Else:	$A \geq D$	Add Equation 4

If the phase is not currently released then use Equation 5.

Equation 1

This equation is made up of two parts: the delay from the initial queue and the delay from the arrivals queue. This is used when the initial queue cannot be fully discharged within the time period specified.

$$a = (n - Dt_1) \qquad d = -D \qquad x = t$$

$$Delay = \frac{t}{2}\big((2n - 2Dt_1) + (t-1).-D\big)$$

$$= \frac{t}{2}\big(2n - D(t+1)\big)$$

$$a = A \qquad d = A \qquad x = t$$

$$Delay = \frac{t}{2}(2A + (t-1).A)$$

$$= \frac{At}{2}(1+t)$$

When these two parts are added together then equation 1 is formed:

$$Delay = \frac{t}{2}\big(2n - D(t+1)\big) + \frac{At}{2}(1+t)$$

Equation 1:

$$= \boldsymbol{\frac{t}{2}\big(2n + (A - D)(t+1)\big)}$$

Equation 2

This equation is calculated in two parts: the delay from the initial queue and the delay from the arrivals queue (during the initial queue discharge period). This equation is used when the initial queue can be discharged within the available time period.

$$a = (n - Dt_1) \qquad d = -D \qquad x = \frac{n}{D}$$

$$Delay = \frac{n}{2D}\left((2n - 2Dt_1) + \left(\frac{n}{D} - 1\right).-D\right)$$

$$= \frac{n(n - Dt_1)}{2D}$$

$$a = A \qquad d = A \qquad x = \frac{n}{D}$$

$$Delay = \frac{n}{2D}\left(2A + \left(\frac{n}{D} - 1\right).A\right)$$

$$= \frac{An}{2D}\left(1 + \frac{n}{D}\right)$$

When these two parts are added together then equation 2 is formed:

$$Delay = \frac{n(n - Dt_1)}{2D} + \frac{An}{2D}\left(1 + \frac{n}{D}\right)$$

Equation 2:

$$= \boldsymbol{\frac{n}{2D}\left((n - Dt_1) + A\left(1 + \frac{n}{D}\right)\right)}$$

Equation 3

This equation deals with dispersing the arrivals queue which has built up during the release of the initial queue. Note that this equation is used when the arrival rate is smaller than the discharge rate.

Appendix 5

$$a = \frac{An}{D} + (A-D)t_1 \qquad d = (A-D) \qquad x = \frac{An}{D(D-A)}$$

$$Delay = \frac{An}{2D(D-A)}\left(\frac{2An}{D} + 2(A-D)t_1 + \left(\frac{An}{D(D-A)} - 1\right).(A-D)\right)$$

Equation 3:

$$= \boldsymbol{\frac{An}{2D(D-A)}\left(\frac{An}{D} + (A-D)t_1\right)}$$

Equation 4

This equation is used when the arrivals queue cannot be fully discharged within the specified time period.

$$a = \frac{An}{D} + (A-D)t_1 \qquad d = (A-D) \qquad x = t - \frac{n}{D}$$

$$Delay = \frac{tD-n}{2D}\left(\frac{2An}{D} + 2(A-D)t_1 + \left(t - \frac{n}{D} - 1\right).(A-D)\right)$$

Equation 4:

$$= \boldsymbol{\frac{tD-n}{2D}\left(\frac{2An}{D} + (A-D).\left(1 + t - \frac{n}{D}\right)\right)}$$

Equation 5

Equation 5 can be used for calculating delay when a phase has not been released. Discharge value is not required for this solution as there is simply a queue steadily building behind the red traffic light.

$$a = (n + At_1) \qquad d = A \qquad x = t$$

$$Delay = \frac{t}{2}(2n + 2At_1 + (t-1).A)$$

Equation 5:

$$= \boldsymbol{\frac{t}{2}(2n + A(t+1))}$$

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