Modelling Disrupted Transport Network Behaviour

By

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B.E (Honours Class 1), B.Comm

A thesis presented in the fulfilment of the requirements for the degree of Doctor of Philosophy

School of Civil and Environmental Engineering

Faculty of Engineering

The University of New South Wales

September 2016

PLEASE TYPE

THE UNIVERSITY OF NEW SOUTH WALES
Thesis/Dissertation Sheet

Surname or Family name: **Wijayaratna**

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Abbreviation for degree as given in the University calendar: **PhD**

School: **School of Civil and Environmental Engineering** Faculty: **Faculty of Engineering**

Title: **Modelling disrupted transport network behaviour**

Abstract 350 words maximum: (PLEASE TYPE)

Current transport modelling tools, utilised for maintenance and development of road infrastructure, assign traffic throughout a network based on traditional equilibrium concepts. These models assume rationality, perfect network knowledge and path cost minimisation of users. Disruptions on a road network such as traffic incidents transform normal driving behaviour and route choice. Hence, these equilibrium concepts cannot appropriately cater for disruptions which restrict the value of the available tools.

This thesis presents an investigation into driving behaviour under disrupted conditions and the subsequent development of traffic assignment models that account for disrupted conditions. It is postulated that disruptions lead to the release of information which results in adaptive behaviour. Information can be through visual cues of the disruption itself, or provided through navigation technology and Advanced Traveller Information Systems (ATIS). Thus, the thesis focuses on two components; impacts of information on driving behaviour and the incorporation of information into network modelling.

The concepts of experimental economics were used to develop two controlled laboratory experiments; the first studied the presence of information on risk attitudes of users. The findings revealed that users became risk neutral in the presence of information resulting in the overvaluation of information sources. The second experiment empirically proved the existence of an online information paradox where the provision of information results in deterioration of network performance. Neglecting these findings may affect the economic appraisal of informational infrastructure and can potentially result in erroneous planning outcomes.

Principles of "User Equilibrium with Recourse" (UER) were used to develop static (Dynamic Equilibrium Assignment with Recourse (DEAR)) and dynamic (Dynamic User Optimal with Recourse (DUOR)) traffic assignment methodologies which account for the adaptive behaviour of users in light of a disruption. Application of the models suggests an increase in system wide costs when accounting for disruptions and highlights the benefits of information provision.

The core contribution of the research is the development of novel modelling techniques that incorporate adaptive behaviour associated with disruptions. Further development of these models can lead to improved assessment of reliability and vulnerability of road networks.

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ABSTRACT

The transport planning process is reliant on modelling tools to appropriately assess and mitigate current issues whilst also developing a sustainable network for the future. In the context of road infrastructure management, modelling approaches used in practice assign traffic throughout a network based on concepts of equilibrium. It is assumed that users of a network make rational decisions based on knowledge of the network characteristics and choose the best route available to minimise travel costs. Disruptions on a network such as traffic incidents, crashes, and inclement weather transforms normal driving behaviour as well as route choice. Accordingly, traditional equilibrium concepts cannot appropriately account for the presence of disruptions which restrict holistic modelling of transport scenarios. This thesis presents an investigation into the understanding of driving behaviour under disrupted conditions and the subsequent development of traffic assignment models that consider the potential for disrupted conditions.

Initially, this research presents an empirical analysis of traffic data on competing parallel routes, comparing normal and disrupted conditions. The findings indicate the presence of adaptive route choice behaviour in disrupted conditions. Thus, this thesis postulates that a disruption results in a release of information to the road user which creates an adaptation of routing and changes travel behaviour. Information can be supplied through visual cues of the disruption itself, such as the development of a queue or the appearance of brake lights or through navigation technology and Advanced Traveller Information Systems (ATIS). Hence, the remainder of the thesis focuses on two components; impacts of information on driving behaviour and the incorporation of information acquisition into network modelling.

Concepts of experimental economics were used to develop a controlled laboratory experiment to study the impact of the presence of information on road users' risk

attitudes. The findings reveal that risk attitudes change in the context of information which has the potential to result in an overvaluation of information sources. Neglecting this behavioural finding significantly affects the economic appraisal of informational infrastructure within road networks.

Using the principles of 'User Equilibrium with Recourse' (UER), the research proposes static (Disrupted Equilibrium Assignment with Recourse (DEAR)) and dynamic (Dynamic User Optimal with Recourse (DUOR)) traffic assignment methodologies. These methodologies consider the adaptive behaviour of users in light of *en route* information acquisition. The novelty of the approaches stem from equilibration of routing policies, a set of feasible adaptive paths, rather than strict deterministic paths used in conventional assignment methods. Applications of the models suggest the increase in system wide costs when accounting for disruptions and in general highlight the benefits of information provision.

Finally, analytical evidence indicated that online information provision in the context of disrupted conditions does not necessarily reduce the travel costs of road users resulting in an Online Information Paradox. This thesis studies the empirical presence of the paradox through a controlled experiment. The paradox was observed throughout all experiment session and the presence of the paradox was statistically significant at a confidence level of 95%. The empirical observation of the Online Information Paradox creates an additional consideration for transport authorities during the evaluation and implementation of ITS and ATIS infrastructure within road networks.

The core contribution of the research effort is to develop novel modelling techniques that can account for disrupted conditions and the adaptive behaviour associated with the disruptions. These approaches provide the foundation for the development of practical tools that are more capable of assessing the reliability and vulnerability of road networks in the presence of disrupted conditions.

ACKNOWLEDGMENTS

There are a number of people and organisations that made this research project a reality. Firstly I would like to thank my supervisors, Professor S. Travis Waller and Dr Vinayak Dixit who have sacrificed their valuable time and passed on their vast knowledge in guiding me through the PhD process. I am incredibly grateful for their invaluable suggestions, detailed explanations and constructive criticism of the work. They have been amazing mentors whom I will always look up to.

Research is a collaborative process. The University of New South Wales and particularly the staff and students at the Research Centre for Integrated Transport Innovation have been pillars of support throughout the process. Specifically, Dr Melissa Duell was an integral contributor to the development of the DEAR model presented in Chapter 4 and has been there from the start of my journey. Dr David Rey and Dr Lauren Gardner have also helped me through many long discussions teaching me about transport and research. I would also like to thank two undergraduate students, Kenneth Lam and Lukas Labutis, whom I was fortunate enough to co-supervise their undergraduate Honours Theses. They provided incredible assistance in collecting and analysing data presented in Chapter 2 and coding the developed algorithms in Chapter 5. I wish to also thank Ms Sarah Gurr from the Roads and Maritime Services of New South Wales, who provided the necessary incident and traffic data.

Finally I would like to thank my family and friends who have helped me immensely and coped with me during the last 4 years. My brother, Sahan, and my dear friends Thomas Brown and Christina Chiu have provided me unconditional support at a technical and emotional level which I will always cherish. I would like especially to thank my father for his enduring engineering wisdom and my mother for proof reading the entire thesis and helping me manage the editing process. Without my family's love, understanding, encouragement and patience, this project would never have been possible.

LIST OF RELEVANT PUBLICATIONS AND AWARDS

The following provides a list of the conference and journal publications that have contributed towards the development of the thesis;

Published or Presented Papers

- Wijayaratna K.P.; Labutis L.N.; Waller S.T. (2014). 'Dynamic User Optimal traffic assignment with recourse'. In: *Proceedings of the 19th International Conference of Hong Kong Society for Transportation Studies, HKSTS 2014 - Transportation and Infrastructure, Hong Kong Society for Transportation Studies Limited*, Hong Kong, (pp. 525 – 532)
- Dixit, V.V. and Wijayaratna, K.P. (2014) 'Value of Information and Risk Attitudes.' In: *Proceedings of the 93rd Transportation Research Board Annual Meeting, 2014,* Washington DC, USA
- Wijayaratna, K.P., Duell, M., & Waller, S.T. (2013). 'Predicting disrupted network behaviour incorporating user equilibrium with recourse.' In: *Proceedings of the 18th International Conference of Hong Kong Society for Transportation Studies, HKSTS 2013 - Travel Behaviour and Society,* Hong Kong, (pp. 633-640).
- Liu, H.; Wang, J.; Wijayaratna, K.; Dixit, V.V.; Waller, S.T. (2015). Integrating the Bus Vehicle Class Into the Cell Transmission Model. *IEEE Transactions on Intelligent Transportation Systems*, 16(5), (pp.2620-2630)

Papers submitted and under Review

- Wijayaratna, K.P. and Dixit, V.V. 'Impact of Information on Risk Attitudes: Implications on Valuation of Reliability and Information', Submitted to the Journal of Choice Modelling (under review, 2015)

Awards

- Kasun Wijayaratna was the recipient of the 2014 Student Research Regional Prize for New South Wales/ACT. The prize was awarded for the most outstanding and practical postgraduate research project and sponsored by the Australian Road Research Board (ARRB) and Roads Australia.

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CHAPTER 1. INTRODUCTION

1.1 Context and Motivation

Transportation infrastructure provides the foundation of economic development, environmental sustainability and quality of life within a community. Commercial and economic development depends on the efficient movement of people, services and freight at a domestic and global scale.

Transport systems need to be able to minimise the costs involved with travel from origin to destination while maintaining the safety and security of all people, goods and services being transported. The decisions regarding our transport infrastructure must also consider the environmental impact as the construction of roads, railways and ports as well as the utilization of land, affects the natural ecosystems. Ultimately, these two factors contribute to the overall quality of life each member of the community experiences. A systematic approach to achieving these goals for a community is through the use of robust and efficient transport modelling tools. These tools offer guidance to Traffic Engineers and Transport Planners in forming and justifying mitigation strategies to resolve existing issues as well as planning for future developments.

Globalisation of economies and the technological advancements in mobility have led to the increased desire and ability to travel longer distances in shorter periods of time. These advancements have also meant that people, organisations and governments can now overcome geographic constraints of activities that could not be conducted previously. Furthermore, population growth throughout the world has increased by over 35% across the last 25 years which has led to a dramatic increase in the amount of travel, in particular on road networks. The ability of planning agencies to meet the demand of travellers and maintain the efficiency and safety of the network will be an increasingly complex task into the future. This emphasises the desperate need for planning tools to assist in the decision making processes within this paradigm.

The focus of this research project is to understand the impact of disruptions or disturbances on road networks with regard to driving behaviour. In turn this new understanding has led to the development of traffic assignment models which can appropriately account for these disruptions. The definitive contributions resulting from this research project enhance traffic modelling methodologies available for transport professionals, and thus provide a greater level of clarity in the decision making process regarding transport infrastructure.

In Australia, the reliance on road transport is evident when observing recent registered vehicle ownership statistics. The number of registered vehicles have increased from 16 million to over 18 million between 2010 and 2015, an increase of 12.1% over the last 5 year period (Australian Bureau of Statistics, 2015). Total travel on road networks in Australia have grown ten-folds over the last 80 years with private road vehicles accounting for about 90 per cent of total passenger transport and is expected to grow at about 1.7% per annum into the future (Bureau of Transport and Regional Economics, 2007). Furthermore, commercial vehicle traffic has been forecasted to grow substantially more than private car traffic at 3.5% per annum. Similar trends can be seen globally and as a result traffic congestion on road networks is a daily occurrence in most metropolitan areas. The physical evidence of the presence of congestion can be seen through reduction in average speeds on road links, greater travel times, and increased queuing throughout networks. Traffic congestion has been shown to result in excessive delays, instability of travel time and increased fuel consumption which leads to considerable economic and social costs (Banister, 2002, Sanderson and Greenwood, 1991, Taylor, 1992). Accordingly, the planning and provision of transport infrastructure to mitigate these costs have become an important objective of many transport professionals. This research study aims to add to the current tools available in management of traffic congestion.

Traffic congestion is generally classified into recurrent or non-recurrent events (Rietveld et al., 2001). In the context of road networks, recurrent congestion is related to expected delays as a result of peak hour conditions and seasonal effects that are created from an imbalance between supply and demand within the network. These delays are normally associated with an obsolete infrastructure system that is not in need of an immediate upgrade. This means that there are sections of the network which lack the capacity to service the demand throughout the entire day. For example, there may be roads that exceed capacity during peak periods, however, these roads experience free flow travel conditions across other times in the day, thus not warranting an upgrade. Considering these prevailing conditions, regular travellers will still perceive this traffic scenario to be reliable as there is an expectation that these delays are likely to eventuate and understood within their decision making.

Non-recurrent congestion, on the other hand, is a result of an uncertain event. These events could occur as a result of inclement weather, the presence of traffic incidents or any other impedance of the flow of traffic. These uncertain events are described within this thesis as 'disruptions'. Non-recurrent congestion, as a result of disruptions to a network, is a significant part of the total level of congestion. The 2003 Urban Mobility Report by the Texas Institute of Transport states that crashes, vehicle breakdowns, weather conditions, special events and road construction and maintenance activities contribute to 50% of all delays incurred on roads in the United States of America (Schrank and Lomax, 2003). More recently, analysis of freeway travel times in the United States of America suggests that users must allocate 3 times the travel time of free flow conditions to ensure that they can achieve on-time arrival at their destination to account for the possibility of uncertain events occurring (Schrank et al., 2012). Given the immense operational impact on road networks, it is imperative to be able to account for the presence of disruptions when assessing our transport infrastructure. This project develops an understanding of the behavioural tendencies of users in light of disruptions through the analysis of empirical field data and controlled laboratory experiments, presented in detail within Chapter 2, Chapter 3 and Chapter 6.

Traditionally, congestion management strategies have revolved around the concept of increasing capacity throughout the road network, i.e. supply management. This has resulted in the funding of arterial roads, motorways and freeways across a number of urban metropolitans, such as Sydney and more famously Los Angeles. However, the development of additional road infrastructure does not provide a sustainable solution to alleviate traffic congestion due a variety of reasons covering social, political, financial and environmental factors (Banister, 2002). In the long term, additional capacity has the potential to induce greater levels of demand than the levels initially forecasted, thus exacerbating the level of congestion (Litman, 2004). The issues of providing additional capacity have resulted in the recent implementation of a number of alternative approaches including travel demand management and peak spreading which aim at managing the demand that utilises the network.

In line with these strategies, the mitigation of disruptions that occur on a network has focussed on the adoption of Intelligent Transportation Systems (ITS). ITS systems encompass a broad range of technologies which provide information to road users that extend from parking demand guidance systems to advanced intersection signalisation systems. The purpose of these systems is to assist users in the decision making process and resolve the uncertainty that is faced during travel. A specific form of ITS, is Advanced Traveller Information Systems (ATIS) which aim to provide road users with information to assist in travelling from their origin to their destination. The presence of incidents, adverse weather or road conditions, recommended speeds and lane or road closures are the common types of information revealed to the user. As a congestion management technique, ATIS systems intend to provide users with greater knowledge of the network conditions so that users will make well informed decisions regarding route choice. In turn, this has the potential to relieve congestion at an aggregate level. Consider the example where a traffic accident occurs on a road section; information about the disruption offers users the possibility to change their route and avoid the impending bottleneck. In other words, ATIS and other information sources aim at reducing the uncertainty that is borne from a disruption that could result in adaptive routing behaviour.

Disruptions that occur on a network give rise to the dissemination of information. The information is provided through; visual cues such as the reduction of speed or the appearance of downstream brake lights and queuing, radio and internet traffic reports, personal navigation systems and ATIS systems via Variable Message Signs (VMS) and public announcements. Thus, in order to effectively capture the behaviour of road users in disrupted conditions, it is imperative to understand the acquisition, valuation and utilisation of information by people when making *en route* travel decisions. Chapter 3 of this thesis presents a controlled laboratory experiment investigating the impact of information provision within road users' choice set on their risk attitudes. A greater understanding of risk characteristics excluding and including information within the choice set can lead to improved valuation of the information provided to the user. Subsequently, this can be accounted for by transport authorities in determining the costs and benefits of the implementation of information systems on road networks. This has the potential for more effective rankings of transport infrastructure projects involving ATIS technology implementation.

In addition, this research project attempts to advance current transport modelling practices to effectively account for disruptions. Currently, transportation models have been utilised as a key planning tool to assist in the decision making process regarding the implementation of transportation infrastructure within road networks. In general, the models are developed by initially constructing a 'base' model which is calibrated and validated to reflect the prevailing traffic conditions. A series of forecasting assumptions are then applied, considering expected population levels and land use characteristics, to model future traffic scenarios. Base models provide transport professionals the ability to assess and rectify existing road network issues while modelling future traffic scenarios assist in the planning and development of infrastructure. These models assign traffic throughout a network based on concepts of equilibrium (static and dynamic equilibrium models). It is assumed that users of the network make rational decisions based on accurate knowledge of the network characteristics and choose the best route available that minimises the travel cost (de Dios Ortúzar and Willumsen, 2011). Under normal day-to-day conditions, in the presence of recurrent congestion and without any unforeseen disruptions, these models accurately portray travel behaviour of network users. As mentioned before, a disruption results in a release of information. The information gathered by a road user can lead to an adjustment of route choice in accordance with the prevailing network conditions. Accordingly, to account for disruptions appropriately within a transport model it is vital to consider the potential of adaptive behaviour by travellers. Furthermore, it is hypothesised within this research study that network users' decision making on route choice will transform in the presence of a disruption. For an example, users may not select the shortest path or path with the minimum travel time in light of a disruption due to the uncertainty surrounding the event. Thus, equilibrium concepts used within current transport models may not be applicable when disruptions are present on a network. This is particularly pertinent in the development of models for the purposes of incident mitigation or disaster management.

This thesis develops novel traffic assignment methodologies accounting for the transformation in decision making in light of a disruption in addition to the adaptive routing behaviour as a result of the information available within the system. Chapter 4 and Chapter 5 present a static and dynamic traffic assignment methodology extending the concept of User Equilibrium with Recourse (UER) presented by Unnikrishnan and Waller (2009). User Equilibrium with Recourse is a static traffic assignment equilibrium model that accounts for *en route* adaptive behaviour when users acquire information. Traditional traffic assignment techniques such as User Equilibrium (UE) assume that users do not adapt their routes and experience a set of average traffic conditions. UER relaxes these assumptions and suggests that travellers have a routing policy or hyperpath which is a collection of paths that are dependent on the state of the network. For an example, consider a network containing two paths, A and B, which have a mid-path connector road allowing users to change from A to B (shown in Figure 1.1). A user may select path A under normal conditions, however if a disruption were to occur on path A the user has the option to adapt and change to path B provided the incident is upstream of the mid-path connector.

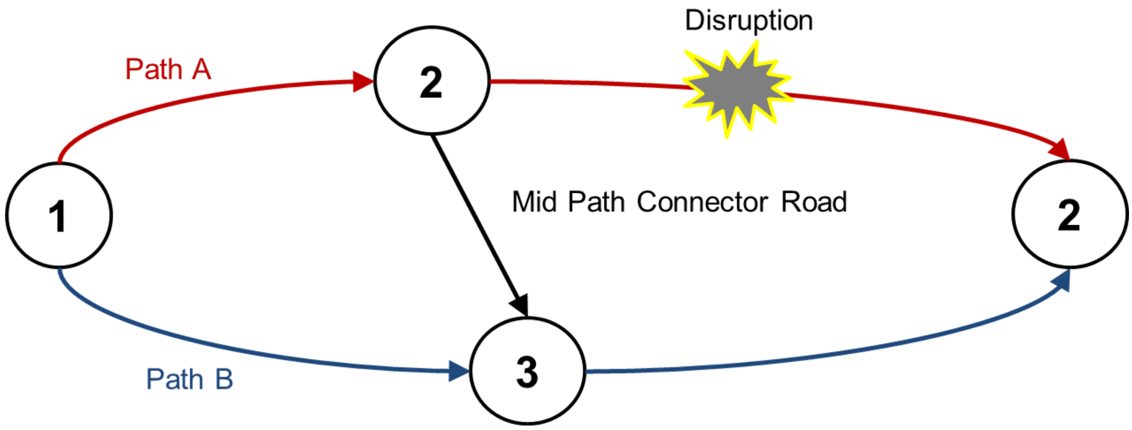


Figure 1.1: The potential for adaptive routing on a sample road network

Equilibrium conditions are achieved if each user on the network selects a minimum expected cost routing policy and no user can unilaterally change their routing policy to improve the experienced expected cost. This concept of equilibrium has been extended by incorporating deviations in the perception of a state of the network by users in Chapter 4 while Chapter 5 presents a dynamic interpretation of the principles defined within the UER framework. These extensions add to the advancement of adaptive traffic assignment techniques whilst developing models that appropriately account for the presence of disruptions on a road network.

Strategic planning of transport infrastructure and the operational management of traffic networks tend to be guided by multiple models. In general, high level strategic planning is based on the information obtained from regional macroscopic transport models that contain a degree of aggregation. On the other hand, traffic management strategies and policies are devised based on the results of detailed microsimulation modelling which considers the behaviour of individual entities. Each model requires inputs, which have been well acknowledged as incredibly complicated in nature, normally aggregating a number of stochastic processes including the most intricate of all, human behaviour. The complexity of modelling results in a degree of error. Thus, the levels of error are compounded by utilising multiple models to guide decision making. The research completed within this thesis adds to the research effort of developing a holistic singular dynamic operational planning model which can be used for both strategic planning and traffic operations management.

1.2 Contribution

The main contribution of this research project is to introduce traffic assignment methodologies that are able to better account for the presence of disruptions within a road network. As mentioned throughout the report, it is pivotal to understand the behaviour of users in light of various disruptions and incorporate these into traffic modelling practices to improve decision making. The research contains novel insights into driving behaviour through the analysis of empirical data and from the observations of controlled laboratory experiments. In addition an attempt is made to further develop the UER traffic assignment framework discussed briefly in Section 1.1 by incorporating users' perceptions of disruptions as well as incorporating temporal dependence in a dynamic traffic assignment approach. The contribution of this thesis can be summarised as follows;

- Obtain an empirical understanding of the impact of disruptions on traffic flow characteristics such as travel speed, travel time and volume, highlighting the presence of adaptive user behaviour. (Chapter 2)
- Understanding the value of information in the context of route choice and the effects on people's risk characteristics (Chapter 3).
- Develop and demonstrate a static traffic assignment model which accounts for the adaptive behaviour of users in light of a disruption as well as the transformation in the perceptions of traffic characteristics as a result of the disruption. (Chapter 4)
- Develop and demonstrate a dynamic traffic assignment model which accounts for adaptive behaviour of users in light of a disruption. (Chapter 5)

- Investigate empirically the presence of theoretical paradoxes of information which yield from the application of adaptive online traffic assignment techniques. (Chapter 6)

1.3 Organisation

The research contributions of this thesis is separated into five chapters, each chapter details the findings of experiments, analysis of empirical data or modelling efforts conducted throughout the project. The chapters of the thesis can be categorised into two streams of research;

- The study of the behavioural impacts of disruptions and information
- The modelling of disruptions and acquisition of information within the traffic assignment paradigm.

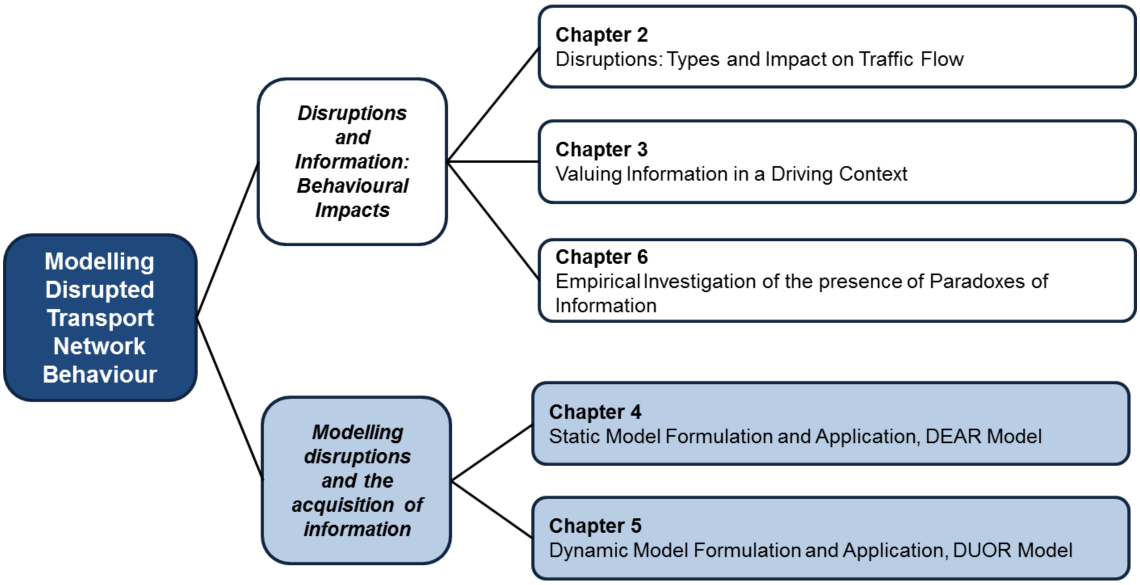


Figure 1.2: Thesis Structure

Figure 1.2 diagrammatically presents the categorisation and division of the chapters of the thesis. As mentioned in Section 1.1, the intent of this study was to gain an understanding of the impact of disruptions on road user behaviour through traffic data analysis and controlled laboratory experiments. The findings of these components of the research project provided the guidance for the next stage of the research; development and advancement of traffic assignment techniques to effectively account for the presence of disruptions. Finally, the results of the modelling efforts as well as studies in literature indicated the presence of information based paradoxes. These paradoxes suggest that the provision of information within a network can at times be detrimental to the overall network performance. The findings led to Chapter 6 of the thesis which is the investigation into the empirical presence of such a paradox. Though each individual chapter can be categorised into either a behavioural investigation or a modelling advancement, this thesis is presented as a development of ideas with a specific flow where each chapter yields a contribution that together amounts to an improved understanding of disrupted transport network behaviour. The development of the research can be described in the research flow diagram presented in Figure 1.3.

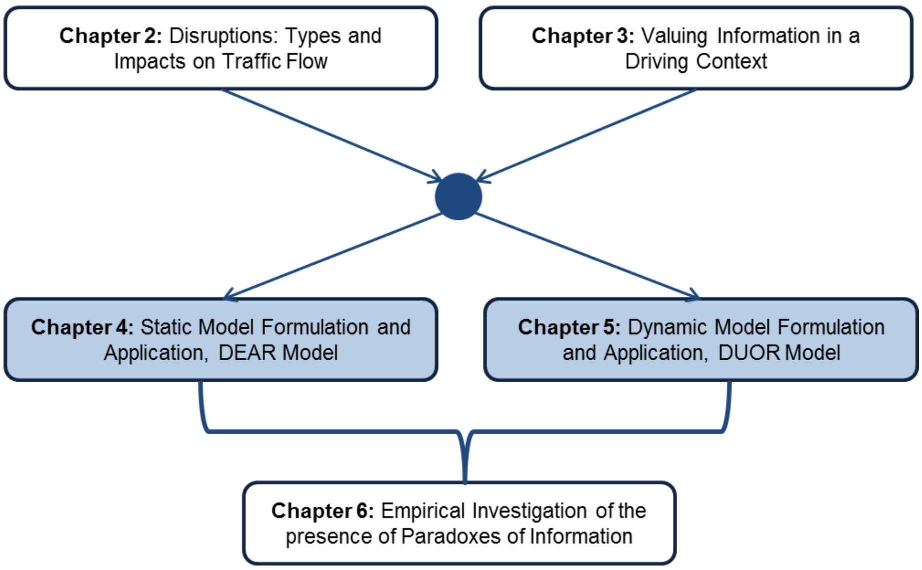


Figure 1.3 Research Flow Diagram

The following sub-sections of the report summarise the content of the core chapters of the thesis.

1.3.1 Chapter 2 - Disruptions: Types and Impact on Traffic Flow

The necessity of a new branch of operational planning models which account for the impact of disruptions is dependent on understanding the nature of a disruption and the observed impacts on road networks. Thus, this chapter conducts an analysis of speed, volume and incident data across a series of competing parallel routes throughout Sydney, Australia. To date, the empirical analysis of traffic flow data considering the presence of short term traffic incidents has not been investigated in great detail. Furthermore, there has been limited research concerning the adaptive behaviour of users in light of a short term disruption. Accordingly this chapter separates and categorises the data, based on the presence of an incident and then compares the travel time and traffic volumes along the competing routes. The findings of this chapter indicate that users adapt their route choice in the presence of an incident balancing average travel times across the competing routes. This emphasises the merit of developing modelling techniques using advanced equilibrium concepts to account for the impact of disruptions on road networks.

1.3.2 Chapter 3 - Valuing Information in Driving Context

The notion that the presence of a disruption results in the discharge of information to the road network highlights the need to understand the behavioural implications surrounding the provision of information. In particular, it is important to understand valuation of information and reliability in the context of route choice. Online information provision serves to resolve the uncertainty of travel time along a route. This chapter conducts a controlled laboratory experiment using methods of experimental economics to measure the risk attitudes of users with and without the presence of information in the choice set. A model derived from Expected Utility Theory is used to infer the risk attitudes of the participants. The results of the analysis indicate that the presence of information in the choice set reduces risk aversion, which causes a reduction in the valuation of information and reliability. It is critical to systematically incorporate these differences into behaviour models, as neglecting this fundamental difference could result in erroneous policy decisions, with respect to overpricing information, or inappropriately allocating funds for information systems. Furthermore, it is clear that incorporating the acquisition of information within the network modelling paradigm will assist in the decision making process of future transport infrastructure requirements.

1.3.3 Chapter 4 - Static Model Formulation and Application: Disrupted Equilibrium Assignment with Recourse (DEAR) Model

Static transportation models are a vital tool that is used in long term planning of civil infrastructure. As described earlier, traditional user equilibrium concepts are not suitable in depicting the behaviour of users in light of a disruption. Accordingly, this chapter presents the disrupted equilibrium assignment with recourse (DEAR) model that incorporates a decision-making process in which users gain information about the uncertainty created by a disruption as they travel though the network. The core of this is built on an existing static model, the Disrupted Network Assignment Model (DNAM), by incorporating an adaptation of the user equilibrium with recourse (UER) model. The DEAR model was applied to a sample network and also the Sioux Falls network highlighting the scalability of the approach. Demonstration of the model indicates the necessity to account for the adaptive behaviour of users in light of a disruption. The results also emphasises the potential system wide travel cost savings that arise from improving the reliability of the system.

1.3.4 Chapter 5 - Dynamic Model Formulation and Application: Dynamic User Optimal with Recourse (DUOR) Model

Dynamic network analysis models provide a more detailed option to describe the state of a road network. These methodologies are able to capture the temporal traffic characteristics of a road network allowing for 'time of the day' analysis. This form of modelling yields operational network models which not only serve as a tool for large scale strategic planning but also assists in the management of traffic operations on a day to day basis. Research into dynamic modelling has led to the development of dynamic equilibrium concepts, such as Dynamic User Optimal (DUO), to improve the estimation of traffic conditions and congestion throughout networks. This chapter of the report extends DUO to DUO with Recourse (DUOR), based on the principles of UER to allow users to change their paths *en route* in response to information received while travelling. This allows for adaptive routing in a time-dependent context to achieve more realistic modelling tools. DUOR is developed as a simulation based traffic assignment approach whereby all feasible options are assessed using a Cell Transmission Model (DUOR-CTM). Demonstration of the approach confirmed the observation of user optimal with recourse equilibrium conditions. In most cases tested information had positive impacts on performance. However, there were also a few examples where information appeared to deteriorate network performance, emphasising the need to account for information in a dynamic context. Nevertheless, the development of a computationally efficient solution method is required in order to assess larger networks with greater degrees of congestion.

1.3.5 Chapter 6 – Empirical investigation of a Paradox of Information

Similar to the presence of the 'Braess Paradox' within the traditional deterministic user equilibrium (UE) model, the UER equilibrium model (mentioned in Section 1.1) analytically exhibits an 'Online Information Paradox'. The paradox suggests that the provision of information between an origin and destination pair increases the travel cost for each network user relative to the scenario where no information is provided. Furthermore, the results from the demonstration networks of the DUOR model also indicate that sources of information may not necessarily reduce the travel costs of the users on the network. This motivated an empirical study of the theoretical paradox using concepts of experimental economics in a controlled laboratory setting. A route choice game depicting the conditions of the theoretical paradox was formulated and administered to participants. The results of the experiment suggest that a statistically significant increase in total system travel cost is present when information is provided to participants. These findings further highlight the need to accurately model the acquisition of information as well as taking necessary precautions when evaluating the incorporation of information systems within traffic networks.

1.3.6 Chapter 7 - Conclusion and Future Research Directions

Chapter 7, the final chapter of the thesis presents the conclusions and future research direction to advance the approaches and methodologies introduced within this project.

CHAPTER 2. DISRUPTIONS: IMPACTS ON TRAFFIC FLOW CHARACTERISTICS

2.1 Introduction

Modelling in transportation involves the representation of the movement of people, goods and services throughout a network. Practitioners use these models to assess and find solutions to mitigate current issues as well as forecasting and planning for future growth and development. In the development of models, it is essential to provide a realistic depiction of travel behaviour. As mentioned in Chapter 1, models representing vehicular traffic flow on road network fail to consider the potential for disruptions and the associated behaviour. Though a number of modelling approaches account for disruptions through the means of scenario analyses, it does not consider the anticipatory and adaptive behaviour of road users in relation to disruptions that a user possesses. It is hypothesised that commuting traffic, based on past experiences, has an understanding of the likelihood of disruptions and alter the route choice and overall decision making in light of a disruption. However, in order to pursue modelling efforts using this behavioural theory, it is necessary to observe the behaviour within a real road network. Accordingly, this chapter conducts an empirical investigation into the impact of short term disruptions on driving behaviour through the analysis of key road network performance metrics; travel time and traffic volume.

Short term disruptions on a road network are defined within this study as traffic incidents. Traffic incidents may include events such as vehicle breakdowns, road crashes, rain and other adverse weather conditions. On the other hand long term disruptions are generally related to catastrophic events related to the failure of civil infrastructure (bridge and tunnel collapses), natural disasters and terrorist attacks where the impacts on travel behaviour last for several days, weeks, months or even years. There have been numerous research efforts assessing the vulnerability and reliability of transport networks in light of long term disruptions

(Danczyk et al., 2010, Giuliano and Golob, 1998, Gordon et al., 1998, Tilahun and Levinson, 2008). These disruptions result in a significant cost to transport authorities and road users, highlighting the importance for research. However, the likelihood of such events is less than that of the presence of day to day short term disruptions. Though these events are less severe the increased likelihood of short term disruptions have a significant contribution to the variability of road network performance experienced by major metropolitan areas (TomTom International, 2015). Thus, it is imperative to understand the behaviour of road users in the presence of traffic incidents in order to develop strategies to mitigate the impacts of short-term disruptions on a road network.

This chapter of the thesis aims to add to the growing body of empirical knowledge regarding the implications of disruptions on road networks by conducting an empirical analysis of the impact of traffic incidents on competing parallel routes within Sydney, Australia. Speed, traffic volume and incident data were obtained for 10 selected routes on the Sydney road network, from Roads and Maritime Services, the road transport authority for the state of New South Wales. As shown in Figure 2.1, the ten routes selected are from different regions of the metropolitan area providing a diverse data set representative of the Sydney Metropolitan. Sydney was selected for this study as it has been established as one of the most congested metropolitan areas in Australia. The presence of traffic incidents on Sydney's road network is a daily occurrence for most routes, providing a rich data set to analyse. The specific research objectives of this study are listed below:

- Investigate the impact of short-term incidents on travel time during peak period traffic conditions on parallel commuter routes.
- Compare the route choice behaviour of users under 'no incident' scenarios and 'incident' scenarios during peak period traffic conditions using traffic volume data on parallel routes.
- Compare travel time variability under 'no incident' scenarios and 'incident' scenarios during peak period traffic conditions using traffic volume data on parallel routes.

- Investigate whether there is adaptive behaviour of road users during incidents when there are only two primary routes between an origin and a destination.
- Highlight the implications of the findings in the context of current transport planning and traffic management approaches and identify possible future directions to better account for incidents on a road network.

The behavioural inferences made from the analysis of the traffic data provide new insight into the impact of traffic incidents. In addition, these findings have also been used in the development of novel traffic assignment models, described in Chapter 4 and Chapter 5 to better capture the presence of disruptions on a network.

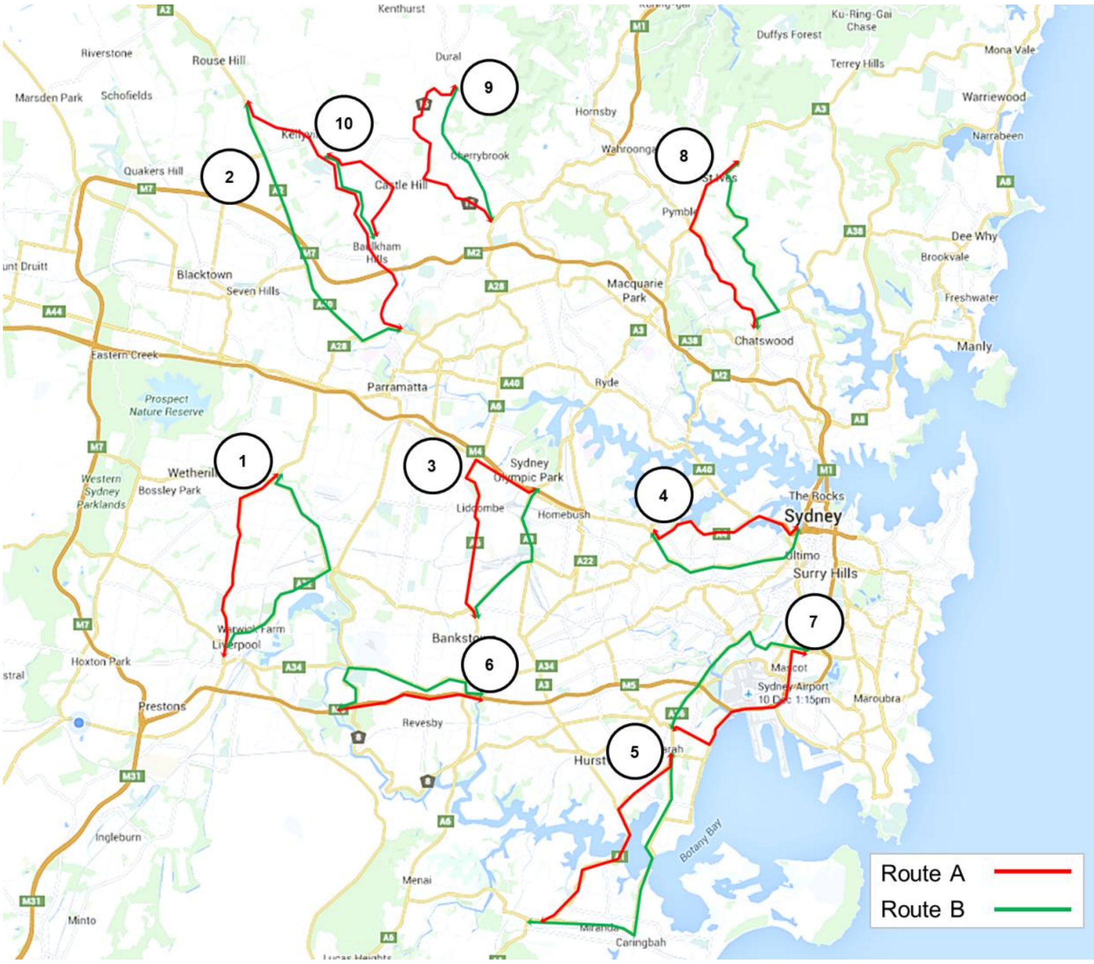


Figure 2.1: Regions of Sydney considered for analysis

The remainder of the Chapter is structured as follows:

- Section 2.2 of the report provides a comprehensive literature review of research and recent empirical studies undertaken in relation to impacts of disruptions on road network performance.
- Section 2.3 details the data acquisition process including data pre - processing and selection of final routes for the study.
- Section 2.4 discusses the data analysis methodology used to assess the impacts of disruptions on travel time and traffic volumes.
- Section 2.5 presents a summary of the results and a discussion of the key observations.
- Section 2.6 discusses the results at a holistic level identifying the implications of these findings within the transport planning field. Limitations of the study and possible extensions have been also explored.
- Section 2.7 presents the conclusions and contribution of this chapter of the research.

2.2 Literature Review

The purpose of this chapter is to conduct an empirical study on the impact of disruptions on the road network. Accordingly, the literature review focuses on previous empirical studies which have investigated disruptions affecting road networks. The following section of the chapter separates the review based on the impact horizon, defined in the introduction as 'short-term disruptions' and 'long-term disruptions'.

2.2.1 Investigations into 'Short-Term Disruptions'

Traffic incidents on road networks have received considerable attention in the theoretical and empirical domains of transportation research. There have been a number of studies which investigate the causality, classification, severity and prediction of short-term traffic incidents. From an empirical study perspective, this form of research has used field data to develop and validate models that predict the occurrence of incidents and crashes.

Abdel-Aty and Radwan (2000) used a negative binomial modelling technique to model the frequency of accident occurrence and involvement. The research discovered that with '*heavy traffic volume, speeding, narrow lane width, larger number of lanes, urban roadway sections, narrow shoulder width and reduced median width*' (Abdel-Aty and Radwan, 2000) the probability of accident involvement increases. This identifies that the presence of congestion is a leading contributor to the increased frequency of crashes and accidents.

A relationship between the geometric characteristics of a road, traffic volumes and accident rates has been well established by Karlaftis and Golias (2002). The study uses a non-parametric statistical methodology, hierarchical tree-based regression. The results show that pavement variables and geometric design have the most influential impact on accident rates. In addition to this study, Golob and Recker (2003) demonstrate that when weather is taken into consideration the impact of traffic volume has a significant influence on the accident frequency.

Incident duration and severity have generally been studied using analytical approaches such as; Poisson regression(Jones et al., 1991), nonparametric regression (Ozbay and Kachroo, 1999), hazard-based models (Nam and Mannering, 2000), decision trees (Smith and Smith, 2001) and Bayesian methods (Ozbay and Noyan, 2006). Garib et al. (1997) used field data to predict the duration and delay caused by an incident. Furthermore, the study collected incident detection and clearance data along with speeds and traffic counts from mainline station of a freeway section in Oakland, Calif to develop a statistical model to forecast delays.

Al-Deek et al. (1995) presented a discussion and an evaluation of analytical methods used to estimate traffic congestion as a result of an incident which reflects the severity of the incident. These methods have been classified into three types, methods based on queuing analysis, methods based on shockwave analysis and methods based on freeway traffic simulation (Al-Deek et al., 1995). For example, (Wirasinghe, 1978), used shock wave analysis to model total delays upstream of an incident which provides a measure for the severity of the incident itself. In addition Morales (1989) applied queuing theory to develop a program for predicting the impacts of minor incidents, such as lane closures. These incident classification and severity studies have provided incredible insight into the impact and prediction of a short-term disruption. However, none of these studies provide comparative performance assessments of 'incident' and 'no-incident' scenarios that may be present on a network, which is the primary objective of this particular component of the research.

The other main research direction investigating short-term incidents is associated with the assessment and determination of reliability concepts. Reliability of a corridor or network is measured using travel time variability. Travel time can be separated into free flow travel time and the additional travel time associated with congestion. The additional travel time may be as a result of predictable delays, such as the presence of excess demand during peak periods, or it could be associated with unpredictable traffic incidents and short-term disruptions. The variance in travel time associated with unpredictable delay defines the reliability of the road corridor of network (Bates et al., 2001). Therefore, it is clear that for studies measuring and valuing reliability, it is essential to understand the impact of short-term disruptions. Comprehensive reviews of studies related to reliability are provided by Noland and Polak (2002) and more recently by Carrion and Levinson (2012). In general, reliability studies have focussed on the development of theoretical frameworks (Jackson and Jucker, 1982, Bates et al., 2001, Small, 1999, Arnott et al., 1990) and empirical studies (Lam and Small, 2001, Small et al., 2005, Ghosh, 2001) which involve either experimental or field data approaches.

Carrion and Levinson (2012) as well as Noland and Polak (2002) have highlighted the reasons for the scarcity of empirical studies within reliability research. The main issues lie with the difficulties in obtaining travel time data, developing methodologies for reasonable controlled experiments and the costs involved in the deployment of surveys to gather data. Furthermore, both the review papers suggest that it is difficult to draw generalised conclusions from these studies as data gathered is case specific. In the context of this research, to date there have been no empirical studies which have approached the analysis of short-term disruptions in terms of comparing traffic data which have and have not been affected by incidents. In addition, the purpose of the data analysis is to observe any trends or relationships between the two incident cases in order to account for such aspects within the modelling efforts presented in Chapter 4 and Chapter 5.

There is a key difference between the mentioned empirical studies and the work described in this chapter. Previous studies consider pooled traffic performance data (considering both incident and non-incident data) to measure mean and standard deviation statistics for a route, corridor or network to assess the reliability. In contrast, the focus of this study is at a more fundamental level. Traffic data have been overlayed with incident data to form separated 'incident' and 'no incident' cases to understand the impact of short-term disruptions on aggregate traffic flow characteristics. A limited number of studies have investigated empirical trends and driving behaviour patterns focussed on long-term disruptions. These studies will be reviewed in the following section.

2.2.2 A Review of Recent Empirical Studies

Empirical investigations are essential for use in calibration of computational and mathematical simulation models of road traffic. These studies provide motivation to consider alternative methodologies which can potentially yield more accurate modelling (Clegg, 2007). As mentioned in Section 2.2.1, to the author's best knowledge, studies similar to the research presented in this chapter have not been investigated in great detail. However, the review paper, 'Disruptions to Transportation Networks: A review' by Zhu and Levinson (2012) provides a broad overview of theoretical and empirical studies on traffic and behavioural impacts of major long-term network disruptions. The paper discusses the impact of severe infrastructure failure, such as the collapse of a bridge, the shutdown of public transit services (resulting in a significant mode shift and affecting road network performance), or the advent of catastrophic weather events. Research surrounding major catastrophes has been prevalent from a forensic and preventative standpoint. A number of studies have been developed to understand methods to mitigate the impacts of disasters and determine traveller behaviour in light of a significant disruption. Even though the contexts of the disruptions are significantly different, these empirical studies have provided guidance whilst conducting this research.

Table 2.1 presents an adaptation and extension of 'Table 1, Empirical studies of traffic on behavioural response to network disruption, (Zhu and Levinson, 2012)'. The table provides a list of disruptions which have been studied in the context of transportation and the associated methodology used in studying the impact on traffic and transit properties of a network. The types of disruptions include bridge collapses, bridge closures, transit strikes, hurricanes and earthquakes which are all unplanned. Other long term planned events that took place such as the Olympic Games in Sydney as well as road maintenance and transport infrastructure construction activities have also been discussed. In a number of cases that have been presented, before, during and after studies highlight the impact of disruptions on mode and route choice.

Out of the eighteen disruptions presented in Table 2.1, five of the more recent events were selected for further discussion. These studies were selected because they provided either, a comprehensive assessment of the impact of the disruption, discussed the traffic impact or detailed the use and reactions towards information systems, all of which are key elements to this thesis. Furthermore, most of these studies made use of traffic data obtained from transport authorities or privately conducted traffic surveys and as such provide direction in relation to data processing and analysis.

Table 2.1: List of Empirical Studies investigating the impact of disruptions (Zhu and Levinson, 2012)

Event	Year	Focus of Study	Traffic Data/Surveys Used	Relevant Literature
New York City Transit Strike, New York City, New York, USA	1966	Ridership changes	Traffic Survey Home interview of transit users	Discussion provided by Zhu and Levinson (2012) and Lo and Hall (2006) with reference made to a study by the New York City Transit Authority (NYCT)
Tasman Bridge Collapse, Hobart, Tasmania, Australia	1975	Traffic impacts	-	Discussion provided by Zhu and Levinson (2012), Goodwin et al. (1998) and Cairns et al. (2002)
Pittsburgh transit strike, Pittsburgh, Pennsylvania, USA	1976	Comprehensive study of impacts	Traffic Counts Manual Occupancy Counts Two telephone surveys, 70% on commuters and 30% on non-commute bus users	Blumstein and Miller (1983)
Knoxville transit strike, Tennessee, USA	1977	Transit ridership losses	Ridership data	(Wegmann et al., 1979)
Orange County Transit Strike, California, USA	1981 1986	Transit ridership losses	Ridership data	(Ferguson, 1991)
Northridge Earthquake, California, USA	1994	Comprehensive study of impacts	Caltrans Detectors Ridership Data HOV Usage data Random Telephone Survey	(Yee et al., 1996)
Kobe Earthquake, Japan	1995	System performance	Detector counts	(Chang and Nojima, 2001)
Centre Street Bridge Closure, Calgary, Canada	1999	Comprehensive study of impacts	Two-day traffic survey Ridership data Manual Occupancy Counts Telephone survey of bridge users	(Hunt et al., 2002)

Event	Year	Focus of Study	Traffic Data/Surveys Used	Relevant Literature
I-880 Highway reopening, California, USA	1999	Comprehensive study of impacts	Mail-in survey, hypothetical questions	Dahlgren (2001)
Sydney Olympics, Australia	2000	System performance	Revenue collection at toll roads Ridership data	Currie and Delbosc (2011)
Los Angeles transit strike, USA	2003	Traffic impacts	Traffic detector data	Lo and Hall (2006) Anderson (2013)
Amsterdam transit strike, Netherlands	2004	Transit users	Web based questionnaire	(Van Exel and Rietveld, 2009)
Hurricane Katrina, New Orleans, Louisiana, USA	2005	Evacuation management	Traffic detector data	(Wolshon et al., 2006) (Wolshon and McArdle, 2009)
Road maintenance, City of York, UK	2005	Traffic impacts	Traffic Video Recordings Number plate matching O-D data	Clegg (2007) Watling et al. (2012)
I-35W Bridge Collapse, Minneapolis, Minnesota, USA	2007	Comprehensive study of impacts	Traffic detector data (MnDOT) Metro Transit Ridership Data Mail in questionnaire	Tilahun and Levinson (2008) (Zhu et al., 2009) Danczyk et al. (2010) Zhu et al. (2010) (Zhu, 2010) Xie and Levinson (2011) Zhu et al. (2012) Di et al. (2014)
Construction of West LRT (Light Rail Transit), Calgary, Alberta, Canada	2010 to 2012	Impact of construction works on traveller behaviour: study concerning the utilisation of information sources	Surveys: Face to face, mail in and online questionnaire	Kattan et al. (2013)
Hurricane Irene, East Coast, USA	2011	Evacuation management	Traffic detector data (TRANSCOM)	Li et al. (2015)
Hurricane Sandy, East Coast, USA	2012	Evacuation management	Traffic detector data (TRANSCOM)	Li et al. (2015)

2.2.2.1 Los Angeles, USA Transit Strike (2003)

Disruptions within mass transit operations affect the performance of all transportation systems. Long term disruptions to public transport services such as labour strikes, removal of routes, vehicle faults and safety issues can lead to a mode shift away from public transport and towards private modes potentially increasing the demand faced on the road network.

The Los Angeles transit strike was a month long 'stop-work' movement carried out by over 8500 mechanics, bus drivers and rail operators associated with the Metropolitan Transportation Authority and other transportation services. The strike lasted from October 14 to November 17 in 2003 and resulted in the unplanned cessation of bus, light rail and rail services for 35 days significantly affecting the travel behaviour of the Los Angeles County area. The disruption resulted in considerable stress on the congested road network within Los Angeles but provided a unique scenario for research to be conducted on the potential impacts of such a disturbance (Lo and Hall, 2006, Anderson, 2013).

Lo and Hall (2006) investigated the impact of the strike on the performance of the highways in Los Angeles. The study used loop detector data of six highways surrounding central Los Angeles collecting flow, travel time and speed data to conduct a 'before and after' empirical analysis. The study reported a general reduction in travel speeds with some sections of the highways experiencing reductions of up to 20% during the strike period. Furthermore, the duration of peak period traffic conditions doubled with on average lower travel speeds and higher travel times exacerbating the congestion observed. The study also acknowledged the low utilisation of public transport within the region, which indicated that cities with greater utilisation may face even worse consequences in light of similar transit strikes.

Recently, Anderson (2013) further investigated the impact of public transit strikes in the context of mode choice, using the Los Angeles transit strike for empirical analysis. As mentioned before, due to the lack of utilisation of public transit in Los

Angeles, the research postulated that individuals who are transit users are most likely to be the people who would commute on severely congested roadways if they were to take private transport. Based on this theory, the study estimates a regression discontinuity design using loop detector data to understand the impact of public transit abandonment. The study revealed that highway delay increased by 47% across the peak periods during the strike and significantly greater than what has been previously estimated to be the impact of such a mode shift scenario. Empirical evidence suggests commuters that travel on public transit are generally the users who would travel on the most heavily trafficked road sections and routes. Thus, during a transit strike or closure, these original public transit commuters could add to the delay on already congested routes. Further, it could also be argued that such unplanned disruptions force unfamiliar drivers onto the road network not allowing for equilibration and inflating the possible negative consequences of the strike.

These studies clearly indicate that disruptions need not directly affect the road infrastructure through an accident, incident or weather event. Therefore, when analysing the reliability and vulnerability of a road network, the performance and state of complementary systems, such as public transport systems, must be taken into account.

2.2.2.2 Road Maintenance, City of York, UK (2005)

Road maintenance is generally a planned disruption that affects the performance of the road network. Though this study focused on unplanned disruptions (traffic incidents), the papers by Clegg in 2007 and Watling, Milne and Clark in 2012 provide insight into survey methodology concerning the impact of disruptions on traveller behaviour. The studies were motivated by the desire to accurately assess traffic conditions of a region during a planned disruption in York, United Kingdom and observe variations in traveller behaviour. In addition the paper by Watling et al. (2012) focussed on comparing field data to the output of a traffic network equilibrium model.

The value of these studies stem primarily from the unique survey method: the application of manual number plate matching. The survey method involved surveyors documenting partial number plate identifications of vehicles at an origin using a Dictaphone and matching these partial identifications at the destination, essentially completing an origin –destination survey (Clegg, 2007). The reason for the adoption of this approach arose due to the belief by the authors of the inadequacy of surveillance data (link flow and travel time data obtained from loop detectors or GPS) in providing useful information to shed light on traveller route choice (Watling et al., 2012). It is highlighted that surveillance data cannot separate ambient daily variation from the impact of the disruption. Despite this, for the objectives of the research presented in this chapter, to understand the general trend observed in normal and disrupted traffic conditions, surveillance data was deemed adequate. Furthermore, as presented throughout the entire Literature Review, there have been a number of conclusive studies which have used surveillance data which have provided insight into the impact of disruptions on a road network (Lo and Hall, 2006, Zhu et al., 2010).

The methodology proposed by Clegg (2007) and Watling et al. (2012) is constrained by the topology of the road network and the geography of the surroundings as surveyors require safe vantage points to observe the number plates. Thus, a site selection process was conducted to ensure the feasibility of the surveys. Similarly in this research, the selection of the competing parallel routes have been considered carefully to ensure the availability of all three sets of data (travel speed, incident and volumes) as well as ensuring that they were genuine competing routes for users of the network.

Number plate data was collected over 11 sites over two weeks considering the closure of Lendal Bridge (a several week closure) and the partial closure (capacity reduction) of Fishergate Street. As expected with a manual collection of data, Clegg (2007) and Watling et al. (2012) provide extensive details on the data pre-processing techniques applied prior to the analysis of the final data set. These include; the removal of problematic data such as missing times, trimming travel time to avoid 'early end' issue and normalising flows and times between sites for zero variance comparison. Statistical analysis had been undertaken using two sided Welch t-test, as this test allows small sample sizes and the possibility that the first mean may be smaller or larger than the second. The presentation of the data pre-processing techniques provided guidance to the management of the data sets conducted for this study.

Clegg (2007) illustrates two primary findings. The disruption reduced the capacity of the link which resulted in an initial adverse reaction by drivers which was followed by a re-equilibration period as travellers adjusted to the disruption. The other finding reflected the habitual nature of travellers related to the recurrence of identical vehicles based on the day of the week and time of the day. A linear model was formulated to further investigate the effect of the disruption on flows and travel times. Modelling was only successful on some sites, but again it was found that both flows and times had an initial transient effect which was followed by a return to normal. Clegg noted the importance that an effect on flow does not have to inherently affect travel time, suggesting that adaptive routing behaviour achieves an equilibrium solution.

Watling et al (2012) further investigates the concept of equilibrium by comparing the empirical data collected to the output of an equilibrium model. The comparison of normal, 'no-incident conditions' suggest the need for the calibration of the parameters associated with travel time and distance present within the generalised cost equation. Upon appropriate calibration, equilibrium modelling provides reliable estimates of the empirically observed flow conditions. The observed data during the disrupted conditions reveal that demand increases on road sections with reduced capacities which result in learning behaviour across time whilst users adapt to the new conditions. These unique aspects could not be captured within the equilibrium model. The findings of the study provide motivation to study alternative approaches to depict disrupted states.

2.2.2.3 I-35W Bridge Collapse, Minneapolis, Minnesota, USA (2007)

The I-35W Bridge over the Mississippi River in Minneapolis Minnesota collapsed on the 1st of August 2007 resulting in the tragic loss of life and devastating impact on the community. The collapse has been the focus of a number of research studies investigating the cause from a structural engineering standpoint and the impact from a transportation and economic perspective. The disaster affected the travel of 140,000 vehicles that used the bridge on a daily basis and in general across the entire Twin-Cities region. However, the event provided a unique opportunity for transport researchers to investigate the impact of the disruption on the performance of the network and the behaviour of the travellers. The collapse resulted in changes to mode choice, route choice, departure time and overall travel. A number of papers have discussed the findings empirical study conducted by Zhu, Levinson and others at the University of Minnesota and this section will review some of these papers (Tilahun and Levinson, 2008, Zhu et al., 2009, Danczyk et al., 2010, Zhu, 2010, Zhu et al., 2010, Xie and Levinson, 2011, Di et al., 2014).

Tilahun and Levinson (2008) present the survey results of people residing in Twin Cities region. The survey covered the region surrounding the disaster but not in the neighbourhoods in the immediate vicinity of the bridge collapse offering the opportunity to investigate the distributed impacts. A total of 215 respondents answered a questionnaire enquiring whether their travels had been impacted by the failure of the bridge, the way they managed the situation and what impacts it had on their day to day activities. Respondents indicated that the bridge was used for non-commuting trips. An interesting finding is that regardless of the utilisation of the bridge prior to the collapse, most respondents changed their travel patterns following the event. The results of the survey were then used to form a logit model to investigate which respondents had been impacted by the bridge failure. Intuitively, the model suggests that the disaster had a greater impact on individuals closer to the site of the collapse (residence or employment location) than respondents further away from the site.

Danczyk et al. (2010) utilised loop detector data of the Minneapolis network to observe the traffic dynamics following the collapse and reopening of the I-35W Bridge. The study indicates that following a disruption an avoidance phenomenon is observed resulting in travel time variability. In addition, the data presented that there was a change in route choice behaviour following the re-establishment of the pre-collapse routes as the utilisation of the newly constructed link was lower than pre-disaster level. A possible reasoning suggested by the authors was that users were reluctant to use the Bridge due to the memory of the event or the impact of the change in travel behaviour following the event.

The 2010 study by Zhu, Levinson, Liu and Harder used and compared loop detector data, bus ridership statistics and responses from a mail-in survey to further investigate the post disaster travel behaviour of the region, with a particular focus on equilibrium concepts. The findings of the study indicate that there was a fluctuation in behaviour for approximately 6 weeks, prior to the resumption of normal travel behaviour.

Xie and Levinson conducted an economic evaluation of the consequences of the bridge collapse in 2011. The study utilised the Twin Cities Seven-County travel demand model to evaluate the economic loss associated with increased travel time in a number of scenarios pre and post of collapse. The study concludes that the failure of the I-35 Bridge resulted in significant economic losses which were fortunately mitigated to a certain degree by the accelerated recovery program.

More recently, Di et al. (2014) further investigated the avoidance phenomenon by considering 'indifference bands' for route switching. Post re-construction, the I-35W Bridge remained underutilised even though it offered travel time savings which did not satisfy traditional shortest path modelling assumptions. The research presents the 'boundedly rational route switching' model which assumes travellers will not switch to the new bridge unless the travel time saving surpasses a certain threshold. The paper discusses a validation of the model and also provides insight into utilisation with old users of the bridge showing contrasting behaviour as compared to users who had never used the bridge prior to the collapse.

The studies surrounding the I-35W Bridge collapse have provided researchers investigating disrupted networks with novel methodologies to conduct before and after field studies as well as a number of unique behavioural findings such as the avoidance phenomenon. These insights have shaped much of the ongoing research into the impact of disruptions on transport networks and were considered carefully when conducting this component of the research, presented in Chapter 2.

2.2.2.4 Construction of West LRT, Calgary, Alberta, Canada (2010 to 2012)

Similar to road maintenance activities, construction activities are considered as planned disruptions which can affect traveller behaviour. The development of the West LRT line in Calgary, Canada between 2010 and 2012 resulted in the reduction in road capacity due to the presence of construction works. The project involved an extension of the West Line by 8.2km affecting the southwest quadrant of the city. The construction required closure of lanes and entire road sections creating a severe disruption to the network for an extended period of time. Recently, Kattan et al. (2013) conducted a detailed study surrounding the impact of the disruption on travel behaviour as well as investigating user response to advanced traveller information. In order to mitigate the effects of the disruption to traffic, the City of Calgary launched the West LRT website to provide information regarding the project. The website informed the community about the construction works and the delays involved then urged people to consider changing departure times as well as to use alternative modes of transport such as public transit or cycling to reduce traffic congestion. In addition Variable Message Signs (VMS) and radio traffic reports served to inform road users of detours and potential re-routing.

Kattan et al. (2013) used a stated preference survey to obtain data regarding mode choice, route choice and general traveller behaviour in light of the disruption. In addition, the survey enquired their opinions on use of the traveller information available throughout the construction period. The study revealed that there was a significant mode shift away from private vehicles towards public transit. The most beneficial source of information provided to users were radio traffic reports that were closely followed by Variable Message Signs (VMS) highlighting the impact of online information systems in mitigating planned road disruptions. Finally the study developed a multinomial logit model to understand the factors which affect travellers' response to VMS. The results of the modelling suggests that driving experience, travel time, employment status and trip purpose had significant effects on traveller rerouting decisions upon receiving online information.

The findings from the study provides insight into travel behaviour as well as the value of different forms of information in the context of construction works and will be beneficial in future construction traffic management practices. However, it should be noted, that the study investigated a pre-planned disruption where users could plan their travel and account for the additional delays. In contrast, the research presented in this chapter focusses on the impact of short-term unpredictable disruptions associated with traffic incidents.

2.2.2.5 Hurricane Irene and Sandy, East Coast of USA, (2011 and 2012)

Hurricanes are natural disasters which to a certain degree are 'planned' events as they can be forecast ahead of time, unlike earthquakes or bushfires. However, the impact of these natural disasters is devastating and the travel behaviour during and following the event requires investigation, in particular when developing evacuation strategies. Li et al. (2015) provides the latest research concerning the impact of Hurricane Irene (2011) and Hurricane Sandy (2012) in the New Jersey area of USA. The study conducts a quantitative analysis of the traffic patterns and highway disruptions which occurred during the evacuation process.

A number of data sources were used to assess the impact of the disruption. The data included; hourly toll plaza volume counts, Traffic Volume Station (TVS) traffic counts, Weigh-in-Motion (WIM) traffic counts, event data collected by TRANSCOM and travel time data collected by a survey company. The extensive array of collected data yielded a number of analysis techniques considering both spatial and temporal variation of data. In general, there were a greater number of evacuees in Hurricane Irene than Hurricane Sandy, however during both events evacuation traffic tended to head inland instead of following major highways north along the shoreline away from the hurricane itself. Although, the frequency of vehicular crashes increased during the hurricane events due to the inclement weather, the frequency of vehicular incidents (non-crash events) remained similar to normal day to day conditions. Bottlenecks and congestion points of fleeing traffic tended to occur at merge points at highway interchanges.

The study conducted by Li et al. (2015) was based on a plethora of rich data sources, it is difficult to compare with the study completed within this chapter of the thesis. Nevertheless, the statistical analysis and modelling techniques applied to analyse the data have been considered for this study.

2.3 Data Acquisition

The key objective of the empirical investigation was to investigate the impact of disruptions on parallel commuter routes in Sydney. Initially, ten sets of parallel route sections were selected for the analysis and are presented in Figure 2.1. The routes were selected based on a commuter perspective and defined as competing commuter routes between origin and destination regions in Sydney. These routes are normally considered from a user perspective and also indicated as alternative routes within GPS navigation tools. The selected routes were;

1. Cumberland Highway Vs Hume Highway - Horsley Drive
2. Windsor Road Vs Old Windsor Road
3. Parramatta Road - St Hillier's Road Vs Centenary Drive - Hume Highway
4. Parramatta Road Vs Western Distributor
5. Princes Highway Vs Rocky Point Road
6. South Western Motorway (M5) Vs Milperra Road
7. General Holmes Drive Vs Princes Highway

8. Mona Vale Road - Pacific Highway Vs Link Road - Archibald Road
9. Old Northern Road - Castle Hill Road Vs New Line Road
10. Old Northern Road - Showground Road Vs Windsor Road

The above route pairs (sets) were selected based on following criteria:

- Each set provides a pair of parallel, competing commuter routes which allow users to alternate between them based on traffic conditions.
- Traffic characteristics such as route lengths and travel times of each pair are comparable.
- Appropriate data such as crash/incident data, traffic volume data and traffic speed data are available from the RMS to undertake a meaningful analysis.

The relevant data sets, necessary for the research tasks, were obtained from Roads and Maritime Services (RMS). Data was collected, across all route sets, for the period between January 2012 and June 2013. RMS provided four sets of data for the selected routes which included; average speed data (aggregated at 15 minute intervals), categorised incident data, hourly traffic volume data and relevant link length data.

2.3.1 Average Speed Data

RMS utilises Global Positioning System (GPS) data of equipped fleet vehicles to derive the required speed data. Vehicles deployed by RMS for data collection are commercial fleet vehicles involving a diverse range of cars, vans and various sized trucks. The final 15 min average speed data value for each road section is determined by aggregating all signals (broadcasted every 62 seconds) from the fleet. The received signals include information of the position of vehicles, direction of travel and speed (at the second of transmission). These signals are processed with respect to road and subsequent link number combinations and all signals received for that 15 minute block are arithmetically averaged and stored.

Average speed data was provided for every 15 minute increment across the duration of the data collection period. For the purposes of this study only the average speed data collected during weekday, peak periods were considered. The derivation of peak periods is discussed in Section 5.1 of the study.

2.3.2 Incident and Crash Data

Categorised incident data was provided by RMS for the assessment period for all the selected routes. The data included the following features;

- ***Time***: Date and time to the nearest minute of the occurrence of the incident
- ***Location***: Road and link number where the incident occurred
- ***Duration***: A categorisation of the length of time that the incident was present on the road section.

The exact durations of the incidents were not provided by RMS; however the categorisations of duration provided an indication of the severity and impact of the disruption on the network. RMS provided further information regarding the types of information that each duration category could represent, as shown in Table 2.2.

Table 2.2: Categorisation of incident data

Duration Category	Type of Incident
1 minute < 15 minutes	Vehicle breakdowns (cars) and minor crashes that do not include more than 2 vehicles
15 minutes < 60 minutes	Larger vehicle breakdowns and crashes
60 minutes < 120 minutes	Significant crashes involving multiple vehicles
120 minutes +	Emergency road works, maintenance works and other construction work zones

Geospatial crash data was supplied as shape files and contained detailed information about crashes including data entries such as type of collision, fatality, whether emergency services were called, location of crash on road, number of vehicles involved and so on. These crashes were found to be already encapsulated in the aforementioned incident data. As a result, the detailed subset of the incident data was not considered in the analysis.

2.3.3 Volume Data

RMS uses a range of counters with permanent and sample roadside collection devices to collect traffic volumes. For the purposes of this study, only permanent roadside collection devices were considered, as sample roadside collection devices do not provide continuous data which could be used to correlate with the collected incident data. Permanent traffic counters provide data related to traffic volumes, speeds and vehicle classification, and the relevant counters are presented in Table 2.3.

Table 2.3: Traffic counter stations considered for the assessment

Set	Traffic Counter	RMS description
Set 1	100001	**Cumberland Highway**, Canley Vale
	60046	**Orange Grove Road**, Cabramatta: At Cabramatta Creek Bridge
	66240	**The Horsley Drive**, Fairfield: Fairfield Railway Line,SL11
	44139	**Hume Highway**, Lansvale: West Of Quest Avenue
Set 2	71180	**Old Windsor Road**, Parklea: South Of Balmoral Road
	50240	**Briens Road**, Northmead: Near Hayes Avenue
	73001	**Windsor Road**, Castle Hill: North Of Showground Road, MR157
	72027	**Windsor Road**, Baulkham Hills: Between Merindah And Parsonage Roads
Set 3	43216	**Rookwood Road**, Regents Park: South Of Lewis Street
	28028	**Hume Highway**, Chullora: East Of Waterloo Rd, RR7118
	43239	**Hume Highway**, Greenacre: North Of Stacey Street, MR190
Set 4	19065	**Parramatta Road**, Camperdown: East Of Cardigan Street
	20012	**Parramatta Road**, Leichhardt: At Goods Railway Line
	25002	**Parramatta Road**, Ashfield: East Of Dalhousie Street
	02381	**Western Distributor**, Pyrmont: Fig Street On/Off Ramps
	20001	**Western Distributor (Anzac Bridge)**, Pyrmont: At Anzac Bridge
	20075	**City-West Link**, Lilyfield: West Of The Crescent, MR650
Set 5	36001	**Princes Highway**, Blakehurst: North Of Tom Uglys Bridge
	36208	**Princes Highway**, Sylvania: North Of Bates Drive
	36002	**Taren Pont Road**, Taren Point: At Captain Cook Bridge

2.3.4 Link Length Data

Link lengths for road links considered in this study were obtained from RMS. These values were considered in conjunction with average speed values to generate travel time results.

2.3.5 Data pre-processing

Collected raw data was pre-processed to create required data sub-sets for analysis. The pre-processing procedure involved the following;

- Determination of relevant days and time periods of data.
- Removal of outlier data.
- Separation of traffic data to develop 'incident' and 'no-incident' data-sets.

The focus of the study was an assessment of the peak period commuter traffic; thus all weekend, public holiday and weekday off peak period data were removed from the data set. Some data obtained from GPS and permanent volume counter stations were incomplete, inconsistent or contained errors which were accounted for and removed prior to analysis, if deemed unusable.

In particular, GPS speed data of vehicles which travel on short links may have grossly exaggerated average travel times if the number of observations is low. This can occur when there is a single fleet vehicle across the 15 minute period which traverses across the link and is stuck in a temporary queue which last for just over 62 seconds. Take for example, a 240m link, a vehicle may just enter the link and be stuck behind a queue due to a vehicle turning right into a side street. The constant stream of opposing traffic doesn't provide the lead driver an opportunity to turn right and the inability to change lanes for the fleet vehicle may mean that the vehicle moves 1m in 62 seconds across the 240m link, resulting in a speed of approximately 0.058km/hr and a road link travel time data point of over 4 hours. However, within the next 62 seconds the lead vehicle clears and the fleet vehicle is able to travel at the sign posted speed limit of 60km/hr over the 240m link, meaning that the travel time data point is 0.25 mins.

This highlights a deficiency of GPS data when the numbers of fleet vehicles passing through a link are insufficient to provide a genuine average. In order to rectify this issue, short link data with limited observations were carefully observed and removed if the travel times were illogically large (greater than 5 times the mean value across the previous three 15 minute intervals and the proceeding three 15 minute intervals).

Finally, as the empirical investigation involved a comparison of 'incident' and 'no-incident' scenarios for each set of competing routes, the incident data set was matched with all the traffic characteristic data sets. In order to systematically match the data, each set of routes were split into two; one route was denoted by 'Red' or 'Route A' and the other by 'Green' or 'Route B'. Based on this identification of each route in each set, the matching process considered the following combinations of 'incident' and 'no-incident' scenarios to analyse the data, presented in Table 2.4 .

Table 2.4: Incident and no-incident data set combinations

Combination of Scenarios	Red – 'Route A'	Green – 'Route B'
C1	No-Incident	No-Incident
C2	Incident	No-Incident
C3	No-Incident	Incident

2.3.6 Final routes

The review of data obtained from RMS following the 'pre-processing' procedure detailed in Section 2.3.2 revealed that some of the selected routes were not viable for further analysis due to an inadequate number of reported incidents along those routes. The limitations in these datasets resulted in discarding of five pairs of routes. Accordingly, only five pairs of initially selected routes were used for further analysis.

The routes retained for further analysis are listed below:

1. Cumberland Highway Vs Hume Hwy - Horsley Drive
2. Windsor Road Vs Old Windsor Road
3. Parramatta Road-St Hillier's Road Vs Centenary Drive-Hume Highway
4. Western Distributor Vs Parramatta Road
5. Princes Highway Vs Rocky Point Road

The above routes are discussed in greater depth, using the 'Red' and 'Green' convention in the following sections.

2.3.6.1 Set 1 – Cumberland Highway Vs Hume Highway and Horsley Drive

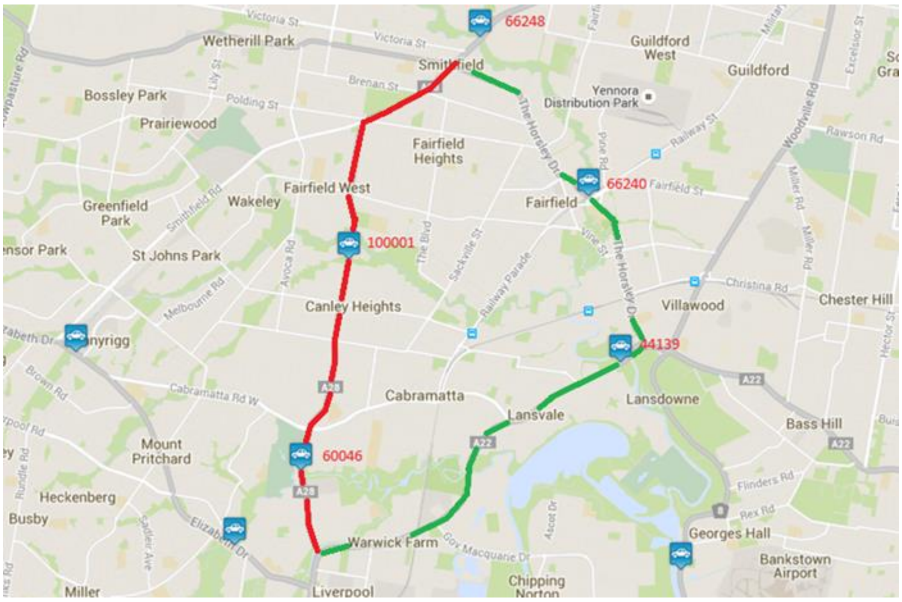


Figure 2.2: Set 1 - Cumberland Highway Vs Hume Highway and Horsley Drive

Set 1 consists of the parallel routes as shown in Figure 2.2. Considering southbound travel, the red, 'Route A' traverses the Cumberland Highway beginning at the intersection from O'Brien Parade with Smithfield Road to the Intersection of The Horsley Drive and Smithfield Road. The approximate length of this route is 8.5km.

The green, 'Route B' follows the Hume Highway and the Horsley Drive. The path begins on the Horsley Drive at the intersection of the Horsley Drive and

Cumberland Highway and finishes at the intersection of The Hume Highway and Cumberland Highway. The approximate length of this route is 11.4km.

2.3.6.2 Set 2 – Windsor Road Vs Old Windsor Road

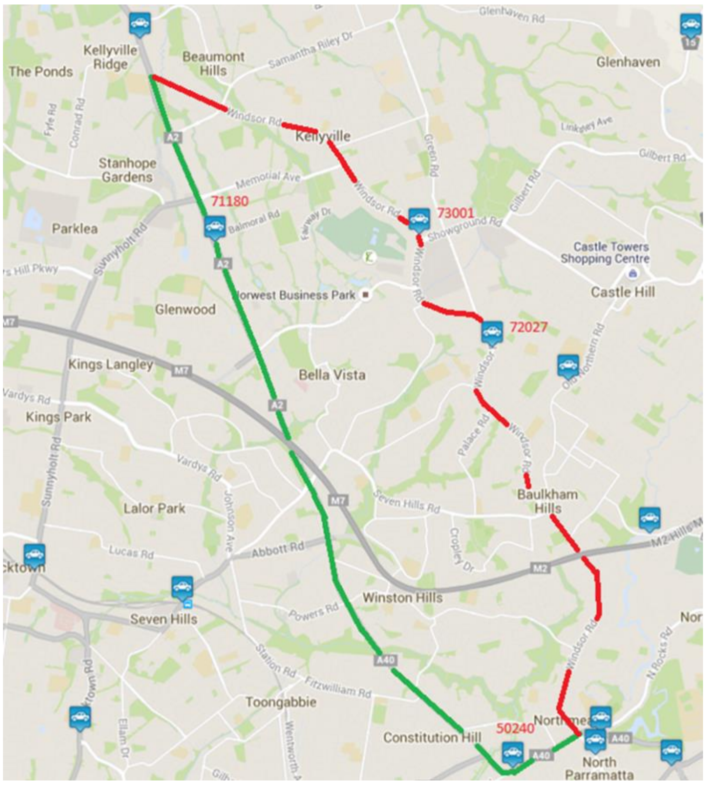


Figure 2.3: Set 2 - Windsor Road Vs Old Windsor Road

Set 2 consists of the parallel routes as shown in Figure 2.3. Considering southbound travel; the red 'Route A' runs along Windsor Road starting from the intersection of Windsor Road and Old Windsor Road to the intersection of Windsor Road and Cumberland Highway. The approximate length of this route is 13.9km.

The green, 'Route B' runs along Old Windsor Road, from the Intersection of Old Windsor Road and Windsor Road through to the intersection of Windsor Road and Cumberland Highway. The approximate length of this section of the route is 13.2 km.

2.3.6.3 Set 3 – Parramatta Road-St Hillier's Road Vs Centenary Drive-Hume Highway

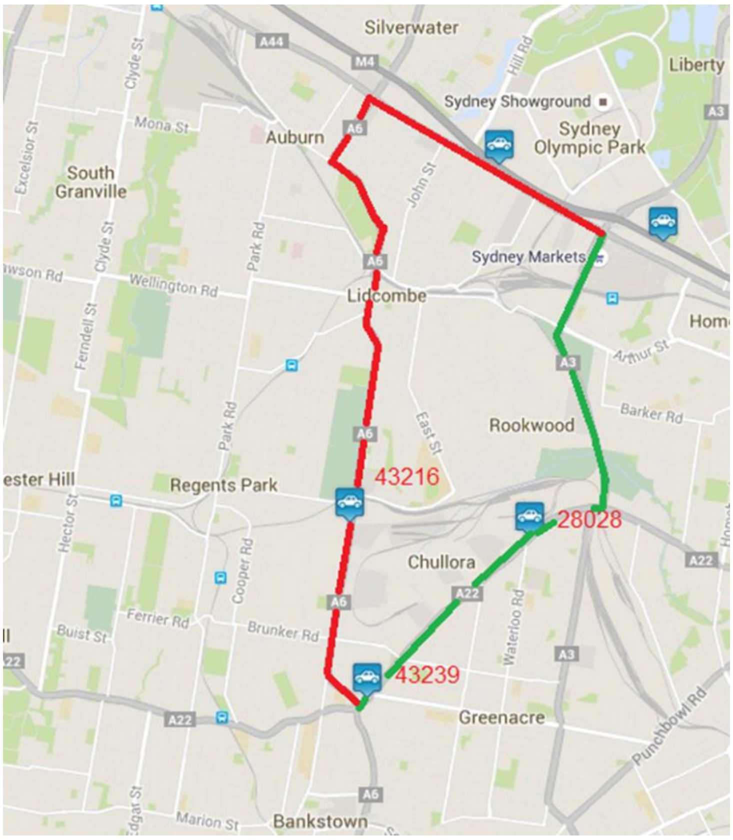


Figure 2.4: Set 3 - Parramatta Road-St Hillier's Road Vs Centenary Drive-Hume Highway

Set 3 consists of the routes presented in Figure 2.4. Considering southbound travel; the red 'Route A' follows initially north along Parramatta Road from the intersection of Parramatta Road and Centenary Drive and then traverses south on St Hillier's Road, Olympic Drive and Joseph Street and Rookwood Road until the intersection of Rookwood Road, Stacey Street and Hume Highway. The approximate length of this route is 10.5 km.

The green, 'Route B' also begins at the intersection of Parramatta Road and Centenary Drive where it continues to run along Centenary Drive, onto Hume Highway up to the intersection of Rookwood Road, Stacey Street and Hume Highway. The approximate length of this route is 8.6 km.

2.3.6.4 Set 4 – Western Distributor Vs Parramatta Road

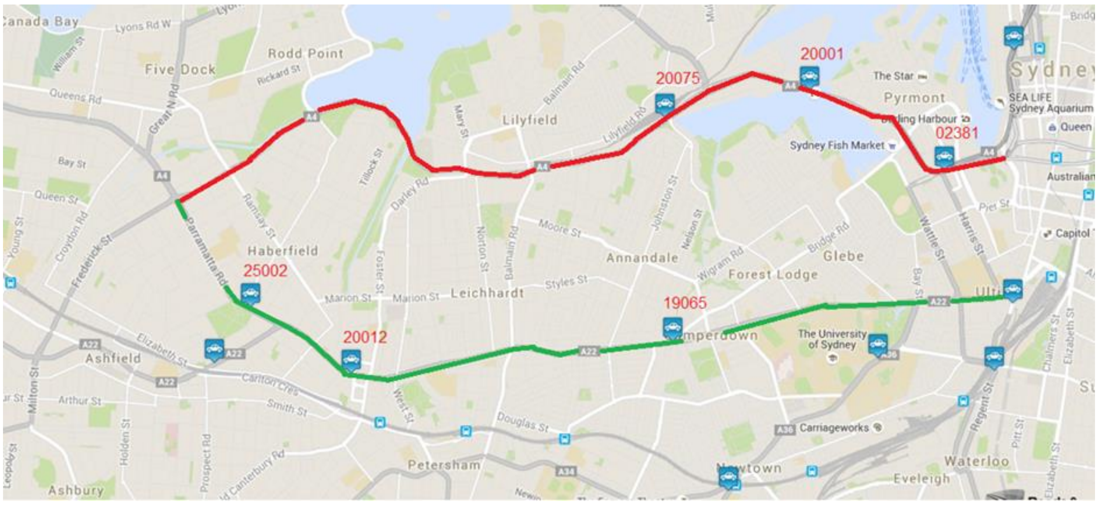


Figure 2.5: Set 4 - Western Distributor Vs Parramatta Road

Set 4 consists of the parallel routes presented in Figure 2.5. Considering westbound travel; the red 'Route A' runs along The Western Distributor Freeway starting at the intersection of the Western Distributor and Kent Street and running along the City West Link (Wattle Street) to the intersection of City West Link and Parramatta Road. The approximate length of this route is 9.0 km.

The green, 'Route B' runs along Parramatta Road from the intersection of Broadway and Harris Street to the Intersection of Parramatta Road and City West Link (Wattle Street). The approximate length of this route is 8.0 km.

2.3.6.5 Set 5 – Princes Highway Vs Rocky Point Road

Set 5 consists of the parallel routes as shown in Figure 2.6. Considering southbound travel; the red 'Route A' runs along Princes Highway from the intersection of Princes Highway and Marshall St to the intersection of Princes Highway and Kingsway. The approximate length of this route is 16.5km.

The green, 'Route B' runs along Rocky Point Road from the intersection of Rocky Point Road and Marshall Street, along Taren Point Road and then onto Kingsway, ending at the intersection of Princes Highway and Kingsway. The approximate length of this route is 11.3 km.

Figure 2.6: Set 5 - Princes Highway Vs Rocky Point Road

2.4 Analysis of Data

A comprehensive methodology was developed to gain an understanding of empirical trends or relationships between short term traffic incidents and fundamental traffic properties such as travel time and traffic flow. In order to investigate the impact on fundamental traffic properties due to short-term incidents, the following tasks were undertaken:

- Hourly traffic volumes on each route were analysed to determine the peak traffic periods.
- Collected data for each route were statistically analysed to interpret the data in a meaningful manner and to establish the impact of incidents on fundamental traffic properties such as speed, travel time and traffic flow.

2.4.1 Peak Period Determination

The impact of traffic incidents on a commuter route is notably high during peak traffic periods where the greatest numbers of people are travelling on the network. Peak traffic periods are considered as the times throughout the day where the network faces considerably higher demands relative to the average. Accordingly, the traffic volume data obtained from RMS for selected routes was used to define the morning and afternoon peak periods for the purpose of this study.

Average hourly, weekday, two-way traffic volumes at midblock locations along the five sets of routes selected for the study are graphically presented in Figure 2.7

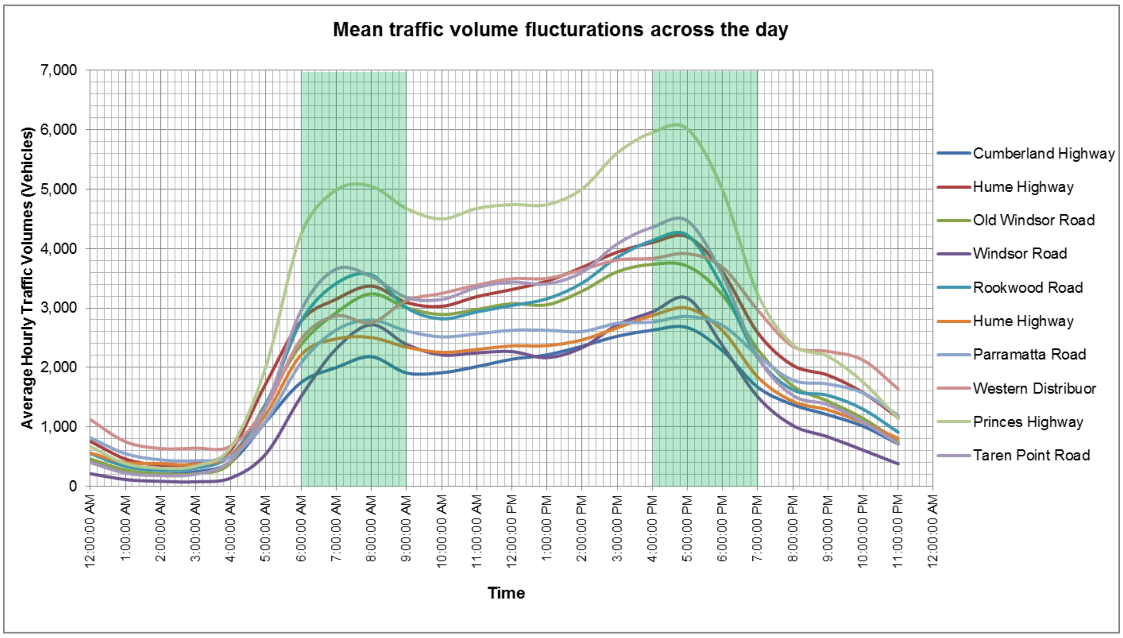


Figure 2.7: 24 hour fluctuation of traffic volumes

Figure 2.7 demonstrates that during week days, there is consistent trend across all the selected routes with high traffic volumes from 6am to 7pm. Furthermore, there are definitive peaks within the traffic count distributions on all the selected routes during the morning and afternoon peak periods. Accordingly, the peak traffic periods for all the selected routes for the purpose of this study is defined as:

- AM (Morning) Peak Period: 6am - 9am
- PM (Afternoon) Peak Period: 4pm -7pm

The average speed, travel time and volume data sets were separated based on peak period and the presence of incidents as follows;

- AM Peak (6am-9am), 'incident' data sets
- AM Peak (6am-9am), 'no-incident' data sets
- PM Peak (4pm-7pm), 'incident' data sets
- PM Peak (4pm-7pm), 'no-incident' data sets

2.4.2 Determination of Travel Time datasets

Travel time data for each link was calculated using the speed data set and the link length data set as discussed in Section 2.3. Considering each link 'i' and for each time interval 't', a travel time data point, '$T_{t,i}$', was calculated using the fundamental equation presented in Equation (2.1) where 'L_i' equals the length of link 'i' and '$S_{avg,t,i}$' is the 15 minute average speed data point of link 'i' for each time interval, 't'.

$$T_{t,i} = \frac{L_i}{S_{avg,t,i}} \tag{2.1}$$

For each route 'R' and time interval 't', data points of route travel time, '$T_{t,R}$' were estimated by aggregating the travel time of each associated link of the route (assuming that 'n' links constitute the route 'R'), as presented in Equation (2.2).

$$T_{t,R} = \sum_{i=0}^{n} T_{t,i} \tag{2.2}$$

2.4.3 Statistical Analysis

Descriptive statistics of the mean and standard deviation of each travel time and volume data sets were calculated and compared to understand the underlying empirical relationships. Furthermore, the principle of equilibrium presented by Wardrop (1952) suggests that travel times on all used paths for each origin and destination pair are equal and minimum. Accordingly, hypothesis testing was undertaken to compare the 'incident' and 'no-incident' travel times of each individual route as well as comparing the competing routes considering the scenario combinations presented in Table 2.4. In this context, estimated 'incident' and 'no-incident' travel times for the identical time intervals were paired.

The hypotheses considered were as follows;

- The null-hypothesis: $\overline{T_1} - \overline{T_2} = 0$
- The alternative hypothesis: $\overline{T_1} - \overline{T_2} \neq 0$

Where;

$\overline{T_1}$ = the mean route travel time for a specific 'no-incident' or 'incident' scenario

$\overline{T_2}$ = the mean route travel time for an alternative 'no-incident' or 'incident' scenario as compared to $\overline{T_1}$

Due to the limited sample size of incident data for some of the 15 minute time intervals, a Welch's T-test was conducted to test the hypothesis. The conventional pooled T-test for independent means assumes equivalence of standard deviation between samples. As this is not guaranteed within the data sets compared, the more general Welch's T-test was used instead, using the formulation presented in Equation (2.3).

$$t = \frac{\overline{T_1} - \overline{T_2}}{\sqrt{SE_1^2 + SE_2^2}} \tag{2.3}$$

Equation (2.3) calculates the t-statistic by considering the difference of the mean travel time ('b_1' and 'b_2') and their respective standard errors ('SE_1' and 'SE_2'). The t-statistics were compared with the t-critical values for a confidence level of 95% which were determined from the Student's t-distribution with the degrees of freedom, 'v', calculated using Equation (2.4)

$$v = \frac{(\frac{S_1^2}{n_1} + \frac{S_2^2}{n_2})^2}{\left[\frac{\left(\frac{S_1^2}{n_1}\right)^2}{n_1 - 1} + \frac{\left(\frac{S_2^2}{n_2}\right)^2}{n_2 - 1}\right]} \qquad (2.4)$$

2.4.4 Route Utilisation

The purpose of this analysis is to understand the impact of disruptions on utilisation of two competing routes under the two scenarios; 'incident' and 'no-incident' scenarios. The metric of 'percentage route occupancy' was used where the proportion (p_A, p_B) of the total traffic using either route A or B was compared. The percentage route occupancy was calculated using Equation (2.5), where 'V_A' and 'V_B' represent the mean volume on route A and route B respectively for the peak period of analysis considered

$$p_A = \frac{V_A}{V_A + V_B} \times 100 \;\; ; \;\; p_B = \frac{V_B}{V_A + V_B} \times 100 \qquad (2.5)$$

2.5 Results

Since there were five pairs of competing routes and multiple data sets that have been analysed the identification and colour coding presented in Table 2.5 is used throughout the description of the results.

Table 2.5: Route identification details

Set ID	Route ID	Route Details
Set 1	Route 1A	Cumberland Highway
	Route 1B	Hume Highway – Horsley Drive
Set 2	Route 2A	Windsor Road
	Route 2B	Old Windsor Road
Set 3	Route 3A	Parramatta Road – St Hillier's Road
	Route 3B	Centenary Drive – Hume Highway
Set 4	Route 4A	Western Distributor
	Route 4B	Parramatta Road
Set 5	Route 5A	Princes Highway
	Route 5B	Rocky Point Road

2.5.1 Travel Time Assessment

Table 2.6 and Table 2.7 present the mean and standard deviation of the route travel times respectively for both the AM and PM peak periods. These tables present the descriptive statistics of the scenario combinations as described in Table 2.4. In general, the mean travel time on a particular route remains stable in both no-incident and incident scenarios, regardless of which route contains the incident. However, what is evident from these results is that Set 1 is most likely not a pair of competing routes as Route 1B (The Hume Highway and The Horsley Drive) has significantly greater mean travel time values than Route 1A (Cumberland Highway). Even though Route 1B is an alternative route from a commuter perspective, from a performance perspective it is clearly more costly to use in terms of travel time. Excluding this set (pair of routes), the pair of routes in all other sets have very similar travel times with marginal increases in travel time under disrupted conditions. This is an unexpected outcome as in practice disruptions result in delays which should increase the overall travel time. An explanation for this observation could be due to a number of reasons, including:

- Instances of minor disruptions which do not necessarily increase travel time;
- Unrecorded incident resulting in an inflation of travel time within the 'no incident' data sets and a deflation of the 'incident' data sets, and
- Cases where travel times are unusually high due to volatility in demand.

Table 2.6: Mean route travel times

Mean route travel times							
Set ID	Route	AM Peak (6am - 9am)			PM Peak (4pm - 7pm)		
		With No Incidents	*An incident on Route A*	*An incident on Route B*	*With No Incidents*	*An incident on Route A*	*An incident on Route B*
Scenario Combination		*C1*	*C2*	*C3*	*C1*	*C2*	*C3*
Set 1	Route 1A	10.49	10.59	10.54	10.51	10.64	10.57
	Route 1B	16.47	16.53	16.67	17.19	17.25	17.26
Set 2	Route 2A	19.11	19.32	19.17	18.71	18.90	18.81
	Route 2B	19.16	19.22	19.56	19.09	19.20	20.15
Set 3	Route 3A	10.41	10.98	10.91	11.52	11.62	11.60
	Route 3B	9.94	9.97	9.98	9.69	9.77	9.83
Set 4	Route 4A	13.13	13.60	13.23	12.98	13.10	13.07
	Route 4B	13.44	13.52	13.89	13.76	13.85	13.83
Set 5	Route 5A	15.74	15.89	15.81	16.06	16.27	16.16
	Route 5B	13.26	13.33	13.38	15.95	16.07	16.22

The standard deviation values presented in Table 2.7 highlight the volatility associated with disrupted transport networks. Even though the mean travel times on competing routes were similar, the standard deviations of the data sets which contain an incident are greater than the no-incident data sets. Thus, it is clear that short-term incidents affect the reliability of a route.

Table 2.7: Standard deviation of route travel times

Standard Deviation of route travel times							
Set ID	Route	AM Peak (6am - 9am)			PM Peak (4pm - 7pm)		
		With No Incidents	*An incident on*		*With No Incidents*	*An incident on*	
			Route A	***Route B***		***Route A***	***Route B***
Scenario Combination		*C1*	*C2*	*C3*	*C1*	*C2*	*C3*
Set 1	Route 1A	0.79	0.97	0.80	0.75	0.85	0.76
	Route 1B	1.07	1.08	1.15	0.97	0.98	0.98
Set 2	Route 2A	1.03	1.14	1.04	0.83	0.93	0.84
	Route 2B	1.41	1.42	1.42	1.10	1.10	1.33
Set 3	Route 3A	0.77	0.77	0.77	0.78	0.85	0.79
	Route 3B	0.96	0.97	1.11	0.89	0.89	0.93
Set 4	Route 4A	0.93	1.02	0.94	0.79	0.87	0.80
	Route 4B	0.63	0.63	0.64	0.56	0.56	0.60
Set 5	Route 5A	0.94	0.98	0.95	0.76	0.93	0.77
	Route 5B	1.39	1.40	1.49	1.64	1.65	1.67

The time-dependent impacts on travel time are presented in Figure 2.8 and Figure 2.9 for Set 1 and Set 2 respectively. Again, the fact that Set 1 is not a competitive route pairing in terms of performance is portrayed graphically with the green travel time curves of the Hume Highway and the Horsley being consistently greater than the red travel time curves of Cumberland Highway. In contrast, Figure 2.9 reflects overlapping curves for both incident and no-incident scenarios for the routes in Set 2 strongly suggesting that they are two feasible options for a user. The shape of the curves indicate that the most congested time interval of the peak period lies between 7:30pm and 8:30pm for Set 1 and 7:00pm and 8:00pm for Set 2 which emphasises the care required when using static peak periods across different regions of a network. Travel time plots of the other route pair combinations are presented in Appendix A which shows similar trends to Figure 2.9.

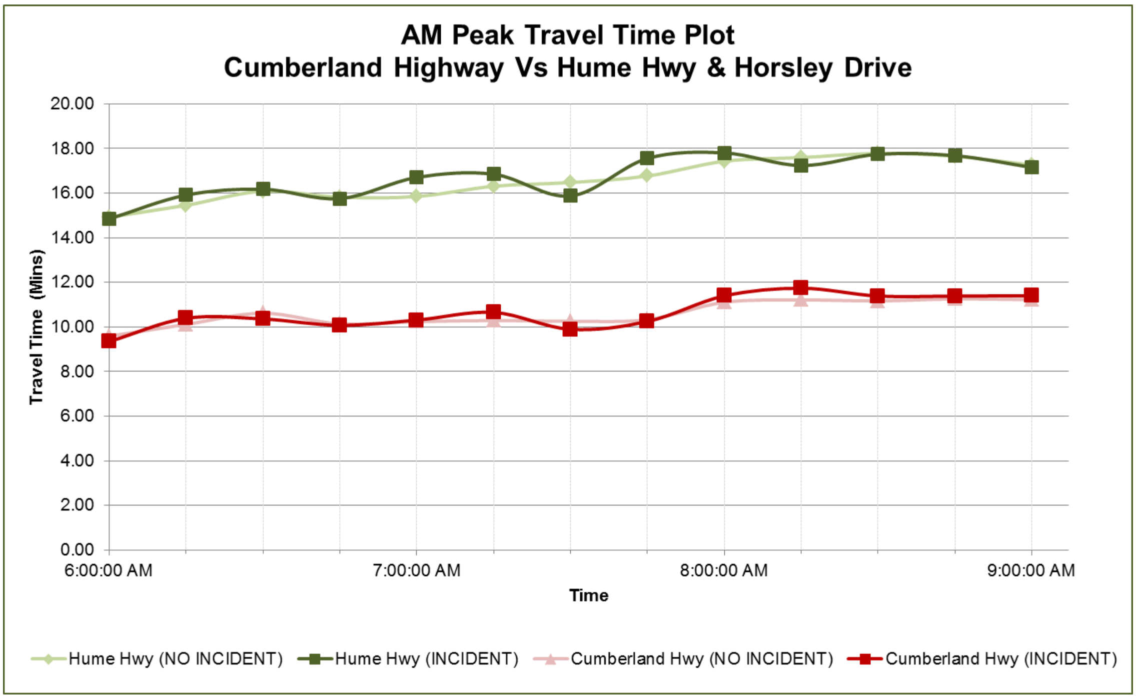


Figure 2.8: Set 1 - AM Peak travel time variation

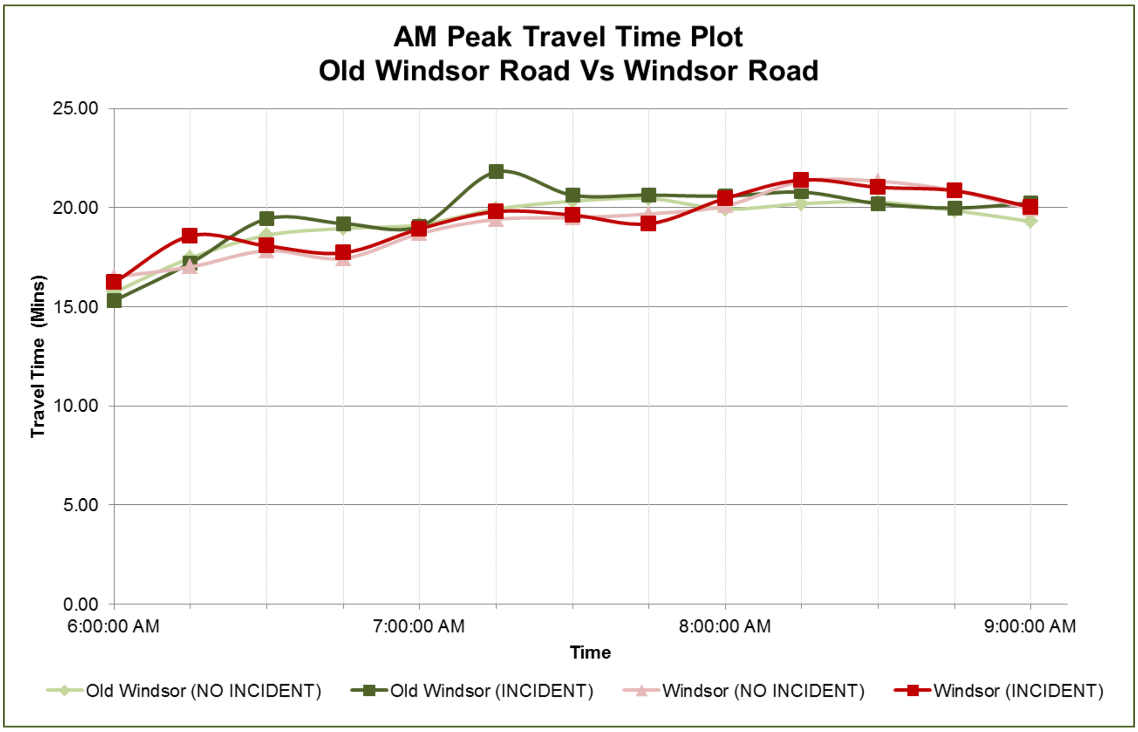


Figure 2.9: Set 2 - AM Peak travel time variation

2.5.1.1 Hypothesis Testing of Travel Time Data

Hypothesis testing was conducted across the mean travel time results of the 'no-incident' and 'incident' data sets to further investigate the stability of travel time.

As mentioned in Section 2.4.3, the Welch's T-Test was used to perform the testing for each 15 minute time interval considering both peak periods. A summary of the hypothesis testing results are provided in Table 2.8 and a complete documentation of the testing is presented in Appendix B. Table 2.8 presents the proportion of 15 minute time intervals out of all the time intervals across each AM and PM peak period, that indicated: 'the null hypothesis could not be rejected at a confidence level of 95%'. The results confirm the finding that incident and no-incident scenarios have a limited effect on the performance of the route. Statistically insignificant differences in travel time were observed for a majority of the 15 minute increments with percentages exceeding 77% for all these cases. However, when comparing the performance of the competing routes it is evident that there are differences in travel times in incident and no-incident scenarios. As described in the previous section, the pair of routes in Set 1 presents statistically significant differences in travel times between both routes.

Statistically different travel times have also been observed across a majority of 15 minute time intervals within Set 3 and Set 5 when comparing the competing routes. The statistical difference may not reflect a practical difference in the context of travel time (Devore et al., 2013). A difference of 30 seconds to 2 minutes can suggest that one route has a statistically lower travel time than the other; however from a commuter's perspective both the routes could be considered as feasible alternatives during AM and PM peak periods. This can be further corroborated with a qualitative assessment of the mean travel times in Table 2.6 where most travel times of one route are within 10% of the other (except for Set 1) which can be perceived by users as equivalent.

Table 2.8: Summary results of the Hypothesis Testing

T-Test Results (%) for Travel time Assessment				
Set	**Combination of Scenarios**		**% Null Hypothesis**	
	Scenario 1	**Scenario 2**	**Morning Peak**	**Afternoon Peak**
Set 1	Route 1A (No Incident)	Route 1A (Incident)	100%	83%
	Route 1B (No Incident)	Route 1B (Incident)	92%	100%
	Route 1A (No Incident)	Route 1B (No Incident)	0%	0%
	Route 1A (No Incident)	Route 1B (Incident)	0%	0%
	Route 1B (No Incident)	Route 1A (Incident)	0%	0%
Set 2	Route 2A (No Incident)	Route 2A (Incident)	92%	100%
	Route 2B (No Incident)	Route 2B (Incident)	75%	58%
	Route 2A (No Incident)	Route 2B (No Incident)	67%	67%
	Route 2A (No Incident)	Route 1B (Incident)	67%	50%
	Route 2B (No Incident)	Route 2A (Incident)	67%	92%
Set 3	Route 3A (No Incident)	Route 3A (Incident)	83%	100%
	Route 3B (No Incident)	Route 3B (Incident)	92%	92%
	Route 3A (No Incident)	Route 3B (No Incident)	42%	0%
	Route 3A (No Incident)	Route 3B (Incident)	25%	0%
	Route 3B (No Incident)	Route 3A (Incident)	25%	0%
Set 4	Route 4A (No Incident)	Route 4A (Incident)	67%	83%
	Route 4B (No Incident)	Route 4B (Incident)	67%	100%
	Route 4A (No Incident)	Route 4B (No Incident)	67%	33%
	Route 4A (No Incident)	Route 4B (Incident)	75%	33%
	Route 4B (No Incident)	Route 4A (Incident)	75%	42%
Set 5	Route 5A (No Incident)	Route 5A (Incident)	83%	92%
	Route 5B (No Incident)	Route 5B (Incident)	100%	92%
	Route 5A (No Incident)	Route 5B (No Incident)	0%	58%
	Route 5A (No Incident)	Route 5B (Incident)	0%	58%
	Route 5B (No Incident)	Route 5A (Incident)	0%	50%

2.5.2 Traffic Volume Assessment

The traffic volume assessment considered hourly traffic volumes at available RMS permanent counter stations across all Sets of routes. Table 2.9 presents the descriptive statistics of mean and standard deviation of volume considering all 'incident' and 'no-incident' scenarios. Similar to the process completed with the travel time data, incident data was matched with volume data to derive the incident scenarios. This resulted in situations where there was limited or no relevant volume data, such as what is presented in Set 1 where no incidents were recorded for the green 'Route B' in isolation to the red 'Route A'. The sum of individual routes within a Set remains relatively stable offering the opportunity to understand the impact of disruptions on utilisation of each of the routes. It is evident from Table 2.9 that the volatility of flow increases in disrupted conditions. This is reflected through the increase in standard deviation of flows experienced throughout the incident scenarios.

Table 2.9: Descriptive statistics of traffic volumes observed across each data set

Traffic Condition		Parameter	Set 1		Set 2		Set 3		Set 4		Set 5	
			1A	1B	2A	2B	3A	3B	4A	4B	5A	5B
AM Peak Period	No Incident	Sample Size	290	268	169	204	148	155	172	92	225	220
		Mean Traffic Volume (veh/hr)	2612	3904	2897	3596	4592	4111	3832	3875	6284	4208
		Standard Deviation (veh/hr)	181	137	168	98	138	74	88	99	242	191
	Incident on Route A	Sample Size	37	34	13	52	21	31	37	22	38	42
		Mean Traffic Volume (veh/hr)	2568	4118	2679	3678	4497	4162	3776	4029	6219	4311
		Standard Deviation (veh/hr)	262	262	468	88	230	111	218	119	348	244
	Incident on Route B	Sample Size	0	0	91	43	41	48	32	26	19	18
		Mean Traffic Volume (veh/hr)	N/A	N/A	2978	3482	4742	4028	4166	3869	6464	4016
		Standard Deviation (veh/hr)	N/A	N/A	142	99	386	245	138	151	159	398
PM Peak Period	No Incident	Sample Size	290	271	299	268	184	186	164	89	207	211
		Mean Traffic Volume (veh/hr)	2849	4308	3159	3886	4746	4488	4522	3602	6208	4567
		Standard Deviation (veh/hr)	168	252	313	82	91	132	112	122	3280	254
	Incident on Route A	Sample Size	47	42	16	20	21	23	32	21	41	21
		Mean Traffic Volume (veh/hr)	2727	4205	3040	3940	4521	4495	4408	3882	6082	4678
		Standard Deviation (veh/hr)	333	428	339	124	257	140	172	127	592	399
	Incident on Route B	Sample Size	0	0	32	22	30	30	39	23	27	19
		Mean Traffic Volume (veh/hr)	N/A	N/A	3428	3846	4876	4395	4742	3485	6342	4446
		Standard Deviation (veh/hr)	N/A	N/A	286	116	250	315	212	172	428	489

Table 2.10: Percentage occupancy of the competing routes

Percentage Route Occupancy							
Set ID	Route	AM Peak (6am - 9am)			PM Peak (4pm - 7pm)		
		With No Incidents	An incident on		With No Incidents	An incident on	
			Route A	Route B		Route A	Route B
Set 1	Route 1A	40%	38%	N/A	40%	39%	N/A
	Route 1B	60%	62%	N/A	60%	61%	N/A
Set 2	Route 2A	45%	42%	46%	45%	44%	47%
	Route 2B	55%	58%	54%	55%	56%	53%
Set 3	Route 3A	53%	52%	54%	51%	50%	53%
	Route 3B	47%	48%	46%	49%	50%	47%
Set 4	Route 4A	50%	48%	52%	56%	53%	58%
	Route 4B	50%	52%	48%	44%	47%	42%
Set 5	Route 5A	60%	59%	62%	58%	57%	59%
	Route 5B	40%	41%	38%	42%	43%	41%

Table 2.11: Percentage shift in the occupancy of the competing routes

Route Occupancy Percentage Shift							
Set ID	Route	AM Peak (6am - 9am)			PM Peak (4pm - 7pm)		
		With No Incidents	An incident on		With No Incidents	An incident on	
			Route A	Route B		Route A	Route B
Set 1	Route 1A	0.0%	-1.7%	N/A	0.0%	-0.5%	N/A
	Route 1B	0.0%	1.7%	N/A	0.0%	0.5%	N/A
Set 2	Route 2A	0.0%	-2.5%	1.5%	0.0%	-1.3%	47%
	Route 2B	0.0%	2.5%	-1.5%	0.0%	1.3%	53%
Set 3	Route 3A	0.0%	-0.8%	1.3%	0.0%	-1.3%	53%
	Route 3B	0.0%	0.8%	-1.3%	0.0%	1.3%	47%
Set 4	Route 4A	0.0%	-1.3%	2.1%	0.0%	-2.5%	58%
	Route 4B	0.0%	1.3%	-2.1%	0.0%	2.5%	42%
Set 5	Route 5A	0.0%	-0.8%	1.8%	0.0%	-1.4%	59%
	Route 5B	0.0%	0.8%	-1.8%	0.0%	1.4%	41%

Table 2.10 and Table 2.11 present the percentage occupancy of each Set of routes considered. There is relatively even division of traffic between the routes. It is clear that there are shifts in traffic from routes with disruptions to routes without disruptions. Shifts of up to 2.5% were observed, with some isolated data points suggesting even greater variations in traffic flow. These observations indicate that users adapt in the presence of disrupted conditions.

2.6 Discussion, Limitations and Future Extensions

The analysis of empirical data on the five pairs of competing routes presented the following key findings.

- Concepts of equilibrium modelling cannot be dismissed as travel times on routes are stable between 'incident' and 'no-incident' scenarios.
- The presence of incidents on a route results in adaptive behaviour.

The first key finding is evident from the hypothesis testing of travel time conducted in section 2.5.1. Current traffic assignment techniques consider Wardrop's User Equilibrium, or recent similar variations of the approach, to model traffic within congested scenarios(de Dios Ortúzar and Willumsen, 2011). Equilibrium concepts suggest that travel times on all used feasible routes are equal and a minimum. In general, the competing routes considered in the study presented differences in travel time which do not support the notion of equilibrium. However, this can be an artefact of the statistical testing procedure which is void of the practical difference expected with measures of travel time(Devore et al., 2013).

Support for the feasibility of equilibrium approaches arise from the stability of the route travel times across 'incident' and 'no-incident' scenarios for each individual route. The hypothesis testing suggested that for most 15minute interval data sub-sets, there were no statistical differences between 'incident' and 'no-incident' scenarios across all 10 routes assessed. However, it must be emphasised that this is by no means a proof of the presence of equilibrium itself. The results presented are case specific and empirical in nature and as such cannot be generalised. Nevertheless, this finding is in line with the current overarching idea of equilibrium modelling in traffic assignment.

In saying this, the route occupancy analysis presented in Section 2.5.1.1 highlights the current deficiencies of the modelling approach. A majority of equilibrium modelling approaches involve assigning traffic to fixed routes from origin to destination based on the costs observed for each link of a network. Disruptions are accounted for in the modelling paradigm by altering the costs associated with impact on a link by the disruption and re-applying the original traffic assignment technique to define a set of different fixed paths between an origin and a destination. The results of the volume assessment indicate that traffic remains similar across all the different combinations of 'incident' and 'no-incident' scenarios prior to the divergent point between the two competing routes. However, the presence of the disruption results in a reduction in traffic volumes on the route with a disruption and a corresponding increase in the volume on the route not containing a disruption. This phenomenon suggests that users adapt routing decisions online after departing from the origin. This empirical finding implies the need to incorporate en route/online adaptive behaviour into traffic assignment techniques to appropriately account for the presence of disruptions.

Furthermore, these findings justify the initial behavioural theory described within the introduction which postulates that users adapt in light of disrupted conditions. In fact, the impact of a disruption on route choice behaviour can be described in the perspective of information dissemination. The occurrence of a traffic incident results in the release of information, from the disruption itself or from technology through on-board navigation systems or ITS infrastructure. This information is acquired by users which forces a reassessment of the routing decision. Therefore it is vital to pursue 'adaptive traffic assignment' techniques, such as User Equilibrium with Recourse (UER) (Unnikrishnan and Waller, 2009), which cater for information acquisition and the resulting behaviour. Extensions of the UER framework are provided within Chapter 4 and Chapter 5 of this thesis to better capture disrupted network conditions.

The results observed within this study are consistent with a few recent studies. In the paper by Watling, Milne and Clarke in 2012, empirical results of a major disruption are compared with the results obtained from equilibrium modelling. The paper recognises that the user equilibrium model could give a 'broad agreement' with directions of change observed in the data. It could not however, capture the '*ambient daily flows, increases in demand and apparent learning effects of travellers' decisions*' (Watling et al., 2012). This sentiment is reflected in the results of this study with the stability of travel times and the variability of traffic flows on competing routes. In addition, Zhu and Levinson (2012) reveal in the recent review paper that current modelling techniques cannot effectively capture the impact of large scale disruptions within a network.

The difficulties and limitations of empirical studies highlighted by (Noland and Polak, 2002) and (Carrion and Levinson, 2012) were faced when conducting this research study. The limitations can be summarised as follows;

- ***Missing and erroneous data***: The data sets obtained from RMS contained missing and erroneous data which required data pre-processing to prevent affecting the overall findings. As mentioned in Section 2.3.4, speed data obtained from GPS technology suffered inaccuracy for shorter link lengths when fleet vehicle demands were scarce. However, this was accounted for during the analysis and thus did not affect the final results or conclusions.
- ***Lack of direct travel time data***: The data sets provided by RMS did not include travel time data. Travel time data sets were calculated through the integration of average speed data and link length data along each of the studied routes. Thus, only an approximation of the travel time could be obtained. Nevertheless, these data sources did provide a satisfactory platform to observe general trends and relationships to compare 'incident' and 'no-incident' scenarios. Future extensions of this study could be the

utilisation of detailed field surveys that specifically measure travel times on competing routes during peak periods.

- ***Small sample issues***: The data pre-processing also involved the formation of subsets of data which considered 'incident' and 'no-incident' scenarios. The incident data were overlayed with the average speed and travel time data sets to create the 'incident' and 'no-incident' subsets. The size of 'incident' subsets was significantly smaller than 'no-incident' subsets, as evident through the counts displayed in Appendix B. The small sample size reduced the emphasis of the statistical comparison and more importantly restricted the assessment of the scenario where incidents occur on both routes.
- ***Utilisation of representative volumes***: The volume analysis undertaken in this study obtains representative midblock volumes across the length of the route. A majority of the routes considered have a number of side streets and at times intersections with other major thoroughfares which result in inflows and outflows of traffic from the route. Ideally, use of volume counters at all major connecting arterial roads or the use of loop detector data along the route would allow a more accurate volume data collection and subsequent analysis.
- ***Lack of Origin-Destination data***: Similar to the issues with the volume data, origin and destination data were not available. This means that the data could include users who did not travel on the entirety of the route, but travelled on only a portion of the route. Possible improvements to this issue may include using origin-destination surveys or number plate recognition data collection procedures to get a true understanding of route choice.

Even though there were a number of data limitations, the novelty of the general trends and observations provide valuable insight into the future modelling of disrupted conditions. Alternative modelling approaches which account for the adaptive behaviour of users can lead to improved decision making and ultimately mitigating the negative impacts of delay and congestion arising from disruptions.

Furthermore, the novelty of this methodology used in empirically investigating short-term disruptions provides a foundation for similar future studies. Replication of this analysis in other urban cities around the world could provide a more generalised and holistic understanding of the impacts of day-to-day disruptions.

2.7 Concluding Remarks and Impact

This chapter of the thesis conducted an empirical investigation of the impact of short-term disruptions on five competing parallel routes within the Sydney metropolitan. Traffic speed, traffic volume, link length and categorised traffic incident data were obtained from the Roads and Maritime Services of New South Wales for the time period between January 2012 and June 2013. Data pre-processing lead to the formation of data sub-sets which described 'incident' and 'no-incident' cases for both the travel time and traffic volume performance metrics.

Analysis of the data indicate that the presence of short-term disruptions do not cause a statistically significant impact on the travel time of a route during the morning and afternoon peak periods. However, disruptions on routes result in adaptive routing behaviour with noticeable shifts in route occupancy. These observations support the need for adaptive equilibrium based modelling efforts which account for the acquisition of information by users in light of a disruption. Models of this nature are investigated from a static modelling perspective in Chapter 4, (Disrupted Equilibrium Assignment with Recourse, (DEAR) model) and from a dynamic perspective in Chapter 5 (Dynamic User Optimal with Recourse, (DUOR) model)

The other primary contribution of this chapter was the presentation of one of the first empirical studies which focussed on the impact of short-term disruptions on road network performance. This methodology could be replicated and enhanced across other regions to further understand the travel behaviour of users under disrupted conditions. Improved understanding in this domain will result in better policies, planning and a more sustainable transport future.

CHAPTER 3. THE VALUE OF INFORMATION AND RELIABILITY IN A DRIVING CONTEXT

3.1 Introduction

One of the key contributing factors affecting the performance of a road network, in terms of reliability and congestion, is the presence of disruptions. It is clear that the uncertainty of a disruption, in particular a non-recurrent disruption, can reduce capacity of a road segment or a portion of a road network. This in turn can increase travel times, ultimately creating unreliability. Information systems provide a way to identify and inform users of these disruptions. The analysis of empirical data presented within Chapter 2 indicates that disruptions within a network results in adaptive routing behaviour. This can be interpreted as the disruption triggering the release of information to users and users updating their route choice based on the information acquired. The information may be revealed to users as a consequence of the disruption itself or, more commonly, the dissemination of its presence through radio, internet and Advanced Traveller Information Systems (ATIS). Thus, in the context of user behaviour in disrupted conditions, it is critical for transportation agencies and practitioners to understand the value travellers place on the reliability of the network and the en route information provided. The core contribution of Chapter 3 is to present results of a behavioural experiment which studied the impact of online information on route choice. In addition, Chapter 3 also discusses the valuation of online information sources and reliability considering the differences in behaviour.

Diffusion of online information concerning driving conditions has become increasingly prevalent throughout transport networks. Information was initially provided with signage for upcoming detours and road works; this was further reinforced with radio traffic reports and the utilisation of Variable Message Signs (VMS). Within the last decade, information has become even more accessible through Advanced Traveller Information Systems (ATIS), GPS navigation

Technology and the Internet. Literature suggests that these information systems serve as a congestion mitigation strategy used in influencing route choice behaviour to distribute traffic in an efficient manner (Mahmassani et al., 1986). Information provision aims to reduce risk or if possible, resolve it completely. If people are aware of the existence of a disruption, they can account for this in their subsequent routing behaviour, reducing the uncertainty or risk associated with the scenario. Risk attitudes influence the value an individual places on information and reliability within a transport network. An individual who is risk averse would have a greater value of information and reliability compared to a risk loving person and therefore an individual's risk attitude affects the willingness to pay for online information acquisition. Thus, if risk attitudes impact the valuation of information by a user, neglecting these impacts could result in disastrous pricing and investment strategies in terms of infrastructure for information provision. This component of the thesis attempts to address the critical question: Do risk attitudes remain the same when people are placed in a context where information acquisition is a choice? The answer to this question has wide ranging impacts on valuation of information and reliability, which are important to understand when managing disruptions on road networks.

Methods of experimental economics were used to design a controlled laboratory experiment to study risk attitudes and the choice of information acquisition. The value of using this approach is the ability for the experimenter to induce utilities and study behavioural parameters. This is not possible with field data, where the lack of control makes it difficult to isolate and study behavioural parameters and test theories. Vernon Smith won the Nobel Prize for Economics for his work on Induced Value Theory (Smith 1976, 1982), which underpins the science of the methods within experimental economics. The experiment formulated in this chapter involved a series of four Multiple Price List (MPL) lottery tasks which were completed by participants with and without the presence of information. A model based on Expected Utility Theory (EUT) was then used to quantitatively infer the risk attitudes of the participants using the choice data obtained from the MPL lottery tasks. Based on the literature reviewed, the formulated experiment and model is the first to explore the impact of information within a choice set on risk attitudes of road users.

The remainder of the Chapter is structured as follows:

- Section 3.2 presents the relevance of this component of the research in the context of previous literature.
- Section 3.3 details the experimental design, recruitment of participants and the overall procedure of the experiment.
- Section 3.4 explains the maximum likelihood procedure used to estimate the risk attitudes using the data obtained from the experiment.
- Section 3.5 discusses the results and observations of the experiment and the quantitative measurement of risk attitudes.
- Finally, Section 3.6 and 3.7 discusses the implications of the results, limitations of the approach and extensions followed by concluding remarks.

3.2 Literature Review

The implementation of ITS and ATIS technology is a rapidly growing venture within the transportation industry. As a result, there have been a multitude of research efforts investigating the value, network performance impact and behavioural implications involved with the incorporation of these systems within transport infrastructure, in particular on road networks. Ben-Elia and Avineri (2015) presents the latest and most comprehensive review of behavioural research associated with travel information. Initially, a discussion of the theoretical modelling approaches to capture driving behaviour is presented and has been used in guiding the estimation procedure to determine the risk attitudes. This is followed by a review of previous research efforts investigating the valuation of information sources and reliability of transport systems by users. The last section of the review deliberates the merits and application of experimental economics to study route choice behaviour in a controlled environment.

3.2.1 Theoretical modelling of Driving Behaviour

A variety of theoretical and methodological approaches have been devised to investigate driving behaviour. Ben-Elia and Avineri (2015) provide a review of the theoretical models applied to choice and behaviour under uncertainty in the transport domain. The models used primarily focus on the following theories: Expected Utility Theory (EUT), Prospect Theory (PT) and Regret Theory (RT) and are discussed briefly.

Von Neumann and Morgenstern (1947) introduced EUT where travellers are assumed to be rational and try to maximise utility by minimising travel costs. Under EUT a user will assign probabilities to certain travel outcomes and consider the product of the utility gained from each outcome and the probability of each outcome to get an expected utility over the entire choice set. A majority of choice models have used this theory as it offers a systematic determination of route selection and a thorough review of these studies are presented in Prashker and Bekhor (2004). Utility maximisation has also been assumed when investigating the impact of information in enhancing users' network performance knowledge (Mahmassani and Liu, 1999, Srinivasan and Mahmassani, 2003). In the experimental domain, there have also been a large number of studies that have used EUT as the theoretical framework (De Palma et al., 2012, De Palma and Picard, 2006, Dixit et al., 2014, Dixit et al., 2013, Dixit et al., 2011). Furthermore, extensions of the EUT model have been used in the valuation of reliability (Hensher and Li, 2012, Hensher et al., 2013, Li et al., 2012).

Behavioural analysts and psychologists have questioned the adequacy of EUT in accurately depicting decision making behaviour, in particular placing doubt over the rationality assumption in uncertain or disrupted conditions (Ben-Elia and Avineri, 2015). This led to the development of Prospect Theory (PT) (Kahneman and Tversky, 1979) and Regret Theory (RT) (Loomes and Sugden, 1982) as alternatives to EUT. PT suggests that risk attitudes depend on the framing of the outcome in the form of gains or losses. In one-shot decision making a user will assess the prospective gains or losses relative to some reference point rather than considering the final outcomes as suggested by EUT. Li and Hensher (2011) provide a review of applications of prospect theory and highlight the advantages as well as a number of limitations involved with these approaches related to the necessity of a reference point when analysing a choice. Support for PT is borne from studies such as Katsikopoulos et al. (2002) and Gao et al. (2010) which confirm the behaviour proposed by the theory. In addition, there have been a few studies which have contradicted the claim that there is an increase in risk aversion for gains and a decrease in risk aversion for losses (Avineri and Prashker, 2005, Erev and Barron, 2005).

In comparison to both EUT and PT, RT has received little attention in the transportation modelling domain. RT postulates that when making a decision, people try and avoid the situation where the alternative options outperform the selected option (Loomes and Sugden, 1982). The advantage of RT is that it does relax the rationality assumption of EUT, however it is not as complex as the PT approach (Chorus, 2012b). There have been presentations of RT which model risky route choices and also provide a relationship with traditional EUT (Chorus, 2012b, Chorus, 2010, Chorus, 2012a). The research conducted by Chorus applies an expected modified utility function to numerically represent risk aversion and regret aversion to jointly determine equilibrium outcomes in a demonstrative binary route choice scenario. This research presents a promising approach that to date has been studied in a limited scope (Ben-Elia and Shiftan, 2010, Chorus, 2012b). The three methodological approaches discussed in this section were all considered carefully as feasible options to conduct the statistical estimation of the risk attitudes and further details of the method used in this component of the research is discussed in Section 3.4 .

3.2.2 Valuation of Information

Information aims to mitigate the presence of risk and uncertainty, therefore the value individuals place on information and reliability is related to their risk attitudes. As mentioned, there are a number of sources of information that are available to a traveller. Ben-Elia and Avineri (2015) categorised information sources as experiential, descriptive, and prescriptive. Experiential information sources are based on past experience of the user and acquired through repeated traversal of the network. Descriptive information details the prevailing state of the network. The information can be provided either pre-trip (a priori) or during a trip (en route or online) based on historic or real time estimation. A bulk of ATIS and ITS systems provide descriptive information to a user. Prescriptive information provides suggestions and guidance of alternative routes or modes that a user can take to achieve a specific objective. For an example, navigation systems relay live traffic information and provide alternative routes to a user to avoid congested roadways.

The focus of this chapter and in general the entire research project is the investigation of the impacts of descriptive online information. Thus, the departure time of users is a foregone decision and will not affect their risk attitudes towards the information provided online. Accordingly, this study differs from the work of Ettema and Timmermans (2006), Arnott et al. (1991) and Jou (2001) that studied the impact of information in the context of departure time. Further to these works, De Palma et al. (2012) developed a theoretical model with heterogeneous risk attitudes, and found that risk neutral and moderately risk averse drivers benefited from information, while risk averse drivers would pay for information which would not necessarily benefit them. However, in all these studies, an important assumption was that people's risk attitudes do not change based on the access to information. If risk attitudes of road users are affected by the presence of information, evaluation processes carried out to determine the feasibility of ATIS infrastructure will also be affected. The costs and benefits of these systems will offer a different utility to the user at different stages of the implementation. For an example, prior to the implementation of an information system, users may have been risk averse and valued the reduction in uncertainty the system offers. However, post implementation if the risk attitudes of users change, the value of the information system will also change. Accordingly, an awareness of changes in risk attitudes will have a significant impact within infrastructure planning and decision making related to ATIS systems made by transport planning authorities.

The impact of information on risk characteristics have been investigated by only a few researchers which have primarily involved Stated Preference (SP) surveys (Abdel-Aty et al., 1997, Avineri and Prashker, 2006). These works portray that travellers will tend to exhibit risk aversion when faced with travel information. Avineri and Prashker (2006) assessed the impact of pre-trip travel time information and performance feedback information in a series of repeated choice exercises. The findings indicate that the control group who were not exposed to information preferred a less reliable route than those who were informed. These results suggest that pre-trip information dissuades users from considering unreliable routes highlighting the significance placed by users on the reliability of the network. On the other hand, Ben-Elia et al. (2008) suggests that information creates risk seeking behaviour. The study conducted a repeated route choice experiment with dynamic online information depicting ranges of travel times. Informed respondents learnt about the travel scenario faster than non-informed respondents and preferred the riskier alternative in the short term. Both these research efforts provide a great insight into the potential for change in risk attitudes in the presence of information.

The key difference between these studies and the experiment presented in this chapter is that information bares a cost and the user must pay to utilise it. Information is within the choice set; however it is not necessarily utilised to reduce the uncertainty involved in making the decision. Furthermore, these studies involved control groups where participants were divided into two groups, one who had access to information whilst the other didn't. The experiment presented in this chapter conducted 2 separate treatments on the same group of participants to understand whether there is a difference in risk attitudes as a result of the presence of information in the choice set. These differences can further propagate the investigation into risk attitudes and driving behaviour as well as provide an understanding of the impact of online information on users' risk attitudes in a controlled laboratory setting.

It should also be mentioned that recently a few Revealed Preference (RP) studies have been conducted to evaluate the impact of pricing on the demand for information. Jou and Chen (2013) conducted a survey among Taiwanese drivers to understand the demand for real-time information under varied pricing and traffic conditions. They found that the presence of non-recurring traffic events resulted in the greatest demand for information. In a similar study conducted by Tseng et al. (2013), it was found that drivers tend to react more strongly to variations in travel time when information is provided. Like the previous works, these studies provide insight into the value of information without taking into consideration the implication of risk attitudes towards the presence of information in the choice set.

3.2.3 Valuation of Reliability

The concept of reliability and its measures, such as travel time variability, has been extensively studied in recent times. Jackson and Jucker (1982), suggest that travellers consider the variability of travel time as well as the expected travel time when selecting a route. Since then, there have been numerous studies (Bates et al., 2001, Brownstone and Small, 2005, Lam and Small, 2001, Batley et al., 2009, Li et al., 2010, Robuste and Soriguera, 2010) over the years which have presented evidence on the value travellers place on reliability while evaluating routes and modes. In fact, travel time reliability has been valued more highly than travel time itself according the study conducted by (Batley et al., 2009). In addition, these studies also highlight the increasing importance of travellers' value of reliability from a planning and operations perspective as it heightens the need for robust networks that can manage uncertainties such as disruptions and unscheduled activities.

Li et al. (2010) provides a review of the different modelling approaches in the valuation of reliability which include;

- The mean-dispersion model (Jackson and Jucker, 1982)
- The scheduling model (Bates et al., 2001, Small, 1982)
- The mean lateness model (Batley and Ibáñez, 2012).

In general, most applications of these models and other empirical valuations of reliability have focussed the standard deviation of travel time (Bates et al., 2001, Brownstone and Small, 2005, Lam and Small, 2001). An alternative way to measure value of reliability is to evaluate the risk premium (Batley, 2007, Beaud et al., 2012). A risk premium is the amount of money an individual would forgo to resolve uncertainty and has been used extensively in Finance and Economics (Pratt, 1964). The paper by Beaud et al. (2012) compares individuals' value of travel time savings under different risky scenarios to measure the value of reliability. Thus, by comparing a risk free scenario to one associated with risk, a 'risk premium' measure is derived. Prior to this study, Batley (2007) extended the seminal works of Pratt (1964) in the context of total travel time and defined a 'reliability premium'. The reliability premium is the '*delay to arrival time that the individual would be willing to pay in exchange for eliminating unreliability in arrival time*'. The risk premium concept has been applied within this component of the research project, however instead of considering the elimination of the unreliability of the arrival time; the premium will be measured relative to the resolution of the delay time through the provision of online information.

Risk attitudes have been incorporated in the measurement of travel time variability and the valuation of travel time savings (Hensher et al., 2011, Hensher and Li, 2012, Hensher et al., 2013, Li et al., 2012). Hensher et al. (2011), Li et al. (2012) and Hensher et al. (2013) present a series of generalised non-linear logit models which incorporates probability weighting of users and their risk attitudes within the utility function. The models apply an extension of conventional Expected Utility Theory (EUT), 'Extended Expected Utility Theory (EEUT)' by incorporating the underlying probabilities of outcomes for an attribute as a probability weighting function. By embedding these behavioural characteristics, the model has the ability to account travel time variability in a holistic manner. The study presents a number of novel empirical findings with the presentation of a new willingness to pay metric, 'value of time variability-embedded travel time savings' (VETTS). Hensher et al. (2013) suggests that the users transform probabilities presented within stated choice surveys resulting in overweighting of outcomes with low probabilities and underweighting of outcomes with high probabilities. This study, presented in this chapter, contrasts previous literature by attempting to understand the impact of exogenous provision of online information on the risk attitudes of users and developing a simple measure to value of reliability using data from a controlled laboratory experiment.

3.2.4 Experimental Economics in Transportation Research

The use of experimental economics in the field of transportation has become more prevalent in recent times. Laboratory experiments have been used to study driving behaviour as well as some specific equilibrium models and paradoxes. A complete review of the application of experimental economics within the field of transportation is detailed in (Dixit et al., 2015).

Even though revealed preference data provide useful insights, due to lack of control in the field, it is extremely difficult to isolate the impact of information on risk attitudes. Therefore we use methods from Experimental Economics to achieve this goal, through using salient incentives that induce the value of the utilities. This property of Experimental Economics is well defined under Induced Value Theory (Smith, 1982). Up to now, there have been a number of controlled laboratory experiments used in transportation to study driver behaviour. In particular there have been studies relating equilibrium principles as well as individual travel behaviour (Rapoport et al., 2006, Nielsen, 2004, Rapoport et al., 2008, Gisches and

Rapoport, 2010, Dixit and Denant-Boemont, 2014). There have also been a few studies which have investigated the impact of information on route choice (Ben-Elia et al., 2013, Denant-Boèmont and Petiot, 2003, Selten et al., 2007, Ziegelmeyer et al., 2008, Selten et al., 2004). These studies are discussed in greater detail as they provided guidance in the design of the experimental methodology.

Experimental economics in transport has predominantly been used to explore equilibrium behaviour. Selten et al. in 2004 and 2007 conducted two separate studies investigating driving behaviour. Selten et al. (2004) investigated day to day route choice of autobahn traffic by utilizing a repeated route choice game with parallel roads but not linking these routes. The results indicate the presence of Nash equilibria; however there are persistent fluctuations in choice exhibited by the participants. Following this study, Selten et al. (2007) conducted further investigations focusing on commuters route choice in the presence of information. The study concludes that increased levels of information are beneficial to drivers; however there is a saturation point where drivers become confused.

In addition there have been a number of studies that have investigated bottleneck congestion focussing on the equilibrium of departure time (Gabuthy et al., 2006, Schneider and Weimann, 2004). The study by Ziegelmeyer et al. (2008) also examined the impact of information on departure time behaviour. The experiment provided insights into the experimental economics methodology and also presented a novel finding. This experiment was based on a discrete version of Arnott et al. (1990) bottleneck model. Participants were required to select departure times in a scenario where early and late arrivals were penalised. Information was revealed to the participants about past departure rates and performance of previous rounds of the experiment. The study concludes that information did not impact departure time behaviour. However, this can be attributed to a 'stranger' design in their experiment where users were randomly assigned to cohorts after every round, and prior information would not have any value in such a setting. Ben-Elia et al. (2013) investigated the impact of information accuracy where descriptive and prescriptive information was provided to participants and experiential information was acquired in a repeated route choice exercise. The findings suggest that increasing the accuracy of information results in a shift to less reliable routes which could be interpreted as greater risk seeking behaviour. Prescriptive information and descriptive information were revealed to have the most significant behavioural impact.

There has been limited experimental research which has investigated risk attitudes related to information in a transport context. However, one of the first experimental economic studies evaluating the impact of information on traffic was conducted by Denant-Boèmont and Petiot (2003) to study how individuals value information under different levels of information in the context of mode choice. Though the authors assumed risk neutrality, they found that individuals tend to pay a higher value for information as the risk increased, suggesting that risk attitudes could play a role. An interesting driving simulator study conducted by Chorus et al. (2013) found that travellers have intrinsic preferences for certain types of information over others, and these preferences do not necessarily relate to the economic value of the information. As mentioned in detail earlier, Ben-Elia et al. (2008) found evidence that information seemed to increase risk seeking behaviour. In fact, the revealed preference study by Tseng et al. (2013) also suggested a change in behaviour with provision to information. This provided an impetus to the main focus of this study, on whether online information influences risk attitudes.

3.3 Experimental Methodology

The experiment was designed to understand route choice behaviour with and without the presence of information within the choice set. The structure involved utilising four multiple price list (MPL) (Holt and Laury, 2002) lotteries considering:

- Two choice tasks without the presence of information but with tolls and
- Two choice tasks with the presence of information

The MPL lotteries contain a series (normally 10) of paired lottery choices, one being of greater risk than the other. The payoffs for each paired lottery remain the same for the series whilst the probability associated with each of the payoffs change. A participant selects the preferred lottery to play for each pair across the series. The concept behind the MPL lottery is that a participant would select the low risk lottery until the high risk lottery provides a greater probability of the higher payoff to occur and when this occurs the participant would cross over to the high risk lottery. An individuals' risk preference can be measured by assessing when participants switch from the low risk lottery to the high risk lottery (Charness et al., 2013). The advantage of using MPL lotteries over other simpler risk elicitation methods is that this approach can estimate parameters of a model (assuming a particular functional form for a person's utility) corresponding to risk preferences (Charness et al., 2013). The ability to measure the degree of risk aversion is essential to understand the impact of the presence of information within the choice set on the risk attitudes of the participant pool.

In this study the lotteries were framed as route choice problems, with uncertain travel times. The tasks required participants to choose between two competing routes, where each route contained 2 possible delay outcomes, across 10 separate lotteries presented to the participants as 'decision scenarios'. One route option contained low variability between the delays (either a 5 minute or 6 minute delay) serving as the low risk option whilst the other option contained a higher variability between the delays (either a 9.75 minute or 0 minute delay) serving as the high risk option.

Relating the experiment back to disrupted networks, the unfavourable delay outcome would reflect the possibility of a disruption affecting the road network, while the favourable delay would represent normal peak period conditions. The low risk route would result in relatively consistent delays regardless of an incident taking place. Under normal conditions users of the route would experience a 5 minute delay as a result of recurrent congestion during the peak period and if there was a disruption users would experience only 1 minute of additional delay.

On the other hand the high risk route would be considerably affected by an incident, resulting in an additional 9.75 minutes of delay relative to normal conditions where it experiences no additional delays relative to the free flow travel time. The probabilities associated with the delay outcomes provide participants the historical performance of each route, depicting the experience road users (in particular commuting traffic) would naturally obtain from day to day travel. The decision scenarios were structured to describe the various driving conditions on the competing routes as well as offering to identify the cross-over point between the high and low risk route options. .

Table 3.1: Comparison of the variance across decision scenarios and between lotteries

Lottery 1 (Route A)				Lottery 2 (Route B)			
Decision	**Delay (minutes)**	**Probability**	**Variance**	**Decision**	**Delay (minutes)**	**Probability**	**Variance**
1	5	10%	0.09	**1**	0	10%	8.56
	6	90%			9.75	90%	
2	5	20%	0.16	**2**	0	20%	15.21
	6	80%			9.75	80%	
3	5	30%	0.21	**3**	0	30%	19.96
	6	70%			9.75	70%	
4	5	40%	0.24	**4**	0	40%	22.82
	6	60%			9.75	60%	
5	5	50%	0.25	**5**	0	50%	23.77
	6	50%			9.75	50%	
6	5	60%	0.24	**6**	0	60%	22.82
	6	40%			9.75	40%	
7	5	70%	0.21	**7**	0	70%	19.96
	6	30%			9.75	30%	
8	5	80%	0.16	**8**	0	80%	15.21
	6	20%			9.75	20%	
9	5	90%	0.09	**9**	0	90%	8.56
	6	10%			9.75	10%	
10	5	100%	0.00	**10**	0	100%	0.00
	6	0%			9.75	0%	

A comparison of the variances of each decision scenario across both routes is presented in Table 3.1 highlighting the difference in reliability of each route. The variance for each scenario is calculated using the formula: $E[X^2] - (E[X])^2$, where 'X' represents the delay outcomes for each decision scenario. It is evident from Table 3.1 that Route B has a considerably higher variance to that of Route A, thus confirming that Route A is a relatively lower risk selection. Decision scenario 10 provides a sanity check for the experiment. In this case, Route A will definitely result in a delay of 5 minutes whilst Route B will have a delay of 0 minutes. Participants who understand the tasks and are aiming at maximising profit will always select Route B in this case. All participants selected Route B suggesting a sound understanding of the experiment procedure.

A participant would initially select the lottery across each of the decision scenarios and the outcome of a specific scenario was dependent on the rolling of a die. Excerpts of two of the choice tasks presented to a participant are shown in Figure 3.1 (without information) and Figure 3.2 (with information). The MPL lottery task with the presence of information offered the opportunity for a participant to pay for information and realise the delay which will incur on both the routes. Given this information, a participant could guarantee minimisation of the delay incurred when travelling.

Decision	Motorway Route Choice A	Arterial Route Choice B	Toll for Motorway Route	Your Choice (Circle one)
1	5.00 min delay if throw of die is 1 6.00 min delay if throw of die is 2-10	0.00 min delay if throw of die is 1 9.75 min delay if throw of die is 2-10	$2.00	A B
2	5.00 min delay if throw of die is 1-2 6.00 min delay if throw of die is 3-10	0.00 min delay if throw of die is 1-2 9.75 min delay if throw of die is 3-10	$2.00	A B
3	5.00 min delay if throw of die is 1-3 6.00 min delay if throw of die is 4-10	0.00 min delay if throw of die is 1-3 9.75 min delay if throw of die is 4-10	$2.00	A B
4	5.00 min delay if throw of die is 1-4 6.00 min delay if throw of die is 5-10	0.00 min delay if throw of die is 1-4 9.75 min delay if throw of die is 5-10	$2.00	A B
5	5.00 min delay if throw of die is 1-5 6.00 min delay if throw of die is 6-10	0.00 min delay if throw of die is 1-5 9.75 min delay if throw of die is 6-10	$2.00	A B
6	5.00 min delay if throw of die is 1-6 6.00 min delay if throw of die is 7-10	0.00 min delay if throw of die is 1-6 9.75 min delay if throw of die is 7-10	$2.00	A B
7	5.00 min delay if throw of die is 1-7 6.00 min delay if throw of die is 8-10	0.00 min delay if throw of die is 1-7 9.75 min delay if throw of die is 8-10	$2.00	A B
8	5.00 min delay if throw of die is 1-8 6.00 min delay if throw of die is 9-10	0.00 min delay if throw of die is 1-8 9.75 min delay if throw of die is 9-10	$2.00	A B
9	5.00 min delay if throw of die is 1-9 6.00 min delay if throw of die is 10	0.00 min delay if throw of die is 1-9 9.75 min delay if throw of die is 10	$2.00	A B
10	5.00 min delay if throw of die is 1-10	0.00 min delay if throw of die is 1-10	$2.00	A B

DECISION ROW CHOSEN BY FIRST THROW OF THE DIE: _________

THROW OF THE DIE TO DETERMINE DELAY: ____________

EARNINGS: ________________

Figure 3.1: Excerpt of Choice Task without Information

Decision	Freeway Route Choice A	Arterial Route Choice B	Information Choice C	Your Choice (Circle one)
1	5.00 min delay if throw of die is 1 6.00 min delay if throw of die is 2-10	0.00 min delay if throw of die is 1 9.75 min delay if throw of die is 2-10	\$2.00	A B C
2	5.00 min delay if throw of die is 1-2 6.00 min delay if throw of die is 3-10	0.00 min delay if throw of die is 1-2 9.75 min delay if throw of die is 3-10	\$2.00	A B C
3	5.00 min delay if throw of die is 1-3 6.00 min delay if throw of die is 4-10	0.00 min delay if throw of die is 1-3 9.75 min delay if throw of die is 4-10	\$2.00	A B C
4	5.00 min delay if throw of die is 1-4 6.00 min delay if throw of die is 5-10	0.00 min delay if throw of die is 1-4 9.75 min delay if throw of die is 5-10	\$2.00	A B C
5	5.00 min delay if throw of die is 1-5 6.00 min delay if throw of die is 6-10	0.00 min delay if throw of die is 1-5 9.75 min delay if throw of die is 6-10	\$2.00	A B C
6	5.00 min delay if throw of die is 1-6 6.00 min delay if throw of die is 7-10	0.00 min delay if throw of die is 1-6 9.75 min delay if throw of die is 7-10	\$2.00	A B C
7	5.00 min delay if throw of die is 1-7 6.00 min delay if throw of die is 8-10	0.00 min delay if throw of die is 1-7 9.75 min delay if throw of die is 8-10	\$2.00	A B C
8	5.00 min delay if throw of die is 1-8 6.00 min delay if throw of die is 9-10	0.00 min delay if throw of die is 1-8 9.75 min delay if throw of die is 9-10	\$2.00	A B C
9	5.00 min delay if throw of die is 1-9 6.00 min delay if throw of die is 10	0.00 min delay if throw of die is 1-9 9.75 min delay if throw of die is 10	\$2.00	A B C
10	5.00 min delay if throw of die is 1-10	0.00 min delay if throw of die is 1-10	\$2.00	A B C

DECISION ROW CHOSEN BY FIRST THROW OF THE DIE: _________

IF CHOICE A or CHOICE B, THROW OF THE DIE TO DETERMINE DELAY: ____________

IF CHOICE C, THROW OF THE DIE TO DETERMINE DELAY:

Select FREEWAY DELAY _________ ARTERIAL DELAY ____________

EARNINGS: ________________

Figure 3.2: Excerpt of Choice Task with Information

Experiments using monetary incentives provide a high degree of control in laboratory setting to study individual preferences (Dixit et al., 2014, Selten et al., 2007). The lottery tasks were incentivised to elicit preferences based on actual choices being made for real consequences. Thus participants were given not only delay information but also the information about the consequence of the delay, enforcing a value of time. The participants received an initial income of $10 for each task and were informed that 1 minute of delay resulted in a $1.00 reduction in income. In addition, the without information choice tasks involved a toll route (Motorway Route) for the lower risk lottery, which when selected incurred a further reduction in income in addition to the delay experienced. In the case of the information choice task, the toll is removed and a fixed cost was charged for the provision of information. The experiment was incentivised to align the participants' goal of profit maximisation from completing the tasks, with the rational driving behaviour characteristic of attempting to minimise expected delays when travelling.

The value of time discussed within the experiment is related to delay time and not the value of travel time. The free flow travel times were equal for both routes and participants were faced with the decision of selecting a route based on the additional delay that could be experienced on either of the routes. It is acknowledged that value of time associated with the delay is considerably greater than that of conventional value of time estimates. The 2012 Austroads Guide to Project Evaluation: Part 4: Project Evaluation data indicates that the value for travel time as $13.17 per person hour (Austroads, 2012), consistent with a number of other studies (Litman, 2009, Carrion and Levinson, 2012). According to the(Bureau of Infrastructure Transport and Regional Economics (BITRE), 2009) which uses data obtained from the 2008 Austroads Guide to Project Evaluation, the value of delay time in dollars/hour/vehicle varies between $30 and $87 in an urban metropolitan setting for private vehicles which is comparable to the applied rate within the experiment. This concept reflected in the premium users' place on reliability (Brownstone and Small, 2005, Small, 1999, Small et al., 2005) where delays in addition to the budgeted travel time or free flow travel time are of greater value than the value associated with the travel time itself.

The payoff for each participant was calculated at the completion of all four choice tasks. The payoffs for the choice tasks not involving the presence of information were determined by the participant first rolling a die to determine which decision scenario that would be selected for payment, and then rolling the die a second time to determine the delay on the route selected by the participant. The choice tasks involving the provision of information required an additional consideration. If a participant chose to obtain information for a specific decision scenario, and if that scenario was selected for payment upon the first roll of the die by the participant, the exogenously assigned cost to obtain information is deducted from the income. The above mentioned participant then rolled the die separately for each of the routes to determine the exact delays. This process resolved the uncertainty of delay on the routes. Based on this the participant would then select the route, and the cost of delay on the chosen route was deducted from the income. Table 3.2 presents the structure of all four tasks. In addition to completing the above tasks, participants were required to fill out a demographic questionnaire. The questionnaire was completed following the choice tasks without information and prior to the choice tasks with information to provide participants a break and ensure the separation of the two sets of tasks. To control for order effects the sequence of the four choice tasks were varied across the sessions. The experiments with the following sequences of tasks were conducted across different sessions.

- Order 0: Low-Toll (Task 1), High-Toll (Task 2), Low-Information (Task 3), High-Information (Task 4)
- Order 1: Low-Information (Task 3), High-Information (Task 4), Low-Toll (Task 1), High-Toll (Task 2)
- Order 2: High-Toll (Task 2), Low-Toll (Task 1), High-information (Task 4), Low-Information (Task 3)
- Order 3: High-information (Task 4), Low-Information (Task 3), High-Toll (Task 2), Low-Toll (Task 1)

Table 3.2: Structure of Choice Tasks

Task	Description	Presence of Information
Choice Task 1 (Low-Toll)	Participants are required to choose between a Motorway Route (Choice A) with high variability of travel time (with the presence of a \$2 toll) against an Arterial Route (Choice B) with lower variability of travel time with no toll.	No
Choice Task 2 (High-Toll)	Participants are required to choose between a Motorway Route (Choice A) with high variability of travel time (with the presence of a \$4) toll against an Arterial Route (Choice B) with lower variability of travel time with no toll.	No
Choice Task 3 (Low-Information)	Participants are required to choose between a Freeway Route (Choice A) with high variability of travel time against an Arterial Route (Choice B) with lower variability of travel time. Neither of these routes contained tolls.	Yes (Cost = \$2)
Choice Task 4 (High-Information)	Participants are required to choose between a Freeway Route (Choice A) with high variability of travel time against an Arterial Route (Choice B) with lower variability of travel time. Neither of these routes contained tolls.	Yes (Cost =\$4)

3.3.1 Recruitment Process

Participants were recruited using the University of New South Wales Australian School of Business (ASB) Experimental Research Laboratory. Individuals could register to be part of human-subject experiments conducted at the University and invitation emails were sent to registered individuals to take part in the study. Admission to participate in the study was contingent on respondents being at least 17 years old and holding a valid driver's license to ensure that participants understood the meaning of route choice in a real driving scenario. The study was completed at the University of New South Wales within laboratory of the ASB Experimental Research group.

3.3.2 Sequence of Events

The study consisted of seven 2 hour sessions of experiments with a total of 156 participants completing all tasks of the experiment. The sessions were held on the following days:

- 7 November 2012, 16 participants (Order 0)
- 15 November 2012, 11 participants (Order 0)
- 16 November 2012, 20 participants (Order 0)
- 20 November 2012, 24 participants (Order 0)
- 26 November 2013, 33 participants (Order 2)
- 28 November 2013, 23 participants (Order 3)
- 14 March 2014, 29 participants (Order 1)

Upon arrival at the laboratory, the participants' driver's licenses were verified, after which they were assigned seating locations within the room. An informed consent form and the study documentation were presented to the participants as per University of New South Wales regulations. The consent form briefly explained the rights and responsibilities of the participants as well as assurance of the confidentiality of the information obtained within the study. The study documentation remained face down on the desk until the study began. The complete set of instructions for the experiment is provided in Appendix C.

3.4 Statistical Estimation of Risk Attitudes

The purpose of the study is to compare risk attitudes of road users with and without the presence of choice to purchase information. The methodology for the estimation process was guided by the assessment of subjective risks presented by (Dixit et al., 2014) as well as the study of risk attitudes across different regions (Dixit et al., 2013). Expected utility theory (EUT) is used as latent choice models to infer the risk attitudes of the participants. As described in the Literature Review (Section 3.2), a number of theoretical modelling frameworks were available for use. The choice of using the expected utility model rather than non-expected utility model was driven by the experimental design, in which we had a random payment protocol. Cox et al. (2014) suggests that due to the compound nature of MPL lottery outcomes using non-expected utility models, such as ones based on the principles of Prospect Theory or Regret Theory, is problematic and can result in incorrect inferences.

It is assumed that the utility of income is defined by the Constant relative risk aversion function presented in Equation (3.1), where, 'x', is the payoff obtained from the lottery and r is the level of the risk aversion. This utility function assumes that users have a constant attitude towards risks expressed as a proportion of the level of income they receive (Friedman and Savage, 1948). The CRRA has been commonly used throughout experimental literature and has been effective in measuring of risk attitudes within the context of the EUT framework throughout a variety of fields including economics, psychology, health as well as transportation (Rasouli and Timmermans, 2014, Abellán-Perpiñán et al., 2006, Andersen et al., 2008, Holt and Laury, 2002). To ensure robust estimation, analysis was also conducted with the Constant Absolute Risk Aversion (CARA) utility function which obtained similar findings.

$$U(x) = \frac{x^{1-r}}{1-r} \tag{3.1}$$

Under CRRA utility, risk neutral behaviour corresponds to '$r = 0$', risk loving behaviour when '$r < 0'$ and risk averse behaviour when '$r > 0$'. The risk aversion parameter, 'r', was estimated using maximum likelihood estimators and a latent EUT structural model of choice. The model uses the selections of the participants, either the binary choice in the without information case or ternary choice in the with information case, as the observed data within the latent class model. In order to measure the inferred risk aversion parameter, a latent index was formulated based on the multinomial logit specification accounting for the potential in any behavioural errors.

In order to explain the concepts of EUT applied for the estimation of the risk attitudes, consider the case with 'k' possible outcomes and probabilities, 'p_k'. As explained in the experimental design, these probability values are communicated to the participants in the task instructions. Therefore, the expected utility for a route can be described using equation (3.2):

$$EU_{i,Route} = \sum_{k=1}^{K} (p_k \times U_k) \tag{3.2}$$

In the binary route choice case within the experiment, where participants could either choose route A or route B, each route had two different outcomes with complementary probabilities of 'p' and '$(1-p)$'. The users were given a fixed *Income (I)* of \$10, while the *Toll (T)* was either \$2 or \$4 (depending on the treatment). Therefore, the expected utility accounting for tolls and delay outcomes can then be expressed as follows:

$$EU_{i,RouteA} = p \times U(I - T - 5) + (1-p) \times U(I - T - 6)$$

$$EU_{i,RouteB} = p \times U(I - 0) + (1-p) \times U(I - 9.75)$$

Where;

I = Income received by each participant for each decision scenario

T = Toll implemented on the Motorway route

p = Probability of the 'good' scenario occurring for either route (5 minute delay or 0 minute delay)

In the case where purchasing information was in the choice set, a participant had three possible choices: Route A, Route B and purchase of information. If a participant chooses to purchase information, the delays on each route are revealed. To realise the consequences of the information alternative in the experiment, the participant was asked to roll the dice once for each of the routes to determine the travel costs. Following this the participant chose the alternative with the lowest travel cost, from which the cost of information 'C' is subtracted. For an example, consider that a participant selects the information choice for decision scenario 6. Firstly, the cost of information would be deducted from the income; say in this case it is the low cost of information so the participant has a remaining income of \$8 (\$10 - \$2). The participant then rolls the die to determine the delay on Route A and the die lands on 2 which results in a delay of 5 minutes. Then, the participant rolls the die again to determine the delay on Route B, the die lands on 8 which results in a delay of 9.75 minutes. Knowing perfectly the delay outcomes for both routes, to maximise the payoff a participant would select Route A (5 minutes delay < 9.75 minutes delay) and obtain a payoff of \$3. However, if the roll of the die to determine the delay for Route B was 5, the delay would be 0 minutes and the participant would have selected Route B to obtain a payoff of \$8.

Accordingly, the expectation of the information scenario must consider the likelihood of each combination of delay outcomes observed for both routes as presented in Figure 3.3. Therefore, the expected utility for the information alternative can be evaluated as a compound lottery of route A and B. This is evaluated by considering the probability of each combination of consequences occurring for both the routes. There are four possible pairs which are shown in the middle column of Figure 3.3. Since individuals minimise their travel costs and maximise their monetary payoffs (the abstraction is shown in the monetary domain), the four alternatives can be merged under the specific condition that $X_b \geq X_a \geq Y_a \geq Y_b$, (which is the case in our lottery choices, where $X_b = \$10, X_a = \$5, Y_a = \$4, Y_b = \$0.25$) to generate the final column in the figure.

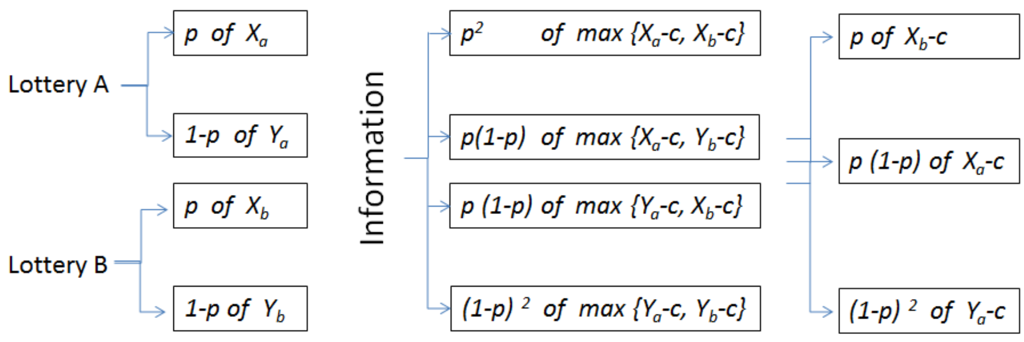


Figure 3.3: Abstraction of the information lottery

Based on Figure 3.3, the expected utilities when information is present in the choice set can be expressed as follows:

$$EU_{i,RouteA} = p \times U(I-5) + (1-p) \times U(I-\ 6)$$

$$EU_{i,RouteB} = p \times U(I-0) + (1-p) \times U(I-9.75)$$

$$EU_{i,Information} = p \times U(I-0-C) + p(1-p) \times U(I-5-C)$$
$$+(1-p)^2 \times U(I-6-C)$$

Where;

I = Income received by each participant for each decision scenario

C = Cost to receive information regarding the delay on each route

p = Probability of the 'good' scenario occurring for either route (5 minute delay or 0 minute delay)

Income, 'I', was fixed at \$10; the cost of information, 'c', is the exogenous cost to access information which was either \$2 or \$4 depending on the treatment. The expected utility, 'EU', for each lottery pair is calculated conditional on a participant's risk attitude 'r'. To estimate the risk attitude we define a latent index, 'ΔEU', as a multinomial logit specification, where individuals choose across the set of uncertain choices without information (Equation (3.3)) and with information in the choice set (Equation (3.4))

$$\nabla EU = \frac{eu_J}{eu_A + eu_B} \tag{3.3}$$

$$\nabla EU = \frac{eu_J}{eu_A + eu_B + eu_{Inf}} \tag{3.4}$$

Where we define;

$$eu_J = e^{[(EU_J/\gamma)/\mu]} \tag{3.5}$$

In these equations, 'J' represents the participants choice of either route A or route B in the without information scenario and route A, route B or information (Inf) in the with information scenario. This form of latent index allows for a link between the observed choices and the measure of risk attitude 'r'. A structural noise parameter, 'μ', is used to scale the latent index to account for behavioural errors (Hey and Orme, 1994). An important contribution to the characterisation of behavioural errors is the 'contextual error' specification proposed by (Wilcox, 2011). It is represented by, 'γ' which is a new, normalising term over the uncertain lotteries. The normalising term 'γ' is defined as the difference between the maximum utility over all prizes among the lotteries and the minimum utility over all prizes in these lotteries. The value of 'γ' varies, in principle, across the lottery choices: hence it is said to be 'contextual' (Dixit et al., 2013). For the Fechner specification, dividing by 'γ' ensures that the normalised EU remains in the unit interval.

Assuming that EUT and the CRRA utility function hold true, the likelihood of the observed responses depends on the estimates of 'r' given the above statistical specification and the observed choices within the experiment. The risk attitudes 'r' are estimated by maximising the log-likelihood expressed as Equation (3.6) and (3.7), for the without information and with information scenarios respectively:

$$\ln \mathrm{L}(r,\mu,y,\boldsymbol{X}) = \sum_i \begin{bmatrix} (\ln(\nabla EU_A) \times \boldsymbol{I}(y_i = 0)) + \\ (\ln(\nabla EU_B) \times \boldsymbol{I}(y_i = 1)) \end{bmatrix} \tag{3.6}$$

$$\ln \mathrm{L}(r,\mu,y,\boldsymbol{X}) = \sum_i \begin{bmatrix} (\ln(\nabla EU_A) \times \boldsymbol{I}(y_i = 0)) + \\ (\ln(\nabla EU_B) \times \boldsymbol{I}(y_i = 1)) + \\ (\ln\left(\nabla EU_{information}\right) \times \boldsymbol{I}(y_i = 2)) \end{bmatrix} \tag{3.7}$$

Where '$\boldsymbol{I}(\cdot)$' is the indicator function, '$y_i = 0{,}1{,}2$' denotes that the participant chose route A, route B or information respectively in driving Task 'i', and '$\boldsymbol{X}$', is a vector of individual characteristics based on the demographic survey. To estimate the impact of information and order effects, the maximum likelihood analysis was generalised to allow the core parameter 'r' to be a linear function of information task and the experimental orders. We extend the model to be, $r = r_0 + \boldsymbol{R} \times \boldsymbol{X}$, where '$r_0$' is a fixed parameter and, '$\boldsymbol{R}$', is a vector of effects associated with the binary variable of information being represented by '$\boldsymbol{X}$'. Accordingly, when information is not present within the choice set, $r = r_0$, whilst the presence of information results in the inclusion of the effects parameter within the estimation.

3.5 Results

A total of 156 participants completed all four tasks of the experiment as well as the demographic survey. Table 3.3 presents a summary of the key participant characteristics observed throughout all the sessions. In general, there was almost equal representation of male and female participants with a slight male domination of 53.5% of the total sample. Approximately 56% of the participants had greater than two years of experience in driving a vehicle suggesting that there was a certain level of understanding in relation to route choice and driving. Given that the participants were recruited from a University staff and student pool, it is acknowledged that the average age of the participants is young at 23.2 years. However, it should be noted that 26% of the participant pool was above the age of 24 indicating that this study did not focus exclusively on undergraduate student behaviour and there was a degree of diversity.

Table 3.3: Summary of Participant characteristics

Characteristic	Values
Gender (Male/Female)	84/72
Driving Experience (>2 years, < 2 years)	87/69
Average Age	23.2
Range of Ages	17 - 41

Each task provided 10 data points and there were 4 tasks in each session, therefore a total of 6240 data points were used in the estimation. The estimation and analysis was carried out using a statistical software package, STATA. The first step was to explore existence of order effects across the sessions. To study the impact of the order effects the EUT model included a dummy variable for each order and the information treatment, which is shown in Table 3.4. The estimation results are presented as *'order_n'* for the particular case of an order without the presence of information within the choice set, and *'info_ord_n'* for the case with the presence of information, where *'n'* is the specific order used for a session. The results indicate that information has an impact on the measured risk attitudes. The value of the risk aversion parameter '*r*' is consistently greater without the presence of information within the choice set across all orders considered. Without the presence of information, the value of '*r*' lies between 0.514 and 0.5866; however, the addition of information in the choice set reduced the '*r*' values to a range between 0.1449 and 0.2759. The results for the risk attitudes without information are consistent with earlier studies (Dixit et al., 2013, Andersen et al., 2010).

Table 3.4: Estimation Results of EUT for each Order

Parameter	Coefficient	Standard Error	Z value	P>|z|	95% Confidence Interval	
r						
order_0	0.561	0.0334	16.79	0	0.4955	0.6264
order_1	0.5866	0.0543	10.81	0	0.4803	0.693
order_2	0.514	0.0625	8.23	0	0.3916	0.6364
order_3	0.5377	0.0725	7.42	0	0.3956	0.6797
info_ord_0	0.2115	0.0324	6.52	0	0.1479	0.2751
info_ord_1	0.1449	0.0569	2.55	0.011	0.0334	0.2565
info_ord_2	0.2759	0.0431	6.41	0	0.1915	0.3603
info_ord_3	0.164	0.0744	2.2	0.028	0.0182	0.3099
LN(μ)						
order_0	-1.739	0.1036	-16.78	0	-1.942	-1.536
order_1	-1.617	0.1829	-8.84	0	-1.975	-1.259
order_2	-1.449	0.1593	-9.09	0	-1.761	-1.137
order_3	-2.015	0.1584	-12.72	0	-2.325	-1.704
info_ord_0	-2.348	0.0796	-29.51	0	-2.504	-2.192
info_ord_1	-2.154	0.1152	-18.7	0	-2.38	-1.928
info_ord_2	-2.34	0.1176	-19.89	0	-2.571	-2.11
info_ord_3	-2.085	0.1434	-14.54	0	-2.366	-1.804

The presence of order effects were investigated by evaluating statistical differences between the coefficients using a conventional 'Z-test' (Paternoster et al., 1998).

$$Z = \frac{b_1 - b_2}{\sqrt{SE_1^2 + SE_2^2}} \tag{3.8}$$

Equation (3.8) calculates the Z-score by considering the difference of the estimated results ('b_1' and 'b_2') and their respective standard errors ('SE_1' and 'SE_2'). The test was conducted considering 95% confidence level. If the Z values exceed 1.96

(or are less than -1.96) there is a significant difference between the estimated values.

The results of the Z-tests, shown in Table 3.5, indicate that there are no order effects present within the experiment, at a 95% significance. All Z-score values comparing combinations of *'order_n'* as well as *'info_ord_n'* amongst themselves respectively (highlighted in blue), are less than 1.96 (or greater than -1.96) suggesting that there are no statistically significant differences between the orders considered. Furthermore the results indicate that there is a statistical difference in the measured risk attitude when comparing without and with the presence of information in the choice set as highlighted by the red numbers which are all greater than 1.96 (or less than -1.96). Based on these results, the participants show lower risk aversion when provided with the choice of information.

Table 3.5: Z-Test Results

Z-test	order_0	order_1	order_2	order_3	info_ord_0	info_ord_1	info_ord_2	info_ord_3
order_0	0	-0.403	0.663	0.292	**7.504**	6.305	5.231	4.866
order_1	0.403	0	0.878	0.541	5.933	**5.617**	4.485	4.588
order_2	-0.663	-0.878	0	-0.247	4.298	4.369	**3.139**	3.603
order_3	-0.292	-0.541	0.247	0	4.108	4.262	3.105	**3.597**
info_ord_0	**-7.504**	-5.933	-4.298	-4.108	0	1.017	-1.194	0.585
info_ord_1	-6.305	**-5.617**	-4.369	-4.262	-1.017	0	-1.836	-0.204
info_ord_2	-5.231	-4.485	**-3.139**	-3.105	1.194	1.836	0	1.301
info_ord_3	-4.866	-4.588	-3.603	**-3.597**	-0.585	0.204	-1.301	0

As order effects are not statistically significant the model is re-estimated with only the information treatment effect to consider the average risk attitudes across the sample of observations. The results of this estimation are presented in Table 3.6. The *'r'* value without the presence of information in the choice set is equal to

0.5544. When incorporating information into the choice set the value of 'r' reduces to 0.2060 again showing a reduction in risk aversion with the presence of information. These trends are particularly evident in Figure 3.4 that graphs the utility functions for each scenario. This finding is fundamentally significant as it suggests that adding the 'purchase of information' within the choice set lowers the risk aversion.

Table 3.6: Estimation of EUT model considering average risk attitudes

Parameter	Coefficient	Standard Error	Z value	P>|z|	95% Confidence Interval	
R						
info	-0.3484	0.0337	-10.35	0	-0.414	-0.282
constant	0.5544	0.0246	22.53	0	0.5062	0.6027
LN(μ)						
info	-0.58	0.0898	-6.45	0	-0.756	-0.404
constant	-1.684	0.0723	-23.3	0	-1.826	-1.543

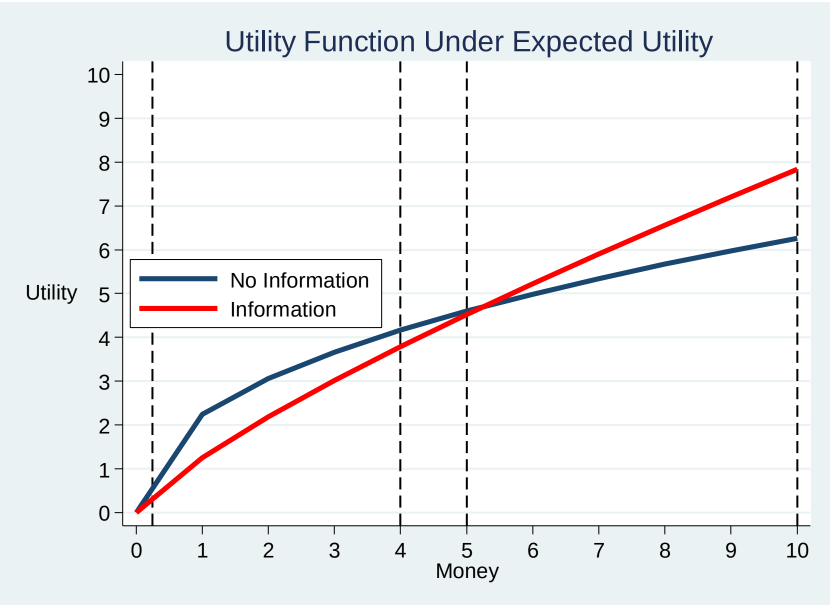


Figure 3.4: Comparison of utility functions with and without the presence of information

In addition, it is observed that the Fechner error in situations where purchase of information enters the choice set is lower than when it does not exist in the choice set (which is statistically significant at a 95% significance level). This implies that there are relatively smaller variances due to behavioural errors when information is present in the choice set. Based on these results, it is evident that the provision of information which resolves the uncertainty of a travel outcome reduces the risk aversion and behavioural error when making a travel decision.

3.5.1 Value of Information

Risk attitudes play an important role in the value people associate to information, in other words, determining how much people would pay for information to resolve the risk associated in travelling on either route. To better understand the impact of differences in risk attitudes when information is in the choice set, we calculate the value of information 'v' for each of the 10 route choice lotteries. The value of information 'v', is determined by the value that an individual would be willing to pay such that the expected utility of information is equal to the maximum expected utility of the competing routes (Equations (3.9)and (3.10)).

$$\max(EU_{i,RouteA}, EU_{i,RouteB}) = EU_{i,Information} \tag{3.9}$$

$$\begin{aligned} \max\left\{ \begin{array}{l} \left(p_i \dfrac{(10-5)^{1-r}}{(1-r)} + (1-p_i)\dfrac{(10-6)^{1-r}}{(1-r)}\right), \\ \left(p_i \dfrac{(10-0)^{1-r}}{(1-r)} + (1-p_i)\dfrac{(10-9.75)^{1-r}}{(1-r)}\right) \end{array} \right\} \\ = p_i\left[\frac{(10-v-0)^{1-r}}{(1-r)}\right] + p_i(1-p_i)\left[\frac{(10-v-5)^{1-r}}{(1-r)}\right] \\ + (1-p_i)^2\left[\frac{(10-v-6)^{1-r}}{(1-r)}\right] \end{aligned} \tag{3.10}$$

It must be noted that the value of 'p_i' and '$(1-p_i)$' were provided to the subjects in the experiment, while the risk attitudes 'r' was estimated from their choice data. Therefore the value of information can be calculated by solving Equation (3.9) for each lottery pair 'i' while considering the risk attitudes. The value of information is solved for by using Equation (3.10).

In order to clarify the terms of Equation (3.10), it is important to reiterate that the participants received an income of $10 for each decision scenario considered. Route A had two delay scenarios which resulted in a loss of either $5 or $6 while Route B had two delay scenarios which resulted in a loss of either $0 or $9.75. As mentioned in Section 3.3, the inclusion of information results in a reduction of income.

Figure 3.5 compares the value of information between the two information regimes. The greatest level of uncertainty regarding the outcome of each pair of lotteries occurs between decision scenario 4 and decision scenario 6 where there approximately an equal likelihood of both the favourable and unfavourable delay outcomes. Thus, participants would value information far more in these scenarios relative to the initial and latter scenarios where either an unfavourable or favourable outcome is known with a 70% or greater probability. This explains why the value of information increases and decreases across the decision scenarios.

The results between the information treatments are found to be remarkably different. It is clear that, if the observed difference in risk attitude is not explicitly incorporated, the value of information tends to be overestimated in less risky situations, i.e. decision scenario 6 onwards, where the probability of the favourable delay outcome of both routes is greater or equal to 60%. This means that when users are faced with a route that for a majority of time performs as expected or with minor delays, the post implementation value of an information system is less than pre implementation, if static risk attitudes are assumed during appraisal. It is clear that neglecting to incorporate this fundamental difference could result in inaccurate feasibility and cost benefit analysis of the implementation of information systems that would ultimately lead to misguided policy decisions. The implication could include the overpricing of information or inappropriately allocating funds for information systems by assuming high information costs.

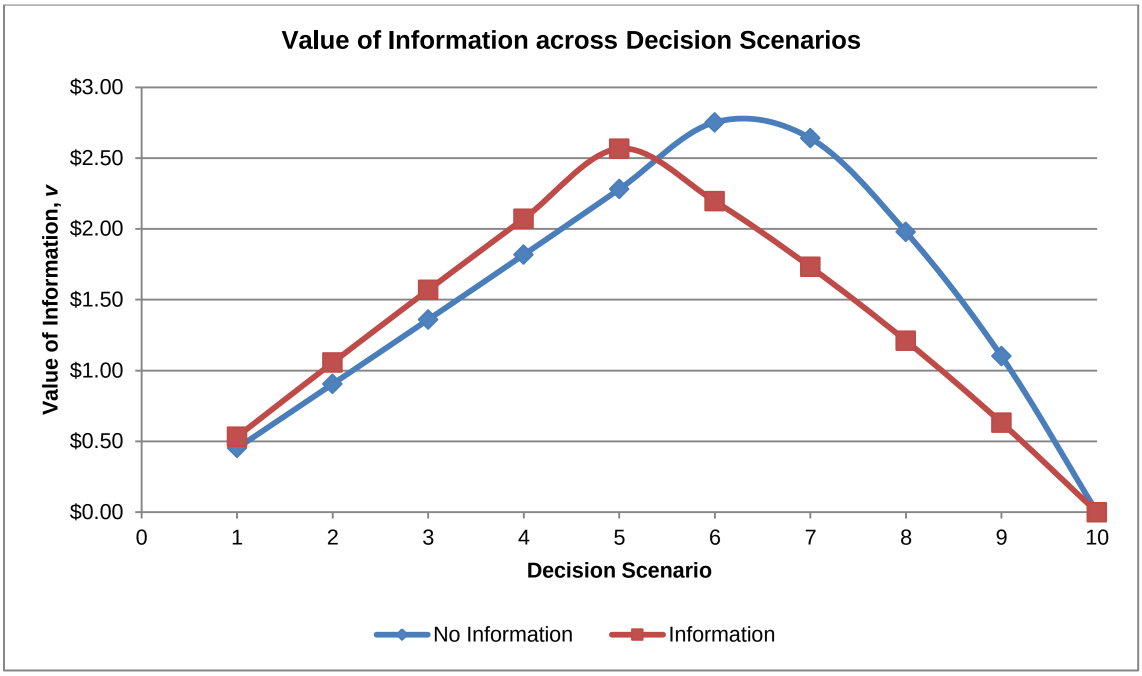


Figure 3.5: Calculated maximum willingness to pay for information

Overall the effect on risk attitudes due to the presence of information has been found to significantly impact the value of information. To be precise, people behave in a less risk averse manner in the presence of information. This is an interesting and a novel behavioural finding that would impact the evaluation of information provision schemes.

3.5.2 Value of Reliability

As discussed in the introduction and literature review, it is well known that risk attitudes influence the value of reliability. The more risk averse an individual is, the more an individual would be willing to pay for reliability. The results of the maximum likelihood estimation indicate that information reduces the degree of risk aversion. However, in both cases, with and without information, participants remained risk averse with values for the parameter 'r' being greater than zero.

As mentioned in the Literature Review, though several studies have used standard deviation of travel time to measure value of reliability (Bates et al., 2001, Lam and Small, 2001, Brownstone and Small, 2005), an alternative way to measure value of reliability is to evaluate the risk premium(Batley, 2007, Beaud et al., 2012). For the purpose of this analysis, a risk premium is defined as the difference between the expected value and certainty equivalent of the risk lottery (or the delay outcomes of each route). The certainty equivalent is the certain amount at which an individual is indifferent to the risky lottery. In the context of travel time, or in the case of this experiment the additional delay time, this would imply:

$$EU_{lottery} = EU_{certain}$$

$$\int_0^{\infty} U(t)f(t)\,dt = U(t_{CE})$$

$$t_{CE} = U^{-1}\left(\int_0^{\infty} U(t)f(t)\,dt\right)$$

$$VOR = Risk\ Premium = EV - t_{CE} = \int_0^{\infty} tf(t)\,dt - t_{CE}$$

In the case of this particular experiment with discrete states transforms the above calculation of the risk premium for a Route 'J' which can be expressed as follows:

$$EV_{routeJ} = \sum_i p_i\, x_i\,; \qquad EU_{routeJ} = \sum_i p_i\, U(x_i); \qquad U(x) = \frac{(x)^{1-r}}{(1-r)} \tag{3.11}$$

$$EU_{routeJ} = U(x_{certain}) \quad \rightarrow \quad x_{certain} = \left((1-r)\sum_i p_i\, U(x_i)\right)^{\frac{1}{1-r}} \tag{3.12}$$

$$VOR = EV_{routeJ} - x_{certain} = \sum_i p_i\, x_i - \left((1-r)\sum_i p_i\, U(x_i)\right)^{\frac{1}{1-r}} \tag{3.13}$$

The expected value and expected utility for each route and each decision scenario can be determined using Equation (3.11), where 'x' represents the payoff an individual would obtain. Equation (3.12) describes the condition for certainty equivalence, and is used to calculate the certainty equivalent ($x_{certain}$). Finally, Equation (3.13) presents the calculation of the Value of Reliability (VOR) which is the risk premium and is defined as the difference between the expected value of taking the uncertain route and the certainty equivalent.

The value of reliability reduces as the level of risk aversion reduces in the presence of information (see Figure 3.6 and Figure 3.7). This result is consistent with the theory that the more risk averse an individual is, the more they are willing to pay for reliability. The variation of the value of reliability described within the figures is consistent with the structure of the experiment, where the most uncertain scenarios being scenario 5 which coincide with the peaks of the curves. Furthermore, it is clear that the willingness to pay for reliability is considerably less for the relatively reliable motorway (freeway) route as compared with the arterial route. The maximum cost of reliability is less than \$0.016 for the motorway route for all decision scenarios while the arterial route has a cost of reliability approaching \$2.00 for decision scenario 5. This is also an intuitive result, as individuals would be more willing to pay for reliability on less reliable routes.

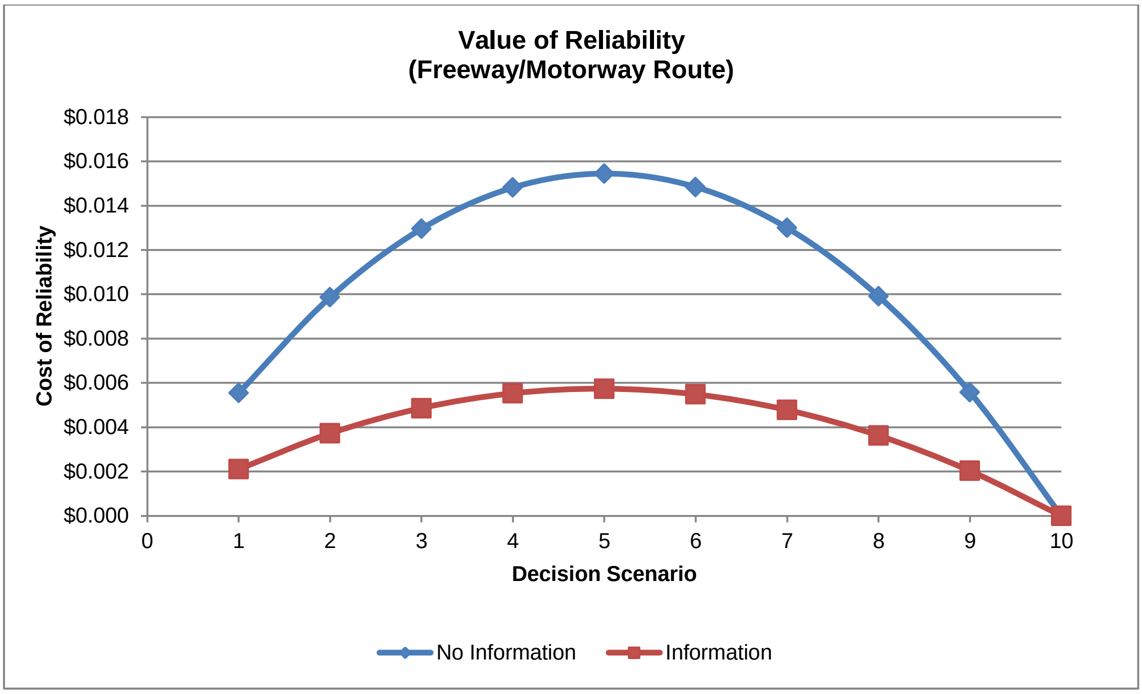


Figure 3.6: Value of reliability for the motorway route (Route A)

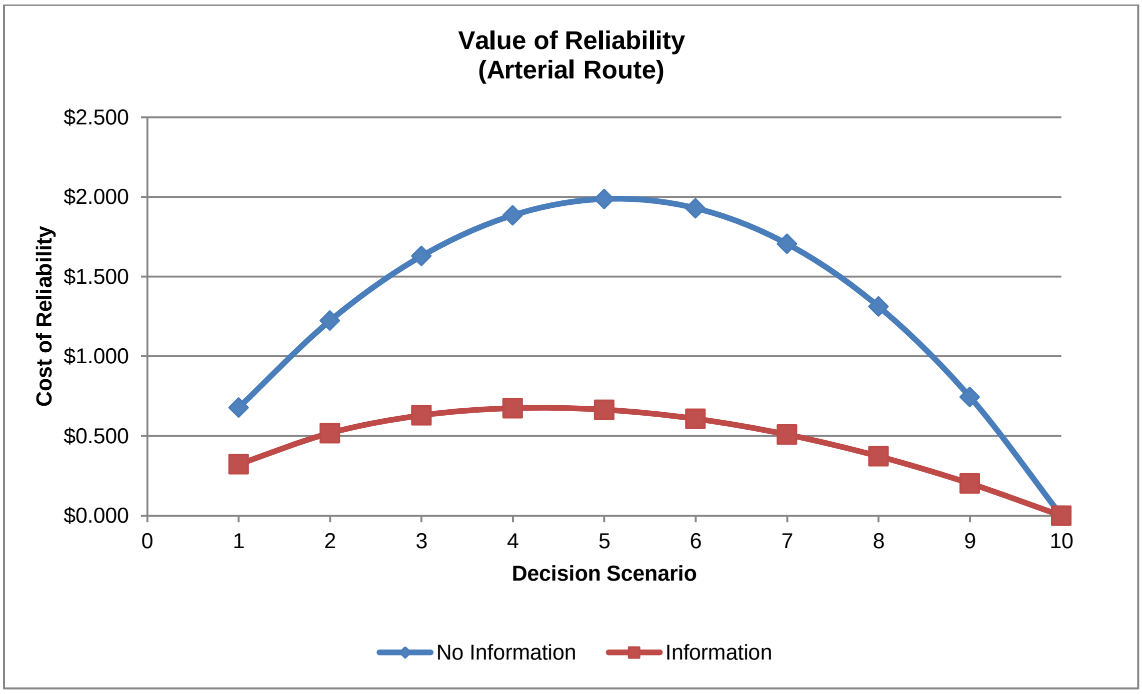


Figure 3.7: Value of reliability for the arterial route (Route B)

3.6 Discussion, Limitations and Future Extensions

The results of the experiment and the subsequent estimation of risk attitudes present the following key findings;

- Risk attitudes change when information is placed in the choice set of users. The degree of risk aversion reduces with the presence of information.
- The effect of the differences in risk attitudes without and with the presence of information has an impact on the valuation of information by users.
- In scenarios where the likelihood of unfavourable delay outcomes are low (probability of 40% or less, depicted by decision scenario 6 onwards) users overvalue information sources prior to implementation. In the opposite scenario where unfavourable delay outcomes are prevalent, users marginally undervalue the benefits of information.
- The value of reliability is greater in the scenario without the provision of information as information reduces or at best resolves uncertainty, such as in this experiment.

The contribution of this component of the research task stems from the controlled experimental approach and the discovery of the changes in risk attitudes between information regimes. The findings imply that the evaluation of online information infrastructure, such as the implementation of Variable Message Signs and other ATIS systems, needs to be considered carefully based on the likelihood of the delay outcomes observed in the field. Information is undervalued when there is a greater likelihood of incidents and disruptions creating relatively unfavourable delay outcomes. However, if these scenarios are not prevalent, users tend to overvalue information systems prior to implementation potentially resulting in a redundant system post implementation. Traffic engineers, transport planners and government authorities alike must be aware of and account for this phenomenon whilst appraising information infrastructure on road networks.

The authors acknowledge that there are limitations within this study. The fundamental abstraction from reality is that delay time and information regarding delay time was the only criteria used by participants in deciding on the route choice. Route choice decisions are in general multi-objective where travellers assess travel time, reliability, tolls, road hierarchy and other factors that could affect their decisions. However, from an experimental perspective, it was necessary to simplify this complex behaviour to isolate the impact of online information on risk attitudes. The other main limiting factor of the study is the use of a University based participant pool which can be argued provides a skewed behavioural experiment. The justification for the use of University pools is based on the experimental work which has been completed throughout literature. Previous studies have yielded incredible insight and a fuller understanding of user behaviour in transport systems which have been applicable to the wider community. However, ideally this experiment should be replicated across a wider demography to confirm the differences in risk attitude.

Extensions of this study are numerous. A non-linear mixed logit model could be formulated and applied to the data-set to understand the impacts of information heterogeneity. The experiment provided the user perfect information allowing for a resolution of the uncertainty in delays on both routes. The availability of perfect information within a transport system is limited and a similar experiment with imperfect information should be conducted to observe if a similar variation in risk attitude is observed. Furthermore, online information is one source of information that affects route choice. Users are exposed to experiential and prescriptive sources of information in addition to the descriptive form discussed in this study(Ben-Elia and Avineri, 2015). Incorporation of other forms of information into a similar experimental framework can be used to identify which form of information affects risk attitudes the most. For an example a repeated game involving two treatments, with and without information could be formulated to assess the experiential information acquisition of users in combination with exogenous information provision. Finally, this experiment focussed specifically on delays in travel and the impact online information had on resolving uncertainty surrounding delay in travel. An interesting adaptation of the experiment could be to focus on pre-trip information considering total travel times and departure time decisions for competing routes and assessing the impact of pre-trip information on the risk attitudes. This type of study would follow the work of De Palma et al. (2012) but from an experimental economics perspective.

3.7 Concluding Remarks and Impact

Information systems, within road transport networks, are used to guide the behaviour of road users in their decision making, in particular their route choice. This study was motivated by the question of whether risk attitudes are different when information exists in a choice set.

This question was investigated by conducting a controlled laboratory experiment based on the methods of experimental economics. A series of four Multiple Price List (MPL) lottery tasks were formulated and presented to the participants in order to measure their risk attitudes with and without the presence of information in their choice set. A model derived from Expected Utility Theory (EUT) was then used to quantitatively infer risk attitudes of the participants.

To the best of the author's knowledge, this study is the first to explore the impact of information on risk attitudes. The results of the experiment indicate that when information is present in a choice set, there is a reduction in risk aversion. This implies that the value of information and reliability could be overestimated if the risk attitudes are not properly calibrated within a transport model. In addition, the presence of perfect information, which can resolve the uncertainty of a travel outcome, is found to reduce the Fechner error, or behavioural error when making route choice travel decisions. These findings are fundamental, and have not been predicted by theory to date and therefore it is critical to explicitly recognise this within behavioural models that are essential to the effectiveness of transport models.

This chapter demonstrates that the reduction in risk attitudes translates to a reduction in people's valuation of information. Neglecting to recognise this can lead to an overestimated value of information and reliability in the presence of information. Accordingly, valuations of civil infrastructure projects involving the provision of online information must take into consideration the changes in risk attitude in order to correctly assess the costs and benefits of the project. It is evident that this study has far reaching implications in the application of information systems for traffic management and planning.

CHAPTER 4. STATIC MODEL FORMULATION AND APPLICATION: THE DISRUPTED EQUILIBRIUM ASSIGNMENT WITH RECOURSE (DEAR) MODEL

4.1 Introduction

Transport system planning and maintenance shape the social, economic and environmental welfare of the community. Government authorities and practitioners use a series of decision tools, which include transport planning models, to determine future policy as well as infrastructure. Therefore, it is important to develop models that best account for the multitude of factors which affect the transport system whilst still providing efficient and robust information to the practitioner to enhance decision making. As mentioned in Chapter 1, traditional transport planning models effectively portray travel behaviour under normal day-to-day conditions. However, in the event of disruptions, user behaviour changes and therefore traditional models have limited capabilities to accurately evaluate network performance. Thus, the contribution of Chapter 4 and Chapter 5 aims to further develop the current models to encapsulate the impact of disruptions on a road network.

The impact of disruptions on user behaviour is evident from the findings of Chapter 2 and Chapter 3 which suggest adaptive routing and a change in risk attitudes of users when information is present in the choice set. Using knowledge learned from; day-to-day experiences, the provision of information from ATIS, and through radio traffic reports, users can recognize the existence and severity of a disruption on a link and react by changing to a more suitable route that is less disrupted. Traditional modelling methods that do not account for adaptive routing will not be able to represent this scenario. Furthermore, it is hypothesised that the presence of a disruption affects the perception of a traveller in how they assess the cost of using one route over another.

This component of the research proposes a static traffic assignment methodology, disrupted equilibrium assignment with recourse (DEAR) model. The DEAR model interacts two separate modelling approaches, the Disrupted Network Assignment Model (DNAM), (Dixit et al., 2012) and the User Equilibrium with Recourse (UER) traffic assignment method (Unnikrishnan and Waller, 2009). DNAM provides a framework for predicting driver reactions to network disruptions by considering travel time perception transformation relative to the severity of the incident. However, DNAM does not consider the uncertainty of the network resulting from a disruption and how users adapt to knowledge of the disruption. Therefore, this research extends DNAM by incorporating an adapted UER model that accounts for re-evaluation of route choice by users in disrupted conditions.

Chapter 3 develops the DEAR framework and applies the model to a demonstration 4-node, 5-link network as well as the real world Sioux Falls road network which has been commonly used throughout transportation research. The framework was tested on the Sioux Falls network considering variations in the severity of the incident, level of overall origin-destination demand and the likelihood of disrupted conditions. The principal aim of the modelling is to understand the network wide performance implications when users not only transform costs in light of a disruption but also learn about the information of a disruption en route to their destination.

The remainder of the Chapter is structured as follows:

- Section 4.2 discusses previous literature associated with transport planning models and provides a background to the DNAM and UER modelling approaches.
- Section 4.3 details the modelling framework and associated assumptions
- Section 4.4 explains the application procedure of the model on the demonstration network and the Sioux Falls network.
- Section 4.5 presents the results of application of the model highlighting the impacts of each variable.

- Section 4.6 and Section 4.7 discuss the implications of the results and future extensions of the proposed DEAR model.

4.2 Background

Models in the traffic engineering and transport planning have been utilised since the 1950s to assist governing authorities in maintaining the current transport infrastructure system as well as guiding the development of future transport initiatives. This section of the chapter provides context for the static DEAR planning model. The review discusses the traditional approaches to static traffic modelling, previous efforts incorporating the behavioural impacts of disruptions on perceptions in travel time, and the development of adaptive static models which account for information acquisition. The DEAR framework has been constructed using an amalgamation of two previously developed approaches, the Disrupted Network Assignment Model (DNAM) (Alsup, 2010, Dixit et al., 2012) and the User Equilibrium with Recourse (UER) traffic assignment technique (Unnikrishnan and Waller, 2009) which are also presented in detail.

4.2.1 Transport Planning Models

The traditional '4-step transport planning model', presented in Figure 4.1 provides the structure for a majority of traffic models used to forecast future demand and performance of the transport systems. Initially the topology of the region is depicted using nodes, links and zones to define sources of traffic generation and attraction as well as the connectivity between these zones. Data regarding the characteristics of the region being modelled, such as population, zoning, road infrastructure, public transport infrastructure, for current and future years, are used as input for the process. The trip generation step determines the total number of trips generated from and attracted to each zone. Trip distribution allocates the generated trips to origin-destination pairs. Mode split then defines the number of trips being undertaken by each mode of transport. The fourth and final step is the assignment of these trips across the transport network, with separate problems for road traffic and public transit. The order and structure of the four step model has been debated and it is important to note that each of the steps can affect the other steps in an iterative manner (de Dios Ortúzar and Willumsen, 2011). Consider an example where the solution to the traffic assignment problem indicates a very high cost for a group of users, these modelled costs could be inputs for the trip generation or trip distribution models to adjust the initial estimates. Traffic assignment models provide estimations of route utilisation, link flows and expected travel costs which are used in developing performance metrics to evaluate the system.

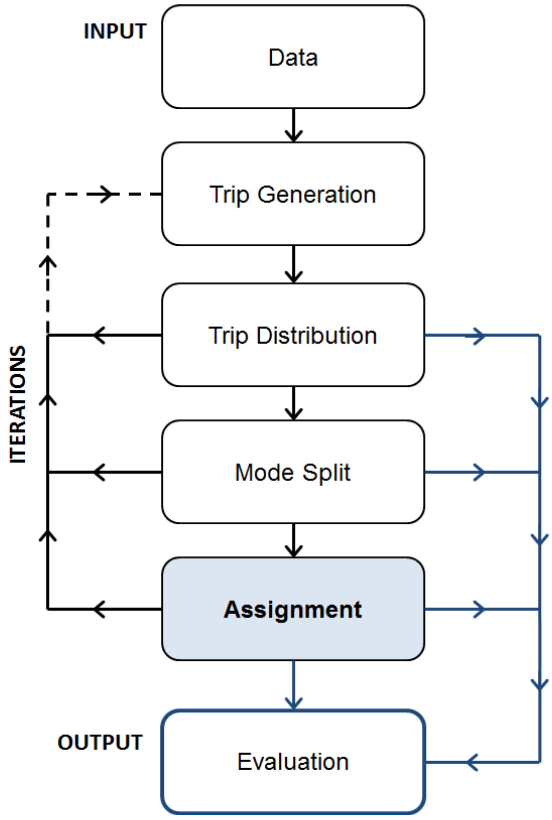


Figure 4.1: Four step transport planning process (de Dios Ortúzar and Willumsen, 2011)

Chapter 4 and Chapter 5 develop traffic assignment models that accounts for the presence of disruptions on a road network. In general, traffic assignment models are based on the economic equilibrium principles of balancing demand and supply. In the context of road transport, travellers serve as the demand whilst the supply is the available road infrastructure within the network. Equilibrium conditions arise when the supply of the network meets the demand to achieve a specific objective. This theory has also been applied within the modelling frameworks presented in Chapters 4 and 5 and thus the fundamental equilibrium conditions applied within transport planning are discussed in detail within this section.

There have been a number of approaches to determine equilibrium situations in static networks, the most common being the User Equilibrium (UE) and System Optimal (SO) scenarios. Wardrop (1952) presented the first and second principles of traffic equilibrium which provided the basis for UE and SO and these are as follows;

1. *'Journey times in all routes used are equal and less than those which would be experienced by a single vehicle on any unused route'*
2. *'Under social equilibrium conditions traffic should be arranged in congested networks in such a way that the average (or total) travel cost is minimised'*

These principles are based on the concept of deterministic utility maximisation where it is assumed users have perfect knowledge about travel costs and network attributes (Wardrop, 1952). UE or Deterministic User Equilibrium (DUE) has been used as the prevalent optimisation criteria for most traffic assignment models as it accurately captures driving behaviour. UE is 'selfish' as it assumes users minimise their own travel time (maximise their utility) without regard for other travellers. Beckmann et al. (1956) developed a nonlinear mathematical representation for UE which was later refined by (Sheffi, 1985) and described in equations (4.1) to (4.4). Equation (4.1) describes the objective of the formulation which has no physical meaning; the link between Wardrop's first principle arises from the optimality conditions. These conditions are not detailed here for brevity but presented in (Sheffi, 1985) and prove that users travel on the least cost path or 'shortest path' with no option to unilaterally change paths.

$$minimise\ f(x) = \sum_{\forall a \in A} \int_0^{x_a} c_a(\omega)\, d\omega \tag{4.1}$$

Subject to:

$$\sum_k h_k^{r,s} = q_{rs} \qquad \forall\, r, s \in N \tag{4.2}$$

$$h_k^{r,s} \geq 0 \qquad \forall\, k \in K\,; \forall r, s \in N \tag{4.3}$$

$$x_a = \sum_r \sum_s \sum_k h_k^{r,s}\, \delta_{a,k}^{r,s} \qquad \forall\, a \in A \tag{4.4}$$

This formulation considers a network comprising of 'N' nodes and 'A' arcs. In the equations, 'c_a' is the cost or travel time of a single link 'a' within the set 'A', while 'x_a' is the flow or volume of vehicles travelling on link 'a'. The total flow from origin 'r' to destination 's' is given as '$q_{r,s}$' while '$h_k^{r,s}$' is the flow on path 'k' from origin 'r' to destination 's'. Additionally, '$\delta_{a,k}^{r,s}$' is a binary variable equal to 1, if path 'k' from origin 'r' to destination 's' uses link 'a' and 0 otherwise (Sheffi, 1985). Constraint (4.2) describes the conservation of demand between each origin and destination pair. Non-negativity is maintained through constraint (4.2) and the relationship between path flow and link flow is determined using constraint (4.3). The novelty and elegance of the UE formulation is that the gradient of the objective function is the shortest path problem allowing for gradient based optimisation methods to determine a user equilibrium solution.

The SO condition, which satisfies Wardrop's second principle, achieves a system wide objective of minimising the travel time of all users on the network as a collective (i.e. minimisation of the *Total System Travel Time*). The system optimal formulation is presented from Equation (4.5) to (4.8) (Sheffi, 1985). The objective function is the only change in the formulation to reflect the objective of minimising the travel time of the system.

$$minimise\, f(x) = \sum_{\forall a \in A} x_a c_a(x_a) \qquad (4.5)$$

Subject to:

$$\sum_k h_k^{r,s} = q_{rs} \qquad \forall\, r, s \in N \qquad (4.6)$$

$$h_k^{r,s} \geq 0 \qquad \forall\, k \in K\,; \forall r, s \in N \qquad (4.7)$$

$$x_a = \sum_r \sum_s \sum_k h_k^{r,s}\, \delta_{a,k}^{r,s} \qquad \forall\, a \in A \qquad (4.8)$$

The SO representation focusses on the concept of marginal cost, defined as the cost to the system by the inclusion of an additional path or link of the system. SO assigns demand to shortest marginal cost path where no user can unilaterally change paths to achieve a lower marginal cost of travel time. Thus, users may benefit at an individual level by changing paths but this does not achieve system optimality. SO solutions provide the best possible performance scenario for a network; it provides a benchmark for the maintenance of road networks where performance measures can be derived from the gap between the current performance and the modelled SO solution. Furthermore, the SO assignment can be used to develop congestion pricing and tolling schemes that shift users from a UE solution to an SO solution (Shen and Zhang, 2009, Duell et al., 2014, Boyles et al., 2010, Gardner et al., 2008).

The traditional approaches to equilibrium modelling assume that the network experiences deterministic demands, users are rational and users have perfect knowledge of network conditions. Several extensions of the traditional UE equilibrium approach have been developed to relax these assumptions and achieve a more realistic model. Some static models which have a relationship with the study of disrupted networks are listed as follows;

- **Stochastic User Equilibrium (SUE)** (Daganzo and Sheffi, 1977, Mirchandani and Soroush, 1987) incorporates probabilistic travel times and heterogeneous perceptions, using either a probit or logit model, to capture travel time perception errors of users in the route choice decision process. This obviates the assumption that users have perfect knowledge of network conditions.

- **Probabilistic User Equilibrium (PUE)** (Lo et al., 2006, Lo and Tung, 2003) considers the equilibration of mean travels of used routes accounting for the fact that each route has a travel time distribution. This method accounts for demand uncertainties and extensions have also accounted for risk aversion and travel time budget constraints of users which can be used to capture disrupted network behaviour.
- **Strategic User Equilibrium (StrUE)** (Duell and Waller, 2015) relaxes the deterministic demand assumption by considering that users have perfect knowledge of the demand distribution. Equilibrium is based on minimisation of expected costs resulting in a fixed proportion assignment. This model accounts for demand uncertainties and is suitable in the long term assessment of large scale regional systems.
- **Late Arrival Penalised User Equilibrium (LAPUE)**(Watling, 2006) uses the concept of schedule delay to include a disutility term to the travel cost which penalised late arrival of users for fixed departure times. The added level of complexity accounts for reliability of the network.
- **User Equilibrium with Recourse (UER)** (Ukkusuri, 2005, Unnikrishnan and Waller, 2009) incorporates adaptive behaviour and information acquisition. Users select a 'routing policy' (a collection of traffic state dependent paths) instead of a path. Equilibrium arises when all users are assigned to the least cost routing policies for each origin-destination pair. This model served as the assignment module of the DEAR model and is described in detail within Section 4.2.5.

The DEAR approach acknowledges the suitability of the traditional UE framework to depict normal day-to-day conditions. However, in order to capture behaviour under disrupted conditions, DEAR considers two additional layers of modelling which account for the transformation travel costs associated with the disruption and the subsequent adaptive routing.

4.2.2 Disruptions and Travel time Perception

The road users' behavioural response to disruptions of a transport network is essential to understand when developing planning models. Stochastic User Equilibrium and extensions have attempted to incorporate perception errors and equilibrate network models based on perceived costs; however these approaches do not account for adaptive behaviour in light of a disruption. Chapter 2 empirically presents that users adapt in light of disruption and travel on alternative routes. A user would assess the cost of the alternatives accounting for the presence of the disruption when deciding on whether to stay on the current path or change. However, the presence of the disruption affects the way people perceive travel costs. Thus, a review of previous studies that focus on travel costs or travel time perception is essential in the development of a model which can account for disrupted conditions.

Limited research has been conducted on understanding the perception of travel time and how it is impacted by disruptions and incidents. There have been some studies conducted about perception and prediction of future activities considering different scenarios in the field of psychology. Griffiths and Tenenbaum (2006) presented an experimental method to test human cognitive perceptions about everyday events. People were asked to predict the duration or extent of everyday events such as human life spans, gross of movies and time taken to bake a cake, given a set of initial conditions. They found that the method was consistent in eliciting people's perception. This was also found by Lewandowski et al. (2009). In addition, they found that people's judgements were close to optimal Bayesian updating, and that *'accurate probabilistic models of the environment play a key role in the solution of inductive problems'* (Griffiths and Tenenbaum, 2006). The above mentioned studies present the case that people's perception of travel time are significantly different from the actual travel times, and these perceptions have a significant impact on choice which will most likely be further impacted by the presence of an incident. To date, Alsup (2010) provides the only thorough investigation into travel time perception and travel time distribution transformation in the context of disruptions. This study conducted a psychological experiment where participants were repeatedly asked what their expected travel time would be on a known route, given a certain disruption. The results indicate that the perceived travel time distributions reflect a transformed version of the actual measured travel time distribution. Alsup (2010) and the associated paper by Dixit et al. (2012) suggest that since routing decisions are based on the people's perception of travel costs, it is important to consider the transformation of travel costs rather than measured travel times when developing planning models.

In general, researches which have explored responses to incidents have studied them in the context of reliability. For instance, Small et al. (2005) found the median value of reliability to be US$5.40 per incident. Brownstone and Small (2005) found in their study of SR91 and I-15 in California, that the people perceive twice the travel time savings that they actually experience by using the express lane. Perceived travel time has significant impacts on travel choices. This can be interpreted in the results found by (Steimetz, 2008), who discovered that people valued congested travel time almost twice as much per minute as uncongested travel time. This was confirmed by (Ghosh, 2001) who found that the best specification to explain route and mode choice included perception error (defined as perceived minus actual time savings). Commuters who overestimated their perception of travel times were more likely to use the toll facility. When considering these studies along with those conducted with the presence of an incident, such as the I-35W bridge collapse, (Danczyk et al., 2010, Zhu et al., 2010) it is vital to understand perception of travel time, and how they are impacted by disruptions and incidents.

There have been several studies that have investigated the perception of travel time comparing different modes (Chapman et al., 2006, Taylor et al., 2009, van Exel and Rietveld, 2010) and the willingness to pay for it. Several of these studies show that perceived travel times significantly differ from actual travel times (Wu et al., 2009). Moreover, Montello (1997) found that the perceived travel time is affected by a number of environmental features including perception of distance, route, and travel effort. The presence of an incident will affect all these features and accordingly affect the perception of travel time. These studies highlight the importance of accounting for user perceptions within transport models. However, there is a gap in knowledge in the application of perceptions within transport models. The next section details one such model, the Disrupted Network Assignment Model (DNAM) (Alsup, 2010, Dixit et al., 2012) that does incorporate the transformation of perceptions in light of a disruption within an equilibrium framework.

4.2.3 Disrupted Network Assignment Model (DNAM)

DNAM is a novel approach in accounting for the impacts of traffic disruptions in transport models. While previous research by Sheu et al. (2001) used stochastic assignment methods to account for the uncertainty created by the presence of a disruption, the DNAM methodology is based on the results from psychological testing of road users to determine how the perceptions of travel time distributions change for different types of incidents.

The DNAM is separated into three phases as shown in Figure 4.2. The first phase determines equilibrium travel times or costs using deterministic user equilibrium (Sheffi, 1985). These flow patterns are then assumed to be the mean link travel times prior to the disruption. The associated standard deviation of each link is determined using traffic volume field data considering the empirical linear mean-standard deviation relationship of travel times (Sirivadidurage et al., 2009).

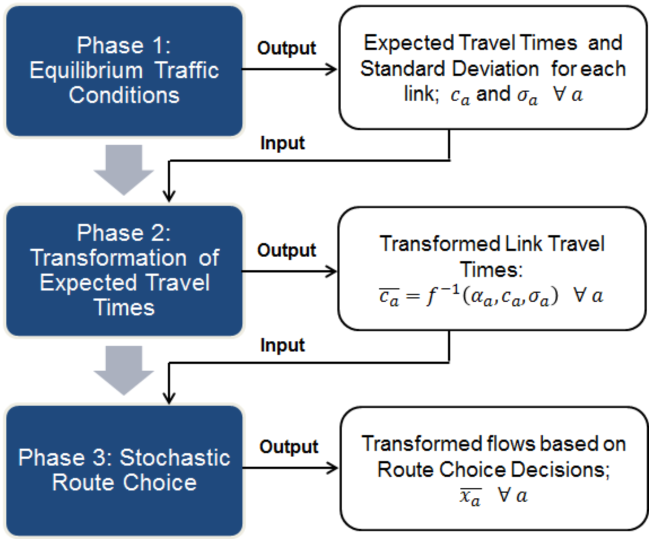


Figure 4.2: DNAM model framework (Alsup, 2010)

The second phase of DNAM transforms these travel costs to account for disruptions on a network using the results of the travel time perception experiments. The experiments found that the change in user perception of link travel costs can be best described using the following expression: $\overline{c_a} = f^{-1}(\alpha_a, c_a, \sigma_a)$ (Alsup, 2010, Dixit et al., 2012). In this formula, '$\overline{c_a}$' is the transformed link travel time, and '$f^{-1}(\alpha_a, c_a, \sigma_a)$' is the inverse cumulative function of the Normal distribution, where 'c_a' represents the equilibrium travel time of link 'a' and σ_a the standard deviation of the link travel time, both determined in phase 1. The term 'α_a' represents the severity of a network disruption, and corresponds to the 'Z' value (standard score) in the inverse cumulative calculation. In addition to transforming the travel times the experimental data was used to define 'α' values for given disrupted scenarios. Behaviour within the experiment indicated that, '$\alpha = 0.45$', represented sunny conditions, '$\alpha = 0.59$' represented rainy conditions (minor disruption), and '$\alpha = 0.91$' represent chemical spill conditions (extreme failure of the link). This satisfied the assumption of the inverse cumulative function of the Normal distribution; as 'α' values approach 1, the transformation of travel times are at it its highest values.

The third phase of DNAM model uses these transformed travel times to assign the traffic using logit model to determine the transformed flows. The application of the DNAM to a demonstration network provided the following findings;

- As the severity of the incident increases, drivers are more likely to choose paths with slightly higher mean travel times but with lower volatility of travel times.
- The predicted flow distributions are dependent on the congestion level, so the demand must be estimated before the predictions are performed to achieve the most accurate results.

Although this model highlighted the importance in accounting for travel time perceptions in uncertain conditions as well as the impact of transforming travel times in light of a disruption, it does not consider the acquisition of information by users when faced with a disruption. This study extends the DNAM framework by considering the en route acquisition of information resulting in adaptive behaviour.

4.2.4 Acquisition of Information in Transport Models: Adaptive Traffic Assignment

Disruptions on a road network result in stochasticity of the road capacities as well as a release of information. Thus, it was imperative to review previous works that have attempted to model driver response to online travel information in stochastic networks from a static network modelling perspective.

The routing behaviour of users in disrupted, stochastic conditions will be different to those in the classical deterministic setting. A number of studies present the idea that users adapt to network conditions to reduce travel costs, in light of information regarding the prevailing traffic conditions (Gao, 2012, Gao and Chabini, 2006, Ukkusuri, 2005, Unnikrishnan and Waller, 2009). This observation was also evident from the empirical analysis of traffic data on parallel competing routes in Sydney, completed in Chapter 2 of this thesis. In fact the paper by Gao (2012) provides an example that justifies the necessity to develop adaptive traffic assignment models to study disrupted conditions. The paper states, '*in a network with random incidents, if one simply sticks to his/her habitual route, s/he could be stuck in the incident link for a very long time. However, if adequate information is available about the incident and the traveller makes use of it and takes a detour, s/he can save travel time. The detour also helps reduce the prohibitively high travel time in an incident situation, and thus provides more reliable travel time*' (Gao, 2012). This type of example suggests that to effectively capture the impact of disruptions on a network, we must not only account for the increased costs associated with the incident but also model routing behaviour in an adaptive context.

Gao (2012) also provides an interesting classification of users' response to information as either reactive or strategic. A reactive user will not consider the availability of information on a route prior to making a travel decision and simply react when information is provided. A strategic user considers the availability of information across the network and makes a routing decision assessing the potential for network uncertainties to be resolved through the acquisition of information. As presented within Gao (2012) and also discovered during this research project, a number of experimental studies have suggested travellers behave strategically and seek information throughout the network (Razo and Gao, 2010, Lu et al., 2012, Lu et al., 2014, Rapoport et al., 2014). There is also an intuitive reasoning for this approach when accounting for disrupted conditions based on learning and experiential knowledge of a traveller. When considering daily commuting, a traveller will have a set of feasible routes to travel between origin and destination and over time develop an understanding of the impacts of various disruptions on the performance of these routes. Based on the available sources of the information and the prevailing traffic conditions, the user will develop a strategy for travel. It should be noted that this scenario is relevant to frequent repeated travel, such as daily commuting and a reactive reaction is more likely by infrequent travellers. From a modelling perspective, the strategic approach is relevant in capturing behaviour of peak traffic conditions which are the critical assessment periods for a majority of infrastructure appraisals.

Therefore, the modelling efforts completed in this research project, used in accounting for disrupted conditions, also consider a strategic approach.

The path strategy concept has commonly been defined in terms of 'hyperpaths' (Marcotte and Nguyen, 1998, Nguyen and Pallottino, 1988, Nguyen and Pallottino, 1989) within the transit assignment problem or 'routing policies' within traffic assignment (Gao, 2005, Gao, 2012, Gao and Chabini, 2006, Unnikrishnan and Waller, 2009). The definition of hyperpath stems from graph theory in mathematics and the definition is dependent on the specific implementation. Within the transportation domain, a hyperpath generally means the number of possible paths between an origin and destination (Unnikrishnan and Waller, 2009). Nguyen and Pallottino (1988) were the first to introduce the concept of hyperpaths to transportation research, where they applied the concept to transit networks. There is a key difference between the transit assignment studies and conventional traffic assignment as the information supplied to the user was related to the presence of transit services and not information about the prevailing traffic conditions. Gao (2012) defines a routing policy as a *'decision rule which specifies what node to take next out the current node based on the current time and real-time information, essentially a mapping from network states to decisions on next nodes… A path is purely topological and is a special case of a routing policy where any decision on the next node is not dependent on the current time or real-time information'*. Ukkusuri (2005) and Unnikrishnan and Waller (2009) echo the definition by (Gao, 2012) within their presentation of User Equilibrium with Recourse, describing a routing policy as a set of possible elementary paths between each origin and destination which is similar to the definition of hyperpath. Thus, based on the previous literature, hyperpath and routing policy can generally be used interchangeably. For consistency, the remainder of this thesis will refer to 'routing policy' when discussing hyperpaths and routing policies.

Static adaptive traffic assignment techniques have received little attention in the past primarily due to the fact that the nature of adaptation is dynamic and time dependent. The advantage of a static model is that it creates a tractable mathematical solution methodology relative to most dynamic formulations. Ukkusuri (2005) initially proposed the concept of User Equilibrium with Recourse (UER) that defines equilibrium based on the minimisation of the expected travel time of a routing policy for each user of the network. Unnikrishnan and Waller (2009) provide a convex mathematical program for static UER. Ukkusuri and Patil (2007) extend UER through the development of Stochastic User Equilibrium with Recourse (STOCH-UER) which accounts for the perception of traveller towards online information as well as adaptive routing in a static setting. The paper presents a methodology to obtain an efficient routing policy, considering the heterogeneity of user perception with a sequential Logit model which avoids enumeration of routing policies. It is important to emphasise that STOCH-UER considers adaptive behaviour and accounts for the heterogeneity of users perceptions associated with online information. In contrast, the DEAR approach considers the transformation of travel costs in the context of a disruption.

Other than the research by Ukkusuri and Patil (2007) there have been only a handful of works which have investigated perceptions of users within an equilibrium modelling framework whilst also accounting for informational impacts. Of note, Henn and Ottomanelli (2006) and Koutsopoulos et al. (1994) apply Possibility Theory and Fuzzy logic to capture user perception of available routes in combination with informational impacts within an equilibrium framework. As explained in Section 4.2.2 the DEAR model differs from these approaches by considering a transformation of link costs based on inverse normal cumulative distribution.

4.2.5 User equilibrium with recourse (UER)

The DEAR model introduced in this chapter seeks to account for the impact of information gained *en route* in disrupted networks by incorporating the UER assignment model. Traditional equilibrium models assume that users deterministically choose minimum cost paths, and then remain on that path regardless of the realised network conditions. In contrast, UER incorporates the acquisition of online information and the potential for the user to adapt their routing decision in response to the information gained. The reader is referred to Ukkusuri (2005) and Unnikrishnan and Waller (2009), where UER is introduced and discussed in detail, including in depth mathematical formulations and solution procedures. A summary of the key feature and the application within the DEAR model is presented in this section.

UER is a static equilibrium model that depicts user recourse based on the acquisition of one-step local information. Realism is achieved in UER by assuming that each link on a road network can experience multiple traffic conditions, referred to as 'states' within the framework. The occurrence of the link states are defined by a probability mass function. Users are aware of the overall functional form of the travel cost of each link but are uncertain about the capacity of the link prior to arrival at the node which contains the outgoing link. Thus, states are ultimately defined by feasible capacity scenarios of each link. At the origin, users select a path to travel to the destination. Upon arriving at a divergent node within a network, information regarding the capacity of all outgoing arcs is revealed and the user has the option to alter from the initial path selected at the origin.

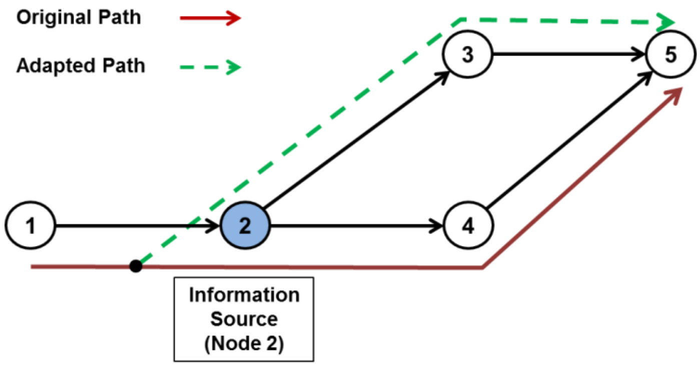


Figure 4.3: Example of routing behaviour depicted within the UER framework

Figure 4.3 presents an example of this routing behaviour. In the example network, Node *1* is the origin and Node *5* is the destination. Node *2* is a divergent node and users can either travel via Node *3* or Node *4* to reach Node *5*. Consider a user who was originally travelling on the path *1-2-4-5*, presented in red. Under the assumptions of UER, at Node *2*, users receive information about the state of Link *(2-3)* and Link *(2-4)*. At this point users have the option to adapt based on the acquired information and select the path represented as a green-dashed line. UER considers not the least cost path but instead a selection of possible paths known as routing policies (Wijayaratna et al., 2013). A network considering user recourse is in equilibrium when *'each user chooses a minimum expected cost routing policy and no user can unilaterally change their routing policies to improve the experienced expected cost'* (Unnikrishnan and Waller, 2009).

Unnikrishnan and Waller (2009) provide a convex mathematical program for static UER considering two scenarios. The first representation (defined as Model A in the paper) assumes that users arriving at an upstream node see the same arc states for all outgoing arcs, meaning that system realisations (combinations of link realisations) are static over the period of analysis. The second representation (defined as Model B) assumes that users see different link states; therefore system realisations occur during the period of analysis.

The notation and formulation presented in Unnikrishnan and Waller (2009) is replicated in this section to clarify the foundation for the assignment technique. A probabilistic network is given as '$G = (N, V, S, P)$', with a set of 'N' nodes and 'V' arcs or links. 'S_{ij}' is the set of possible states and 'P_{ijs}' is the associated probabilities for each link state '$s \in S_{ij}$' which is applied for each link, '$(i, j) \in V$'. 'R', denotes the set of all system states. A system state '$r \in R$' defines a combination of discrete states of all links on the network. The probability of a system state '$P(r)$' is the product of the probability of all link states which contribute to the system state, 'r'. Further, 'c_{ijs}' represents the cost of link, '$(i, j) \in V$', in link state '$s \in S_{ij}$' and let 'c_{ij}^{r}' refer to the cost of link '$(i, j) \in V$' in system state '$r \in R$'. Set 'L' represents the number of routing policies, where a single policy is defined as, '$l \in L$'. A routing policy can be represented by a sequence of conditional links, where the link is conditioned on either the link state or the system state. A conditional link conditioned on link states is represented as '$i - j - s$' which considers link state '$s \in S_{ij}$'. Similarly, conditioned on system states, '$i - j/r$' represents link '(i, j)' in system state '$r \in R$'. An incident variable 'γ' defines if a conditional link is part of a routing policy as shown in Equation (4.9);

$$\gamma_{i-j/r}^{l} = \begin{cases} 1 \text{ if the arc } (i,j) \text{in system state } r \text{ is in routing policy } l \\ 0 \text{ otherwise} \end{cases} \tag{4.9}$$

The development of the DEAR framework considered the Model A representation and is replicated from (Unnikrishnan and Waller, 2009) between Equation (4.10) and Equation (4.13). The paper reveals that if the cost functions have a symmetric Jacobian and are strictly increasing, the formulation will have a unique solution.

$$minimise\, Z[v, H] = \sum_{ijr} \int_{x=0}^{v_{i-j/r}} P(r) c_{i-j/r}(x) dx \tag{4.10}$$

Subject to:

$$v = \Delta H \tag{4.11}$$

$$t = BH \tag{4.12}$$

$$H \geq 0 \tag{4.13}$$

Where

$v_{i-j/r}$ = the flow on conditional link $i - j/r$

v = the conditional link flow matrix

Δ = incidence matrix, $|R||V| \times |L|$

H = column vector of flows on all routing policies between each origin and destination pair

B = trip-routing policy adjacency matrix

A solution methodology based on the Frank-Wolfe algorithm is provided and the existence and uniqueness of the equilibrium are discussed. This involves an optimal policy sub-problem, where if the link states are independent, a variant of the Online Shortest Path algorithm presented by Waller and Ziliaskopoulos (2002) can be used to determine the minimum expected cost routing policies. If the link states are correlated the R-SSPR algorithm proposed by (Polychronopolous and Tsitsiklis, 1996) is used. Unnikrishnan and Waller (2009) also presented that UER generally results in lower travel times than traditional equilibrium approaches emphasising the benefit of information provision, however, the paper also presents a paradox within the framework where information provision deteriorates network performance and is studied in great detail within Chapter 6 of this thesis. The UER approach provides the ideal assignment tool for the development of the DEAR model as it is able to reflect empirical findings of routing behaviour in disrupted conditions by considering adaptive behaviour.

4.3 Disrupted Equilibrium Assignment with Recourse Framework

This section describes the methodology of the DEAR framework diagrammatically presented in Figure 4.4.

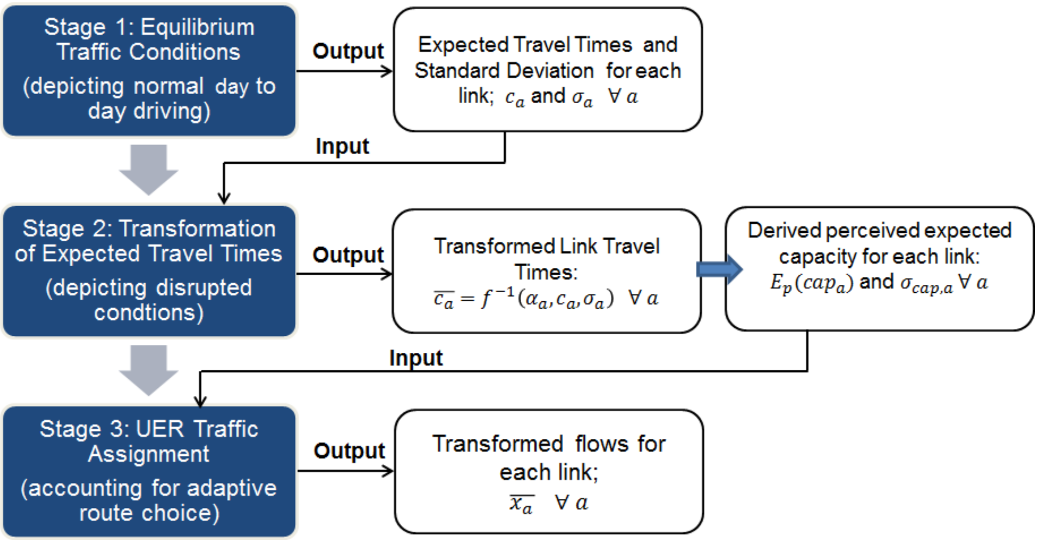


Figure 4.4: Summary of DEAR model framework

While the structure of the modelling procedure is similar to (Alsup, 2010) and Dixit et al. (2012), DEAR offers the potential to evaluate the impact of *en route* information by implementing UER to assign traffic, following the transformation of the travel times, to account for users adaptive route choice behaviour.

The DEAR approach is separated into three stages. The first stage accounts for the 'normal conditions' in a network, which may be interpreted as the foundation of a user's knowledge. The second stage transforms these conditions to account for the presence of a disruption based on the travel time perceptions of users. The final stage re-assigns traffic using UER to account for the information gained during travel, where the states of traffic are defined by the transformed conditions derived from the perceptions of the user. Therefore, the first two stages have been used in defining the knowledge that users have of the network and their perception of the disrupted conditions, while the final stage accounts for how users will react to knowledge and online information regarding the presence of a disruption.

4.3.1 Stage 1: Equilibrium Traffic Conditions

Stage 1 of the DEAR model is similar to that of the DNAM model where equilibrium traffic conditions are determined to depict normal driving conditions. Deterministic User Equilibrium (UE) assignment of flows is applied to calculate equilibrium conditions. This is a well-established assignment model, and the reader is referred to Sheffi (1985) for an extended description of the convex mathematical programming formulation which has also been briefly described in Section 4.2.1.

This work uses the traditional Franke Wolfe algorithm to compute the equilibrium flow assignment patterns. The iterative Frank Wolfe approach considers a convex combination algorithm that provides a linear approximation of an objective function (Frank and Wolfe, 1956). In order to apply the Frank Wolfe method, the objective function must be convex and differentiable which is the case for the UE formulation.

Correspondingly, users also have knowledge of the volatility of travel times in a network under normal conditions. The DEAR model assumes that link travel times are normally distributed (Herman and Lam, 1974) and accordingly the volatility on link 'a' can be described by the standard deviation of travel time, 'σ_a'. The UE model only outputs the expected link flows and corresponding travel times but not the standard deviation of travel times. Thus, in order to measure standard deviation of travel time for each link, a Monte Carlo sampling procedure was applied. The capacity of each link was assumed to be a random variable with a normal distribution to complete the sampling. The equilibrium flow values ($x_a \; \forall \; a \in \; A$) were used in the procedure to generate a value of capacity for each link based on the normal distribution and an input coefficient of variation. Travel times were then calculated for the sampled capacity value and the sampling was repeated 10,000 times to gain an estimate for the standard deviation of travel time for each link.

4.3.2 Stage 2: Travel Time Transformations

In order to account for the conditions in a disrupted network, the DEAR model incorporates a method of transforming link costs identical to the method presented in DNAM, as per Section4.2.3. DNAM was developed using the results of the psychological experiment which investigated the perception of travel time in the presence of disruptions. The findings suggest that the transformation of the link travel times is best represented by the inverse cumulative Normal distribution and the expression derived from that study is presented in Equation (4.14).

$$\bar{c_a} = f^{-1}(\alpha_a | c_a, \sigma_a) = \{x: F(\bar{c_a}|c_a, \sigma_a) = \alpha_a\} \qquad (4.14)$$

Where,

$$\alpha_a = F(\bar{c_a}|c_a, \sigma_a) = \frac{1}{\sigma\sqrt{2\pi}} \int_{-\infty}^{\bar{c_a}} e^{-\frac{(t-\mu)^2}{2\sigma^2}} dt$$

As shown in the DNAM model, '$\bar{c_a}$' is the transformed link travel time, and '$f^{-1}(\alpha_a, c_a, \sigma_a)$' is the inverse cumulative function of the Normal distribution, where 'c_a' and 'σ_a' represent the equilibrium travel time and standard deviation determined in Stage 1. The term 'α_a' (presented in Section 4.2.3) represents the severity of a network disruption where a value approach 1 indicates catastrophic failure of the link. The transforms applied represent quantified shifts from the mean link costs obtained from Stage 1 to reflect the presence of disrupted conditions in Stage 2 of the modelling. For the demonstration of the model, it is assumed that the standard deviation of the link travel times remains unchanged between normal and disrupted conditions; however it is acknowledged that the standard deviation of travel time will be affected and should be measured and validated against field data.

4.3.3 Stage 3: UER Assignment

The third stage of the DEAR model finds expected link flows considering the possibility of disrupted network conditions. In the DEAR interpretation, the presence of a disruption results in the release of information to the users of the network. Users may receive information through visual cues such as increased queue lengths or the increased frequency of brake lights or through Variable Message Signs provided by Intelligent Transport System infrastructure. Based on these indicators people will re-evaluate their route choice decisions based on their past experiences and perceptions of travel time for all the possible routes at that specific decision point. This behaviour is captured using the UER assignment method (Unnikrishnan and Waller, 2009). It should be noted that this work incorporates a version of UER in which the probabilistic link states are independent in nature and are perceived identically across all users of the network.

Stage 2 of the DEAR model directly outputs transformed *travel times*; this stage of the model infers *link states* by assuming that capacity and travel time are direct products of one another. Therefore, perceived expected capacity ($E_p(Cap_a)$) of the disrupted conditions are derived through the BPR link cost function using the transformed travel times obtained in Stage 2. This derived link capacity reflects users' perception in light of a disruption on the road link. '$E_p(Cap_a)$' defines one possible link state that a user could encounter. Additional link states are determined using the coefficient of variation relationship derived from DEAR Stage 1. The model presented is a static network planning model which utilises static link cost functions which results in the link capacity state experiencing the same coefficient of variation as the travel time. Considering this assumption, the standard deviation of capacity, '$\sigma_{Cap,a}$' can also be estimated.

Using parameters $E_p(Cap_a)$ and $\sigma_{Cap,a}$, the three traffic states used in this application of the DEAR model are presented in Table 4.1. These states depict variations of the perceived conditions with states being qualitatively interpreted as 'perceived', 'better than perceived', and 'worse than perceived'. State 2, which reflects the good state, considers link capacity to be equal to what was originally assigned to the network when performing the DUE assignment for normal conditions, defined as '$Cap_{a,n}$' which is the non-transformed ('n') capacity of link 'a'. This was deemed more realistic than considering the '$E_p(Cap_a) + \sigma_{Cap,a}$' as this could potentially exceed the non-transformed original capacity ($Cap_{a,n}$) of the link. Furthermore, the better than perceived conditions depict incident free conditions where the total capacity of the infrastructure remains available to use for all travellers.

Table 4.1: Network States used for Modelling

	State	Link State (Capacity)	Probability of Occurrence
1	Perceived Disrupted Conditions	$E_p(cap_a)$	0.682
2	Better than Perceived Disrupted Conditions (Normal Conditions)	$Cap_{a,n}$	0.159
3	Worse than Perceived Disrupted Conditions	$E_p(cap_a) - \sigma_{cap,a}$	0.159

The probability of occurrence is obtained from the normal distribution as it is assumed that travel times are normally distributed. DEAR-based UER assignment results in transformed flows accounting for the perception of users in disrupted conditions as well as the potential for adaptive routing as a consequence of the disruption.

4.4 Application of the DEAR model

The modelling approach described in the previous sections offers an alternative to traditional static traffic assignment methods by accounting for both the adaptive behaviour of users and the transformation in travel time perceptions that occur in light of a disruption. In order to assess the value of the framework, the model was applied to a simple demonstration network consisting of 4 nodes and 5 links presented in Figure 4.5 as well as the Sioux Falls network, presented in Figure 4.6.

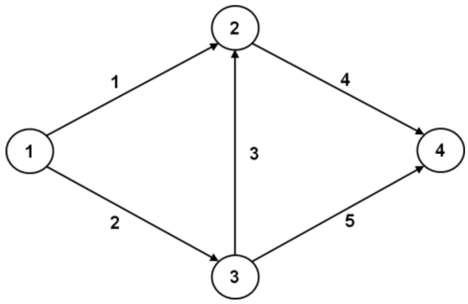


Figure 4.5: Demonstration 4 node, 5 link network

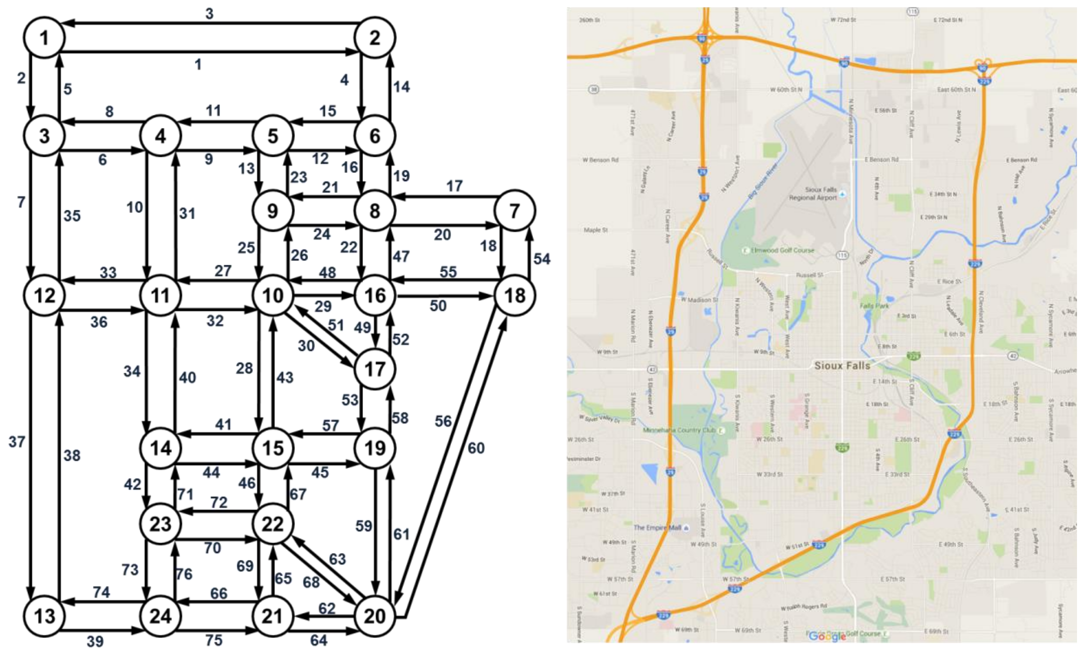


Figure 4.6: Sioux Falls Network

The demonstration network served to justify the feasibility of the modelling approach and highlight the impact of not accounting for adaptive behaviour. Thus, path level descriptions of the results are provided for a single level of demand analysing the impact of disruption severity. Applying the model within a more realistic network, such as the Sioux Falls network presented the robustness, efficiency and practicality of the approach.

Sensitivity testing was applied for the Sioux Falls network considering the variation of the following parameters within the model;

- **Severity of incident**, 'α'
- **States of the network**
- **Probability of Traffic States**
- **Demand levels**

The severity of an incident impacts the perceptions of travel time significantly (Dixit et al., 2012). Thus in order to assess varying disruption scenarios based on severity, values of alpha from 0.5 to 0.9, incremented every 0.1 were tested across all scenarios. Alpha values of less than 0.5 reflect a transformation of conditions which exceed the performance of the normal conditions, not reflecting disrupted conditions and accordingly were not assessed.

Three general network states are defined within Table 4.1. The capacity of the links for State 2 were identical to the original capacities, reflecting good or normal prevailing traffic conditions, whilst the capacity of the links for State 3 were one standard deviation less than the expected perceived capacity assumed for State 1. The likelihood of occurrence of the states was 68.2%, 15.9% and 15.9% for State 1, 2 and 3 respectively. The variances between the states and likelihoods assumed provided the 'Base Scenario', however in reality these parameters are dependent on the history of the traffic conditions faced by the network. Thus, sensitivity analysis was conducted by considering alternative scenarios defined as 'Scenario 1' and 'Scenario 2', presented in Table 4.2. The scenarios were developed by altering the reduction in capacity of State 3, considering $-0.5\sigma_a$ and $+1.5\sigma_a$ and the associated probabilities obtained from the normal distribution.

- ***Scenario 1*** depicts a network which displays a lower variation in expected link capacity between each of the link states. However, there is a lower likelihood of the expected perceived conditions. This is reflective of a real network that suffers a number of random minor incidents regularly where commuters in general experience conditions to be moderately worse or better than the expected perceived disrupted conditions (State 1).
- ***Scenario 2*** depicts a network which displays a higher variation in expected link capacity between the states. In contrast to Scenario 1, there is a higher probability of the expected perceived disrupted conditions of State 1. This is analogous to a network that experiences perceived or better than perceived traffic conditions for a majority of the time, but at times can be faced with extreme disrupted cases resulting in significant constraints on the capacity.

Table 4.2: Sensitivity analysis considering different capacity states and probabilities

	Scenario 0 (Base Condition)		Scenario 1		Scenario 2	
State	Link State (Capacity)	Probability	Link State (Capacity)	Probability	Link State (Capacity)	Probability
1	$E_p(Cap_a)$	0.6820	$E_p(Cap_a)$	0.3830	$E_p(Cap_a)$	0.8666
2	$Cap_{a,n}$	0.1590	$Cap_{a,n}$	0.3085	$Cap_{a,n}$	0.0667
3	$E_p(Cap_a) - \sigma_{Cap,a}$	0.1590	$E_p(Cap_a) - 0.5 \times \sigma_{Cap,a}$	0.3085	$E_p(Cap_a) - 1.5 \times \sigma_{Cap,a}$	0.0667

The probabilities of the states have been obtained directly from the normal distribution related to the degree of deviation relative to the perceived disrupted conditions. However, when applying the model in practice, the states and likelihood of the states will be defined using historical incident and traffic flow data specific to the region being modelled. As such, sensitivity was conducted on the probability of the states for the Base Scenario to determine the impacts of state probabilities on the performance metrics of the network. Instead of using the normal distribution, the probability for State 1 of the network was defined using binary logic. Either the perceived disrupted capacity conditions occur or do not occur for a link on a network resulting in a probability of 50% for State 1. This value was held fixed for the assessment, while the likelihood of worse than expected conditions and better than expected conditions were varied by 10% as presented in Table 4.3. The probability scenarios are defined from 'P0', which reflects the situation where State 3 (worse than perceived conditions) cannot occur, to 'P5' where State 2 (better than perceived conditions) cannot occur.

Table 4.3: Sensitivity analysis considering different probabilities of states

State	Link State (Capacity)	Probabilities					
		P0	P1	P2	P3	P4	P5
1	$E_p(Cap_a)$	0.5	0.5	0.5	0.5	0.5	0.5
2	$Cap_{a,n}$	0.5	0.4	0.3	0.2	0.1	0.0
3	$E_p(Cap_a) - \sigma_{Cap,a}$	0.0	0.1	0.2	0.3	0.4	0.5

Congestion may also provide interesting effects on the performance metrics extracted from the DEAR framework. Accordingly, 3 demand levels were assessed. An initial 'Base Demand' was defined to create traffic conditions which were neither too congested nor uncongested and was based on an assessment of the capacity of the network tested. An 'Uncongested Demand' was devised by deducting 25% of the demand of the Base Demand and a 'Congested Demand' by increasing the demand by 25%. The percentage increases were assumed for the purposes of demonstration and application. Table 4.4 presents the sensitivity analysis investigating the impact of demand, each state scenario (Scenario 0, Scenario 1, Scenario 2) were examined under the different demand levels.

Table 4.4: Sensitivity analysis considering different demand levels

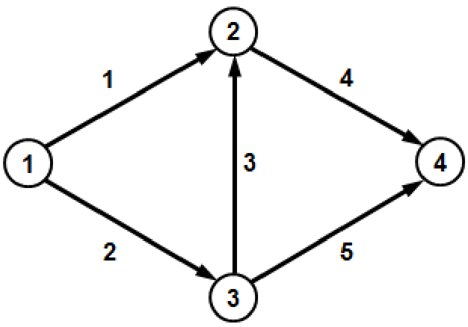
	Scenario 0 (Base Conditions)	Scenario 1	Scenario 2
Base Demand	D1	D2	D3
Low Demand	D4	D5	D6
High Demand	D7	D8	D9

4.5 Modelling Results

The results of the modelling are separated into two sections. The first section discusses in detail the application of the model on a demonstration network highlighting the key differences between the DEAR model and existing modelling methodology. The second set of results presents a comprehensive analysis of the key parameters of DEAR on the Sioux Falls Network.

4.5.1 Demonstration Network

This section demonstrates the proposed DEAR modelling framework that accounts for the impact of en route information on user behaviour in disrupted network conditions. The sample network is similar to the well-known Braess's paradox network. Figure 4.7 contains the sample network and associated network parameters. There are three possible paths that users can utilise; travelling along Link *1* and Link *4* (defined as Path *1*), travelling along Link *1*, Link *3* and Link *5* (defined as Path *2*) and travelling along Link *2* and Link *5* (defined as Path *3*). The model was assessed at a fixed demand of 4000 vehicles with varying levels of alpha between 0.45 and 0.95 to understand the impact of the severity of a disruption on the traffic flow conditions.



Link	Link Cost Functions
1	$c_1 = 7.5[1 + 0.15(x_1/1800)^4]$
2	$c_2 = 13.3[1 + 0.15(x_1/1800)^4]$
3	$c_3 = 2[1 + 0.15(x_1/1800)^4]$
4	$c_4 = 3.75[1 + 0.15(x_1/1800)^4]$
5	$c_5 = 6.67[1 + 0.15(x_1/1800)^4]$

Figure 4.7: Demonstration network and associated link cost functions used for analysis

Figure 4.8 presents a comparison of the path travel costs of the DEAR model to that of the deterministic user equilibrium (DUE) assignment. The horizontal axis indicates the level of severity (represented by the alpha value in the DEAR model

Stage 2), and the vertical axis shows the travel time of a path in minutes. DEAR does not consider minimum cost paths but rather minimum cost routing policies which allows for adaptive behaviour and so all three paths have slightly different expected costs. For an example, if a user travels from Node 1 to Node 2, there is the option for the person to either travel to 4 through Node 3 or travel directly to Node 4 based on the prevailing traffic conditions. Figure 4.8 also shows the DUE path costs in the situation that does not account for information or adaptive routing but still considers the transformation of travel costs associated with the disruption. Both models clearly indicate that perceived travel costs increase as the severity of the disruption increases, highlighting the importance of accounting for disruptions as well as the severity associated with a disruption.

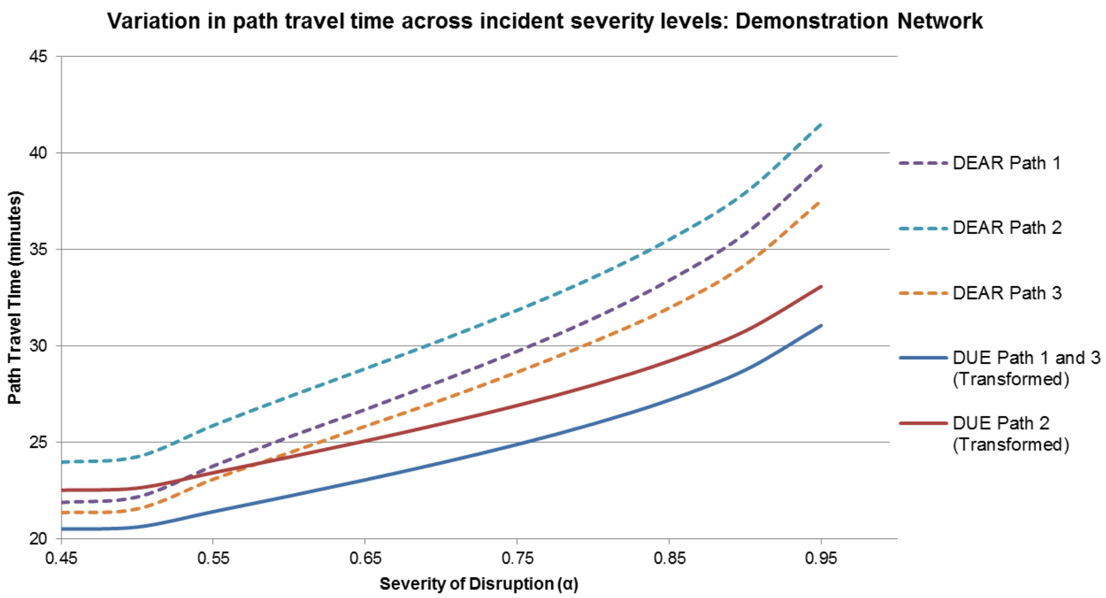


Figure 4.8: Comparison of travel costs between DEAR and DUE models

The DEAR model also presents a further inflation of travel costs consistent with the findings of Unnikrishnan and Waller (2009) indicating that the information of a disruption affects travel costs. The path travel costs are similar for both the DEAR and transformed DUE model ranging between 20 and 25 minutes for non-disrupted cases where alpha is less than or equal to 0.5. However, as alpha increases, the path costs in DEAR increase by up to 80% for a disruption case of severity 0.9, while in the DUE case it only increases by 51% which could be a result of the adaptive path choice behaviour.

Figure 4.9 presents a comparison of path flows between the DEAR and DUE model with increasing severity of disruption. Again, the horizontal axis shows an increasing level of severity. However, the vertical axis of Figure 4.9 represents path flows. The DUE model results in identical flows regardless of the incident severity as users are assigned to the least cost path. The DEAR model accounts for the user perceptions of disruptions as well as allows for adaptive route choice which accordingly shows a variation in path flow. As the severity of the disruption increases there is a reduction in flows for path 2 and 3 and an increase in flow for path 1. Furthermore, the peaks presented in the DEAR model path flow graphs indicate a shift from better than average travel conditions (α < 0.5) where users deflate their expected travel times to disrupted conditions (α > 0.5) where users inflate expected travel times thus resulting in the variation of path flows.

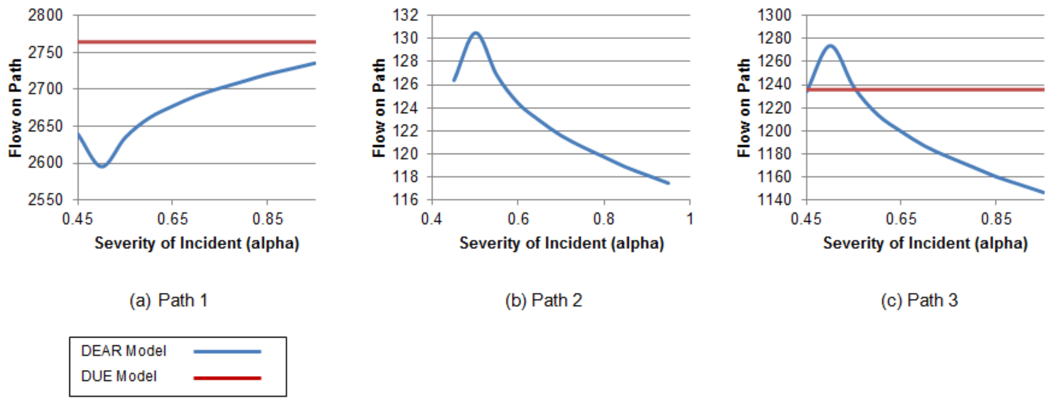


Figure 4.9: Comparison of variation in path flows between DEAR and DUE

4.5.2 Sioux Falls Network

The Sioux Falls network was used to test the sensitivity of the parameters within the DEAR model. Table 4.5 presents the network properties and demand levels that were considered for the assessment (Bar-Gera, 2015).

Table 4.5: Sioux Falls Network properties used for analysis

Sioux Falls Network Properties	
Number of Nodes	24
Number of Links	76
Number of Zones	24
Total Base Origin-Destination Demand (trips)	360600
Low Demand (75% of Base) (trips)	270450
High Demand (125% of Base) (trips)	450750

The Expected Total System Travel Time, which measures the system wide travel costs considering the possibility of multiple states on a road network, was used as the primary performance metric to analyse the modelling results. The ETSTT can be expressed using the following equation:

$$ETSTT = \sum_{a \in A} \sum_{i=1}^{n} P(S_i) \times C_i(x_a) \times x_a \tag{4.15}$$

Where the network contains a set of 'A' links, '$P(S_i)$' equals the probability of state i and '$C_i(x_a)$' is the cost of link 'a' in state 'i' given a modelled flow value of 'x_a'. The term 'n' defines the total number of states that a link experiences which in this case is equal to 3. In addition to this metric, the deviation in link flows provide a useful indicator of the potential differences that could occur with the application of DEAR in level of service assessments and management of links on a road network.

4.5.2.1 Impact of Disruption Severity

An increase in disruption severity yields a deterioration of the network performance. Similar to the presentation of the results of the demonstration network, the scenario testing conducted for the Sioux Falls network again highlights these intuitive results as shown in Figure 4.10 where ETSTT increases as the severity of the disruption increases.

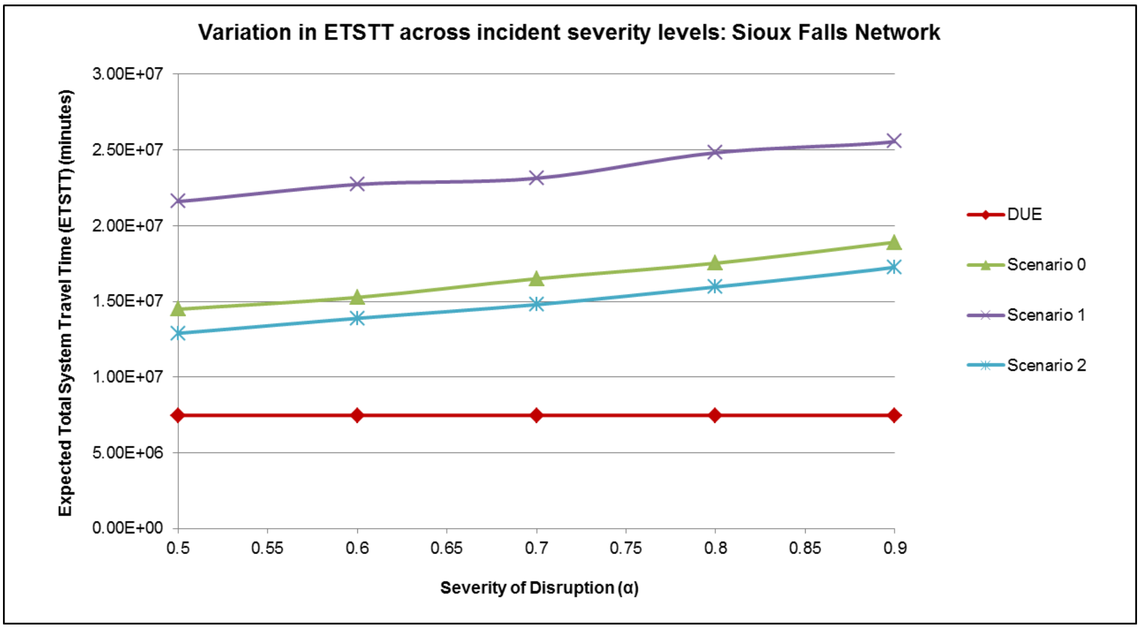


Figure 4.10: Impact of disruption severity on ETSTT across test scenarios

Considering the Scenario curves, the gradients are all similar, indicating a relatively uniform increase in ETSTT. The percentage change in ETSTT between disruption severity alpha values of 0.5 and 0.9, range between 18% (Scenario 1) and 34% (Scenario 2). However each scenario results in vastly different ETSTT values relative to the deterministic user equilibrium TSTT. Scenario 0, the base conditions, result in a significant increase in ETSTT of between 93% and 153% as compared to the original DUE solution which does not account for disruptions nor adaptive behaviour of users. Scenario 1 had a more exaggerated difference with increases of ETSTT ranging between 188% and 242%. Scenario 2 had the least impact on ETSTT with percentage increases between 70% and 130%. The near doubling of travel times could be associated with the ability of the DEAR model to account for the presence of disruptions as separate link states. Rather than defining a deterministic capacity for each link of the network, DEAR considers a state based capacity which creates greater levels of congestion and as a result increases in system travel costs. The large deterioration of performance within Scenario 2 could be explained by the uncertainty associated with the network states. As the likelihood of the 'worse than perceived conditions' increases, the

ETSTT increases. In Scenario 2, there is almost an equal likelihood of each of the assumed network states, with only a 38.3% likelihood of the expected perceived conditions thus users are uncertain of the prevailing conditions and there is a greater probability of worst possible scenario.

Link flows vary considerably across the scenarios assessed as shown in Figure 4.11. The column chart presents the flow on every link of the Sioux Falls network under each scenario considered for a disruption severity alpha equal to 0.7. Analysing the mean and median absolute deviation of all link flows from the DUE conditions for each scenario across all disruption severity values considered is graphed in Figure 4.12. Consistent with the ETSTT results, the greatest deviation in link flows occurs within Scenario 1 whilst the least deviation occurs with Scenario 2. An interesting observation across all the scenarios is the gradual reduction in deviation as the severity of the disruption increases. This may be explained by the notion that the potential for extremely severe disruptions heightens the loss aversion characteristics of users and creates a reduction in adaptive behaviour.

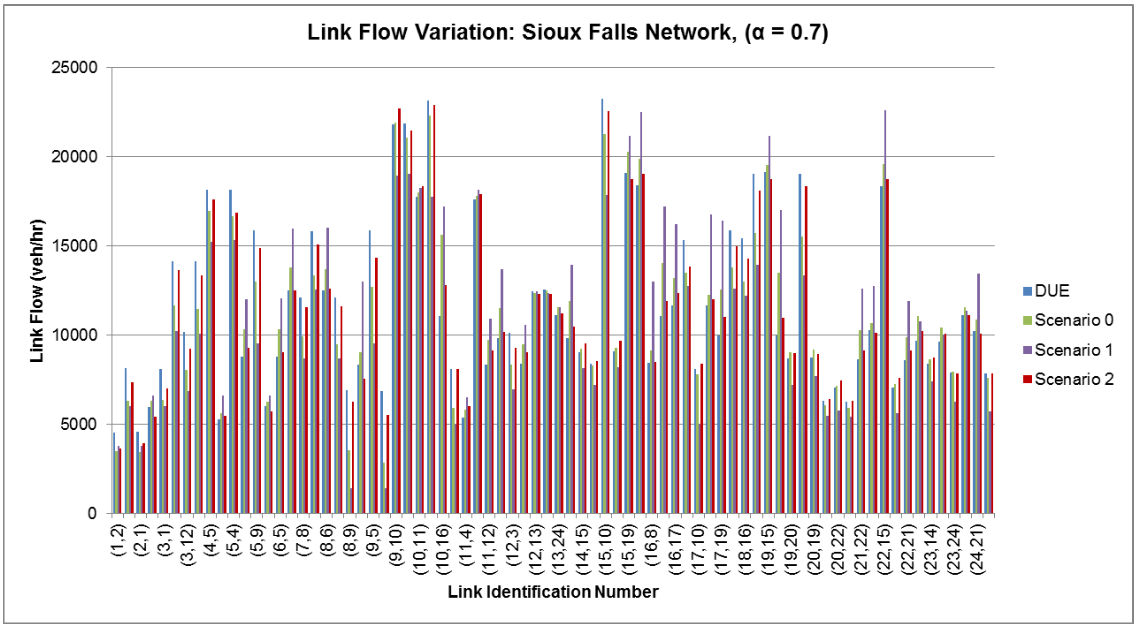


Figure 4.11: Variation in link flows across test scenarios for a given disruption severity

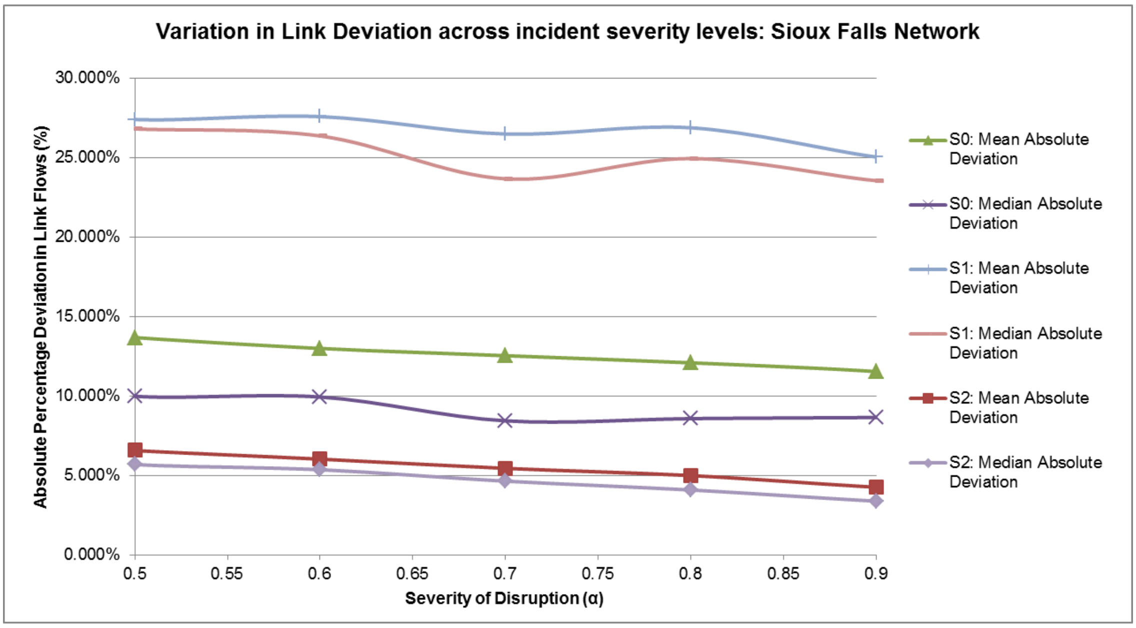


Figure 4.12: Mean and Median absolute deviation results across Scenario 0, 1 and 2

4.5.2.2 Impact of State Probability

Table 4.6 and Figure 4.13 present the results of the state probability sensitivity analysis for the baseline demand conditions and disruption severity alpha values between 0.5 and 0.9. The probability scenarios range from relatively good conditions (P0 has 0% likelihood of state 3, 'worse than perceived conditions') to poor conditions (P5 has 0% likelihood of state 2, normal traffic conditions without any disruptions, or 'better than perceived conditions'). Thus, it is expected that as the probability of state 3 increases, the ETSTT increases, which is the case from P0 to P3. However as depicted in all the ETSTT curves, in Figure 4.13, the ETSTT value decreases gradually (between 5% and 12%) from scenario P3 to P5. This observation suggests that uncertainty in link states rather than the state of the network plays a significant role in the system wide costs, further corroborating the observations of the sensitivity analysis concerning disruption severity. P3 experienced the greatest ETSTT across all disruption severities examined. This scenario had a relatively equal likelihood of all 3 states with a greater weighting towards the worse than expected conditions. P5 had no chance of the good traffic state, but this scenario performed similarly to P2 which had a 30% likelihood of the better than perceived conditions. To put it simply, reliability is a key determinant in the performance of a network, a network which always has a stable capacity can yield more efficient movement of travellers than a network which consists of links that experience fluctuations in capacity.

Table 4.6: ETSTT results of probability sensitivity assessment

State	Link State (Capacity)	Probabilities					
		P0	P1	P2	P3	P4	P5
1	$E_p(Cap_a)$	0.5	0.5	0.5	0.5	0.5	0.5
2	$Cap_{a,n}$	0.5	0.4	0.3	0.2	0.1	0.0
3	$E_p(Cap_a) - \sigma_{Cap,a}$	0.0	0.1	0.2	0.3	0.4	0.5
ETSTT (α = 0.5)		1.09E+07	1.66E+07	2.20E+07	2.44E+07	2.15E+07	1.97E+07
ETSTT (α = 0.6)		1.12E+07	1.69E+07	2.36E+07	2.51E+07	2.29E+07	2.11E+07
ETSTT (α = 0.7)		1.15E+07	1.79E+07	2.47E+07	2.71E+07	2.44E+07	2.26E+07
ETSTT (α = 0.8)		1.19E+07	1.87E+07	2.57E+07	2.84E+07	2.61E+07	2.43E+07
ETSTT (α = 0.9)		1.25E+07	1.97E+07	2.71E+07	3.00E+07	2.85E+07	2.63E+07

Another interesting point to note is that the impact of disruption severity increases as the likelihood of the State 2 (‘better than perceived’) traffic conditions depreciate. This is evident with the separation of the ETSTT curves in Figure 4.13. In addition, the percentage difference in ETSTT, between each disruption severity value tested, ranges between 2% and 5% for P0. The range increases to between 7% and 8.5% for P5. This is an intuitive result as the transformation in travel times associated with the disruption is compounded by the increased likelihood of disrupted conditions.

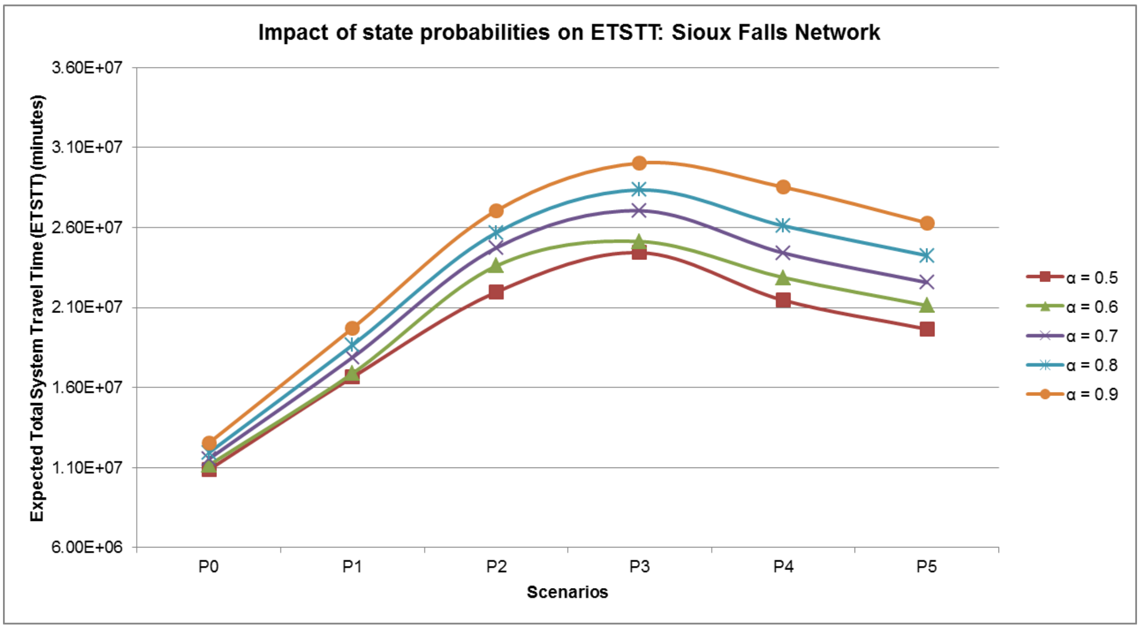


Figure 4.13: Variation in ETSTT across different probability scenarios

4.5.2.3 Impact of Demands

Figure 4.14 presents the variation in ETSTT across the different demand scenarios assessed. The results for the low demand (75% of the original demand value) and base demand scenarios are similar, with the greatest ETSTT occurring for the Scenario 1 states and associated probabilities. However, for the high demand case, presented in model assessments D3, D6 and D9, it is clear that when the variance in the capacity of the 'worse than perceived' is increased in Scenario 2, the ETSTT is the greatest. This trend occurs, regardless of the low likelihood of the state and can be attributed to a saturated network. If all links on the network experience a high degree of utilisation, the ability for users to adapt in the advent of a disruption is limited. Thus, the realisation of an extreme state, such as state 3 will result in a significant addition to travel times of all users. Therefore, the presence of improbable but extreme disruptions will have a greater effect in a user's decision making as the overall demand for the network increases.

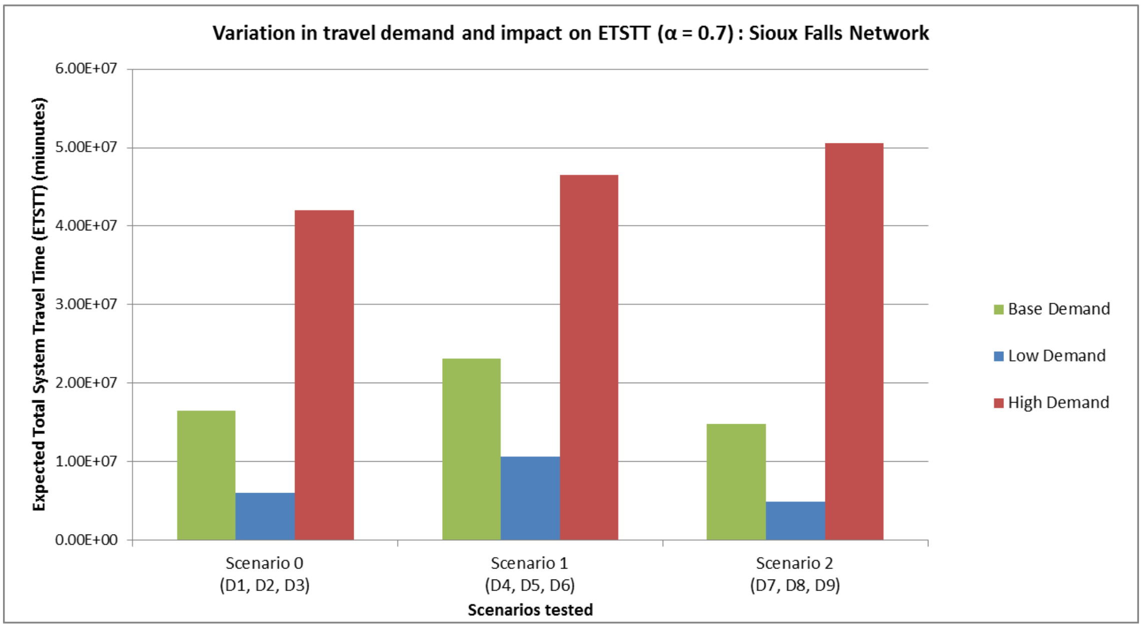


Figure 4.14: Variation in the level of demand and the impact on ETSTT

4.6 Discussion, Limitations and Future Extensions

The application of the DEAR model framework to a demonstration network and the Sioux Falls network presented the following findings;

- Perceived travel costs increase as the severity of the disruption increases, emphasising the importance of accounting for disruptions as well as the severity associated with the disruption.
- When the probability of the 'worse than perceived conditions' increases, the ETSTT increases. This is an intuitive result, where greater degrees of capacity reduction result in higher congestion levels and increased travel times.
- Uncertainty plays a significant role in the performance of the model. When the model considers only 2 active states (for an example, probability scenarios P0 and P5) the ETSTT times are significantly lower than when there is an almost equal likelihood of all 3 states occurring such as 'Scenario 2' and probability scenario P3.

- A reduction in link flow deviation is observed when disruption severity increases. This could be explained by the fact that the increased likelihood of extreme scenarios result in loss aversion behaviour where users are reluctant to adapt in light of disrupted conditions.
- The presence of unlikely extreme events increase travel time more significantly as the overall demand for the network increases.

The demonstration of the DEAR model provides common sense results where travel costs increase by incorporating the possibility of a disruption being present on the network and the travel cost perceptions of users associated with disruption. Based on these results, the most significant outcome is the degree of importance transport planning authorities should place on reliability assessment. The results indicate that the minimisation of the number of link states can result in significant improvements to the network, thus it is vital for planning authorities to develop disruption mitigation strategies to reduce the supply side variability of road networks.

It must be emphasised that the demonstration of the model was conducted on a hypothetical basis with synthetic demands. Furthermore, the application of the model involved assumptions for each of the critical parameters which defined the model; the severity of the disruptions which could occur on the network, the link capacity values for the construction of each state, the probability of occurrence of each state and the level of demand within the network. Based on the sensitivity analysis conducted for the Sioux Falls network, these four parameters have a significant impact on the results of the modelling. Therefore, to apply the DEAR framework in practice, it is essential to obtain detailed incident data logs and traffic characteristic data for the road network being investigated in order to calibrate and validate the base model. Initially a portion of the data could be used to determine the capacity states for each link of the network by classifying disruptions into categories (e.g. breakdowns, crashes, flooding) and then assessing the average impact of these incidents on the capacity of each link. The probability of occurrence of each of the categorised states can then be estimated by considering the proportions of each category of incident. The model can then be formed and validated against the remainder of the data set collected. Practical application of this model is the ultimate objective of this research effort which can yield in a static planning model that accounts for the presence of disruptions on a network and the associated adaptive behaviour of users.

Further improvements of the DEAR methodology could be the consideration of correlated link states which would involve the use application of the R-SSPR algorithm proposed by Polychronopolous and Tsitsiklis (1996) to determine the least cost routing policy. The model also assumes homogeneity in information acquisition. It may be possible to integrate this structure of modelling with the STOCH-UER presented by Ukkusuri and Patil (2007) to also capture users perceptions of information as well as disruptions within the model to enhance the realism. Finally, the model could also be relaxed further to include imperfect information regarding the presence of incidents resulting in errors in interpretation of the state of the network by the user. This type of extension will add to the growing literature concerning information system accuracy.

4.7 Concluding Remarks and Impact

This chapter proposes a novel modelling framework called the disrupted equilibrium assignment with recourse (DEAR) model that accounts for the impact of online information learned throughout travel on route choice in disrupted conditions. The DEAR model includes an adapted version of two previous models; DNAM which transforms user perception based on experimental data, and UER which accounts for adapting routing behaviour in network users. The DEAR model considers people's perceptions and experiences within disrupted conditions as the source of information which dictates route choice when conducting the adaptive assignment. The DEAR framework was applied within a demonstration network as well as the Sioux Falls network to showcase the scalability of the model. The results indicate the necessity to account for the transformation of perceptions in disrupted conditions echoing the findings of the DNAM. Furthermore, there is also a need to include adaptive routing based on information gained during travel to appropriately capture the performance of the network. Travel costs and flows differed considerably relative to the standard DUE model. The results of the DEAR approach also highlighted the importance of reliability within a road network. The reduction of the number of different traffic states that a road network can experience results in significant improvement in travel costs. The next steps to advance the DEAR concept will be the development and application considering field data to appropriately define the key parameters of the model.

CHAPTER 5. DYNAMIC MODEL FORMULATION AND APPLICATION: THE DYNAMIC USER OPTIMAL WITH RECOURSE (DUOR) MODEL

5.1 Introduction

Traffic assignment models have generally been classified into two broad categories, static and dynamic. Static models have been used extensively throughout history due to their tractability, simplicity and computational ease. There are three common assumptions used in developing traditional static traffic assignment models that result in mathematically rigorous formulations and present unique solutions. The three assumptions; the traveller is rational and has perfect information about the network properties and costs associated with travel, the travel time on a link is dependent only on the properties of that link alone, the demand assigned to the model is static and does not vary with time, are reasonable for normal day to day modelling of aggregate behaviour in stable networks. However, they cannot capture the realism of most traffic networks, in particular in capturing disrupted network behaviour.

As described in Section 4.2.1, there have been a number of research efforts which have aimed to relax these core assumptions to provide more realistic static models. To this extent, Chapter 4 adds to the suite of static models by developing a traffic assignment model which accounts for adaptive routing behaviour and changes in travel time perception in light of a disruption. The application of models such as this and other similar advanced static equilibrium models can provide useful aggregate level statistics, beneficial for long term planning. However, there are some fundamental properties of traffic networks that cannot be captured through the static approach.

The most important property which is not captured in a static model is the dynamic nature of traffic flow. Traffic is a result of the movement and interaction of vehicles traversing between origins and destination across time. Therefore, it is clear that the eventuation of congestion is constantly varying in a spatial and temporal context. Chiu et al. (2011) states that static traffic assignment approaches use time-invariant variables incapable of explaining the intricate relationship between the demand for travel, time and costs associated with travel. Static models use link cost functions or volume-delay functions to describe the presence of congestion in terms of average travel times. These functions assume that for a given link, every vehicle experiences the same cost. Thus, it is not possible to capture merging or overtaking behaviour or the accumulation of vehicles on a section of a road. Based on this limitation, static models cannot adequately describe the development of queues, the presence of bottlenecks on a network or the spill over of traffic at the boundary of a network (Peeta and Ziliaskopoulos, 2001). These phenomena are common in the context of disrupted networks, thus dynamic approaches to modelling traffic were investigated to gain a further understanding of the research topic.

In practice, to overcome the limitations of static modelling, operational microscopic models have been employed to capture the behaviour of individual vehicles across time and space. However, microscopic models are derived from car-following behavioural models and are restricted to the analysis of corridors or smaller areas primarily due to the extensive calibration and validation requirements and computational burden. Thus, it is difficult for microscopic models to provide regional evaluations of traffic conditions which are only feasible through equilibrium-based route choice approaches.

Dynamic Traffic Assignment (DTA) models have the ability to meet the limitations of the static and microscopic approaches. DTA models aim to capture the dynamic nature of traffic at a regional level through a variety of analytical and simulation based approaches. In the context of modelling disrupted network behaviour, DTA based approaches offer a highly realistic method that is able to capture the presence of the disruption, the development of queues and spillbacks and most importantly the ability for adaptive routing. The core assumption throughout the thesis is that disruptions result in a release of information from the disruption itself as well as from ITS and ATIS systems. These information sources are acquired by the user to make their future travel and routing decisions. Accordingly, the focus of Chapter 5 is to develop a dynamic approach to effectively capture the behaviour of users accounting for the behaviour in disrupted conditions.

This chapter proposes the Dynamic User Optimal with Recourse (DUOR) approach which is an extension of the Dynamic User Optimal (DUO) theory to capture the adaptive, time dependent behaviour of users in a stochastic road network. Similar to the principles of the static UER model (described in detail within Chapter 4), the DUOR equilibrium principle considers the probability of road networks existing in multiple states, reflecting the uncertainty of travel arising due to the presence of disruptions. Users develop route choice policies to account for this uncertainty with the goal of minimising their expected travel time. An equilibrium solution for the network occurs when all users on the network travel using the least cost routing policy. The DUOR concept is applied through simulation based methodology, DUOR-CTM that uses the Cell Transmission Model to propagate traffic. This chapter describes the presence of DUOR solutions on a number of demonstration networks highlighting the potential of the approach as a future DTA framework. Furthermore, the network wide costs and benefits associated with online information are analysed to showcase the application of the model.

Chapter 5 is structured as follows:

- Section 5.2 describes literature surrounding DTA modelling and previous approaches to account for information acquisition by users and resulting adaptive behaviour.
- Section 5.3 presents the DUOR concept detailing the key assumptions of the approach
- Section 5.4 explains the DUOR modelling methodology and the simulation based application of the concept

- Section 5.5 presents the results of application of the model and a discussion of the presence of equilibrium solutions and other observations.
- Section 5.7 concludes the chapter with a discussion of the potential practical implications and extensions of the modelling approach

5.2 Literature Review

The review of literature aims to provide an examination of the research surrounding dynamic traffic assignment (DTA) as well as the incorporation of informational impacts within dynamic modelling methodologies. Initially, dynamic equilibrium principles are discussed to clarify explicitly the foundations for Dynamic User Optimal with Recourse (DUOR). The review then discusses previous dynamic modelling approaches with a particular focus on simulation based methods. Finally previous research related to the consideration of information acquisition in a dynamic environment is discussed to present the contribution of the modelling effort.

5.2.1 Equilibrium Principles: Dynamic User Equilibrium (DUE) and Dynamic User Optimal

There are numerous definitions of dynamic equilibriums present throughout literature (Chiu et al., 2011). As such, the definitions assumed for this study are clearly stated within this section of the report. Dynamic equilibrium conditions tend to be the time dependent versions of the equivalent static equilibrium models (Peeta and Ziliaskopoulos, 2001). Dynamic User Equilibrium (DUE) and Dynamic System Optimal (DSO) are the time dependent extension of the traditional static User Equilibrium (UE) and System Optimal (SO) representations (Wardrop, 1952). Accordingly it is assumed that under DUE (Wardrop, 1952);

'*The time dependent journey travel times on all used routes are equal and less than those which would be experienced by a single vehicle on any unused route for a given departure time*.

The concept of Dynamic User Optimal (DUO) has at times been used interchangeably with DUE (Ge et al., 2014). The study by Ge et al. (2014) provides a thorough discussion of the conflicting definitions observed in literature. The study itself defines DUE and DUO under different equilibrium tolerance scenarios highlighting that DUE is a special case of DUO with a variable tolerance. Ge et al. (2014) defines DUO as;

'The situation/s where each individual user travelling between a specific origin and destination cannot unilaterally change their path to reduce their travel cost whilst accounting for the prevailing traffic conditions.'

This definition of DUO is consistent with the findings of Ge et al. (2014). Furthermore it has also been used by Golani and Waller (2004) and Waller and Ziliaskopoulos (2006). The development of Dynamic User Optimal with Recourse (DUOR) is an extension of these definitions and is formally presented within Section 5.3

5.2.2 Dynamic Traffic Assignment Models

Investigation into DTA methodologies has been one of the most active research areas in transportation across the last three decades. The work by Peeta and Ziliaskopoulos (2001), 'Foundations of dynamic traffic assignment: The past, the present and the future', and the Transportation Research Circular E-153, 'Dynamic Traffic Assignment: A primer' by Chiu et al. (2011) provide the fundamental understanding of dynamic traffic assignment in the development of the DUOR modelling framework.

DTA models have the ability to capture time dependent travel behaviour and the subsequent impacts on traffic flow. As mentioned before, DTA approaches can avoid the limitations of static volume-delay functions (VDFs). Thus, DTA models can realistically account for the development of congestion (queuing, spillback, lane changing and merging behaviour) and information based effects (Balakrishna et al., 2013, Chiu et al., 2011). The other clear advantage of the DTA approach is requirement for a convergence on an equilibrium solution based on experienced travel costs (Duthie et al., 2013, Chiu et al., 2011). Convergence of models is essential in the context of transport planning as it provides uniqueness in the solution and performance metrics extracted from the model. Therefore, convergence will offer the practitioner the ability to appraise and rank potential road infrastructure projects with clarity (Duthie et al., 2013).

Furthermore, Duthie et al. (2013) and Chiu et al. (2011) suggests that the ideal method of obtaining the traffic flow characteristics is through traffic simulation consistent with traffic flow theory to ensure that realism, such as volumes not exceeding capacity, is maintained. In highlighting the basic advantages of dynamic models, there are some disadvantages compared to the static approach which include the reduction in tractability of some models and increased computational burden associated with depicting temporal variation. These factors were taken into consideration in the development of the DUOR framework and also defined the overall modelling objectives of the thesis. DUOR is a novel concept proposed herewith, as such one of the key contributions of the work is to clearly explain DUOR and identify the difference between existing approaches. Following this, based on the DTA primer, it is imperative to determine the existence of equilibrium DUOR conditions for a network in order to assess the potential future applications of the method.

There have been a number of solution methods that have been formulated for DTA models which include; optimisation based formulations, variational inequality formulations, optimal control formulations, and simulation-based methods. The following subsections provide a brief overview of some of the works related to each of the different solution methodologies.

5.2.2.1 Optimisation Formulations

Optimisation or sometimes known as 'mathematical programming' approaches formulate the problem in a discretised time setting (Peeta and Ziliaskopoulos, 2001). The mathematical approach was pioneered by Merchant and Nemhauser

(1978a) and (1978b) who provide a framework to determine System Optimal (SO) conditions for a simple single destination, fixed demand scenario. The formulation used link performance and exit functions, and the programming formulation was non-convex and non-linear. Carey (1986) extends the approach and developed a convex non-linear program by altering the link exit functions, however application to multiple destination networks resulted in further non-convexity issues. Ziliaskopolous (2000) provides a linear programming formulation for a single-destination SO-DTA problem using the cell transmission model (CTM) presented by Daganzo (1994). The CTM avoids the need for link performance functions; hence it is able to model dynamic traffic flow more realistically. Ziliaskopolous shows that the DTA problem can be modelled as a linear program (LP) which can improve efficiency in solving DTA problems.

The key advantage of the mathematical approach is the tractability; however as described within a few of the seminal works have drawbacks. The main concern is non-convexity (Carey, 1992) and the algorithmic induced FIFO limitations which results in unrealistic overtaking of vehicles within the models. Another major problem is the issue of 'holding back'. Holding back occurs with SO mathematical programming models when it is favourable to stop vehicles from exiting a link, even when there is available capacity on the following link. This is clearly not representative of true traffic flow as drivers will proceed when there is available capacity in the upstream road section. The holding back problem can also be seen in cell transmission models (Doan and Ukkusuri, 2012). Finally, optimisation models also suffer some similar problems to static models through the use of link performance functions (Ban et al., 2008, Chow, 2009) bottleneck models (Ramadurai et al., 2010), and exit flow models (Carey, 1987) to propagate traffic. Though these flow propagation techniques account for time-varying properties, they may not account for realistic traffic dynamics within links.

5.2.2.2 Optimal Control Formulations

Optimal control DTA formulations are similar to optimisation based formulations, but are defined in a continuous rather than discrete-time setting. Accordingly similar convexity and holding issues exist with these approaches (Peeta and Ziliaskopoulos, 2001) limiting the realism of the models. Another significant limitation is the lack of solution method for general networks (Peeta and Ziliaskopolous, 2001).

Friesz et al. (1989), Ran and Shimazaki (1989a) and Ran and Shimazaki (1989b) developed link-based optimal control formulation for UE and SO criteria in single and multiple destination networks. Simplifications have been presented in these works which have led for computational feasibility yet they do not model congestion realistically and ignore the FIFO issue for multiple destinations (Peeta and Ziliaskopolous, 2001). Of relevance to this research, Ran et al. (1992) uses an optimal control model to solve an instantaneous dynamic user-optimal (DUO) traffic assignment problem. The formulation presents a convex program and a unique solution which encouraged the investigation of the DUOR approach.

5.2.2.3 Variational Inequality Formulations

Dafermos (1980) first introduced the variational inequality (VI) method to static traffic assignment problems, where congested networks are studied and an algorithm is provided to solve the problem. In general, VI formulations consider fixed-point or complementarity problems. Dynamic equilibrium formulations have been developed by Friesz et al. (1993), Zhang and Nagurney (1995), (Zhang and Nagurney, 1996) and Wie et al. (1995). VI formulations offer an alternative analytical approach to DTA modelling; thus, suffer the limitations described in the previous sections. The work by Wie et al. (1995) highlights limitations using a VI approach, the work proves that a DUE exists and provides a heuristic algorithm to solve. However, the exit flow functions necessary for the model creates unrealistic traffic flow characteristics, and since the formulation was path-based, enumeration is necessary to determine potential paths. Ran et al. (1996) further investigated

DUO using a link-based VI model to avoid route enumeration. The necessity and sufficiency of the model was proven to show consistency with DUO conditions.

5.2.2.4 Simulation Based Approaches

It is clear that the analytical approaches suffer a number of limitations in the ability to reflect realism within the traffic assignment model. Simulation-based approaches may (Ziliaskopolous, 2000) or may not be (Ben-Akiva et al., 2003) formulated as a mathematical program. The key element of these models is that they all use simulation as a solution methodology in an effort to enhance realism. In general, simulation based approaches consist of three main components; a traffic simulator, a path generator, and an assignment module (Levin et al., 2014). The traffic simulator serves to evaluate the network performance, the path generator determines the time-dependent least-cost path for each origin-destination pair and the assignment module assigns traffic based on the results of the path generator. This process is repeated iteratively until an equilibrium solution is obtained. Levin et al. (2014) provide a comprehensive discussion concerning the convergence of simulation-based DTA approaches suggesting that the method selected affects computational efficiency.

There have been a number of simulation-based DTA studies that have specifically focussed on the impact of ITS technology. Mahmassani and Peeta (1993) formulated a dynamic UE and SO traffic assignment problem to explore the impact of information through ATIS systems. Sensitivity analysis of the demand was completed and they discovered that information provision aimed at achieving a system optimal solution could be more beneficial than descriptive, non-cooperative information, especially as demand levels increase. The study used the mesoscopic simulator, 'DYNASMART', to model the flow of traffic which avoids FIFO violations and 'holding back' present in analytical approaches. Mahmassani and Peeta (1995) extended the study of the SO formulation by exploring the optimisation of system performance through the provision of real-time routing information. These models provide valuable insight into the network impacts of information. However, they do not account for stochasticity of networks or the provision of online information and are also computationally inefficient for larger networks.

The Cell Transmission Model (CTM) has been used as a traffic simulator in recent years for the application of DTA methodologies (Szeto, 2013) and is used within this study. The CTM is a macroscopic traffic simulation model introduced by Daganzo (1994) based on the concepts of hydrodynamic flow theory. CTM divides every link in the network into cells with a specified vehicle capacity (N) and flow capacity (Q). Vehicles propagate throughout the network according to flow conservation and capacity constraints. Daganzo provides equations to account for the merging of two links and also the divergence of a link into two separate links, allowing the CTM to be generalised for any network. The main advantage of this approach, like other simulation approaches is that traffic dynamics such as queue spillback and traffic interaction across links can be captured. However, Daganzo shows that the computational time and memory requirements are much greater than typical static traffic assignment models.

Since its inception, CTM has been incorporated in a number of DTA frameworks. As mentioned earlier, Ziliaskopolous (2000) formulated a single destination System Optimum Dynamic Traffic Assignment (SO-DTA) problem as a linear program by representing the flow propagation relationships with linear constraints. Similar works by (Li et al., 1999) and Li et al. (2003) highlight the value of combining CTM with analytical solution methodologies to obtain rigorous and realistic models. Ziliaskopolous and Waller (2000) introduced an internet-based GIS that brings spatio-temporal data, models and users in a single framework. They used a simulation-based DTA model called 'RouteSim', a model based on the CTM for traffic propagation. This allows realistic modelling of demand and supply dynamics by including time-dependent cell capacities. However, these applications can still face the issue of 'holding-back' and there have been a few studies which have attempted to remedy this issue. For an example, Shen et al. (2007) proposed an iterative approach to ensure that vehicles are released to the adjoining cell given that there is spare capacity. Doan and Ukkusuri (2012) present a summary of the different methods used to cater for 'holding back' and present a SO-DTA formulation for multiple Origin-Destination (O-D) pairs.

Dynamic user equilibrium and user optimal conditions have also been investigated using CTM frameworks. Lo (1999) and Lo and Szeto (2002) proposed a user equilibrium based DTA model that obtain travel time values from CTM simulation. Waller and Ziliaskopoulos (2006) introduced a combinatorial optimisation algorithm for solving the dynamic user-optimal (DUO) problem, which runs efficiently for single destination networks. They use a model incorporating the CTM as a traffic simulator to avoid link exit functions and accurately model realistic traffic flow. They also show that the algorithm can be extended heuristically to be applied to multi-destination networks. This work served as guide in the development of the DUOR-CTM model.

Ukkusuri and Waller (2008) use the CTM to study dynamic user equilibrium to accurately model shockwaves and link spill overs. The study compares the dynamic user equilibrium network design problem (DUE NDP) and an existing dynamic system optimal network design problem (DSO NDP). Furthermore, the formulation is extended to account for demand uncertainty within a network. The vast body of literature indicates the benefits of using CTM as an option to simulate the impact of adaptive behaviour within networks. Accordingly, CTM served as the foundation for the modelling effort within the study.

5.2.3 Dynamic Traffic Assignment in Stochastic Adaptive Environments

A disruption within a road network results in stochasticity of the available capacities of road sections and, as shown throughout the thesis, adaptive behaviour from the information gained about the disruption. Thus, in order to effectively capture the impact of disruptions within a traffic model, dynamic traffic assignment needs to be applied within stochastic and adaptive environments.

It is important to note that over the last 3 decades there has been a considerable volume of research concerning the incorporation of traveller information within dynamic traffic modelling. A number of equilibrium frameworks have been developed to assess the value and impact of information. Studies by Hall (1996) and Dong et al. (2006) consider the impact of access to perfect information sources. Lo and Szeto (2004) and Yin and Yang (2003) discuss the implications of imperfect information by introducing error distributions to path travel times related to the source of information. Ben-Akiva et al. (1991) and Mahmassani and Liu (1999) present formative research concerning the impact of learning or experiential information on road networks. These studies provide insight into dynamic information modelling, yet contrast the modelling approach considered in this thesis which is based on the ideology of strategic routing.

Strategic routing involves the consideration of routing policies, as described in Chapter 4 are a set of 'traffic state' or 'information dependent' paths. The concept of a routing policy and its applications in static frameworks are discussed in detail within Section 4.2.4. Further to these works, there have been a limited number of studies which consider routing policies in dynamic equilibrium setting. Hamdouch et al. (2004) extended the static variational inequality model developed by Marcotte et al. (2004) that replaced rigid capacity assumptions in place of cost functions. Hamdouch et al. (2004) developed a dynamic version of the model in the context of strategic adaptive routing using discrete-time flow variation. Friesz et al. (1994) presented a tatonnement or 'trial and error' model to determine the interplay between traffic disequilibria and equilibria. The study examines day-to-day flow under either complete or incomplete information about the previous day, and finds that over time equilibrium is achieved. Friesz et al. (1996) further developed the approach and presented mathematical models based on variational inequality and optimal control to determine dynamic urban network flows, again in the context of information. The mode accounts for adaptive behaviour but not under stochastic network conditions.

As mentioned in Section 4.2.1, the shortest path-problem is the sub-problem of equilibrium traffic assignment problems. Fu and Rilett (1998) developed a heuristic solution algorithm to study the stochastic shortest-path problem in dynamic networks where information is known *a priori*. Further optimal solutions of non-polynomial complexity are given in Hall (1986) and Miller-Hooks and Mahmassani (2000) (Least Expected Time, LET algorithm) which determine the least expected travel time path between two nodes in a network where travel times are stochastic and time-dependent. Though these algorithms account for stochasticity in the network they do not consider online information resulting in adaptive behaviour.

Considering adaptive routing on stochastic networks, a number of algorithms have been developed that determine the 'shortest-routing policy'. Croucher (1978) initially explored the stochastic shortest-path problem allowing for recourse using a heuristic algorithm. Andreatta and Romeo (1988) developed 'stochastic shortest path with recourse' which considered the case where links on a route may suffer significant degradation and alternative paths would have to be used for traversal by users. Psaraftis and Tsitsiklis (1993) examined shortest path problems in acyclic networks and considered the potential of users waiting at nodes for favourable link conditions to determine an optimal routing policy. Miller-Hooks (2001) extended the LET algorithm by developing the label correcting Adaptive Least Expected Time (ALET) algorithm and the label setting 'S-DOT' algorithm that accounts for online recourse.

In the context of information acquisition, Waller and Ziliaskopoulos (2002) presented the time-invariant online shortest-path (OSP) algorithm that accounts for limited forms of spatial and temporal dependency, with a pseudo-polynomial complexity. The application of the OSP algorithm suggests that paths containing sources of online information result in improvements of traffic conditions, and the benefits of information provision increase with network size. More recently, Gao and Chabini (2006) studied adaptive routing in a stochastic time-dependent network where link travel times are modelled as random variables with time-dependent distributions. In their approach, at a particular node in the network, users have an *a priori* understanding of the state dependent link travel time distribution and decide which node should be taken next based on the state of the link, the location of the downstream node, and also the current time. This concept is further developed in an algorithm that considers stochastic dependency of link travel times and the impact of perfect online information. An exact algorithm, 'DOT-SPI' is presented, and several heuristic approximations are provided to improve efficiency. Gao and Huang (2012) extended these concepts and developed a heuristic algorithm, 'DOT-PART' which accounts for the lack of perfect online information and the potential for partial online information.

The objective of this modelling effort is to understand adaptive routing in a stochastic time dependent network which accounts for information acquisition, thus offering a more thorough understanding of disrupted conditions. To the author's best knowledge there has only been one such DTA modelling approach.

Gao (2005) established a framework for optimal routing policy problems in stochastic, time-dependent (STD) networks, and further developed a dynamic traffic assignment model to account for online adaptive routing. The research developed the equilibrium representation as a fixed-point problem and determines a heuristic solution algorithm based on the method of successive averages (MSA). Application of the model emphasises the value of information in reducing travel time and improving reliability under equilibrium conditions. Conversely, the research also presents scenarios of information saturation across the network demand negating any possible improvements for the network.

Gao (2012) extended the previous research (Gao, 2005, Gao, 2012, Gao and Chabini, 2006) to model strategic route choice under real-time information provision. The DTA model integrated three major components: optimal routing policy generation (Gao and Chabini, 2006), a routing policy choice model (Gao et al., 2008) and a routing policy loading model. Routing policies and information are generalised to avoid common simplifying assumptions such as 'full' or 'no' information and users pick routes strategically considering entire paths and not on a link by link basis. However, equilibrium solutions are based on the stabilisation of link travel time distributions. Similar to before, application of the model suggests lower expected travel time and lower standard deviations of travel time with the provision of information.

The studies by Gao have been seminal in the development of dynamic adaptive stochastic traffic assignment techniques and provide valuable insight into the costs and benefits of information. However, the models developed in these studies are analytical in nature. In contrast, the DUOR-CTM framework defined in this chapter of the thesis is a simulation based DTA model that accounts for adaptive behaviour in the presence of information within a stochastic time-dependent network. As mentioned in Section 5.2.2, there is a growing need to develop simulation based DTA approaches to better capture traffic flow characteristics such as queue spillback and shockwaves. Therefore, the DUOR-CTM serves as the first effort to bridge this particular research gap.

5.3 Dynamic User Optimal with Recourse (DUOR)

The concept of 'Dynamic User Optimal with Recourse' (DUOR) is derived from the static definition of User Equilibrium with Recourse (UER) (Unnikrishnan and Waller, 2009). The UER framework is described in detail within Section 4.2.5 where equilibrium conditions are an extension of the tradition UE framework and defined as; *'if each user chooses a minimum expected cost routing policy and no user can unilaterally change their routing policies to improve the experienced expected cost'* (Unnikrishnan and Waller, 2009).

The dynamic extension of UER would be Dynamic UER which would suggest that the time dependent cost of all used routing policies would be equal to the minimum expected cost. Dynamic User Optimal with Recourse (DUOR) is similar to DUER except that each used policy need not have equal travel times. Instead, it is only characterised by the principle that no user can unilaterally change policies to improve their travel time. This means that one user may experience a greater travel time than another user with a different policy, but may not be able to experience the reduced travel time themselves by switching to that policy.

Dynamic User Optimal with Recourse (DUOR) was defined as an extension of DUO based on the principles of UER;

'the situation where each individual user travelling between a specific origin and destination cannot unilaterally change their routing policy to lower their travel cost whilst accounting for the prevailing traffic conditions' (Wijayaratna et al., 2014).

The key difference between conventional DUO and DUOR is that, in DUOR, a user can also alter their journey *en route* dependent on the traffic conditions. DUOR is relevant due to the discrete nature of the CTM. The CTM relies on modelling discrete vehicles travelling throughout the network rather than continuous quantities, and gives integer solutions as a result. Hence it is unlikely that the CTM will result in true DUER, and the term 'DUOR' will be used from now on to more accurately describe the results. Similar to the argument raised by (Ge et al., 2014) DUER is a special case of DUOR and as such the integrity of the model is maintained.

Gao (2005) describes a 'routing policy based equilibrium' which is identical to the definition of DUER. Furthermore her research used this definition of equilibrium to develop a comprehensive DTA model which is described in Section 5.2.3. Even though the definitions are identical, the representation of equilibrium within the DTA modelling framework is described in terms of equilibration of link travel time distributions which indicates that each user has achieved the least cost policy resulting in DUER conditions. In contrast, the DUOR-CTM proposed within this research considers equilibrium at a path and policy level. It is important to note that observation of equilibrium in a simulation environment is the primary goal of this research task. Obtaining simulation based equilibrium conditions in the context of DUOR presents the potential to capture information acquisition and account for disruptions in a robust manner whilst accounting for the realism of adaptive behaviour.

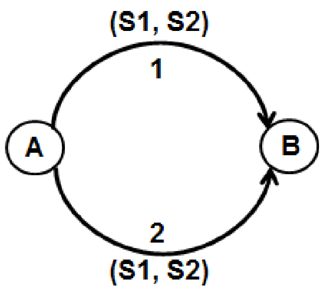
5.4 Modelling Framework (DUOR-CTM)

DUOR equilibrium conditions were investigated using the proposed Dynamic User Optimal with Recourse - Cell Transmission Model (DUOR-CTM). Thus, the underlying principles surrounding UER (as DUOR is the dynamic extension of UER) were applied to the general Cell Transmission Model (CTM) presented by (Daganzo, 1994) to develop a time dependent simulation model accounting for adaptive routing in the presence of *en route* information.

5.4.1 Link States, Network States and Routing Policies

The DUOR-CTM model determines routing policies based on network traffic states. Each link on the network may experience different states, as described in Section 4.2.5 and combinations of link states result in different network states. The states of the links are defined by capacity variations within the CTM model that depict the presence of disruptions. For example consider a simple 2-link, 2-node network where each link experiences 2 different traffic states (S1 and S2), where S1 reflects free flow conditions and S2 reflects incident conditions. There would be a total of 4 network state realisations for this topology. When information about the network state is provided, a user would have a specific path for each network state realisation. A routing policy is the combination of the state dependent paths. Thus, for this example there would be 16 feasible routing policies as presented in Figure 5.1.

Link states are assumed to be independent in this model. However, correlations between link states are accounted for as routing policies are assigned for all possible combinations of link states that constitute a network state. This exhaustive approach ensures that every scenario is taken into consideration.



Network State	State: Link 1	State: Link 2
NS1	S1	S1
NS2	S1	S2
NS3	S2	S1
NS4	S2	S2

Routing Policy	Selected Path/Link for each Network State			
	NS1	NS2	NS3	NS4
P1	1	1	1	1
P2	1	1	1	2
P3	1	1	2	1
P4	1	1	2	2
P5	1	2	1	1
P6	1	2	1	2
P7	1	2	2	1
P8	1	2	2	2
P9	2	1	1	1
P10	2	1	1	2
P11	2	1	2	1
P12	2	1	2	2
P13	2	2	1	1
P14	2	2	1	2
P15	2	2	2	1
P16	2	2	2	2

Figure 5.1: Determination of Routing Policies for 2 node, 2-link network

5.4.2 Cell Transmission Model

As detailed within Section 5.2.2.4, the CTM provides the ideal platform to dynamically simulate a traffic network to understand the travel behaviour of individual vehicles. Using a traffic simulator based on traffic flow theory, circumvented the need for link cost functions, which have limitations in describing congestion effects. The CTM simulation process applied within this study is described briefly, however, for a thorough understanding of the mechanics of a general CTM model refer to (Daganzo, 1994) and (Daganzo, 1995).

A road network consists of nodes and links, where a link constitutes a road segment and a node is an intersection or source for traffic generation or attraction. The CTM defines links as a series of cells and vehicles are transmitted through the cells from each origin to each destination. In the CTM, a specified discretised time interval is initially assumed to simulate the vehicles.

A road segment or link is divided into cells spatially where the length of the cells (L_i) is determined by the distance travelled by a vehicle travelling at free-flow speed (v_{f_i}) during one time interval (t). Each cell can contain a certain number of vehicles, N_i, which is dependent on the jam density (J_i). The cell can transmit a specific number of vehicles during each time interval, 'Q_i', which is dependent on the capacity of the road segment 'C_i'. These cell property equations are detailed in Equations (5.1), (5.2) and (5.3), where the subscript 'i' refers to either a cell or corresponding road link.

$$L_i = v_{f_i} t \tag{5.1}$$

$$Q_i = C_i t \tag{5.2}$$

$$N_i = L_i J_i \tag{5.3}$$

Vehicles progresses through the network depict the following flow propagation equations, which are discrete approximations to hydrodynamic flow theory;

$$n_i^{t+1} = n_i^t + y_i^t - y_{i+1}^t \tag{5.4}$$

$$y_i^t = min(n_{i-1}^t, Q_i^t, \delta(N_i^t - n_i^t\ )) \tag{5.5}$$

Where;

i = the cell 'i' within a road segment

$i-1$ = the cell upstream of cell 'i'

$i+1$ = the cell downstream of cell 'i'

n_i^t = number of vehicles in cell 'i' during time interval 't'

y_i^t = inflow of vehicles into cell 'i' during time interval 't'

Q_i^t = transmission flow capacity (where the minimum of the current and preceding cell capacities are considered) of cell 'i' during time interval 't'

δ = the ratio of the free flow speed and backward propagation speed, wave speed coefficient

N_i^t = maximum holding capacity of vehicles in cell 'i' during time interval 't'

Equation (5.4) depicts the conservation of flow, where the cell occupancy at time '$(t+1)$' adds the inflow and deducts the outflow at time 't'. Equation (5.5) defines the propagation of flow to the next upstream cell by considering the capacity constraints. Additional assumptions made regarding the simulation of traffic include;

- A first in first out (FIFO) policy was maintained throughout the modelling
- Overtaking was allowed within cells but not between cells. This allowed vehicles to form different queues at divergent cells for different movements, while leaving normal cell-to-cell flow within links unaffected.
- Convergent cells gave priority to vehicles waiting in the preceding cells for the longest amount of time. If vehicles had been waiting an equivalent amount of time, the flow was governed by the vehicle that entered the network first. This assumption considers that in reality, these 'tie' arrival scenarios result in an arbitrary movement of vehicles which are governed by the risk attitudes and driving aggression of the motorists involved in the tie. Thus, the logic applied within the simulation is valid.

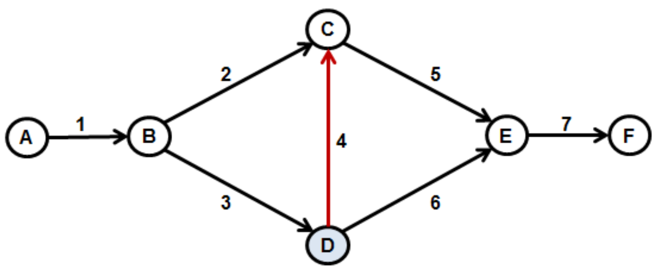
5.4.3 Online Information Provision

Adaptive routing will only occur if online information regarding the performance of the untraversed portion of the feasible paths of the network is provided to the user. It is assumed that for defined 'information source' nodes within the network the performance of the untraversed stochastic links within the network are revealed. Perfect full information of the state of the links and the associated capacities of the stochastic links is provided at the information source nodes. Thus, the location of the information source affects the routing policies available to a user.

Consider the 6 node, 7 link network presented in Figure 5.2 and Figure 5.3. In this network, there are 3 feasible paths which are;

- Path 1: *A-B-C-E-F* (Links: 1-2-5-7)
- Path 2: *A-B-D-C-E-F* (Links 1-3-4-5-7)
- Path 3: *A-B-D-E-F* (Links 1-3-6-7)

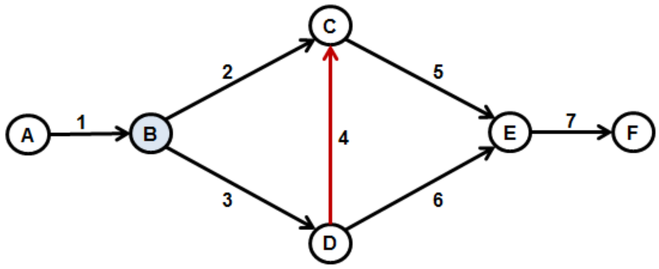
Only link 4 experiences multiple traffic states with a capacity variation as a result of a disruption thus resulting in 2 network traffic states. If node D provides information to a user about link 4, there are 5 possible routing policies available for a user, as shown in Figure 5.2. In this scenario a user who picks Path 1 has no information regarding the state of the network and will pick the path each and every time. Only the users who select link 3 (either Path 2 or Path 3) has the option to adapt.



Routing Policy	Path: Network State 1	Path: Network State 2
P1	Path 1	Path 1
P2	Path 2	Path 2
P3	Path 3	Path 3
P4	Path 3	Path 2
P5	Path 2	Path 3

Figure 5.2: Routing policies when information is provided at node D

Figure 5.3 presents the case where information regarding the state of link 4 is provided at node B. In this case all possible path combinations are feasible as users of Path 1 can adapt because information was provided prior to divergence of Path1 to Path 2 and Path 3.



Routing Policy	Path: Network State 1	Path: Network State 2
P1	Path 1	Path 1
P2	Path 2	Path 2
P3	Path 3	Path 3
P4	Path 1	Path 2
P5	Path 2	Path 1
P6	Path 1	Path 3
P7	Path 3	Path 1
P8	Path 2	Path 3
P9	Path 3	Path 2

Figure 5.3: Routing policies when information is provided at node B

Routing policies are determined based on the location of the information source nodes in the network as well as the degree of information provided by the nodes. Thus, the model offers a great degree of flexibility to assess a number of hypothetical scenarios and can control the dissemination of information.

5.4.4 Determination of DUOR Conditions

An iterative simulation approach was applied to determine the DUOR conditions defined in Section (5.3). Figure 5.4 presents a diagram of the modelling process. Considering a single origin-destination pair with a fixed demand and 'n' network states with a given probability of occurrence, the simulation process begins by initially assigning all the vehicles to any one of the feasible routing policies available for the network. Individual cell transmission models depict each state of the network by applying alterations to the cell capacity and cell propagation capacity. The costs (travel time) experienced by each vehicle for each state are computed with each CTM simulation. These costs were then used in calculating the expected travel cost '$E_j(C)$' for each vehicle 'j', considering all 'n' states of the network, as shown in Equation (5.6).

$$E_j(C) = \sum_{i=1}^{n} P(S_i)\, C_j(S_i) \tag{5.6}$$

Where,

$P(S_i)$ = Probability that state 'i' could occur

$C_j(S_i)$ = Travel cost (travel time) of vehicle 'j' in state 'i'

The permutation of routing policies (set of routing policies selected by all users within the demand) was then tested to see if DUOR conditions are satisfied. This was completed by simulating alternate policies for individual users and checking whether a user is 'unable to switch to an alternative policy to reduce their expected travel cost', if this was the case DUOR was achieved. Iteration of different policy combinations was tested to determine all feasible DUOR solutions for the network.

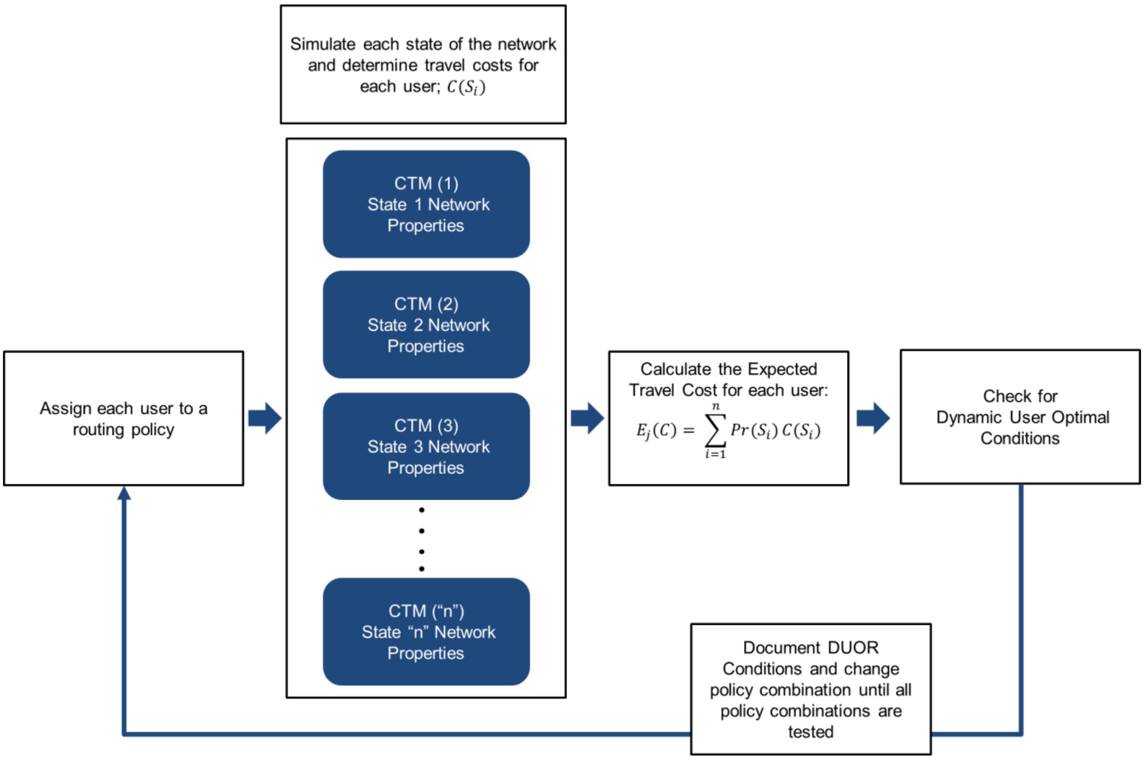


Figure 5.4: Dynamic User Optimal with Recourse Framework (Wijayaratna et al., 2014)

A brute force enumeration algorithm was used to determine DUOR solutions (Wijayaratna et al., 2014) that followed the process described in Figure 5.4. This algorithm considers all possible permutations of route choices users can make and as such results in an incredibly high complexity. The complexity of the algorithm is presented using big O notation where 'v' represents the number of vehicles, 'P' represents the number of policies, 'P_p' represents the number of permutations of policies, and '$f(v, P)$' represents the running time as a function of the number of vehicles and policies:

$$f(v, P) = O(P_p \times v \times P)$$

$$f(v, P) = O(P^v \times v \times P)$$

$$f(v, P) = O(vP^{v+1})$$

$$f(v, P) \approx O(vP^v)$$

It is evident that this approach is computationally inefficient resulting in several days of processing to evaluate demonstration networks under congested conditions. However, it was important to develop an algorithm which provided an exhaustive search as determination of DUOR conditions in a simulation environment was one of the principle aims of the study. The intention was to observe and understand the behaviour of individual vehicles or users within small demonstrative networks and then in the future determine more efficient solution algorithms to apply on realistic networks.

5.5 Application of DUOR-CTM

The DUOR-CTM model was applied on two demonstrative networks; a 4 node, 4 link network (Network A) and a 6 node, 7 link network (Network B). The application was conducted to identify the existence of DUOR conditions and also assess the impact of online information provision. Thus, for each network assessed, 'information' and 'no information' cases were derived. The 'no information' case results in users not being provided information of the prevailing traffic conditions at an information source node. Under these conditions, the adaptive nature of the modelling approach is removed as without information a user would not change paths. Adaptive routing policies are no longer considered and users revert to considering paths.

Performance results are explained using the Expected Total System Travel Time (ETSTT) metric which is the sum of all expected costs of each user within the network, the demand for each routing policy (policy flows) and the associated link flows.

5.5.1 Network A

Network A is a 4 node, 4 link network which contains two paths between origin *A* and destination *D* as presented in Figure 5.5. This network experiences 2 possible network states. Link *2* has the possibility of suffering disrupted conditions, where the capacity of the link halves under state 2 conditions. Accordingly there are 4 possible routing policies available for a user; always use link *2*, always use link *3*; use link *2* in state 1 conditions and link *3* in state 2 conditions and vice-versa (see Table 5.1).

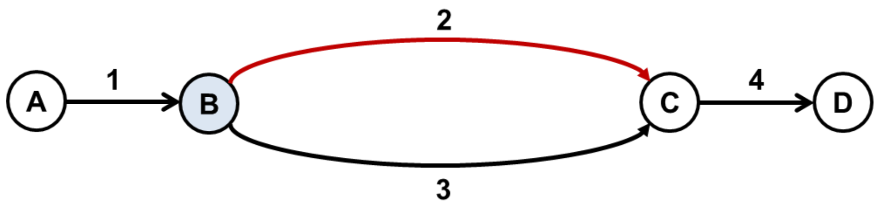


Figure 5.5: Structure of Network A

Table 5.1: Routing policies for traffic conditions assumed in Network A

Routing Policy	Path: Network State 1	Path: Network State 2
P1	1-2-4	1-2-4
P2	1-3-4	1-3-4
P3	1-2-4	1-3-4
P4	1-3-4	1-2-4

Under the 'no information' scenario users would either use Link *2* or Link *3* and would not adapt between network state scenarios thus resulting in the consideration of only P1 and P2. The road infrastructure properties of the network and the associated CTM parameters are presented in Table 5.2 and Table 5.3 respectively.

Table 5.2: Road infrastructure properties of Network A

	Network State 1				Network State 2			
Link	**Length** (km)	**Capacity** (veh/h)	v_f (km/h)	**Jam Density** (veh/km)	**Length** (km)	**Capacity** (veh/h)	v_f (km/h)	**Jam Density** (veh/km)
1	1	3000	50	120	1	3000	50	120
2	2	1200	60	40	2	600	60	20
3	2	1200	60	40	2	1200	60	40
4	1	2400	50	96	1	2400	50	96

Table 5.3: CTM Parameters of Network A

	Network State 1		Network State 2	
Link	**N**	**Q**	**N**	**Q**
1	10	5	10	5
2	4	2	2	1
3	4	2	4	2
4	8	4	8	4

5.5.1.1 Results

The DUOR-CTM model was applied for a variety of demand scenarios ranging from 4 to 12 vehicles considering the 'no information' and 'information' scenarios. Furthermore, sensitivity analysis was conducted regarding the likelihood of disrupted conditions on Link 2 which yields network state 2. Table 5.4 presents the results of the modelling. The most significant observation is the presence of multiple DUOR conditions across all scenarios constructed. In Table 5.4, the 'number of DUOR solutions' refers to the equilibrium conditions which resulted in the corresponding ETSTT value. For this particular network, every DUOR solution obtained across the scenarios tested produced a unique ETSTT confirming DUOR conditions. The results also indicate benefits of online information especially in the congested scenarios of 10 to 12 vehicles.

Table 5.4: Sensitivity Analysis of Network A model results

Demand (vehicles)	Number of DUOUR Solutions	Probability of Network State 2 (Disruption on Link 2) (ETSTT) (s)							
		5%		10%		20%		50%	
		Info.	No Info.	Info.	No Info.	Info.	No Info.	Info.	No Info.
4	24	1062.3	1062.3	1062.6	1062.6	1063.2	1063.2	1065.0	1065.0
5	72	1332.6	1332.6	1333.2	1333.2	1334.4	1334.4	1338.0	1338.0
6	72	1596.9	1597.2	1597.8	1598.4	1599.6	1600.8	1605.0	1608.0
7	288	1867.2	1867.2	1868.4	1868.4	1870.8	1870.8	1878.0	1878.0
8	432	2137.5	2137.8	2139.0	2139.6	2142.0	2143.2	2151.0	2154.0
9	864	2408.1	2408.7	2410.2	2411.4	2414.4	2416.8	2427.0	2430.0
10	1728	2684.4	2684.7	2686.8	2687.4	2691.6	2692.8	2706.0	2709.0
11	5184	2955.0	2955.6	2958.0	2959.2	2964.0	2966.4	2982.0	2985.0
12	5184	3225.6	3226.8	3229.2	3231.6	3236.4	3241.2	3258.0	3264.0

The number of equilibrium solutions increases with the greater levels of demand which is evident with only 24 solutions considering a demand of 4 vehicles and 5184 solutions when considering the more congested conditions of 12 vehicles. The numbers of DUOR conditions increases with greater levels of demand as there are more feasible permutations for greater numbers of vehicles. The number of feasible policies is equal to the number of network states to the power of the demand in the network. For example, the scenario simulating 12 vehicles has 4^{12} = 16,777,216 total policy permutations, and 5184 of these policy permutations resulted in DUOR solutions. In addition, Figure 5.6 presents that the proportion of DUOR solutions relative to the total number of feasible policy permutations decreases with increasing traffic volumes. This suggests that increased congestion levels limit the likelihood of optimal policies being included within an individual's choice set.

Table 5.5 presents a comparison of the policy flow distribution with and without the presence of information.

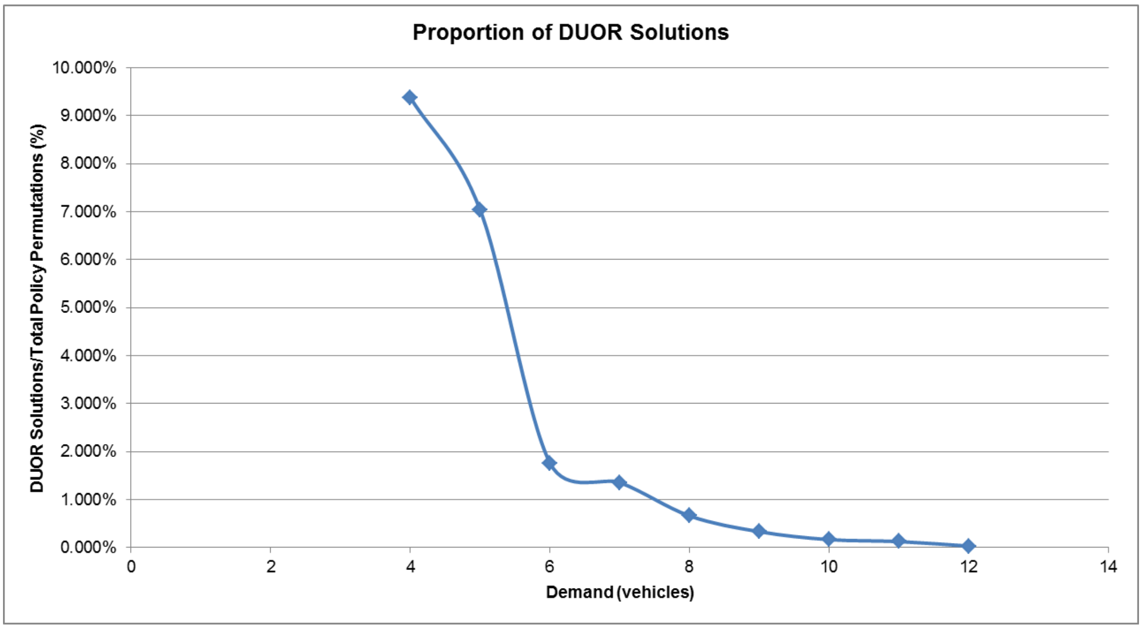


Figure 5.6: Proportion of DUOR solutions relative to total possible policy permutations

The table shows the scenario which had 12 vehicles and a probability of a disruption of 20% on Link 2. The policy flows for the 'no information' case suggest that 8 people choose P1 whilst 4 people choose P2. Whereas when information is incorporated P3 and P4 become more heavily utilised. This indicates that people, when provided with online information, will change route if the state of the network is not favourable which is consistent with the empirical indications of Chapter 2. Another point to note is that there are multiple policy flow patterns resulting in the same ETSTT and thus DUOR solution.

Table 5.5: Policy assignment for a demand of 12 vehicles on Network A (probability of disruption on Link 2 is 20%)

Policy	Number of Vehicles Using Policy					
	With Information					Without Information
P1 (1-2-4/1-2-4)	6	5	4	3	2	8
P2 (1-3-4/1-3-4)	4	3	2	1	0	4
P3 (1-2-4/1-3-4)	2	3	4	5	6	0
P4 (1-3-4/1-2-4)	0	1	2	3	4	0
No. Permutations	**256**	**1280**	**2112**	**1280**	**256**	**2**

Aggregation of the policy flows provides network state based path flows presented in Table 5.6. In the information case, all DUOR policy flow patterns result in the same state based path flows again emphasising that equilibrium conditions have been obtained at a path level. The table highlights the key benefit of adaptive traffic assignment techniques. In the 'no information' scenario path 1-2-4 has a flow of 8 vehicles while path 1-3-4 has a flow of 4 vehicles which is identical to the flow pattern with information in network state 1. However, in the 'information' scenario, under disrupted conditions there is a shift in flow from path 1-2-4 to path 1-3-4 with each path containing 6 vehicles. Thus, by not accounting for adaptive behaviour and the acquisition of online information there is the potential to underestimate flows on path 1-3-4. This example highlights the importance of this form of modelling producing different results which may affect project rankings and infrastructure prioritisation.

Table 5.6: Path assignment for a demand of 12 vehicles on Network A (probability of disruption on Link 2 is 20%)

Path	No Information	With information	
	Expected State	Network State 1	Network State 2
1-2-4	8	8	6
1-3-4	4	4	6

5.5.2 Network B

Network B is a slightly larger network which contains 6 nodes and 7 links. There are three paths between origin A and destination F as presented in Figure 5.7. As with Network A, this network experiences 2 possible network states as only Link 4 experiences a change in capacity between link states. Link 4 has the possibility of suffering disrupted conditions, where the capacity of the link is 600 veh/hr in state 1 and 2400 veh/hr in state 2. Thus, in this scenario, state 1 depicts disruption conditions. Accordingly there are 5 possible routing policies available for a user as presented in Table 5.7.

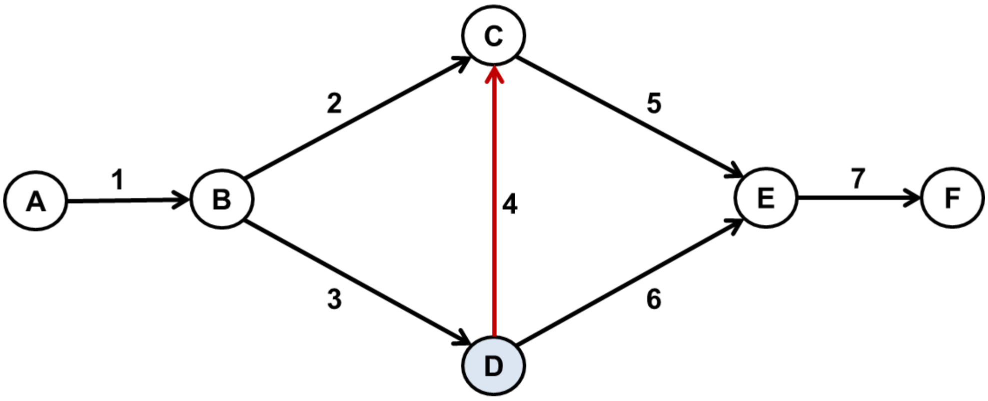


Figure 5.7: Structure of Network B

Table 5.7: Routing policies for traffic conditions assumed in Network B

Routing Policy	Path: Network State 1	Path: Network State 2
P1	1-2-5-7	1-2-5-7
P2	1-3-4-5-7	1-3-4-5-7
P3	1-3-6-7	1-3-6-7
P4	1-3-4-5-7	1-3-6-7
P5	1-3-6-7	1-3-4-5-7

The road infrastructure properties of Network B and the associated CTM parameters are presented in Table 5.8 and Table 5.9 respectively.

Table 5.8: Road infrastructure properties of Network B

	State 1				State 2			
Link	**Length** (km)	**Capacity** (veh/h)	v_f (km/h)	**Jam Density** (veh/km)	**Length** (km)	**Capacity** (veh/h)	v_f (km/h)	**Jam Density** (veh/km)
1	1	3000	50	120	1	3000	50	120
2	3.2	1200	50	40	3.2	1200	50	40
3	2	600	50	20	2	600	50	20
4	1	600	60	20	1	2400	60	60
5	2	600	50	20	2	600	50	20
6	3	1200	50	40	3	1200	50	40
7	1	1200	50	48	1	1200	50	48

Table 5.9: CTM Parameters of Network B

	Network State 1		Network State 2	
Link	**N**	**Q**	**N**	**Q**
1	10	5	10	5
2	3	2	3	2
3	1	1	1	1
4	2	1	6	4
5	1	1	1	1
6	3	2	3	2
7	4	2	4	2

5.5.2.1 Results

Similar to the analysis conducted in Network A, demand values ranging between 4 and 11 vehicles were assessed for Network B, considering a likelihood of a disruption of Link 4 being equal to 20%. In contrast to the 2-link network, the increased complexity of the network resulted in non-unique DUOR solutions and variations in the policy and path flow. The cause of this is most likely due to the definition of user-optimality, where equilibration is dependent on unilateral shifts in policy and not equality in policy costs. Furthermore, the discretised nature of the CTM can create variances in the flows and costs of the system. This highlights a significant drawback of the approach and the current need for an enumerative algorithm to present every possible outcome of DUOR. However, all the DUOR solutions obtained are still informative in describing the potential flows within a network under adaptive and stochastic conditions.

Table 5.10: Performance of Network B, (State 2 probability is 20%)

	Avg. ETSTT (s)	
No. vehicles	With Information	Without Information
4	2040.00	2040.00
5	2576.21	2576.00
6	3106.80	3108.00
7	3653.25	3652.00
8	4191.33	4194.00
9	4754.69	4752.00
10	5299.76	5304.00
11	5874.23	5870.0

Table 5.10 presents the 'Average ETSTT' results of all DUOR solutions for the demands considered. In general information benefits the systems, however for a demand of 5, 7, 9 and 11 vehicles there is an indication that information may be of a detriment to the system. The greatest detrimental difference in ETSTT is for a demand of 11 vehicles and complete results of the ETSTT values and policy flows are presented in Table 5.11 and

Table 5.12

Table 5.11: ETSTT results for Network B, demand set to 11 vehicles

With Information			Without information		
Result	**ETSTT**	**No. of DUOR Solutions**	**Result**	**ETSTT**	**No. of DUOR Solutions**
1	5838.0	24	**1**	5838.0	24
2	5847.6	3	**2**	5886.0	48
3	5876.4	3			
4	5886.0	80			
Avg. ETSTT	**5874.23**		**Avg. ETSTT**	**5870.00**	
Total DUOR Solutions		**110**	**Total DUOR Solutions**		**72**

Table 5.12: Policy assignment results for Network B, demand set to 11 vehicles

	No. Vehicles Using Policy												
Policy	**With Information**									**Without information**			
1-2-5-7/1-2-5-7	4	4	4	4	5	4	5	5	5	4	5	4	5
1-3-4-5-7/1-3-4-5-7	2	3	3	3	2	4	2	2	3	3	2	4	3
1-3-6-7/1-3-6-7	3	3	3	4	4	3	3	3	3	4	4	3	3
1-3-4-5-7/1-3-6-7	1	0	1	0	0	0	0	1	0	0	0	0	0
1-3-6-7/1-3-4-5-7	1	1	0	0	0	0	1	0	0	0	0	0	0
No. Permutations	**2**	**17**	**17**	**24**	**16**	**16**	**1**	**1**	**16**	**24**	**16**	**16**	**16**

The range of ETSTT presented in Table 5.11 suggest a degree of variability, however it is interesting to note that the range of ETSTT is identical for both the 'no information' case and the 'information' case. It is also evident that a DUOR solution could manifest an ETSTT of up to 5886.0 in the 'information' case and similarly the ETSTT in the 'no information' case can be as low as 5838.0 indicating the potential for a paradoxical scenario where online information is a detriment to the system. A possible reason could be as a result of overreaction by users gaining the information. Users arriving at D are informed that the state of Link *4* is good (capacity = 2400 veh/hr) and as a result all users take path *1-3-4-5-7* saturating the path and increasing the costs for the system as a whole. It is possible that without information, users consider their experiential knowledge that a disruption on Link 4 results in considerable delays (associated with the reduction in capacity to 600 veh/hr) resulting in a more even distribution of flow across the paths lowering the ETSTT value. However, given the non-uniqueness observed in the results, future development of the model and further congested scenarios need to be investigated to appropriately identify this phenomenon.

5.6 Discussion, Limitations and Future Extensions

The DUOR-CTM is a foundation model that suffers computational inefficiency as a result of the brute force enumeration necessary to determine DUOR solutions. As a consequence, the application of the model was only feasible for small demonstration networks. However, the results obtained from these demonstrations are profound. Firstly, the DUOR-CTM approach presented DUOR equilibrium solutions indicating the feasibility of the approach. Secondly, in the context of disrupted networks, the model is able to capture the stochastic environment created by a disruption in a time-dependent framework as well as the adaptive behaviour of users in light of a disruption. And finally, the model offers the first simulation based DTA framework to evaluate the impact of online information as presented in the results within Section 5.5. The application of the model provided the following findings;

- Information generally maintains or improves system performance and is consistent with the finding of Gao (2012).
- Multiple unique equilibria in terms of ETSTT were observed for the 2-path network whilst a number of non-unique DUOR solutions were observed for the complicated network.
- The results of the 2-path network suggest that not capturing adaptive behaviour in the presence of online information could potentially result in underestimation of traffic flow on links.

Computational inefficiency was the most significant limitation of the modelling approach. In addition to the networks presented, a variety of other similar demonstrative networks were also tested to determine if shorter run times could be achieved. However, as described in Section 5.4.4, the complexity of the enumerative algorithm results in run times for small networks exceeding 24hrs for moderate demand levels. Thus, congestion effects were minimal limiting the effects of information. In addition, only two network states were assessed throughout the analysis. This was achieved by restricting the impact of disruptions to only a single link within the network and providing only a single source of information. In reality there will be considerably more stochasticity within a network and greater number of locations where users can obtain information which would ultimately add further computation burden.

A heuristic algorithm can be developed to determine the least cost routing policy for each user and avoid the complete enumeration of each policy combination and the subsequent simulation within the CTM framework. For the purposes of the initial development of the model, enumeration was deemed necessary to determine all possible equilibrium solutions and manifestation of DUOR conditions within the traffic simulation environment. The value of the development of a heuristic algorithm is enhanced by the results presented in Figure 5.6. The proportion of DUOR solutions relative to the total policy permutations reduces significantly with increased levels of demand suggesting that convergence to unique solutions may be a distinct possibility for highly congested networks.

An alternative approach that is being investigated is to develop an extension of current adaptive shortest path approaches (or shortest policy approaches). In particular a dynamic version of the Online Shortest Path (OSP) algorithm Waller and Ziliaskopolous (2002) could be formulated for policy enumeration and then incorporated within the CTM framework, circumventing the need for enumeration.

Significant effort should be put in place for the development of the DUOR approach and associated simulation based DTA frameworks as it has a number of practical applications, particularly within disrupted network modelling. Accounting for adaptive time-dependent behaviour in stochastic networks ultimately defines users' reactions in light of a disruption. A user would gain information about the disruption in real time, assess the possible routing options for the remainder of the journey and select the remainder of the path based on this information. This is reflected in simulation models like DUOR-CTM and analytical models such as Gao (2012). A glimpse of the implications for this form of modelling was evident in the results presented within Table 5.6 where not accounting for adaptive behaviour resulted in an underestimation of the flow. These types of performance measure differences can affect project rankings and appraisals of road infrastructure.

Finally, these models provide the most realistic approach to appropriately assess the benefits of online information and overall ATIS infrastructure. If the computational constraints can be overcome, the current DUOR-CTM framework has the adequate flexibility to provide information at different locations on the network and under different levels (partial or full) allowing for the appropriate evaluation of such systems.

5.7 Conclusion

This chapter of the thesis aimed to develop a dynamic model to capture behaviour in light of disruptions on a network. As indicated in Chapter 2 and 4 of the thesis, disrupted conditions lead to a release of information to a user which can result in adaptive routing behaviour. In order to depict this phenomenon the Dynamic User Optimal with Recourse (DUOR) equilibrium theory is presented and an associated simulation based DTA framework, Dynamic User Optimal with Recourse – Cell Transmission Model (DUOR-CTM) is proposed. The model determines a path-based DUOR solution for a single-origin destination pair.

An enumerative approach was developed to evaluate all possible permutations of routing policies and comprehensively assess the presence of DUOR solutions. Application of the model focussed on validating the presence of DUOR solutions and studying the effects of information provision, setting the groundwork for further research in this area.

Demonstration of the model on sample networks indicates that there is the presence of multiple DUOR solutions. The complexity of the network affects the uniqueness of the DUOR solutions, with more complex networks showing a variation in Expected Total System Travel Time (ETSTT) and policy flows across the optimal solutions obtained. In addition, the presence of information was shown to improve the ETSTT especially in conditions with greater levels of congestion within the network. However, there were observations of minor negative impacts with the provision of information for specific network topologies and demand levels highlighting the need for further investigation. Further observations within the results emphasise the need for rigorous planning and assessment when considering the implementation of information systems within road networks.

The computational burden is a drawback of the framework and is currently being addressed through the consideration of heuristic and shortest policy algorithms. Future work will involve development of the DUOR-CTM model to reduce the computational burden, investigation into the presence of non-unique solutions and ultimately the application of this type of model to larger, more realistic networks.

The DUOR-CTM framework provides a better approach to modelling disrupted network conditions. The key contribution of this modelling effort is borne by attempting to combine two complex realisms within traffic in a single simulation model. Though many dynamic approaches have attempted to capture either the dynamic nature of traffic flow or the impact of information provided to users, there have been limited studies which encapsulate the two aspects. Thus, by accounting for both realisms, the DUOR-CTM can lead to more accurate and reliable traffic assignment solutions. The work completed in this chapter provides the foundation for future simulation based dynamic traffic models that account for adaptive behaviour in stochastic environments.

CHAPTER 6. EMPIRICAL INVESTIGATION OF THE PRESENCE OF PARADOXES OF INFORMATION

6.1 Introduction

Alleviating congestion is a major focus for traffic engineers and transport planners. An initial solution to the problem was investment into the construction of transportation infrastructure, to provide increased capacity within the network, providing users' additional routes to travel to their destinations. Braess in 1968 (Braess et al., 2005) presented analytically that construction of an additional link that connects two alternative routes which run parallel with an origin and destination pair, as shown in Figure 6.1, may increase the total travel cost of all users of the network. This result is known as the Braess Paradox and has been shown to be true by Rapoport et al. (2009) and Morgan et al. (2009) using methods of experimental economics in a controlled laboratory setting.. Lately, the existence of the paradox in the field was observed in Seoul, Korea, and in New York, United States of America (Chung et al., 2012). In Seoul, the Namsan #2 Tunnel was closed for 2 years for maintenance and repair work which resulted in an unexpected improvement in traffic conditions. A similar scenario eventuated as a consequence of closing the 42nd Street in New York.

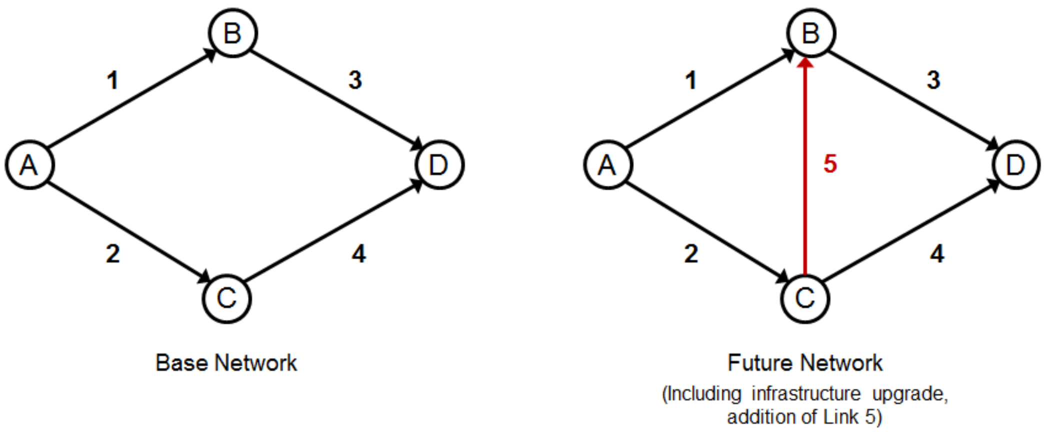


Figure 6.1: Braess Paradox Networks

The emergence of the Braess Paradox and the similar Down-Thomson Paradox (Mogridge, 1987) has forced transport planning to consider additional measures other than increasing capacity to reduce congestion within networks. One approach is to focus on traffic management practices to better utilise the current infrastructure in an attempt to avoid congestion events. As described throughout this thesis, the provision of information to network users through ITS and ATIS systems has been used as a tool to manage the demand of traffic on a network. The intention of these systems is to reduce the uncertainties of travel and as a result improve decision making regarding route choice. For an example, travellers can be informed of disruptions present on the road network, those affected by the disruption may decide to alter their route choice saving time at an individual level and this has the potential to flow onto a positive system wide impact. Chorus et al. (2006) presents a detailed review of a number of analytical and simulation based research efforts that have investigated the impact of information on congested networks which support the notion that information provision improves performance. However, there have been a few studies that have suggested the provision of incomplete or imperfect information regarding route capacities and travel times can lead to a deterioration of performance (Arnott et al., 1991, Mahmassani and Jayakrishnan, 1991, Rapoport et al., 2014, Hall, 1996).

It is clear that the implementation of these systems affects the behaviour and travel patterns of users on the network. Accordingly, it is essential for transportation planning models to account for these behavioural implications and this has been a recently researched topic in both static and dynamic contexts (Gao, 2012, Gao and Chabini, 2006, Henn and Ottomanelli, 2006, Koutsopoulos et al., 1994, Unnikrishnan and Waller, 2009). User Equilibrium with Recourse (UER) (Unnikrishnan and Waller, 2009), which was presented in detail within Chapter 4 of the thesis, is a static equilibrium model that incorporated the impact of online information acquisition on the assignment of traffic. The paper also presents the analytical existence of a 'Braess Paradox' of Information where the provision of information increases the total system travel costs which is a detriment to the viability of the information system. Further to this, the DUOR model presented in Chapter 5 suggests the possible emergence of a similar paradox again emphasising the potential downside of information systems. The static UER paradox has only been presented theoretically and it is essential to investigate the phenomenon further in a physical setting. The presence of the paradox in a real world setting will force transport planners and engineers to further evaluate the implementation of information systems within transportation networks, highlighting the importance of the research.

Accordingly, the focus of this Chapter of the thesis is the investigation into the 'Braess Paradox' of Information presented in the UER framework, using concepts of experimental economics. In order to remove confusion with the traditional 'Braess Paradox', the paradox observed within the UER framework will be defined as the 'Online Information Paradox' for the remainder of the thesis. The paradox was investigated using a controlled and incentivised laboratory experiment involving a computerised route choice game. The game was designed to understand the route choice behaviour of participants under two information regimes:

- A treatment where participants had no access to online information termed as the 'no information' case
- A treatment where participants had access to full perfect online information, termed as the 'information' case.

Empirical data related to path utilisation and total system travel costs were extracted from the experiment to compare with theoretical equilibrium solutions and also identify the presence of the paradox in a physical setting. In addition the impact of learning and the impact of prevailing traffic conditions was also analysed at an aggregate level.

The remainder of the Chapter is structured as follows:

- Section 6.2 presents the background of this component of the research, discussing the application of Experimental Economics in the study of traffic paradoxes and other similar empirical investigations into online information impacts.
- Section 6.3 describes the theoretical evolution of the 'Online Information Paradox'
- Section 6.4 explains the experimental design, recruitment of participants and the overall procedure of the experiment.
- Section 6.5 presents the observations from the experiment and the comparison of the empirical results with the defined theory.
- Section 6.6 and Section 6.7 conclude by presenting a discussion of the limitations and scope of the study and highlighting the key findings.

6.2 Literature Review

The background to this component of the research is similar to that of Chapter 3. The aim here, as with Chapter 3, is to further investigate the impact of information on driving behaviour and route choice. However, unlike the previous experiment, this part of the research also investigates the network wide implications resulting from the observed behaviour. Again it is important to highlight that Ben-Elia and Avineri (2015) have provided the latest review of behavioural research associated with travel information. The comprehensive documentation of research conducted across the last decade indicate that information has the ability to assist individuals in coping with uncertainty but the benefits on a network wide scope are debatable. This empirical study adds to the growing body of literature assessing the merits of information systems from a road network performance perspective.

Ben-Elia and Avineri (2015) categorised information sources as experiential, descriptive, and prescriptive and relate the studies based on the categorisation. In this particular study, experiential and descriptive information was considered at an aggregate level as the route choice game involved online information that detailed travel cost for the participant (descriptive) and the game was repeated for 20 periods (experiential). In general, studies have found that information results in benefits for a system, however, as mentioned before, researchers have proposed potential adverse effects that can be a result of information provision (Ben-Akiva et al., 1991, Mahmassani and Jayakrishnan, 1991, Uang and Hwang, 2003, Galizio et al., 1979, Ben-Elia and Avineri, 2015);

- Oversaturation: The volume of information exceeds the cognitive capabilities of the individual user and as such results in decision making that does not correlate with the information provided
- Concentration and Overreaction: All travellers acquire the information and make identical decisions, thus moving congestion from one location of the network to another. This can result in an overreaction to the conditions.

Outside of these hypotheses, there have been limited studies that have investigated the provision of information and the impact on network performance. The studies conducted up to now are either experiment based or field observations. This particular study relates to the empirical observance of an analytical paradox. Thus, the remainder of the literature review will focus on studies conducted in the experimental economics domain related to information dissemination and traffic paradoxes in addition to a discussion of the traffic assignment method that underpins the Online Information Paradox.

6.2.1 Application of Experimental Economics: Study of paradoxes and Online Information

The use of experimental economics in the field of transportation has become more prevalent in recent times and is highlighted in Section 3.2.4 of the thesis. Laboratory experiments have been used to study driving behaviour as well as some specific equilibrium models and paradoxes. Since some applications of experimental economics have already been detailed, this section will focus exclusively on studies regarding paradoxes and online information acquisition. As mentioned in Chapter 3, a complete review of the application of experimental economics within the field of transportation is described in Dixit et al. (2015) highlighting the strengths and weaknesses of the approach as well as reviewing a number of applications. The article suggests that some of the evidence for traffic paradoxes presented in the past can be attributed to experimental artefacts, thus care was taken in the design of this experiment in an attempt to avoid these pitfalls.

During the past decade there has been a number controlled laboratory experiments conducted on the traditional Braess Paradox (Meinhold and Pickhardt, 2009, Rapoport et al., 2008, Rapoport et al., 2009, Rapoport et al., 2006) and the Downs Thomson paradox (Morgan et al., 2009). Rapoport et al. has presented work between 2005 and 2009 discussing the results of experiments carried out regarding the Braess Paradox. These studies simulate simple traffic networks that are susceptible to the Braess Paradox within a controlled laboratory environment (Rapoport et al., 2009). Participants were recruited to take part in an incentivised computerised route choice game where they were exposed to a base network as well as a network with an additional link, as presented in Figure 6.1, to understand the variation in behaviour presented in the Braess Paradox. The participants were informed of the cost functions used within the network and then asked to select routes, following each round of route selection participants were provided with information about their route choice, their travel cost (which impacted the payoff at the end of the experiment) and the routes the other participants selected. This game was repeated for each network multiple times to understand whether replicable patterns of behaviour emerge (Rapoport et al., 2009). By repeating the game, participants gained experience allowing the study to observe convergence in behaviour that either supported or did not support evidence of the paradox.

Rapoport et al. (2006) studied the Braess Paradox with varying demand or participant levels. The results were consistent with theory, at low levels of demand the additional link reduced travel costs and improved the traffic scenario, but with increasing demand there was an increase in travel costs and depreciation of the network conditions relative to the base scenario. Rapoport et al. (2009) again confirmed the presence of the Braess paradox with an increased number of participants and suggested that with learning and experience the paradox is further exacerbated. This set of studies by Rapoport and others provided the foundation for the investigation into the Online Information Paradox.

The most relevant studies which must be acknowledged are the investigations related to real-time online information acquisition by Lu et al. (2012) and a follow up study by the same team Lu et al. (2014). Similar to this study, Lu et al. (2012) conducted an experiment where participants faced a 3 route network and with the possibility of an incident occurring on one of the routes. As with this study, treatments 'with' and 'without' descriptive online information provided at a downstream node were assessed to understand the impact of information. In addition, the study also investigated the impact of providing information about past performance of the entire network (all paths on the network), 'the foregone payoff' which is provided in this experiment. The findings of the study show that information reduces the overall network travel time and increases the travel time reliability. However, an interesting result from Lu et al. (2012)is that the benefits of the provision of information depreciate as details of the foregone alternative are provided to the participants. The follow up study conducted in 2014 by Lu et al. considered a greater sample size and also considered the case of providing feedback on subsequent rounds regarding the chosen alternative. Similar positive results, regarding the provision of information, were observed in the follow up study. Another notable finding was observed where 90% of the participants chose to travel on the paths that would provide them information about the conditions of the network. This suggests that the concentration and overreaction phenomena are possible leading to a deterioration of travel conditions. It is clear that travellers desire information within a road network, providing impetus for the investigation of the theoretical online information paradox. In addition to studying a specific paradox where information deteriorates the travel costs within a network, there are notable differences in the experimental methodology between this study and the studies conducted by Lu et al. (2012) and Lu et al. (2014). The primary difference is that the previous studies used a fixed incentivisation scheme while performance based incentivisation, abiding by the principles of experimental economics, was used in this study. Overall, these reviewed studies provided incredible foresight into the application of online information based experiments such as the one presented in this current research.

More recently, there have been two experiments that have specifically investigated the impact of pre-trip information on route choice that have also highlighted paradoxical scenarios (Raporport et al, 2014; Knorr et al, 2014). Both these studies investigate decisions utilising networks with two alternative congestible routes which vary unpredictably. Knorr et al, 2014 discusses the role of pre-trip information as well as the learning effect when selecting between a tolled route and an un-tolled route. The study details the results of three laboratory experiments where participants received either 'no information', 'perfect information', or 'partial information' regarding the prevailing traffic conditions prior to making a series of repeated route choice decisions. By structuring the experiments in this format, the authors were able to observe learning behaviour in addition to the impact of varying degrees of information. Another objective was to compare the route choice pattern with the traditional User Equilibrium (Wardrop, 1952).

A stable distribution of participants between the competing routes was not observed across the 50 repeated rounds of the game and as such the study deemed it unlikely that a Wardropian User Equilibrium solution exists. Learning was observed across the 50 rounds of each of the experiments where participants gradually improved their decision making and reduced their travel costs. And the final key finding is that the provision of information to the entirety of the demand does not yield significant benefits to any individual traveller. This study provided some insightful contributions regarding the role of information and learning behaviour. However, in contrast to the experiment presented in this chapter, the study did not focus on any paradoxical scenarios.

Rapaport et al, 2014 presents an experiment designed to examine a model presented by Lindsey et al. (2014). The analytical model proposed by (Lindsey et al., 2014) is based on the classical 'two-route network' model (Knight, 1924, Pigou, 1920). The paper revealed analytically '*if free-flow costs on the two routes are unequal, travel cost functions are convex, and capacities are positively and perfectly correlated, then in equilibrium, paradoxically, total expected travel costs increase with the provision of pre-trip information about travel conditions on each route*' (Rapoport et al, 2014). The experiment tests the model predictions in a controlled laboratory setting using the concepts of experimental economics where participants were financially incentivised. Participants undertook a route choice task under two separate treatments, one without the provision of information and another with the provision of pre-trip information regarding the travel conditions of each of the routes. Travel conditions were defined in terms of quadratic convex cost functions dependent on the utilisation of each route. Each route had two cost functions, depicting 'good' and 'bad' conditions. Participants were provided the qualitative description of traffic conditions, as a source of information, prior to each round of the 'with information' treatment. The findings of the study were consistent with the paradoxical findings of theoretical model presented by Lindsey et al. (2014) suggesting that information is detrimental when conditions on both routes are perfectly correlated whilst information is beneficial when conditions are uncorrelated.

These recent studies have been significant contributions to the adoption of experimental economics into the investigation of route choice behaviour in light of pre-trip information. The work by Rapoport et al. (2014) also adds to growing body of empirical research confirming traffic congestion paradoxes. However, this part of the research project focusses on the role of online information rather than pre-trip information whilst also attempting to identify the empirical presence of an Online Information Paradox, thus adding to the body of literature.

6.2.2 Theory of User Equilibrium with Recourse

The User Equilibrium with Recourse model has been described in detail across Chapter 4 and Chapter 5 and is again presented in brief within this section of the thesis to refresh the reader of its core principles and relate to the presentation of the Online Information Paradox.

UER is a static equilibrium model that accounts for one-step local information and user recourse on account of gaining that information (Unnikrishnan and Waller, 2009). An important assumption within this framework is that link cost functional forms are known although the link capacities are uncertain prior to departure. Only upon reaching an upstream node within a network does a user begin to gain information about the capacity state of the following link. Thus, in a UER scenario, each link on the network could possess multiple states with a certain probability of occurrence. Depending on the state of the link, a user would choose the next link to travel on to reach their destination. To account for users' response to network conditions, UER considers a selection of possible paths known as routing policies instead of the least cost path. Information provided mid-path (for example, due to the presence of ITS technology such as a VMS board) regarding the state of the link only affects the class of users that will change their path *en route*. A network considering user recourse is in equilibrium when *'the expected cost of all used routing policies is minimum and equal and no user can unilaterally change their routing policies to improve the expected cost'*. The 2009 study by Unnikrishnan and Waller presents a demonstration of the user recourse equilibrium, considering a set of specific link costs and states, which suggests that the provision of information can result in a flow pattern that deteriorates the travel costs of each user and subsequently for the system as a whole. This paradoxical phenomenon was discussed in Section 3.4, 'Braess Paradox: Model A' within the Unnikrishnan and Waller (2009) User Equilibrium with Recourse paper and a similar example is presented in detail in the following section.

6.3 Online Information Paradox

An example of the 'Online Information Paradox' is discussed in detail within this section. Figure 6.2 and Table 6.1 presents the network, link states and the associated link costs considered. The network services 12 units of demand travelling between the origin node A and the destination node D. Users travel along one way links with the possibility of using three competing routes, A-B-D, A-C-B-D and A-C-D. If a user travels on link A-B, there is no option to alter the route in reaching the destination D. However, if a user selects link A-C there is the possibility of using either link C-B and B-D to reach D or use the direct link from C-D. Thus, the people initially selecting link A-C can adapt their route depending on the prevailing traffic conditions of link C-B or link C-D if they are provided information prior to travelling on these links. Unlike the Braess Paradox it is important to note that there is not an upgrade in road infrastructure resulting in the creation of alternative routes, there is only the provision of information at a point between the origin and destination, in this case information is provided at node C. The paradox compares the results of the User Equilibrium with Recourse traffic assignment model with and without the presence of perfect information. The information provided at node C is related to the state of link C-B, where 20% of the time the cost of using link C-B is equal to 20 units and the remaining 80% of the time the cost of using link C-B is equal to 1 unit. All other links within the network have a single state with no variation in cost functions as presented in Figure 6.2 and Table 6.1.

Table 6.1: Summarised Network Properties

Link	Link No.	State	Probability	Cost Function
(A-B)	1	1	1	10
(A-C)	2	1	1	x_{A-C}
(B-D)	4	1	1	x_{B-D}
(C-B)	3	1	0.2	20
(C-B)	3	2	0.8	1
(C-D)	1	1	1	10

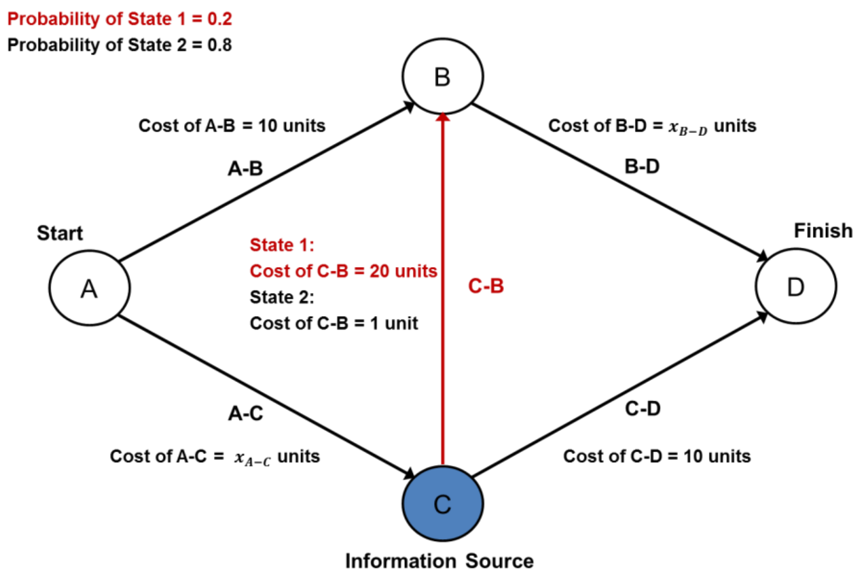


Figure 6.2: Online Information Paradox Network: Link States and respective cost functions

This scenario is analogous to road *C-B* experiencing a disruption such as an accident or breakdown during State 1 which results in the closure of lanes and the increase of travel cost for all users. It is acknowledged that using a combination of linear functions and constant values for the cost of links is a significant simplification of the traditional non-linear convex cost functions, such as the Bureau of Public Roads cost function, used throughout network modelling applications. There are two primary reasons for the simplification of the link costs within this example. Firstly, simplification allows for a tractable analytical solution which can be calculated easily in addition to enhancing the understanding of the paradox for a reader who is not familiar with concepts of equilibrium modelling. Secondly, it was essential to derive an example that could be used for the behavioural experiment which could be understood by the participants in a short period of time. By using linear functions and constant values, the participants effectively received information about the travel costs, which in reality they would receive through travel time indicators from on-board navigation systems or Variable Message Sign (VMS) travel time indicators.

Even though the representation of the link costs strays from the traditional approach, there is a degree of realism in the simplified costs assumed. The justification for each of the link costs are as follows:

- Link *A*-*B*, Link *C*-*D*: ***(Cost = 10)***
    - These links experience no congestion and have a free flow travel cost of 10 units. This can reflect the scenario where a multi-lane roadway has been constructed in the expectation of future increases in demand. Currently these links have an excess in capacity and as such allow for free flow travel in all traffic scenarios.
- Link *A*-*C*, Link *B*-*D*: ***(Cost =*** x_n ***, where n = A-C, B-D)***
    - These links experience congestion and the cost is linearly dependent on the number of users travelling on the roadway. Each traveller contributes to a single unit increase in the travel cost of the link. The cost ranges from 0 units (if not traversed on) to 12 units (if the entire demand were to use either of the links)
- Link *C*-*B*: ***(Cost = 20 (State 1), Cost = 1 (State 2))***
    - The cost of link *C*-*B* varies from one constant value to another depending on the state of the network. Considering 'State 1' conditions, the cost of the link is 20 units, relatively high compared to all other links of the network. State 1 depicts a situation where *C*-*B* experiences a disruption resulting in the closure of lanes and the restriction of speed which results in a significant increase in travel time. Regardless of the demand using this link, under these disrupted conditions all users face a travel time of 20 units due to the speed reduction. In contrast, during 'State 2' conditions, the cost of the link is 1 unit, which is low relative to all other links. Thus, in this case the link represents a high speed freeway that exhibits free flow conditions.

6.3.1 Theoretical Equilibrium Conditions

Developing robust and consistent traffic assignment models has been a key objective of traffic engineers and transport planners since the 1960s. A number of equilibrium models have been proposed to capture the routing and mode choice behaviour of users on transport networks. A few of the well-known equilibrium models are the User Equilibrium model (Wardrop, 1952), the Stochastic User Equilibrium Model (Daganzo and Sheffi, 1977) and the Mixed Strategy Nash Equilibrium Model (Bell, 2000). However neither of these static analytical models account for the acquisition of online information which can result in adaptive user behaviour, which led to the development of adaptive static models such as the UER model presented by Unnikrishnan and Waller (2009). The following theoretical equilibrium conditions have been calculated to compare with the results of the experiment;

- User Equilibrium (UE);
- Expected User Equilibrium (EUE);
- User Equilibrium with Recourse (UER);

Each of these equilibrium conditions contains a series of underlying assumptions and is discussed in detail within the following sub-sections.

6.3.1.1 User Equilibrium (UE);

UE defines a traffic network to be in equilibrium when, '*the journey times in all routes actually used are equal and less than those which would be experienced by a single vehicle on any unused route*' (Wardrop, 1952). The assumptions of the UE model do not cater for multiple traffic states of links or the network as a whole. Thus, to appropriately assess UE equilibrium conditions, scenario analysis considering all different combinations of link state realisations, needs to be conducted. In this example only link *C-B* experiences multiple states resulting in two scenarios. The UE equilibrium conditions for the example discussed earlier in Section 3 are presented in Table 6.2.

Table 6.2: User Equilibrium (UE) Traffic Conditions

State 1 UE Conditions: **(Cost of C-B = 20 units)**			State 2 UE Conditions **(Cost of C-B = 1 unit)**		
Path	**Flow**	**Path Cost**	**Path**	**Flow**	**Path Cost**
ABD	6	16	**ABD**	3	19
ACBD	0	32	**ACBD**	6	19
ACD	6	16	**ACD**	3	19
Total System Travel Cost (TSTC)		**192**	**Total System Travel Cost (TSTC)**		**228**

The behavioural understanding that underpins this approach considers that users experience both states of the network across an extended duration of repeated travel between the origin and destination. Based on the experiences gained and perfect *a-priori* knowledge of the link states and the costs of the links associated with the states, each user selects the path that will minimise their total travel time for each given state. This equilibrium solution does not capture the uncertainty or likelihood of the occurrence of each link or network state and assumes that people are aware of the traffic conditions prior to making a path choice. These assumptions are rather unrealistic; especially in the context of information provision as this form of knowledge obtained by a user would mean that ATIS systems were redundant. The presentation of this equilibrium solution serves as a comparison to the other equilibrium solutions and also to determine if at an aggregate level users approach this type of behaviour over repeated identical travel decisions.

6.3.1.2 Expected User Equilibrium (EUE);

The EUE approach is similar to UE as it considers the minimisation of all utilised path travel costs. However, instead of considering separate scenarios, EUE considers the expectation of link costs to account for all possible link states. This model assumes that users experience different states of the network, however instead of having perfect knowledge of the realisation of each state, they develop an understanding of the average travel conditions. In relation to the assessment of the Online Information Paradox this model serves as a representation of the case of 'no online information provision'. In other words, when information is not provided, it is assumed that users consider the expected cost of travelling on each link of the network prior to selecting the route and departing from the origin. The lack of information results in non-adaptive behaviour. Considering this example, travellers on link A-C are not aware of the traffic conditions of either link C-D or link C-B and accordingly considered expectations of the costs to determine the minimum cost path. Thus, under the 'no information' case, the EUE solution decomposes to the UE solution assuming expected link costs and is shown in Table 6.3.

Table 6.3: Expected User Equilibrium (EUE) Traffic Conditions

EUE Conditions		
Path	**Flow**	**Path Cost**
ABD	6	16
ACBD	0	16.8
ACD	6	16
Total System Travel Cost (TSTC)		**192**

For the assumed 12 units of demand, the expected cost of using link C-B is 4.8 units (0.2×20+0.8×1) and the expected costs of all other links would be the costs presented in Figure 6.2 as costs are identical across both link states. It is clear that utilisation of link C-B will be undesirable as users will have to bare not only the cost of C-B but also the cost of B-D, which is dependent on the number of travellers using path A-B-D as well as path A-C-B-D. Solving for user equilibrium with expected link costs yield the following solution; 6 units would use route A-B-D and the remaining 6 units would use A-C-D. The cost for each individual is 16 units whilst travelling on either route and the total system travel cost is 16×12 = 192.

6.3.1.3 User Equilibrium with Recourse (UER)

In order to determine the equilibrium solution for the 'information' case, the UER solution is calculated (Unnikrishnan and Waller, 2009). As mentioned earlier, this equilibrium model caters for the adaptive behaviour of travellers in light of information and as such individuals consider traffic state dependent routing policies rather than paths when traversing the network. The five routing policies which an individual would consider in this example are presented in Table 6.4. To clarify the meaning of a 'routing policy', specific examples from Table 6.4 can be explained. If a user selects P1, the path A-B-D will be used regardless of the state of the network. Alternatively, if a user selects P5, path A-C-D is used if Link C-B is experiencing State 1 conditions and path A-C-B-D is used if Link C-B is experiencing State 2 conditions, where the conditions of the link are revealed at node C.

Table 6.4: Route policies for users within the example network

Policies	State 1	State 2
P1	A-B-D	A-B-D
P2	A-C-B-D	A-C-B-D
P3	A-C-B-D	A-C-D
P4	A-C-D	A-C-D
P5	A-C-D	A-C-B-D

The core assumption of this traffic assignment technique is that all users arriving at an upstream node observe the same link states for all outbound links. The state of each link is static throughout the assessment, for the entirety of the demand traversing the network. This assumption is identical to 'Model A' presented within Unnikrishnan and Waller (2009). The scenario can be compared to an incident disrupting traffic for a period of time or the presence of sustained peak period congestion in only a portion or segment of a network.

Table 6.5: User Equilibrium with Recourse (UER) Traffic Conditions

UER Conditions									
Policy Statistics					**Path Statistics**				
Policies	**State 1**	**State 2**	**Policy Flow**	**Policy Cost**	**Path**	**State 1 Flow**	**State 1 Cost**	**State 2 Flow**	**State 2 Cost**
P1	A-B-D	A-B-D	4	18	**A-B-D**	4	14	4	19
P2	A-C-B-D	A-C-B-D	0	20.8	**A-C-B-D**	0	32	5	18
P3	A-C-B-D	A-C-D	0	20.8	**A-C-D**	8	18	3	18
P4	A-C-D	A-C-D	3	18					
P5	A-C-D	A-C-B-D	5	18					
Total System Travel Cost (TSTC)			**216**						

The UER solutions calculated for this example indicate that 4 units of demand select *P1*, 3 units select *P4* and 5 units select *P5*. This means that the expected cost for each individual considering any of the selected routing policies is 18 units and the total system cost is 516 as shown in Table 6.5.

Comparing the 'no information' case (Table 6.3) with the 'information' case (Table 6.5), it is clear that individual travel costs and system performance depreciates in light of information. The provision of information has increased the individual (from 16 to 18) and total system travel cost (from 192 to 216) of travel highlighting the caution required when implementing information systems within transportation networks. As expected when information is not provided, users lack the opportunity to adapt as an alteration in route choice is uninformed and as such path utilisation remains static across the different link states experienced. Users do not consider separate states but take the expectation over all the possible states when assessing link costs. In the case where information acquisition is possible, path flow changes dramatically. If link *C-B* is experiencing State 1 conditions, none of the demand utilised path *A-C-B-D* whilst in State 2 conditions a majority of the demand (5 units of demand) used path *A-C-B-D*. This example will serve as the foundation for the design of the experiment.

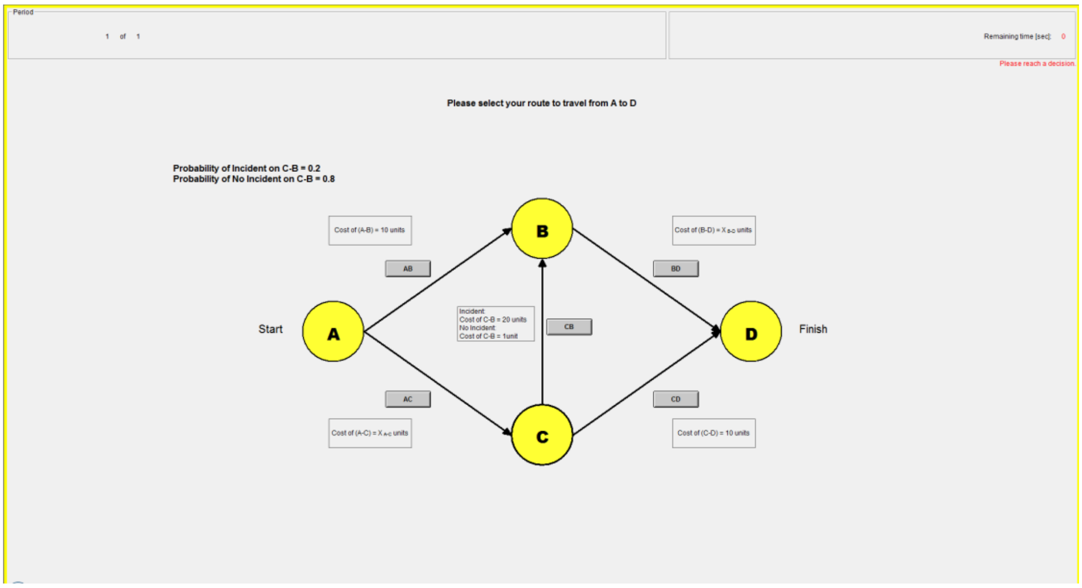
6.4 Experiment Design

6.4.1 Tasks

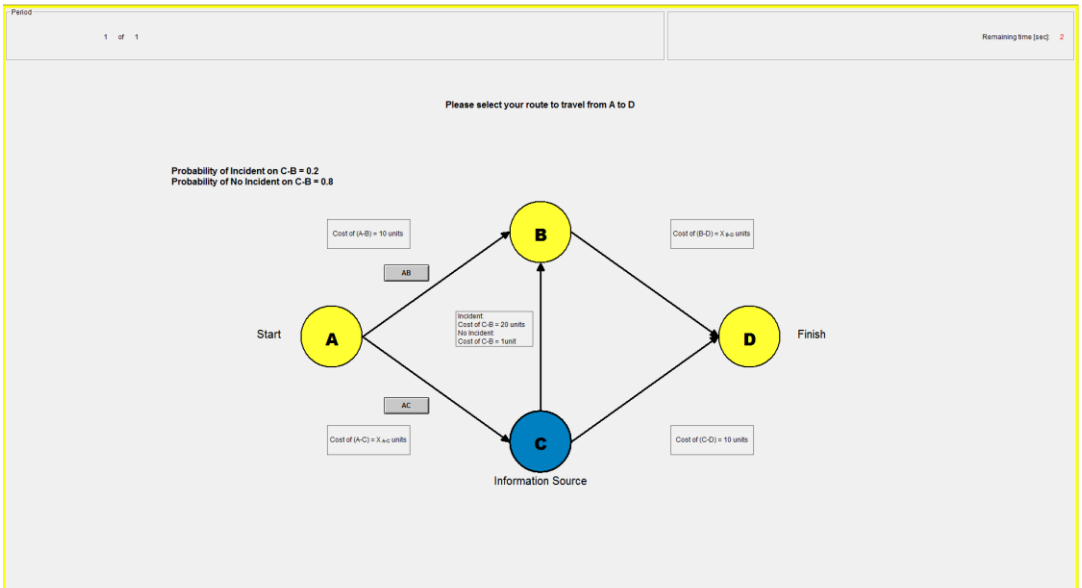
A computerised route choice game was formulated to study the empirical presence of the Online Information Paradox and served as the core element of the experiment. The papers by Rapoport et al. 2014 and Knorr et al 2014 provided guidance in determining the procedure and structure for the experiment. The experiment was programmed and conducted using software specifically designed for the application of economic experiments, zTree (Fischbacher, 2007). The computerised route-choice game replicated the network properties and demand conditions described in Section 6.3.1. Groups of 12 participants, where each participant represented a unit of demand, played the role of motorists who repeatedly had to travel between a specified origin and destination. As presented in the example, the participants had a choice of 3 routes, A-B-D, A-C-B-D and A-C-D. At the completion of each decision period, the traffic conditions experienced by all participants were revealed to each participant prior to making the next routing decision. The state of the link C-B was determined randomly through z-Tree but satisfied the likelihood of occurrence of 20% for State 1 and 80% for State 2, this means that each group faced State 1 conditions in 4 out of the 20 periods for each treatment. The purpose of divulging personal and network performance of each journey was to capture any learning effects across both information regimes. Even though there is a unique equilibrium solution for both, the no information (expected user equilibrium) and full information (user recourse equilibrium) scenarios, there are numerous ways the participants can arrange themselves to achieve the equilibrium solution. Take for example the no information case; the user equilibrium solution indicates that route A-B-D and route A-C-D will contain 6 units of demand each. The participants have 924 (C(12,6)) different combinations of achieving this flow pattern with only the history of the previous periods performance and without any communication with other participants indicating a very complex coordination problem (Rapoport et al., 2014, Rapoport et al., 2009, Selten et al., 2007). Based on the difficulty of the task, humans achieving equilibrium flow patterns on average is a significant observation. In order to investigate the presence of the Online Information Paradox, two treatments were carried out;

- ***Treatment 1***: No Information provision
- ***Treatment 2***: Information provided at Node C regarding the prevailing traffic conditions on link C-B

Participants were provided a network that was similar to that presented within Figure 6.2. The only difference being that instead of referring to the traffic state of link C-B as 'State 1' and 'State 2', the route selection was placed in the context of an incident occurring on link C-B. State 1 referred to 'Incident' conditions on link C-B and State 2 referred to 'No Incident' conditions. This contextualisation was undertaken to place participants in a realistic driving scenario that they may face on their daily commutes. The z-Tree representation of the network used across both treatments during the experiment is shown in Figure 6.3. The method in which participants selected a route varied based on the treatment. Treatment 1, involved no provision of information, this meant that each participant selected the entirety of the route from origin A to D. Treatment 2 included the provision of information at node C, as a result participants performed the route selection in a staged manner on a link by link basis. A participant who selects link A-B has no alternatives other than to complete the journey to D by selecting B-D. However, a participant who selects A-C can acquire information at node C and then make the decision to proceed along C-B and B-D or directly travel to D using C-D. Figure 6.3(b) clearly displays the difference to a participant with information node C coloured in blue instead of yellow and the presence of buttons related to the active stage of the game (in this case the first stage of selecting A-B or A-C) rather than the entirety of the route.



(a) No Information Scenario



(b) Information Scenario

Figure 6.3: z-Tree Network Representations presented to participants

In addition, participants completed a multiple price lottery (MPL) task to gain information about their risk attitudes prior to completing the computerised route choice tasks (Holt and Laury, 2002, Charness et al., 2013). The MPL task was similar to what was presented in Chapter 3. In this experiment, the MPL lotteries contained a series (10 in this experiment) of paired lottery choices, one being at a greater risk than the other. The low risk lottery consisted of a payoff of either AUD$5.00 or AUD$4.00 whilst the high risk lottery consisted of a payoff of either AUD$9.75 or AUD$0.25. The payoffs for each paired lottery remained the same for the series whilst the probability associated with each of the payoffs changed, in this case by increment of 10% across all 10 lotteries. A participant had to select which lottery he or she would prefer to play for each pair across the series of lotteries. As explained before, the concept behind the MPL lottery is that a participant would select the low risk lottery until the high risk lottery provides a greater probability of the more favourable payoffs and when this occurs the participant would cross over to the high risk lottery. An individual's risk preference can be measured by assessing when each participant would make this switch from the low risk lottery to the high risk lottery (Charness et al., 2013). After completing the primary tasks, the participants were asked to fill out a short 10 minute demographic questionnaire. These activities were included to understand the characteristics of the participants when analysing the results of the experiment.

Appropriate monetary incentivisation to ensure participants' decisions had realistic consequences is a key aspect of experimental economics. Incentivisation in this experiment involved a static participation fee of AUD$5 and performance based rewards related to the multiple price lottery and each of the computerised route choice tasks. The payoff for the risk assessment task was paid by randomly selecting a paired lottery out of the series of 10 and determining the outcome of the lottery, a participant could receive anywhere between AUD$0.25 and AUS$9.75. In terms of the route choice tasks, each participant received an income of 45 units for each period of both tasks. The payoff for a round was calculated by deducting the travel cost experienced by each participant from the initial income. At the end of both treatments, a random period from each task was selected and the payoff associated with that round was paid to each participant, where every unit equalled AUD$0.25. On average, a participant was able to earn approximately AUD$25 across the session.

The route choice tasks involved repeated decision making that can give rise to participant fatigue affecting decision making and ultimately the results of the experiment. Accordingly a pilot test was conducted to assess the number of feasible periods that could be played by a participant. A group of 12 colleagues from the Research Centre for Integrated Transport Innovation at UNSW participated in the pilot study and were asked to provide feedback on the length of the experiment and comment on how many periods should be put in place. The pilot test was conducted over a 2hr period, where 20 periods of each task were completed. The participants revealed that this length of time and number of periods neared the limits of their cognitive capabilities and that anymore periods would be strenuous for participants. It is acknowledged that the number of periods used for this experiment is significantly lower than that conducted recently by Knorr et al. (2014) and Rapoport et al. (2014), which used 50 rounds per treatment and 80 rounds per treatment respectively. However, these experiments involved a decision between 2 routes reducing the cognitive load on the participants. Furthermore, the information based task involved staged decision making based on the acquisition of online information which increased the time taken to complete each round. Based on these key differences, and the findings of the pilot test it was decided to undertake 20 periods of each treatment to minimise the impact of mental fatigue.

6.4.2 Recruitment Process

As with the experiment completed in Chapter 3, participants were recruited using the Australian School of Business (ASB) Experimental Research Laboratory at the University of New South Wales. Individuals who had registered to be part of human-subject experiments conducted at the University were invited by email to take part in the study. Admission to participate in the study was contingent on respondents being at least 17 years old to ensure that participants understood the meaning of route choice in a real driving scenario.

6.4.3 Sequence of Events

The study was completed at the University of New South Wales within the laboratory of the ASB Experimental Research group. The laboratory used for the experiment contained computer workstations with sufficient spacing between participants to prevent from collusive activities. Each session consisted of a total of 24 participants who were randomly separated into 2 groups of 12 participants to complete the route choice tasks. This was completed to maximise the available resources within the laboratory.

Upon arrival, identification of the participants was verified; after which, the participants were assigned seating locations within the laboratory. An informed consent form and the study documentation were presented to the participants as per University of New South Wales regulations. The consent form briefly explained the rights and responsibilities of each participant as well as assurance of the confidentiality of the information obtained within the study. The instructions of the experiment remained face down on the desk until the study began. The complete set of instructions of the experiment is provided in Appendix D. The procedure of the experiment which took place is summarised as follows;

1. Participants completed the MPL task.
2. Participants completed the computerised route choice tasks across both Treatment 1 and Treatment 2
3. Participants completed the demographic questionnaire
4. Participants' payoffs across the MPL and route choice tasks were calculated and each participant was paid.

To control for order effects the sequence of the treatments were varied across the sessions. The experiments with the following sequences of tasks were conducted across different sessions.

- Order 0: MPL Task; Treatment 1 (No Information), Treatment 2 (Information), Questionnaire.
- Order 1: MPL Task; Treatment 2 (Information), Treatment 1 (No Information), Questionnaire

The study consisted of six 2 hour sessions of the experiment that were held on the following days:

- 23 September 2015, (Order 0)
  - Session 1: 24 participants
  - Session 2: 24 participants
  - Session 3: 24 Participants
- 7 October 2015, (Order 1)
  - Session 4: 24 participants
  - Session 5: 24 participants
  - Session 6: 24 Participants

6.5 Results

A total of 144 participants completed the experiment across the six sessions conducted. A summary of the key characteristics of the participants is presented in Table 6.6. There was a balance between genders with approximately 47% of the participants being male and 53% female. Similar to the experiment conducted in Chapter 3, the participants were recruited from student and staff pool at the University of New South Wales. Thus, it is acknowledged that the average age of the participants is relatively young at 22.14 years. However, there was a range of ages considered between 18 and 40 presenting some variety in the sample. The crucial element of the study is the investigation into driving behaviour, thus it was important that the participants had some driving experience. More than 68% of the participants had greater than one years' experience in driving a vehicle suggesting that a majority of participants had a sound understanding of the concept of route choice.

Table 6.6: Summary of participant characteristics

Characteristic	Values
Gender (Male/Female)	67/77
Driving Experience (>1 year, < 1 year)	98/46
Average Age	22.14
Range of Ages	18 - 40

Each period of the computerised route choice game provided a traffic assignment pattern (1 observation) which could be compared with the theoretical equilibrium results. Since each session consisted of two groups of 12 participants a total of 40 observations were recorded for each treatment. Therefore across the six sessions conducted, there were 240 observations for each treatment. From an individual choice perspective, each participant made 20 routing decisions for each treatment. This resulted in a data set of 2880 individual choices for each treatment. The data obtained was statistically analysed to compare with the predictions of the theoretical model and also observe any instances of learning or convergence towards a singular traffic assignment pattern. The key performance metrics assessed are that of path utilisation or flow patterns and the Total System Travel Cost (TSTC) which describes the system wide performance of the network.

6.5.1 Comparison with Analytical Solutions

The comparison of the observed experiment results and the analytical solutions was completed by assessing path statistics and total system travel costs. Initially, the path flow statistics of the experiment are discussed to highlight any specific trends related to either of the information regimes considered. The path flow statistics for both Treatment 1 and Treatment 2 are presented in Table 6.7 and Table 6.8 respectively. It is evident from these results that there are distinctly different path utilisation patterns between the treatments. When participants were not provided information, regardless of the state of the network the mean path utilisation remained relatively stable with approximately 5 people using path *A-B-D* and *A-C-D* while 2 people using *A-C-B-D*. This is not an unexpected result as participants would not have been aware of the state of the network and chose non adaptive paths based on experience. In contrast, the provision of information resulted in significantly different path utilisation based on the state of the network. During the incident conditions (State 1), where link C-B had a higher travel cost of 20 units, on average there were little to no users of path A-C-B-D, approximately 4 used A-B-D while 8 used A-C-D. However, under normal conditions (State 2), A-C-B-D was the most heavily used path with mean flow values nearing 5 participants, A-B-D contained just above 4, whilst A-C-D contained almost 3. This fluctuation in flow is evident when comparing the overall standard deviation of the path flow ($\sigma_{Flow,All,N}$ and $\sigma_{Flow,All,I}$). Without information the standard deviation varied between 1.276 and 1.320 across the 3 paths, however in the presence of information the standard deviation ranged from 1.380 to 2.319 reflecting the adaptive behaviour.

Table 6.7: Path Flow Statistics of Treatment 1: No Information

Treatment 1: No Information						
	Mean Flow $\mu_{Flow,S1,N}$	**Standard Deviation of Flow** $\sigma_{Flow,S1,N}$	**Mean Flow** $\mu_{Flow,S2,N}$	**Standard Deviation of Flow** $\sigma_{Flow,S2,N}$	**Overall Mean Flow** $\mu_{Flow,All,N}$	**Overall Standard Deviation of Flow** $\sigma_{Flow,All,N}$
State	1	1	2	2	Overall	Overall
A-B-D	4.896	1.292	5.130	1.326	5.083	1.320
A-C-B-D	2.188	1.424	1.688	1.341	1.788	1.369
A-C-D	4.917	1.485	5.182	1.216	5.129	1.276
Total	12		12		12	

Table 6.8: Path Flow Statistics of Treatment 2: Information Provided at Node C

Treatment 1: Information Provided at Node C						
	Mean Flow $\mu_{Flow,S1,N}$	**Standard Deviation of Flow** $\sigma_{Flow,S1,N}$	**Mean Flow** $\mu_{Flow,S2,N}$	**Standard Deviation of Flow** $\sigma_{Flow,S2,N}$	**Overall Mean Flow** $\mu_{Flow,All,N}$	**Overall Standard Deviation of Flow** $\sigma_{Flow,All,N}$
State	1	1	2	2	Overall	Overall
A-B-D	4.292	1.458	4.286	1.364	4.288	1.380
A-C-B-D	0.146	0.772	4.828	1.214	3.892	2.195
A-C-D	7.563	1.382	2.885	1.364	3.821	2.319
Total	12	0	12	0	12	

Table 6.9 presents a comparison of the analytical path flow solutions calculated in Section 3 and the observed mean path flow results from the experiment. The EUE solution depicting the 'no information' case suggested that there will be a 50% split of the demand on route *A-B-D* and *A-C-D*, resulting in 6 demand units on each route and zero usage of *A-C-B-D*. The observed mean flows differ from this solution, with a mean flow of 1.788 on path *A-C-B-D*. On average, across the entire data set there were 1 to 2 participants who selected *A-C-B-D*. This can be explained by individuals hoping that State 2 conditions would prevail and they would be able to significantly reduce their travel cost by encountering the 1 unit of cost on link *C-B*. This tends to suggest that the EUE solution is not capturing the behaviour of users in the 'no information' case. However, it should be noted that across the last 2 to 3 periods of Treatment 1, participants learnt from the experiences of the previous rounds and there was an indication that over a greater number of periods the EUE solution may have been observed. The UER solution provides the theoretical representation of Treatment 2, where participants are provided information at node *C* of the network. UER solutions are presented in terms of routing policy usage and as such the path flows need to be disaggregated for each

state of the network. Comparing the observed state based mean path flow to the theoretical solution indicates that the UER solution is closely depicting the empirical behaviour presented within the experiment. The rounded values of each of the observed mean path flow values match exactly with the theoretical UER solution.

Table 6.9: Comparison of empirical and theoretical path utilisation

Treatment 1: No Information				
	State	**A-B-D**	**A-C-B-D**	**A-C-D**
EUE Solution	E(S1,S2)	6	0	6
Observed Mean Path Flow	S1	4.896	2.188	4.917
	S2	5.130	1.688	5.182
	Overall	5.083	1.788	5.129
Treatment 2: Information provided at Node C				
	State	**A-B-D**	**A-C-B-D**	**A-C-D**
UER Solution	S1	4	0	8
	S2	4	5	3
Observed Mean Path Flow	S1	4.292	0.146	7.563
	S2	4.286	4.828	2.885

Table 6.10 displays a comparison of the travel costs between the ‘no information’ scenario and the ‘information’ scenario. As discussed in the analytical presentation of the Online Information Paradox, the experiment also presents the case that the mean Total System Travel Cost (TSTC) increases from 210.629 to 219.163 cost units when information is provided to the participants. In other words, the provision of information has deteriorated the travel conditions for the users of the network. However, the difference in mean TSTC between the two treatments is less than what was predicted in theory. The analytical solution suggests a difference of 24 cost units far greater than the 8.534 units observed during the

experiment. This can be attributed to participants using A-C-B-D in the no information scenario resulting in a higher travel cost on average for the entire system and straying from the EUE solution.

Another interesting observation is the difference in the standard deviation of the TSTC between the information scenarios. Intuitively, there is a far greater standard deviation in costs when no information is provided, as participants face the greater rewards and losses associated with selecting route A-C-B-D and the uncertainty of the cost of link C-B. Consider a hypothetical scenario where 1 out of the 12 participants selects A-C-B-D and 6 select A-B-D while the remaining 5 use A-C-D. If C-B does not have an incident, the single user of the route experiences a travel cost of 14 (6 + 1 + 7) much lower than the mean travel costs presented. However, if C-B does have an incident the travel cost increases dramatically to 33 (6 + 20 + 7), a difference of 19 units. It is clear that if more participants select C-B in the 'no information' case, there is the possibility for greater variability in the TSTC value as it is calculated by multiplying the path cost by the path flow. This contrasts the situation presented in Treatment 2, as individuals are able to adapt if State 2 of link C-B eventuates and there is an incident. This result suggests that though information has the potential to increase system travel costs, there is a reduction in the variance of the travel costs observed within the system and thus, offers a greater degree of reliability.

Table 6.10: Comparison of mean travel costs between treatments

	Treatment 1: No Information	**Treatment 2: Information Provided at Node C**	
State	E(S1,S2)	S1	S2
Cost of A-B-D	16.871	14.438	19.115
Cost of A-C-B-D	18.588	32.146	17.828
Cost of A-C-D	16.917	17.708	17.714
Observed TSTC	**210.629**	**219.163**	
σ_{TSTC}	24.948	15.470	
Theoretical TSTC	192	216	

To further corroborate the observed empirical presence of the Online Information Paradox, a paired T-test was completed to determine if the mean TSTC values were significantly different between the treatments. If the T-statistic exceeds the T-critical value there is a significant difference between the observed TSTC values. Table 6.11 clearly shows that the T-statistic is more than twice the critical value and thus there is a significant difference between the two cases at a confidence level of 95%. In addition, the p-value approaches zero emphasising the degree of significance of the result and the empirical presence of the Online Information Paradox.

Table 6.11: Statistical testing comparing the TSTC between Treatments: T-test Results

TSTC	Treatment 1: No Information	Treatment 2: Information Provided at Node C
μ	210.629	219.163
σ	24.948	15.470
Observations	240	240
	Paired T-test	
T-statistic	4.53811	
T-critical	1.96994	
p-value	0.00001	

The sample used for the above statistical assessment contained repeated measures of the mean TSTC for the same group of participants across both treatments. For an example, group 1 contained 20 repeated measures of mean TSTC, for each period across the game, under each information regime. In order to account for the dependence in observations, group statistics were analysed and another paired T-test was conducted. The group descriptive statistics and the results of the statistical testing are presented in Table 6.12. The findings are consistent with Table 6.11 with a p-value less than 0.05 and the presence of the Online Information Paradox is statistically significant.

Table 6.12: Statistical analysis considering group based results

Session	Group	No Information		Information		Difference in Means
		Mean	Standard Deviation	Mean	Standard Deviation	
1	1	212.200	26.411	220.300	13.739	8.100
	2	209.650	25.887	218.600	12.701	8.950
2	1	209.800	19.259	215.800	11.181	6.000
	2	210.550	21.333	220.600	14.233	10.050
3	1	217.500	36.699	215.900	10.228	-1.600
	2	212.600	34.015	229.150	26.650	16.550
4	1	213.850	35.445	216.400	14.591	2.550
	2	208.750	16.676	215.800	15.477	7.050
5	1	204.700	15.815	220.800	17.025	16.100
	2	211.850	20.254	217.600	13.068	5.750
6	1	205.350	16.925	219.100	13.082	13.750
	2	210.750	22.583	219.900	16.613	9.150
Observations						12
Mean of Differences						8.533
Standard Deviation of Differences						5.280
Standard Error of Differences						2.202
t-statistic						3.876
t-critical						2.201
p-value						0.003

The order of tasks carried out within the experiment can at times affect the behaviour of participants. Accordingly, statistical testing was conducted to assess the impact of order on the TSTC results of each of the treatments. There were only 2 different orders considered, either the Treatment 1 was presented to participants first (defined as Order 0 in Section 6.4.3) or Treatment 2 was presented first (defined as Order 1 in Section 6.4.3). Sessions 1, 2 and 3 were conducted using Order 0, while Sessions 4, 5 and 6 were conducted using Order 1.

In this analysis independent samples were compared for the purpose of determining whether there were differences in the mean TSTC of the participants in session 1 to 3 with that of the participants in session 4 to 6. Accordingly a pooled and un-pooled T-test was completed to compare the mean TSTC values for each order within each treatment as shown in Table 6.13. The un-pooled Welch's T-test was used as the standard deviation of the TSTC values between the treatments was different, questioning the suitability of the pooled T-Test. The results of the T-tests suggest that there are no statistically significant differences between the orders considered as all T-statistics are less than half of T-critical value and all p-values exceed 0.35.

Table 6.13: Statistical testing assessing the impact of Order: T-test Results

TSTC	Treatment 1: No Information		Treatment 2: Information Provided at Node C	
	Order 0	**Order 1**	**Order 0**	**Order 1**
μ	212.05	209.208	220.058	218.267
σ	27.51832086	22.107	16.0798	14.849
Observations	120	120	120	120
	Pooled T-test	**Welch's T-test**	**Pooled T-test**	**Welch's T-test**
T-statistic	0.8819	0.8819	0.8967	0.8967
T-critical	2.2557	2.0639	2.2557	2.3060
p-value	0.3787	0.3866	0.3708	0.3961

The comparison of the empirical results of the experiment and the analytical solutions strongly indicate the possibility of the physical manifestation of the Online Information Paradox. However, the analysis conducted within this section of the paper focussed on aggregated statistics such as mean path flow, path cost and Total System Travel Cost (TSTC). In order to understand more about route choice behaviour further analysis was undertaken and is discussed in the following sections.

6.5.2 Network Wide Learning

The route choice tasks was repeated over 20 periods, meaning that across both treatments participants were exposed to experiential information which was revealed at the end of each round. Therefore, the temporal or periodic changes in path flow and TSTC can be assessed to observe the presence of network wide reinforced learning. Prior to the discussion of this component of analysis, it must be stated that these period based statistics have been derived from obtaining mean values across the 12 groups of participants (2 groups per session across 6 sessions), i.e. mean values have been calculated using 12 observations for each period of the experiment. Thus, the results are discussed broadly with the need to conduct further replications of the experiment to provide a thorough quantitative analysis with a greater sample size.

Figure 6.4 and Figure 6.5 show the variation in mean path flow across the periods of the experiment for Treatment 1 and Treatment 2 respectively. The path flow diagram for Treatment 1 provides an interesting result which suggests that the EUE analytical solution should not be dismissed. The graph shows that during periods 17 through to 20, the mean behaviour of each group of participants converges towards the equilibrium path flow pattern of 6 units using path A-B-D and 6 units using path A-C-D. Furthermore, the learning of the participant pool is clearly evident as there is a distinct trend away from the use of path A-C-B-D and towards the use of either A-B-D or A-C-D. This could be an indication of the psychological hot-stove effect (Denrell, 2006, Denrell and March, 2001) where participants gain the experience of high travel costs of path A-C-B-D associated with an incident period in a previous round and are then reluctant to select the path.

For completeness the mean path flow for the information case is presented in Figure 6.5. There is a high degree of volatility in route choice with no clear trend visible within this graph. In saying this, the diagram should not reveal a great deal of information as the analytical solution suggests that people equilibrate on a routing policy basis rather than path basis. Instinctively, a volatile path utilisation diagram is expected as the provision of online information offers a user the option to adapt. In the context of this example, a user may always select A-C-B-D however when an incident occurs on C-B, it is unlikely the user will continue to use A-C-B-D

and will most likely shift to A-C-D. This is evident in Figure 6.5 as a majority of the State 1 (incident) realisations occur between period 10 and 15 where there is a clear reduction in flow of A-C-B-D and a spike in the flow of A-C-D.

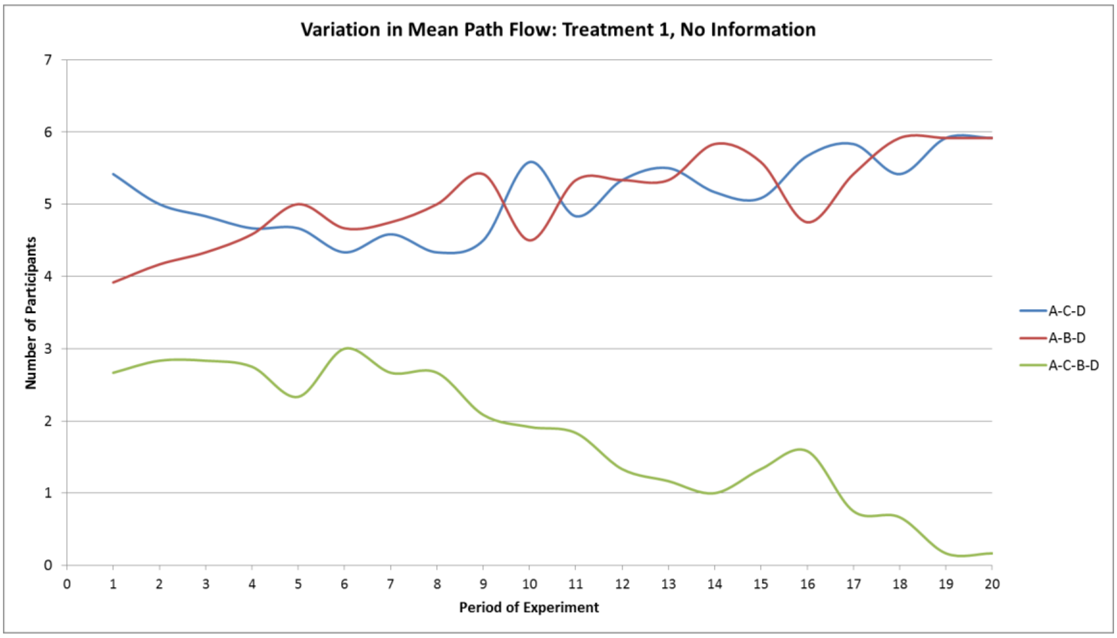


Figure 6.4: The variation in mean path flow across periods of the experiment: Treatment 1

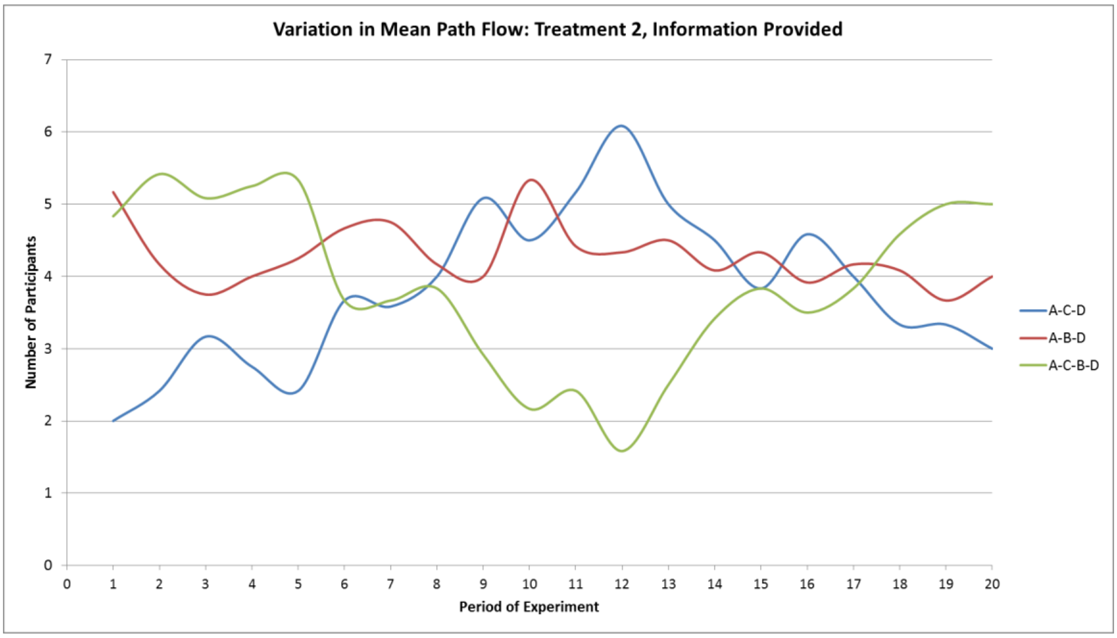
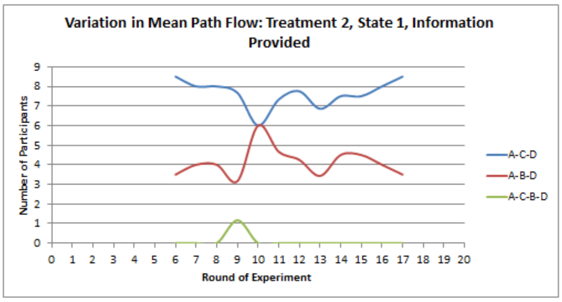


Figure 6.5: The variation in mean path flow across periods of the experiment: Treatment 2

To further underline this concept, Figure 6.6 presents a comparison of the State 1 path flow pattern with the State 2 path flow pattern. These graphs have been plotted with even less data than before as there aren't 12 exclusive observations of either State 1 or State 2 for each period. In total the State 1 graph was formed with 48 observations for the periods where an incident occurred (which occur between period 6 and period 17) and the State 2 graph was developed considering 192 observations. These figures indicate a greater level of stability; however no clear learning element is evident. A possible explanation for this observation is that when information is provided *en route* a user is reliant on these sources of information and does not retain past experiences of travel times and delays as readily as when there is no access to traffic performance information. In other words users become reactive travellers rather than being a proactive or planned traveller. A user will select a route that either is not readily exposed to unreliability (A-B-D) or will take the alternative knowing that he or she has the opportunity to adapt if there is a source of delay.



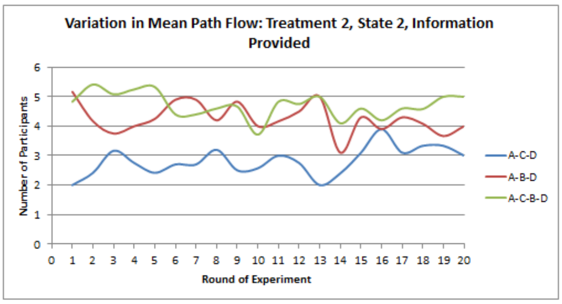


Figure 6.6: The variation in mean path flow across the periods of the experiment: State 1 and State 2 disaggregation of Treatment 2

Figure 6.7 depicts the variation in TSTC across each group of each session considering both treatments. The blue coloured curves represent the 'no information' case while the red coloured curves represent the 'information' case. Though there is significant instability within this diagram it is interesting to observe the behaviour of periods 16 to 20 for both treatments. Excluding a significant outlier in period 16 (Session 4, Group 1) there appears to be a convergence towards the theoretical equilibrium solutions of both scenarios. In fact, the mean TSTC for period 17 to 20 (36 observations for each treatment) is 196.312 for the 'no information' scenario and 218.667 for the 'information' scenario which is very close to the theoretical values of 192 and 216 respectively. The high levels of volatility associated with Treatment 1 is most likely due to participants bearing the risk of high travel costs in the pursuit of potentially low travel costs. This risk could increase their final payoff, especially during the initial periods of the experiment.

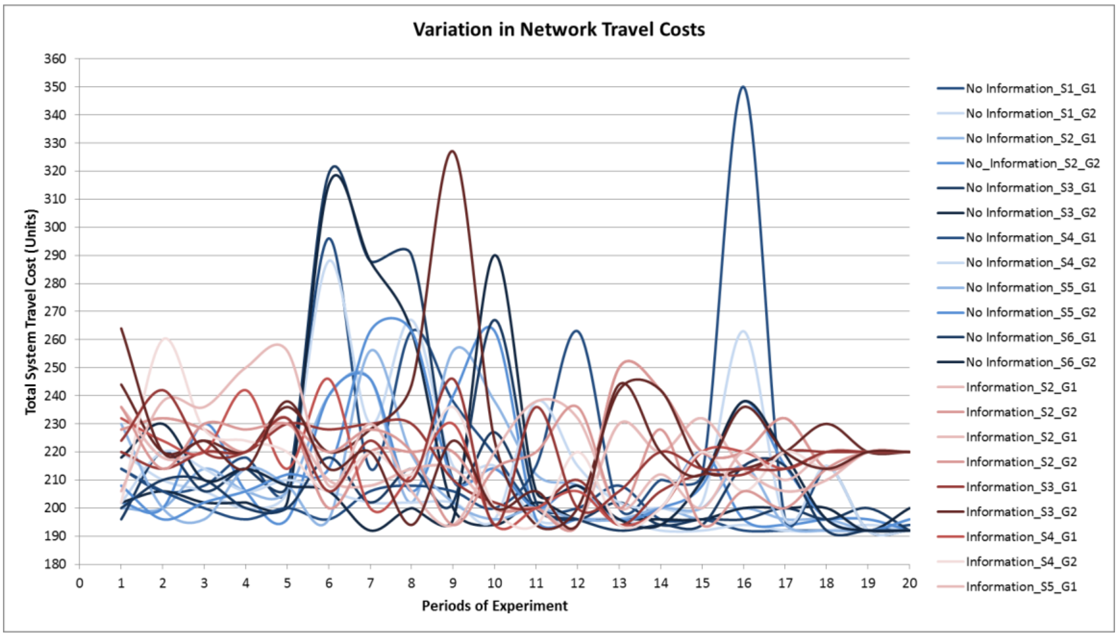


Figure 6.7: Variation in Total System Travel Costs across of all participant groups across each period of the experiment

Figure 6.8 presents the variation of the mean TSTC for each period considering the two treatments studied. The greater volatility of the no-information scenario is clear again with the presence of blue data points in excess of 240 units and less than 195 units. Trend lines for each of the treatments are presented and the manifestation of the Online Information Paradox is again highlighted. The red 'information' trend line lays above the blue 'no information', however both TSTC lines are downward sloping presenting network wide learning from the participants. Even though communication and collusion was strictly controlled throughout the experiment, participants experience the travel costs of the previous round and alter their route choice in the next round, in an attempt to reduce their travel costs.

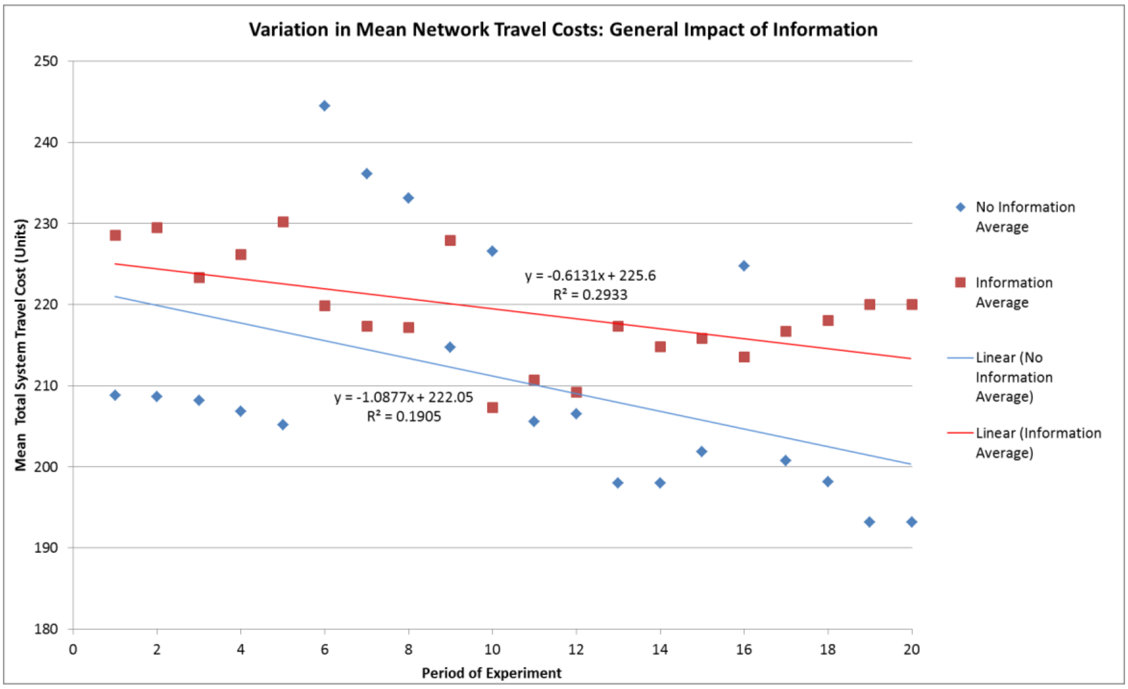


Figure 6.8: Variation in Mean Total System Travel Cost across each period of the experiment

The presence of learning puts into question the statistical analysis presenting the empirical existence of the Online Information Paradox, conducted in Section 6.5.1, as data from all 20 periods of the experiment was analysed. It could be argued that the emergence of the paradox is an artefact of the data set. It is clear that the participants were learning throughout the initial rounds of the experiment resulting in exploratory behaviour which is not reflective of their true behaviour. Including these learning periods in the data set may create a bias in the statistical measures and incorrectly present a significant paradox observation. In order to determine the potential for a biased result, data from the initial periods of the experiment were excluded and the mean and standard deviation of TSTC was recalculated for both treatments. Table 6.14 presents a systematic removal of data and the repeated measurement of TSTC statistics comparing the 'no information' scenario with the 'information' scenario. The removal of data associated with a single period, results in a reduction in sample size of 12 observations; as such the removal process was terminated at the point where sample size reduced to 36 (elimination of the first 16 periods where the data analysis considered the performance of periods 17 to 20 across all 12 groups of participants) to maintain a sufficiently large sample size and provide meaningful conclusions. All 18 assessments presented in Table 6.14 support the existence of the Online Information Paradox and are statistically significant at a 95% confidence level. This analysis suggests that the presence of the paradox is not an artefact of data exposed to learning effects.

Another line of argument could be that as only 20 periods were considered for each treatment and therefore, the learning process of the participants did not converge to static decision making. This is entirely plausible; however, indications throughout all conducted sessions were an eventual convergence towards relatively static path flows between periods 17 to 20, as presented in Figure 6.7, providing a basis for an aggregate stabilisation of decision making. Furthermore, the results of the systematic removal of data suggest that when participants learn about the travel costs involved in the example, the strength of the paradox increases. Assessment number 6 and 7 of Table 6.14 (highlighted in orange) presented the least difference in Mean TSTC of 4.711 units and had the greatest p-value of 0.0477 respectively. From this point onwards, the difference range increased to the greatest level observed in assessment number 18 of 24.5 units which is similar to the theoretical difference of 24 units and p-values approached zero. Therefore, whilst accounting for the impact of learning by participants, there remains strong statistical evidence of the empirical presence of the Online Information Paradox.

Table 6.14: Statistical analysis considering learning behaviour of participants

Assessment Number	Data Periods Considered	Treatment	Number of Observations	Mean TSTC	Standard Deviation of TSTC	Difference in Mean TSTC	Paired T-Test p-value
1	All	1	240	210.629	24.948	8.533	8.99E-06
		2	240	219.163	15.470		
2	2-20	1	228	210.724	25.495	7.947	6.42E-05
		2	228	218.671	15.294		
3	3-20	1	216	210.838	26.092	7.231	4.76E-04
		2	216	218.069	15.180		
4	4-20	1	204	210.995	26.765	6.765	4.65E-04
		2	204	217.760	15.472		
5	5-20	1	192	211.255	27.523	5.979	1.83E-03
		2	192	217.234	15.601		
6	6-20	1	180	211.661	28.360	4.711	8.59E-03
		2	180	216.372	15.512		
7	7-20	1	168	209.315	25.158	6.810	4.77E-02
		2	168	216.125	15.381		
8	8-20	1	156	207.256	23.284	8.776	3.42E-03
		2	156	216.032	15.634		
9	9-20	1	144	205.104	21.046	10.833	2.15E-04
		2	144	215.938	15.897		
10	10-20	1	132	204.227	21.053	10.621	9.47E-06
		2	132	214.848	12.669		
11	11-20	1	120	201.992	18.417	13.608	1.08E-05
		2	120	215.600	12.595		
12	12-20	1	108	201.593	19.012	14.556	3.36E-09
		2	108	216.148	12.178		
13	13-20	1	96	200.979	19.022	16.042	5.88E-10
		2	96	217.021	11.553		
14	14-20	1	84	201.405	20.256	15.571	1.39E-08
		2	84	216.976	9.270		
15	15-20	1	72	201.972	21.766	15.361	4.74E-07
		2	72	217.333	7.453		
16	16-20	1	60	202.000	23.578	15.633	9.03E-06
		2	60	217.633	6.582		
17	17-20	1	48	196.313	7.217	22.354	5.86E-20
		2	48	218.667	5.025		
18	18-20	1	36	194.833	5.557	24.500	7.45E-22
		2	36	219.333	3.061		

6.5.3 The Impact of Traffic States

Table 6.14 indicated a statistically significant presence of the Online Information Paradox at a confidence level of 95% for all the assessment sets considered while systematically removing data. However, assessment number 7, consideration of experiment periods 7 through to 20 only, obtained a p-value of 0.0477 greater than all other assessments and presenting the weakest significance.

This result could be attributed to participant learning and the fact that during the first 6 rounds, participants were exploring the options manifesting in the paradox. An alternative explanation could be as a result of the impact of the traffic states, which were described to the participants as 'Incident on Road *C-B*' (State 1, Cost of Link C-B = 20) and 'No Incident on Road *C-B*' (State 2, Cost of Link C-B = 1). Out of the 20 periods, 4 periods were randomly assigned to depict State 1 conditions within the route choice game. The 4 random periods were different for both treatments and satisfied the probability of occurrence of 20% for consistency with the analytical example. The fulfilment of the probability criteria was not revealed explicitly to the participants to prevent counting of states and forecasting. Participants received the information that 'there is a 20% chance of an incident occurring on road segment *C-B*' which provided an indication of the historical performance of the road for each participant**.** The presence of State 1 conditions is shown in Table 6.15.

Table 6.15: Presence of State 1 during each Session and Treatment of the experiment

Session	Treatment	Periods of State 1 ('Incident on link C-B')			
1	**1**	6	8	9	10
	2	7	12	14	16
2	**1**	6	7	8	10
	2	9	11	12	13
3	**1**	6	7	9	10
	2	6	10	11	12
4	**1**	11	12	16	18
	2	10	11	13	14
5	**1**	7	8	16	17
	2	9	13	15	17
6	**1**	10	14	16	17
	2	8	9	10	12

Across the 6 sessions and for both treatments there was not one instance of State 1 occurring during periods 1 through to 5. In half of the treatments, the first realisation of State 1 occurred in either period 6 or 7. Also exactly 50% of all State 1 conditions occurred between period 6 and period 10. Thus, participants were learning about the 'normal' or 'good' set of traffic conditions between periods 1 and 5 and were only able to gauge the variability of each route after the manifestations of State 1, which occurred from period 6 onwards, resulting in further learning. The lack of presence of incident conditions may have resulted in the participants gaining confidence in the use of route *A-C-B-D*. Thus, when the incidents were realised during periods 6 through to 10 there were some individuals who chose route *A-C-B-D* and suffered the consequences of the incident. In the no information scenario, no adaptive behaviour was possible and the participants who selected *A-C-B-D* faced very high travel costs. In the presence of information a participant could make the decision on using the risky link *C-B* after knowing about the traffic conditions of the link. Accordingly the TSTC for the case with no information increased and the TSTC for the information case decreased resulting in the decreased significance of the paradox for assessment 7 presented in Table 6.14. This could be a reason for the weaker significance of the paradox and a clear indication of the value and benefit of information in uncertain conditions. Another interpretation of these results can be that the likelihood of the realisation of State 1 increased to nearly 27% (4 out of 15) by the beginning of period 6 as until that time State 1 had not occurred. The greater likelihood of poorer traffic conditions reduced the reliability of the system and as such participants enjoyed the benefits of information for that particular round.

Analysis of each participant's travel costs adds to the discussion of the impact of traffic states. Figure 6.9 and Figure 6.10 present the mean and standard deviation variations of individual user's travel costs across the periods of the experiment for Treatment 1, while Figure 6.11 and Figure 6.12 provide the variations for Treatment 2. A colour scale from green to red (low values to high values) has been applied to the graphs to highlight the temporal variance in cost and standard deviation. Within these figures, the realisation of State 1 conditions have been emphasised with a thick black border. Figure 6.10 and Figure 6.11 clearly portray that when information is not present, the individual travel costs increased considerably during State 1 conditions and moreover there is the greatest degree of standard deviation on these occasions. On average, State 1 standard deviations of individual user cost in the no information scenario exceed 4, whilst in State 2 conditions the value is closer to 1. However, for a number of groups, the experience of State 1 conditions led to an adjustment in route choice and a reduction in mean individual travel costs. This is particularly evident in Session 1 where the mean cost was 24 units in the period when first faced with the incident. Then, in period 10, when faced with the incident for the 4th and final time, the mean cost for each user reduced to 18.5 units. This observation again emphasises the learning behaviour of users.

Mean Individual User Travel Costs: Treatment 1 (No Information)

Period	Session 1		Session 2		Session 3		Session 4		Session 5		Session 6	
	Group 1	Group 2	Group 1	Group 2	Group 1	Group 2	Group 1	Group 2	Group 1	Group 2	Group 1	Group 2
1	17.833	18.333	16.667	16.833	16.333	16.833	17.833	16.833	19.167	17.333	16.667	18.167
2	17.167	17.500	16.667	16.667	18.333	17.167	17.167	18.333	16.667	16.333	17.500	19.167
3	17.333	17.167	17.833	19.167	17.167	16.833	16.667	17.833	16.333	16.833	17.500	17.500
4	18.167	16.667	17.167	17.167	17.833	16.833	16.333	17.167	17.833	17.167	16.667	17.833
5	17.167	17.167	17.167	16.333	17.333	16.833	16.667	17.500	17.333	17.667	16.667	17.333
6	24.667	24.000	20.000	20.000	26.583	26.250	16.333	17.167	16.333	17.833	18.167	17.167
7	17.833	19.167	20.500	20.500	24.000	24.000	17.167	16.833	21.333	21.917	16.833	16.000
8	21.917	22.250	16.833	17.167	24.167	21.917	17.333	16.833	18.250	21.917	17.833	16.667
9	19.833	17.917	21.333	20.000	17.500	16.667	17.167	16.833	16.833	17.500	16.833	16.333
10	18.250	17.917	19.833	21.917	18.917	16.167	16.667	16.333	16.333	17.833	22.250	24.167
11	16.667	16.333	17.667	16.333	16.667	16.833	17.917	19.833	16.667	16.667	16.833	17.167
12	16.667	16.333	17.333	16.333	16.333	16.333	21.917	17.917	16.333	17.333	16.333	17.333
13	17.333	16.333	16.333	16.333	16.833	16.333	16.667	16.833	16.333	16.333	16.000	16.333
14	16.333	16.000	16.667	16.667	16.167	16.333	17.500	16.667	16.667	16.667	16.167	16.167
15	16.333	16.000	16.333	18.333	16.333	16.333	17.667	16.833	16.667	17.333	16.167	17.500
16	16.000	16.167	16.667	16.333	16.333	16.667	29.167	21.917	17.917	19.833	17.917	19.833
17	16.000	16.000	16.333	16.167	16.667	16.667	16.333	16.333	16.167	17.917	17.917	18.250
18	16.000	16.000	16.333	16.333	16.333	16.667	17.917	17.917	16.000	16.333	16.000	16.333
19	16.000	16.167	16.000	16.333	16.667	16.000	16.000	16.000	16.000	16.000	16.000	16.000
20	16.167	16.000	16.000	16.000	16.000	16.667	16.000	16.000	16.000	16.333	16.000	16.000
Group Mean	**17.683**	**17.471**	**17.483**	**17.546**	**18.125**	**17.717**	**17.821**	**17.396**	**17.058**	**17.654**	**17.113**	**17.563**

Figure 6.9: Variation in Mean User Travel Costs across periods of the experiment (Treatment 1: No Information)

Standard Deviation of Individual User Travel Costs: Treatment 1 (No Information)

Period	Session 1		Session 2		Session 3		Session 4		Session 5		Session 6	
	Group 1	Group 2	Group 1	Group 2	Group 1	Group 2	Group 1	Group 2	Group 1	Group 2	Group 1	Group 2
1	1.030	0.492	0.778	1.267	0.888	1.267	1.030	1.267	0.718	2.060	1.969	2.725
2	0.835	1.567	0.778	0.778	0.492	0.835	0.835	0.492	1.969	0.888	1.567	2.329
3	2.462	0.835	1.030	0.718	0.835	1.267	0.778	1.030	0.888	1.267	1.567	1.567
4	2.290	1.670	0.835	0.835	1.030	1.267	0.888	0.835	1.030	0.835	0.778	1.030
5	0.835	0.835	0.835	0.888	2.462	1.267	0.778	1.567	2.060	0.492	0.778	2.060
6	8.500	8.863	6.606	6.606	9.258	9.498	0.888	0.835	0.888	1.030	2.725	0.835
7	1.030	2.329	6.544	6.544	8.863	8.863	0.835	1.267	6.344	7.902	1.267	0.000
8	7.902	7.794	1.267	0.835	8.778	7.902	2.060	1.267	4.864	7.902	1.030	0.778
9	6.617	4.776	6.344	6.606	1.567	0.778	0.835	1.267	1.267	1.567	1.267	0.888
10	4.864	4.776	6.617	7.902	4.963	1.030	0.778	0.888	0.888	1.030	7.794	8.778
11	1.670	0.888	0.492	0.888	1.670	1.267	4.776	6.617	0.778	0.778	1.267	0.835
12	1.670	0.888	2.060	0.888	0.888	0.888	7.902	4.776	0.888	2.462	0.888	2.060
13	2.462	0.888	0.888	0.888	1.267	0.888	0.778	1.267	0.888	0.888	0.000	0.888
14	0.888	0.000	1.670	1.670	1.030	0.888	1.567	0.778	0.778	1.670	1.030	1.030
15	0.888	0.000	0.888	3.025	0.888	0.888	0.492	1.267	1.670	2.462	1.030	1.567
16	0.000	1.030	1.670	0.888	0.888	1.670	9.292	7.902	4.776	6.617	4.776	6.617
17	0.000	0.000	0.888	1.030	1.670	0.778	0.888	0.888	1.030	4.776	4.776	4.864
18	0.000	0.000	0.888	0.888	0.888	1.670	4.776	4.776	0.000	0.888	0.000	0.888
19	0.000	1.030	0.000	0.888	1.670	0.000	0.000	0.000	0.000	0.000	0.000	0.000
20	1.030	0.000	0.000	0.000	0.000	1.670	0.000	0.000	0.000	0.888	0.000	0.000
Group Standard Deviation	**3.907**	**3.704**	**3.340**	**3.594**	**4.726**	**4.398**	**4.237**	**3.100**	**2.566**	**3.594**	**2.828**	**3.396**

Figure 6.10: Variation in Standard Deviation of User Travel Costs across periods of the experiment (Treatment 1: No Information)

The information case presented in Figure 6.11 and Figure 6.12 is quite different to that of the no information case. State 1 conditions result in lower mean user cost compared with the State 2 conditions. These observations are consistent with the theoretical UER solution. The provision of information results in an over utilisation of Link A-C as users can obtain information about the state of Link C-B by travelling to node C. Instead of an equal distribution of 6 units of demand for A-B-D and A-C-D resulting in a mean user cost of 16, there are 4 units using A-B-D and 8 using either A-C-D during State 1 conditions (mean user cost of 16.667) or 5 using A-C-B-D and 3 using A-C-D in State 2 conditions (mean cost of 18.333). When comparing treatments, there is a considerable reduction in individual travel costs and the standard deviation across all individuals within a group with the presence of information in State 1 conditions. This again highlights the benefit of the provision of perfect information. However, what is also evident in these diagrams is that under State 2 conditions, information results in an increase of individual costs and consequently the deterioration of the system performance. In this example, the deterioration of the system outweighs the benefits of information resulting in the presence of the paradox.

Mean Individual User Travel Costs: Treatment 2 (Information)

Period	Session 1		Session 2		Session 3		Session 4		Session 5		Session 6	
	Group 1	Group 2	Group 1	Group 2	Group 1	Group 2	Group 1	Group 2	Group 1	Group 2	Group 1	Group 2
1	18.333	19.167	19.667	19.000	18.333	20.333	19.333	16.833	17.167	19.667	18.667	22.000
2	19.667	19.667	18.167	19.333	17.833	18.333	18.667	21.667	19.833	17.833	20.167	18.333
3	18.667	17.167	18.333	19.000	18.333	18.667	18.333	19.000	19.667	19.167	18.333	18.667
4	18.667	19.333	18.333	18.333	18.333	18.333	20.167	18.667	20.833	19.000	18.333	17.833
5	18.333	18.667	19.167	19.333	19.167	19.667	17.833	18.333	21.333	19.167	19.333	19.833
6	21.667	18.333	17.500	16.667	19.000	18.333	20.500	17.167	17.333	18.333	17.167	17.833
7	16.667	16.667	17.333	18.333	19.167	19.000	16.667	18.333	19.167	19.000	18.667	18.333
8	18.333	18.667	17.833	18.333	19.167	20.333	17.667	17.667	17.167	18.333	17.500	16.167
9	18.333	18.333	17.833	18.333	17.500	27.250	19.167	19.667	16.167	16.167	20.500	18.667
10	18.333	18.333	16.667	16.667	16.833	18.667	16.167	16.667	18.333	17.833	16.167	16.667
11	18.333	18.333	16.667	16.667	16.667	16.167	16.667	16.167	19.833	18.333	19.667	17.167
12	18.667	16.667	16.167	16.167	17.500	16.667	17.167	18.333	19.333	19.667	16.667	16.167
13	17.667	20.167	19.167	20.833	16.167	20.167	16.167	16.167	16.667	16.667	17.167	20.333
14	16.167	16.167	18.333	20.167	17.167	20.167	16.667	16.667	17.667	19.000	18.333	18.333
15	19.333	18.333	19.333	18.333	17.667	17.833	18.333	18.333	16.667	16.167	17.833	17.667
16	16.667	16.667	17.833	18.333	17.667	17.833	18.333	17.167	18.333	17.167	17.833	19.667
17	18.333	18.667	17.167	19.333	18.333	18.333	17.833	18.333	17.500	16.667	17.833	18.333
18	18.333	18.333	17.500	17.833	18.333	19.167	18.333	17.833	18.333	17.833	18.333	17.833
19	18.333	18.333	18.333	18.333	18.333	18.333	18.333	18.333	18.333	18.333	18.333	18.333
20	18.333	18.333	18.333	18.333	18.333	18.333	18.333	18.333	18.333	18.333	18.333	18.333
Group Mean	**18.358**	**18.217**	**17.983**	**18.383**	**17.992**	**19.096**	**18.033**	**17.983**	**18.400**	**18.133**	**18.258**	**18.325**

Figure 6.11: Variation in Mean User Travel Costs across periods of the experiment (Treatment 2: Information)

Standard Deviation of Individual User Travel Costs: Treatment 2 (Information)

Period	Session 1		Session 2		Session 3		Session 4		Session 5		Session 6	
	Group 1	Group 2	Group 1	Group 2	Group 1	Group 2	Group 1	Group 2	Group 1	Group 2	Group 1	Group 2
1	1.775	2.758	1.303	0.000	0.492	2.462	1.826	1.267	0.835	1.303	1.231	0.000
2	1.303	1.303	2.725	1.826	1.030	0.492	1.231	0.651	0.389	1.030	0.835	0.492
3	1.231	0.835	0.492	0.000	0.492	1.231	1.775	0.000	1.303	0.718	0.492	1.231
4	1.231	1.826	0.492	0.492	0.492	0.492	0.835	1.231	1.030	0.000	1.775	1.030
5	0.492	1.231	2.329	1.826	0.718	1.303	1.030	0.492	0.492	2.329	1.826	0.389
6	0.651	0.492	2.714	1.969	0.000	1.775	2.714	0.835	2.060	0.492	0.835	1.030
7	1.969	1.969	2.060	0.492	2.758	0.000	0.778	0.492	0.718	0.000	1.231	1.775
8	0.492	1.231	1.030	0.492	0.718	2.060	0.492	0.492	0.835	0.492	2.714	1.030
9	0.492	0.492	1.030	0.492	2.714	8.719	2.758	1.303	1.030	1.030	6.544	3.114
10	0.492	0.492	1.969	1.969	1.267	1.231	1.030	1.969	0.492	1.030	1.030	1.969
11	1.775	1.775	1.969	1.969	1.969	1.030	1.969	1.030	0.389	0.492	1.303	0.835
12	3.114	1.969	1.030	1.030	2.714	1.969	0.835	0.492	1.826	1.303	1.969	1.030
13	0.492	0.835	2.329	0.577	1.030	2.887	1.030	1.030	1.969	1.969	0.835	2.462
14	1.030	1.030	1.775	0.835	0.835	0.835	1.969	1.969	0.492	0.000	0.492	0.492
15	1.826	0.492	1.826	0.492	0.492	1.030	0.492	0.492	1.969	1.030	1.030	0.492
16	1.969	1.969	1.030	0.492	0.492	1.030	1.775	0.835	0.492	0.835	1.030	1.303
17	0.492	1.231	0.835	1.826	0.492	0.492	1.030	0.492	2.714	1.969	1.030	0.492
18	0.492	0.492	1.567	1.030	0.492	0.718	0.492	1.030	0.492	1.030	0.492	1.030
19	0.492	0.492	0.492	0.492	0.492	0.492	0.492	0.492	0.492	0.492	0.492	0.492
20	0.492	0.492	0.492	0.492	0.492	0.492	0.492	0.492	0.492	0.492	0.492	0.492
Group Standard Deviation	**1.698**	**1.653**	**1.823**	**1.604**	**1.500**	**3.140**	**1.820**	**1.576**	**1.822**	**1.500**	**2.118**	**1.837**

Figure 6.12: Variation in Standard Deviation of User Travel Costs across periods of the experiment (Treatment 1: No Information)

6.6 Discussion, Limitations and Future Extensions

The results of the experiment indicate the empirical presence of the Online Information Paradox, where the provision of online information deteriorates the network performance and increases the travel costs for users. The key findings can be summarised as follows;

- Provision of online information has the potential to increase total system travel costs, however there is a reduction in the variance of the travel costs and as a result can offer a greater level of reliability.
- Learning is clearly evident in the 'no information' scenario as initial use of the risky route A-C-B-D reduces in the later periods of the experiment. There is an indication of the 'hot stove effect' where the experiences of the incident conditions on link C-B cause aversion of route A-C-B-D.
- Learning appears to be limited in the information scenario as users become reactive travellers reliant on the provision of information.
- Strong statistical evidence for the empirical presence of the Online Information Paradox is maintained whilst accounting for learning by participants
- Traffic states define the benefits of information; in scenarios where there is considerable volatility in the prevailing network conditions, information will reduce the uncertainty and improved travel costs for the user and system as a whole.

The findings are consistent with the observations made by Lu et al. (2012) and Lu et al. (2014) where travel time variability reduces in the presence of information. The standard deviation of TSTC in the information case across all assessments was considerably lower than that of the no information case suggesting a more reliable system.

It is also important to emphasise that online information provision, in general, will reduce travel costs and improve the efficiency of a network at an analytical and empirical level as shown through a number of studies (Kim et al., 2005, Emmerink et al., 1995, Lu et al., 2012, Lu et al., 2014). The general impact of information provision was explained succinctly in Balakrishna et al. (2013). A traveller makes decisions based on the knowledge obtained through personal experience and exogenous information. Personal experience is limited by the lack of knowledge of all available options and is impacted by uncertainties such as the presence of bad weather and incidents within the network. The provision of exogenous information through ATIS is intended to alleviate the cognitive stress of the decision making and improve the quality of the decision for the user as well as the network. However, what is evident from this study and that of Rapoport et al. (2014) concerning pre-trip information is that for specific network topologies, there are situations where the provision of information can deteriorate network performance. Accordingly, based on the theoretical presentation of the UER framework and the corroborating empirical evidence, careful consideration of network structure is essential to avoid the emergence of such a paradox when evaluating the implementation of ATIS and ITS systems within road infrastructure.

It is acknowledged that there are limitations within this study. The fundamental abstraction from reality is that travel cost was the only criteria used by participants in deciding on the route choice. Route choice decisions are in general multi-objective where travellers do think about travel time, reliability, tolls, road hierarchy and other factors that could affect their decisions (Papinski et al., 2009). The network and costs functions used to assess the paradox within the experiment are simplifications of reality. Routes consist of multiple links, with multiple nodes where alternative routes could be taken. However, there is justification for this approach in an experimental as well as a cognitive context. In order to ensure control and reliability within an experiment, each participant must be able to comprehend the task to gain valuable insights (Dixit et al., 2015). In addition the simplification can be considered realistic as individuals cannot acquire and process all alternatives completely and naturally reduce choice sets and simplify complex cost structures by evaluating the most important components (Simon, 1955, Simon, 1982).

Similar to the experiment conducted in Chapter 3, the other two limiting factors from the experiment is the use of a University based participant pool and the consideration of 20 periods per treatment. A number of experiments have used student or University based participant pools to derive important findings related to all fields of research and in particular within the transportation field (Knorr et al., 2014, Koutsopoulos et al., 1994, Lu et al., 2012, Lu et al., 2014, Rapoport et al., 2014, Rapoport et al., 2008, Rapoport et al., 2009) . Furthermore, Dixit et al. (2013) conducted a study which presented no discernible difference between the use of student pools and a general pool of participants in a simulation experiment. However, ideally this experiment should be replicated on a wider demography to confirm the presence of the paradox. Finally, the use of only 20 periods per treatment is considerably less than previous studies which have looked at 40 periods or more. The reason for the limitation for the number of periods was based on a qualitative pilot study which assessed participant fatigue that deemed any more than 20 periods would be too great a demand for a participant. Though fewer periods were considered, there was stabilisation of travel costs within the last 3 to 4 periods of each treatment and a degree of convergence in decision making was observed. Future replications of the experiment could be conducted with an extended time period, 4 hours instead of 2 hours, with a break in between treatments to allow for more periods to be considered.

Further studies that can be extensions of this research involve the identification of the Online Information Paradox in the field using loop detector data or origin-destination surveys. Field identification will truly confirm the presence of the paradox and potentially validate the use of adaptive traffic assignment techniques such as UER. Confirmation will force planning authorities to ensure that these paradoxes do not arise with the implementation of information infrastructure. Authorities can achieve this by applying theoretical traffic assignment models that account for adaptive behaviour and the acquisition of online information to assess the impact of additional informational infrastructure.

6.7 Concluding Remarks and Impact

The primary aim of this study was to investigate the empirical presence of a theoretical transportation paradox, defined as the 'Online Information Paradox'. The paradox suggests that the provision of online information deteriorates the travel conditions for individual users as well as the system as a whole. The analytical presence of the paradox was derived from two equilibrium models; the Expected User Equilibrium (EUE) solution explained the case where individuals did not have access to information while the User Equilibrium with Recourse (UER) solution depicted the case of online information dissemination at an intermediate node between origin and destination. The concepts of experimental economics were used to develop a controlled incentivised laboratory experiment consisting of a repeated computerised route choice game. The game emulated a 3 route stochastic network with an intermediate node that allowed a user to swap routes. The stochasticity of the network was dependent on the presence of an incident on a single link of the network with a given probability of occurrence.

Aggregate statistics of path flow and Total System Travel Costs (TSTC) were used to compare the empirical findings with the theoretical findings. A total of 12 groups of participants completed the experiment and the Online Information Paradox was observed in 11 of the 12 cases and its presence across all the data was statistically significant at a confidence level of 95%. The results suggest that the EUE solution underestimates the TSTC of the 'no information' scenario; however the behaviour of the participants in the information scenario is consistent with that of the UER solution. A possible reason for the underestimation could be that the lack of information results in greater levels of exploratory behaviour. This behaviour in turn created greater travel costs for the users and strayed from the EUE solution. On the other hand when information was provided, the uncertainty surrounding the incident was reduced and the participants were reactive travellers based on the information provided. The reactive behaviour resulted in greater volatility of path flow in the information case; however user and system travel costs had significantly lower standard deviations supporting the claim that information improves travel time reliability.

The observation of the Online Information Paradox in a controlled setting creates an additional consideration for transport authorities during the evaluation and implementation of ITS and ATIS infrastructure within a road infrastructure context. Further replications of such experiments and more importantly field based identification of the phenomena will require transport professionals to be aware of the paradox much like that of the traditional Braess Paradox. Moreover, professionals need to utilise adaptive traffic assignment techniques, such as UER, the DEAR model and the DUOR model, to appropriately model the acquisition of information on a road network. Thus, this Chapter highlights the value of the research conducted in Chapter 4 and Chapter 5 as well as advocating further attention to this research area.

CHAPTER 7. CONCLUSION AND FUTURE RESEARCH DIRECTIONS

Disruptions on a road network create uncertainty and thus affect driving behaviour which needs to be accounted for within transport planning models. This thesis can be separated into two streams of research:

- Investigating the behavioural impacts on route choice and decision making in the presence of a disruption.
- Incorporation of incidents and disruptions within the network modelling paradigm.

Figure 7.1: Key concept of the research framework

The key concept postulated, and to a certain extent reflected in the findings of the research, can be described using Figure 7.1. The idea can be succinctly stated as, 'Disruptions lead to the release of information which affects driving behaviour'. Information here is described in a very general sense with a multitude of sources ranging across experiential, descriptive and prescriptive forms. For an example, consider a crash occurring on a motorway and the subsequent queue that emerges behind the incident. A user can gain information from visual cues such as the presence of brake lights and the existence of the queue itself and assess the situation based on previous experiences. Furthermore, the user may acquire information through ITS and ATIS technology such as variable message signs, through live traffic updates on the internet and radio describing the prevailing traffic conditions. Another possibility a user may have is access to GPS navigation technology that prescribes alternative routes to bypass the delays associated with the incident. Hence, to model disruptions on a network we must model the acquisition of information by a user concerning the disruption. This conceptual framework laid the foundation for the research efforts discussed within the thesis.

Initially, an empirical study of the impact of disruptions on traffic performance metrics was investigated to provide guidance for the requirements of the modelling approach. Though there have been a number of empirical studies investigating the impact of natural disasters, infrastructure failures and planned disturbances (Anderson, 2013, Carrion and Levinson, 2012, Danczyk et al., 2010), there has been limited research into the implications of shorter term disturbances such as road crashes and breakdowns. Chapter 2 presents the empirical study which used, travel speed, route length, traffic volume and incident data to compare the performance of a series of 5 competing parallel routes within the Sydney Metropolitan network. The incident data was overlayed with calculated travel time data and volume data to understand the implications of a disturbance on the routes.

The statistical analysis presented two novel findings. Firstly, travel times and travel speeds for a route remained statistically similar with and without the presence of an incident. Secondly, volumes fluctuated on the competing routes depending on the presence of a disruption. There were cases where there was a 5% reduction in utilisation of a route in the presence of a disruption. The findings suggest that users acquired information about the incident and adapted their behaviour in an attempt to mitigate the additional delays associated with the disruption. As with all empirical studies, there were data limitations and the need to collect further fine grained data in a variety of urban environments to confirm the observations. Nevertheless, this chapter provides impetus to study the impact of information provision on the risk characteristics of road users discussed in Chapter 3. Furthermore, it serves as a source of empirical justification for the adaptive equilibrium modelling frameworks that were developed within Chapter 4 and Chapter 5.

The provision of descriptive information through ITS and ATIS technology has been implemented by transport authorities to alleviate the impact of disruptions on a road network. To date, risk characteristics have not been accounted for when evaluating the costs and benefits of these systems. Chapter 3 aimed to fill this gap in research by studying the impact of information provision on risk characteristics of drivers using a controlled laboratory experiment. The experiment involved the use of Multiple Price Lotteries, framed as competing routes, where one route was riskier than the other. The choice data was analysed using a model based on Expected Utility Theory to infer the risk attitudes with and without the preference of information in the choice set.

The results of the modelling suggest that users' risk attitudes change from risk averse to risk neutral in the presence of information. This has considerable repercussions when evaluating projects concerning the implementation of road information by planning authorities. In scenarios where transport systems are reliable (low variability in performance), users tend to overvalue information prior to the implementation of information systems which is an important consideration in the valuation of these systems. This research also indicates that the value of reliability is greater in the scenario without the provision of information, as information reduces or resolves uncertainty. These findings have been consistent with a number of reliability related studies which suggest that information provision is the key to solving unreliable networks.

Further investigation into the impact of information on risk characteristics is possible through the investigation of non-linear mixed logit models which can account for the heterogeneity effects that information can create. In addition, the accuracy of information could also be tested in a laboratory setting to observe the effects of incorrect information on people's risk attitudes and valuation of information. This is particularly relevant when developing natural disaster warning systems that are utilised during disrupted conditions, such as bushfire alerts in Australia.

Chapter 4 and Chapter 5 gathered the understanding obtained from the behavioural research in Chapter 2 and 3 to develop modelling frameworks which accounted for disrupted network conditions. The models evolved from the concepts of User Equilibrium with Recourse (UER) presented by Unnikrishnan and Waller (2009). UER is an adaptive static equilibrium that accounts for information acquisition ideally suiting the exploration of disrupted network behaviour. Instead of equilibrating on paths, the approach considers that users equilibrate on routing policies which are a set of state dependent paths.

Chapter 4 presents a static model, the Disrupted Equilibrium Assignment with Recourse (DEAR) model which considered the transformation of travel time perception in light of disrupted conditions as well as the associated adaptive behaviour. The model considers people's perceptions and experiences within disrupted conditions as the source of information governing route choice. The model was developed by incorporating two previous models; the Disrupted Network Assignment Model (DNAM) and the UER framework. Application of the model indicated the necessity to not only account for the transformation of perceptions in disrupted conditions but also to include for the ability of users to adapt their routes based on information gained during travel. Findings of the sensitivity analysis on model parameters reiterated the behavioural findings with regard to reliability. Networks which experience greater reliability or consistency in traffic conditions result in lower system wide costs. Thus, it is important to capture the behaviour of users in disrupted conditions as well as devise strategies to mitigate the impact of disruptions to obtain more reliable networks.

Various assumptions of the DEAR methodology could be relaxed in the future to investigate different information and disrupted contexts. The consideration of correlated link states to model dispersive disrupted conditions, such as flooding, can be achieved through the use of the R-SSPR algorithm (Polychronopolous and Tsitsiklis, 1996). Heterogeneity of information acquisition could also be captured by incorporating the STOCH-UER model proposed by Ukkusuri and Patil (2007) to include perceptions towards information as well as disruptions on the network.

Disruptions are dynamic in nature. An incident or crash can occur on a link; the traffic immediately following the incident begins to queue, traffic upstream of the incident gains information of the disruption and over time adaptive behaviour takes place. Thus, in order to properly capture this behaviour a dynamic modelling effort was undertaken in Chapter 5. This chapter extends Dynamic User Optimal (DUO) to DUO with Recourse (DUOR) based on the underlying principles of UER. This time dependent equilibrium accounts for adaptive routing in light of information acquisition. The DUOR concept is applied through a simulation based DTA model, Dynamic User Optimal with Recourse - Cell Transmission Model (DUOR-CTM). The CTM serves as the traffic simulator to propagate traffic. An enumerative solution procedure was applied to small demonstration networks with the primary objective of identifying DUOR solutions and the dynamic impact of information on system performance.

Multiple DUOR equilibria were discovered on the networks assessed. Some networks produced unique solutions, whilst others presented non-unique solutions which could be a consequence of the discretisation of time and space within the CTM framework. The complexity of the enumeration process resulted in computational inefficiency of the model and further work is currently being carried out to apply the model on more realistic networks. Heuristic algorithms as well as the adaptation and formulation of 'shortest policy' algorithms can possibly overcome the burden. In general, the results of the modelling presented positive impacts of online information provision. However, there were indications of negative impacts highlighting the need to account for information in a dynamic context.

Even though there are limitations with the DUOR-CTM approach, the presence of equilibrium in this framework is notable as this is the first simulation based DTA model to account for dynamic traffic effects, adaptive routing and acquisition of online information. DUOR-CTM presents a foundation model to extend into the future and potentially apply in practice as an operational network planning model which can assist traffic engineers, transport planners and government authorities in developing a sustainable road infrastructure system.

Finally, Chapter 6 contains an experiment that aimed to empirically verify the presence of the 'Online Information Paradox' identified in the UER framework. The paradox suggests that the provision of information results in an overall increase in the total system travel time. Furthermore, similar to the static paradox, Chapter 5 also indicates the possibility of negative information impacts in a dynamic setting. This study places attention on the long standing idea that the provision of information is always beneficial in the mitigation of disrupted conditions and will reduce overall travel costs for the user.

Chapter 6, similar to Chapter 3, uses the concepts of experimental economics to develop a computerised route choice game to study the presence of the Online Information Paradox. The game involved participants traversing a 3-path stochastic road network, where one link of the network experienced an incident. The network consisted of an intermediate node which allowed participants to change routes mid-path prior to traversing the stochastic link. Two treatments were applied, one where users did not have online information and the other where information was provided to observe the presence of the analytical paradox. The results of the experiment were conclusive with the Online Information Paradox being observed in all sessions. The TSTC of the no information scenario was significantly lower than the TSTC of the information scenario at a confidence level of 95%. Even though the system experienced greater travel costs, the provision of information enhanced reliability with a considerably lower standard deviation of user and system costs across the conducted sessions.

This empirical finding is of similar nature to the observation of the Braess Paradox in a laboratory setting. Replications of this experiment and similar experiments in conjunction with field data validation will confirm the presence of the paradox. The existence of the paradox, even in a laboratory setting strongly emphasises the need to develop and use adaptive traffic assignment techniques, such as UER, the

DEAR model and the DUOR model, to adequately account for the acquisition of information on a road network.

This thesis provides behavioural and methodological insight into the modelling of disrupted behaviour within road networks. It is clear that disruptions and the information associated with disruptions, impact the risk characteristics of the user and results in adaptive behaviour. Also each chapter arrived at the conclusion that adaptive assignment techniques are essential to capture behaviour of users in disrupted conditions. Future research should focus on the development of a consolidated model that accounts for the supply side impact of disruptions as well as the behavioural reactions associated with the incident. Accounting for both these features will make it possible to develop more accurate models which in turn lead to improved decision making and ultimately a more sustainable transport future.

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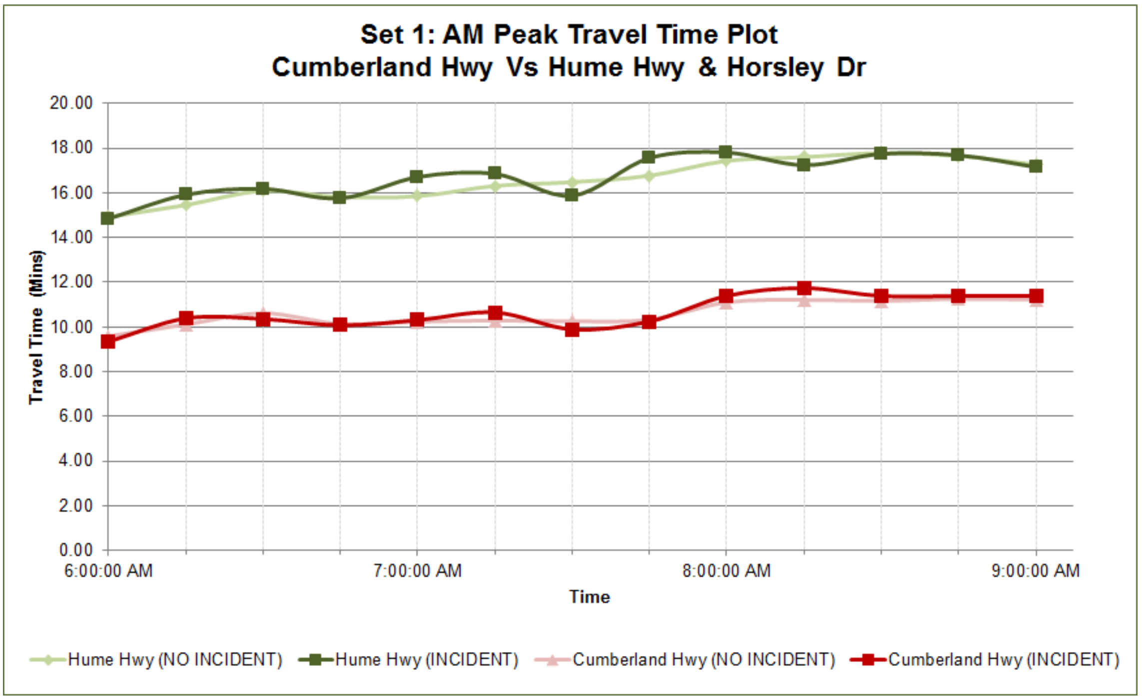
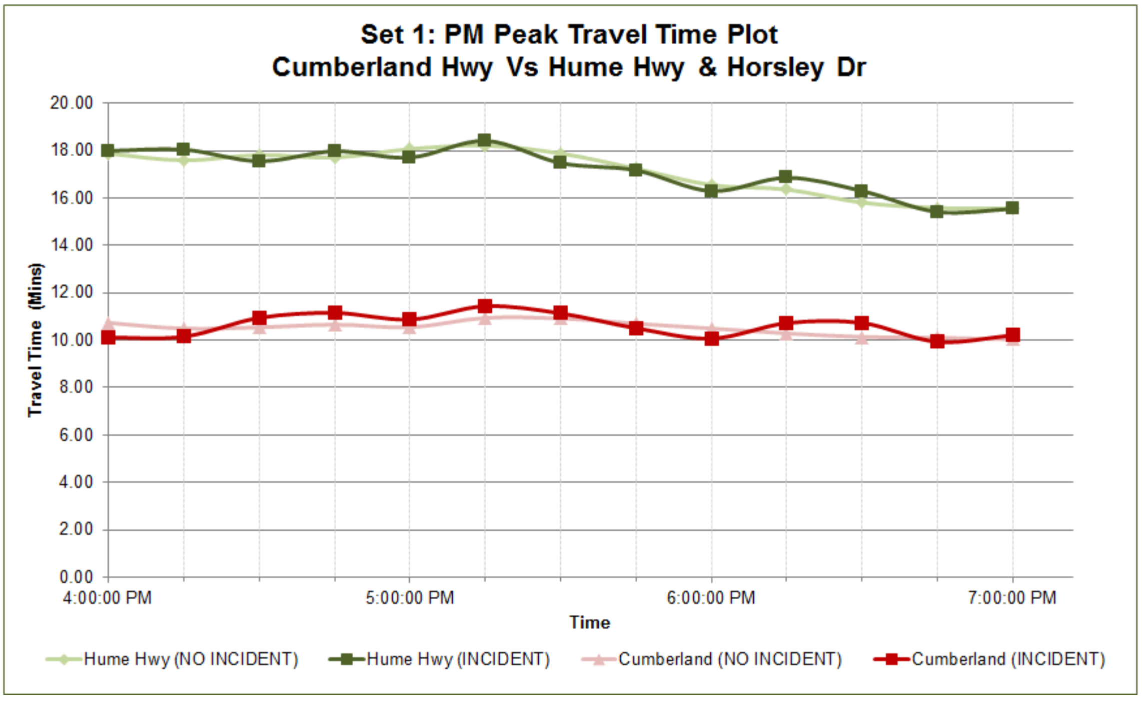
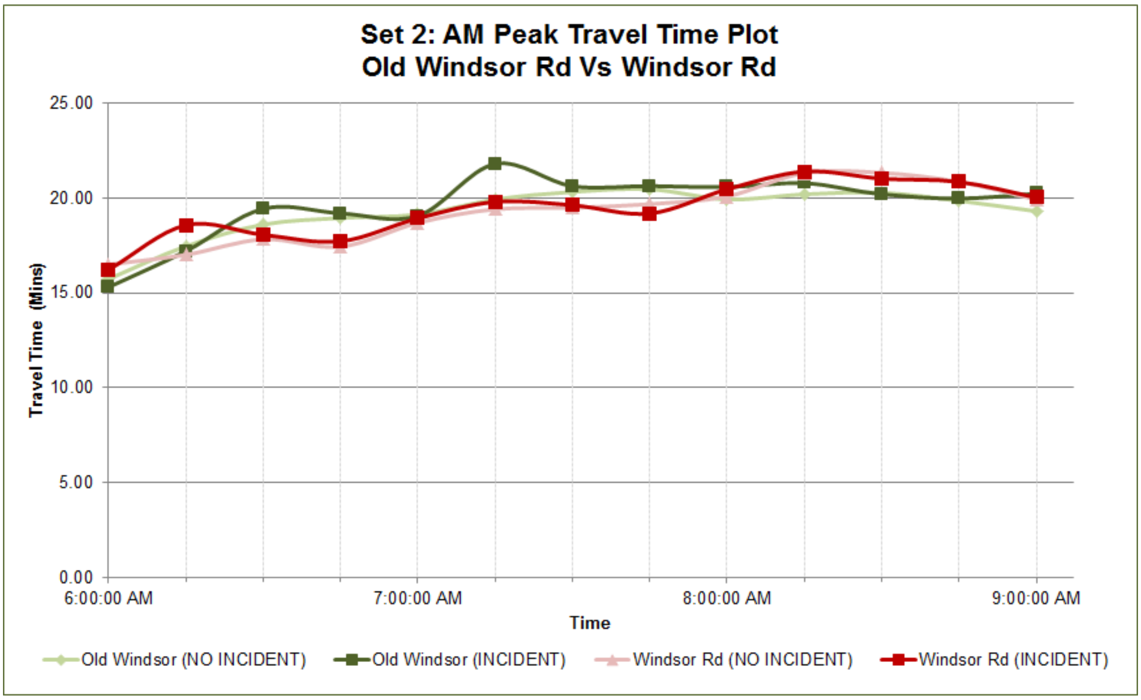
APPENDIX A: AVERAGE TRAVEL TIME PLOTS (CHAPTER 2)

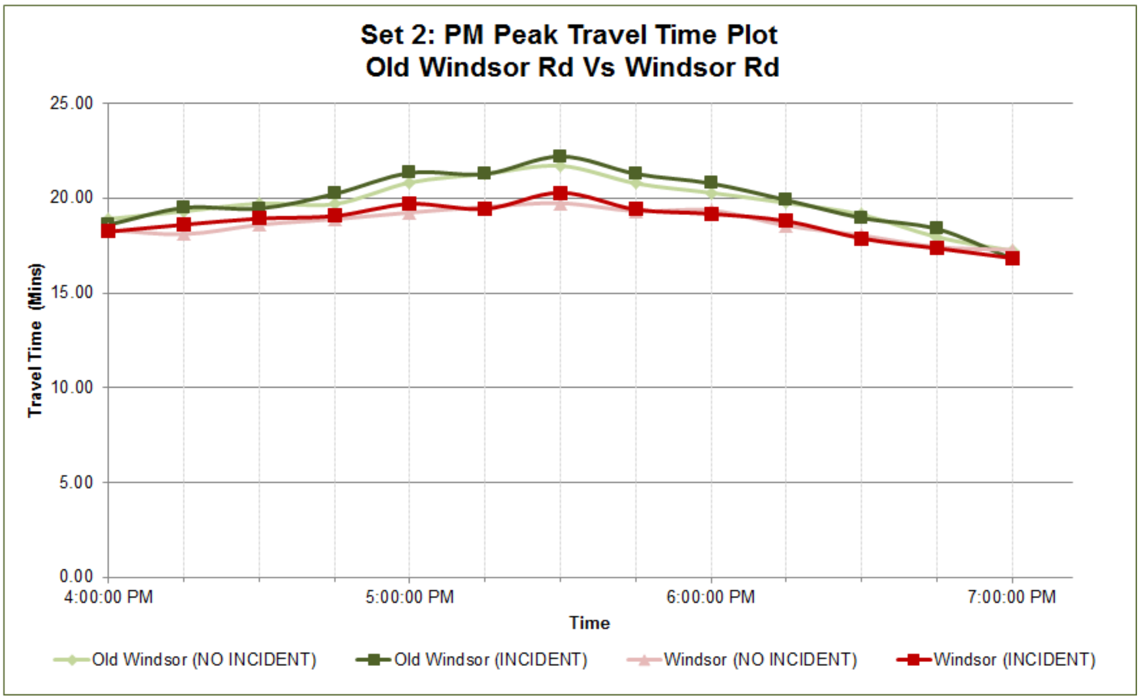
<u>Set 1</u>: Cumberland Highway Vs Hume Highway and Horsley Drive



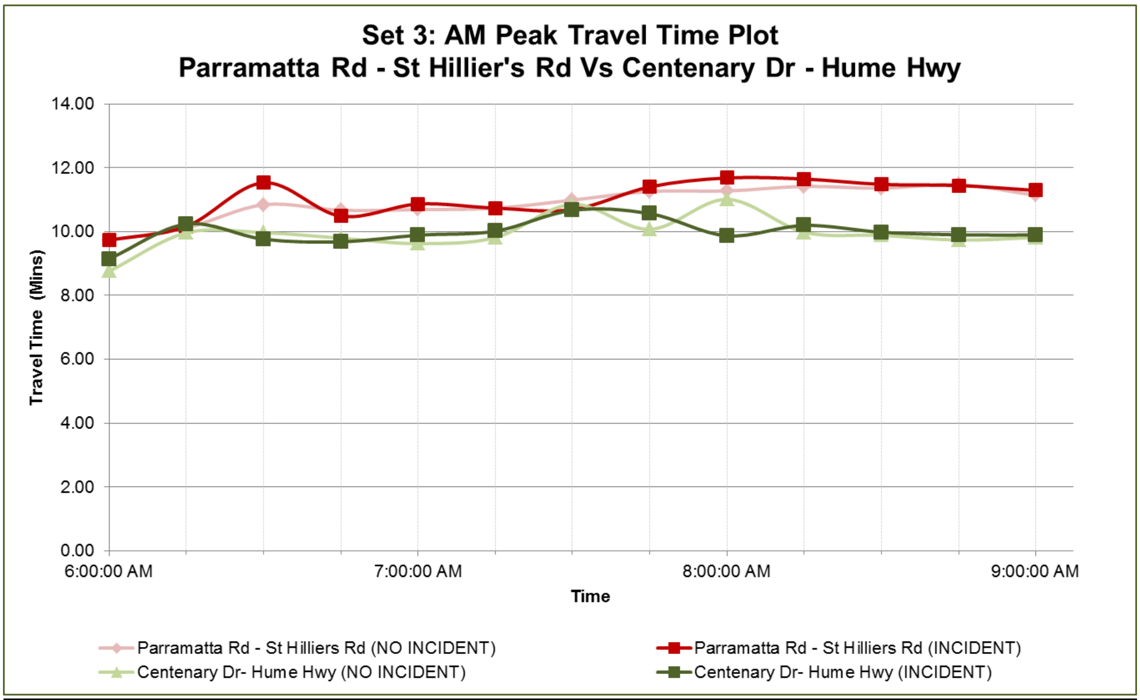


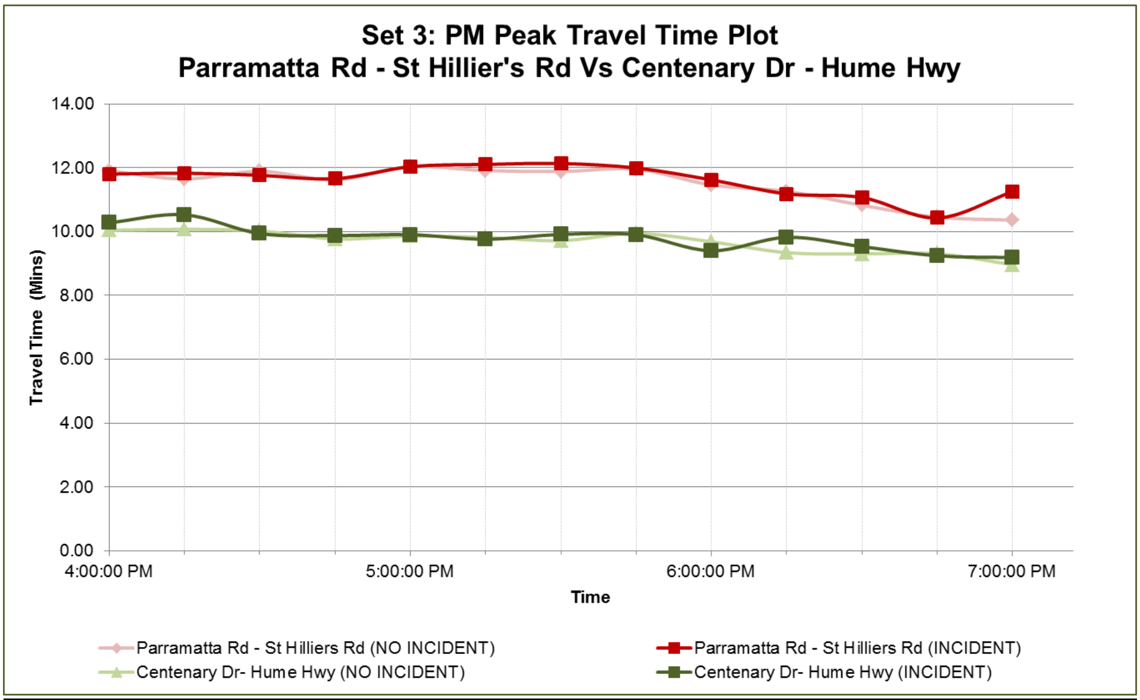
***Set 2*: Windsor Road Vs Old Windsor Road**



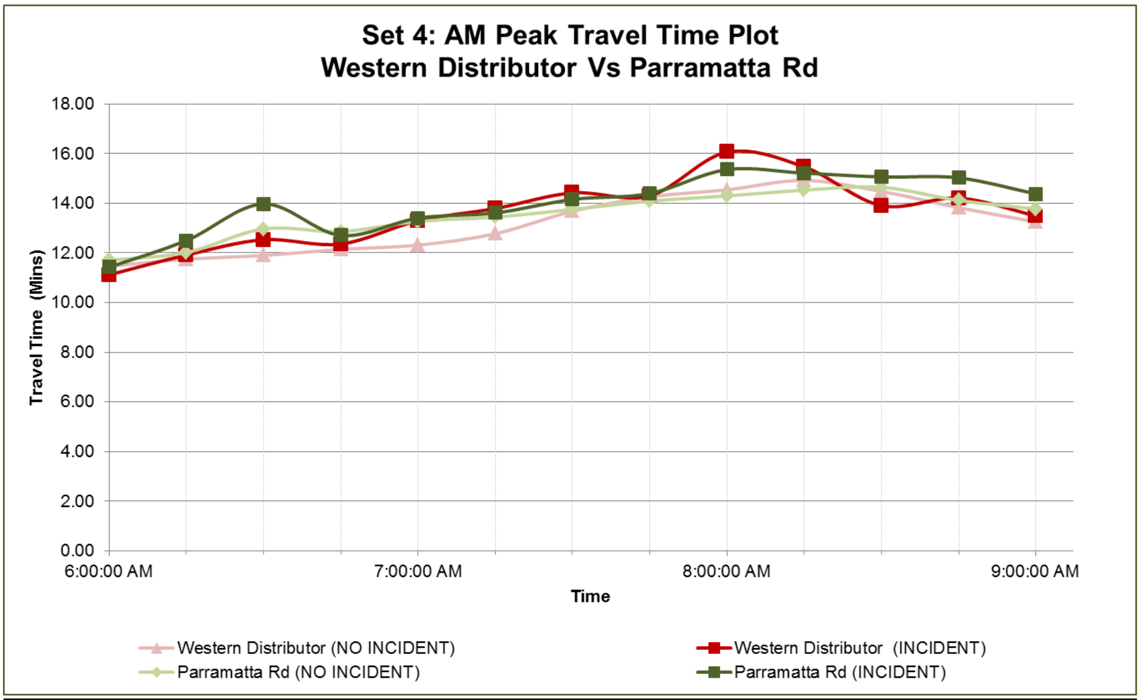


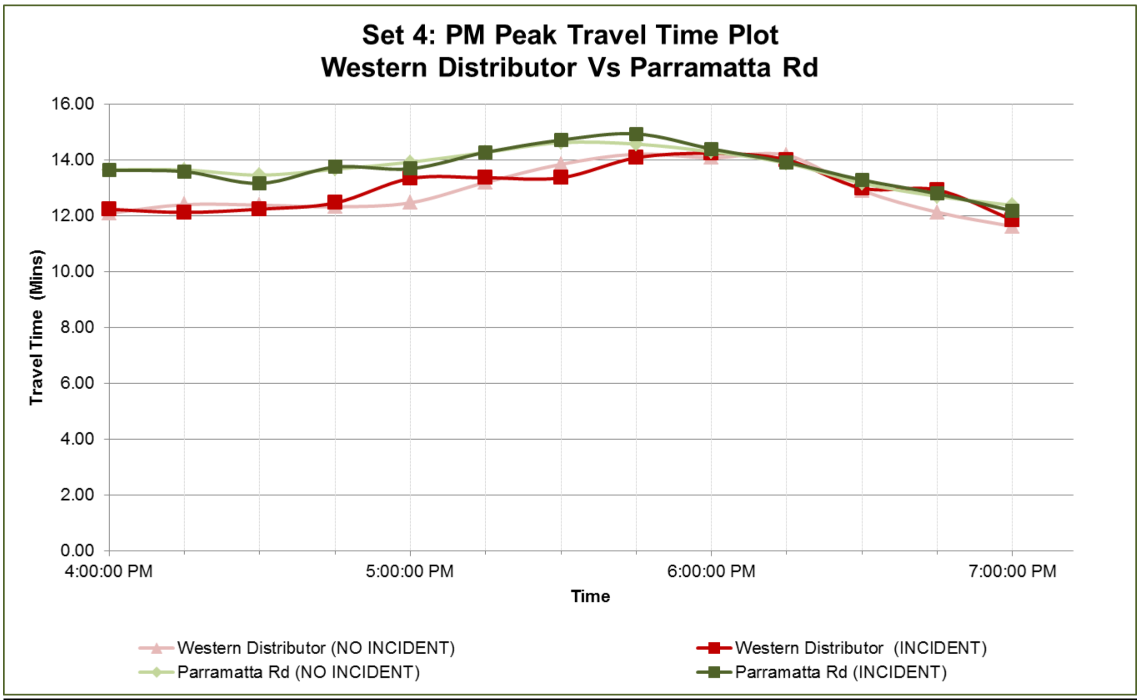
***Set 3*: Parramatta Road – St Hillier's Road Vs Centenary Drive – Hume Highway**



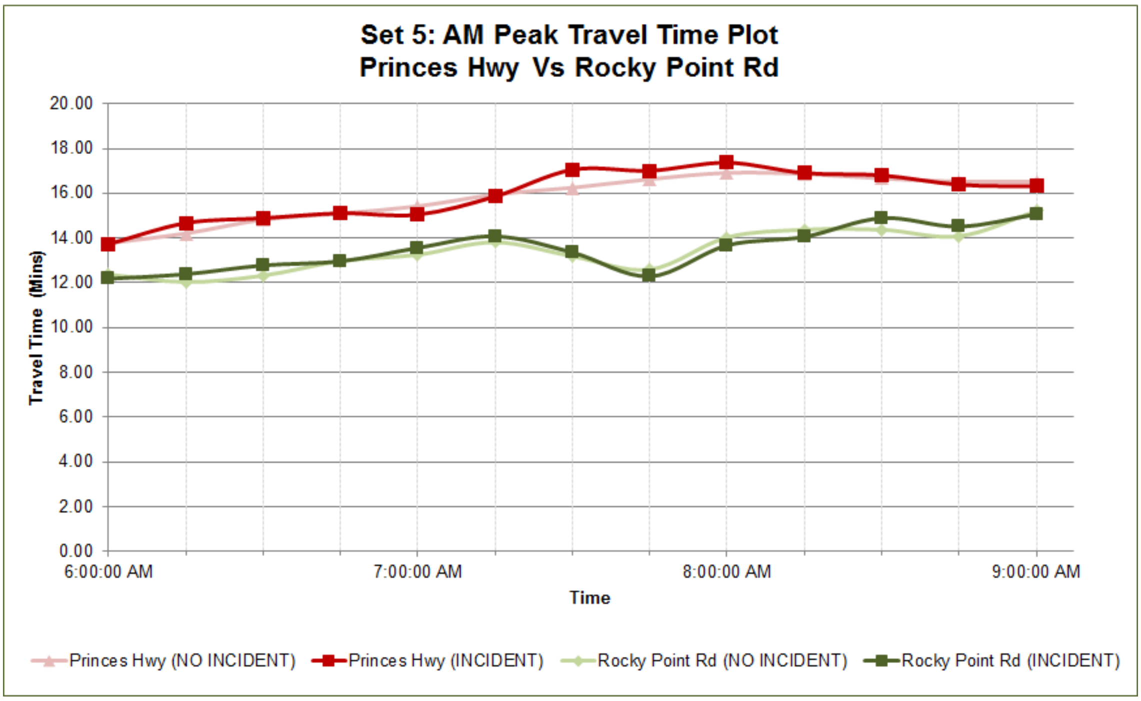


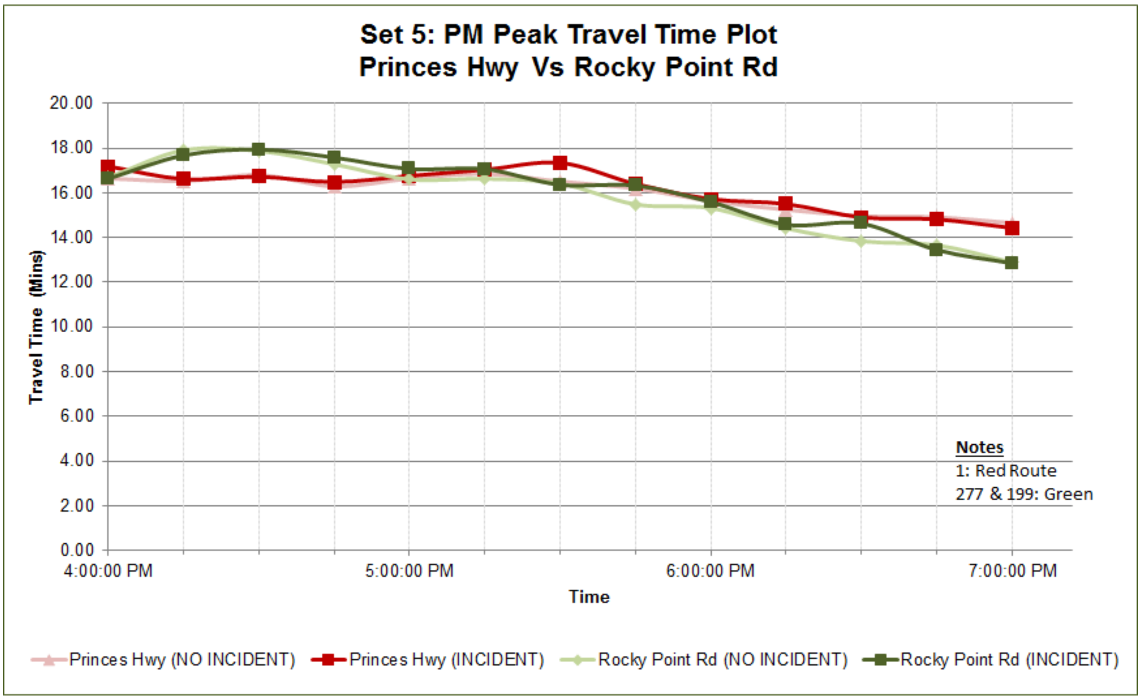
***Set 4*: Western Distributor Vs Parramatta Road**





***Set 5*: Princes Highway Vs Rocky Point Road**





APPENDIX B: HYPOTHESIS TESTING OF TRAVEL TIME DATA (CHAPTER 2)

__Set 1__: Cumberland Highway Vs Hume Highway and Horsley Drive

AM Peak Results

ID	Route 1A (NO INCIDENT)			Route 1A (INCIDENT)			Hypothesis Testing Results				
Route Name	Cumberland Hwy			Cumberland Hwy							
Time (AM Peak)	Std. Dev. (Mins)	Avg. TT (Mins)	N	Std. Dev. (Mins)	Avg. TT (Mins)	N	Std. Error (Mins)	v	t_{stat}	t_{crit}	Reject Null Hypothesis?
6:00 AM - 6:15 AM	0.21	9.59	293	0.86	9.34	4	0.43	3.00	0.57	3.18	NO
6:15 AM - 6:30 AM	0.50	10.11	322	0.95	10.39	4	0.47	3.02	0.58	3.18	NO
6:30 AM - 6:45 AM	1.07	10.61	342	1.02	10.36	6	0.42	5.20	0.61	2.57	NO
6:45 AM - 7:00 AM	0.55	10.14	361	1.02	10.07	6	0.42	5.05	0.15	2.57	NO
7:00 AM - 7:15 AM	1.01	10.24	353	0.95	10.31	12	0.28	11.87	0.26	2.20	NO
7:15 AM - 7:30 AM	1.07	10.29	343	0.97	10.65	14	0.27	14.31	1.36	2.14	NO
7:30 AM - 7:45 AM	0.74	10.25	349	0.93	9.89	7	0.35	6.15	1.02	2.45	NO
7:45 AM - 8:00 AM	0.89	10.33	345	0.99	10.24	9	0.33	8.34	0.25	2.31	NO
8:00 AM - 8:15 AM	0.98	11.10	321	1.10	11.39	10	0.35	9.45	0.82	2.26	NO
8:15 AM - 8:30 AM	0.93	11.21	311	0.96	11.74	13	0.27	12.96	1.95	2.18	NO
8:30 AM - 8:45 AM	0.81	11.17	317	0.94	11.38	12	0.28	11.62	0.79	2.20	NO
8:45 AM - 9:00 AM	0.81	11.25	337	1.03	11.38	12	0.30	11.49	0.44	2.20	NO
Overall Peak Statistics	0.80	10.52	3994	0.98	10.60	109	0.09	111.97	0.77	1.98	NO
							% Null Hypothesis				100.00%

ID	Route 1B (NO INCIDENT)			Route 1B (INCIDENT)			Hypothesis Testing Results				
Route Name	Hume Hwy - Horsley Dr			Hume Hwy - Horsley Dr							
Time (AM Peak)	Std. Dev. (Mins)	Avg. TT (Mins)	N	Std. Dev. (Mins)	Avg. TT (Mins)	N	Std. Error (Mins)	v	t_{stat}	t_{crit}	Reject Null Hypothesis?
6:00 AM - 6:15 AM	0.26	14.92	351	0.87	14.84	4	0.44	3.01	0.19	3.18	NO
6:15 AM - 6:30 AM	0.79	15.45	367	1.05	15.91	4	0.53	3.04	0.87	3.18	NO
6:30 AM - 6:45 AM	1.11	16.08	369	1.14	16.18	6	0.47	5.15	0.20	2.57	NO
6:45 AM - 7:00 AM	1.47	15.82	372	1.12	15.75	5	0.51	4.19	0.12	2.78	NO
7:00 AM - 7:15 AM	1.00	15.85	363	1.21	16.70	11	0.37	10.42	2.33	2.23	YES
7:15 AM - 7:30 AM	1.41	16.31	362	1.18	16.85	14	0.32	14.47	1.66	2.14	NO
7:30 AM - 7:45 AM	0.82	16.48	368	1.14	15.87	6	0.47	5.08	1.29	2.57	NO
7:45 AM - 8:00 AM	1.40	16.77	366	1.18	17.56	10	0.38	9.71	2.09	2.26	NO
8:00 AM - 8:15 AM	0.97	17.43	367	1.26	17.80	11	0.38	10.36	0.98	2.23	NO
8:15 AM - 8:30 AM	1.34	17.59	362	1.18	17.24	13	0.33	13.13	1.06	2.16	NO
8:30 AM - 8:45 AM	1.33	17.78	367	1.18	17.74	12	0.35	11.93	0.11	2.20	NO
8:45 AM - 9:00 AM	1.01	17.65	357	1.31	17.68	16	0.33	15.81	0.09	2.13	NO
Overall Peak Statistics	1.07	16.51	4371	1.15	16.68	112	0.11	116.00	1.51	1.98	NO
							% Null Hypothesis				91.67%

ID	Route 1A (NO INCIDENT)			Route 1B (NO INCIDENT)			Hypothesis Testing Results				
Route Name	Cumberland Hwy			Hume Hwy - Horsley Dr							
Time (AM Peak)	Std. Dev. (Mins)	Avg. TT (Mins)	N	Std. Dev. (Mins)	Avg. TT (Mins)	N	Std. Error (Mins)	v	t_{stat}	t_{crit}	Reject Null Hypothesis?
6:00 AM - 6:15 AM	0.21	9.56	290	0.26	14.90	290	0.02	551.24	275.30	1.96	YES
6:15 AM - 6:30 AM	0.49	10.08	320	0.78	15.42	320	0.05	535.93	103.14	1.96	YES
6:30 AM - 6:45 AM	1.06	10.60	328	1.11	16.07	328	0.08	652.69	64.66	1.96	YES
6:45 AM - 7:00 AM	0.54	10.06	343	1.47	15.74	343	0.08	433.89	66.99	1.97	YES
7:00 AM - 7:15 AM	1.01	10.23	345	1.00	15.84	345	0.08	687.86	73.46	1.96	YES
7:15 AM - 7:30 AM	1.06	10.28	335	1.41	16.30	335	0.10	621.29	62.40	1.96	YES
7:30 AM - 7:45 AM	0.73	10.21	310	0.82	16.43	310	0.06	610.73	100.02	1.96	YES
7:45 AM - 8:00 AM	0.88	10.24	300	1.40	16.68	300	0.10	505.16	67.57	1.96	YES
8:00 AM - 8:15 AM	0.97	11.08	311	0.96	17.40	311	0.08	619.97	81.53	1.96	YES
8:15 AM - 8:30 AM	0.93	11.19	284	1.34	17.57	284	0.10	504.24	66.21	1.96	YES
8:30 AM - 8:45 AM	0.80	11.08	310	1.33	17.70	310	0.09	508.60	75.08	1.96	YES
8:45 AM - 9:00 AM	0.80	11.22	317	1.01	17.62	317	0.07	601.75	88.40	1.96	YES
Overall Peak Statistics	0.79	10.49	3793	1.07	16.47	3793	0.02	6974.36	276.66	1.96	YES
							% Null Hypothesis				0.00%

ID	Route 1A (NO INCIDENT)			Route 1B (INCIDENT)			Hypothesis Testing Results				
Route Name	Cumberland Hwy			Hume Hwy - Horsley Dr							
Time (AM Peak)	Std. Dev. (Mins)	Avg. TT (Mins)	N	Std. Dev. (Mins)	Avg. TT (Mins)	N	Std. Error (Mins)	v	t_{stat}	t_{crit}	Reject Null Hypothesis?
6:00 AM - 6:15 AM	0.21	9.60	3	0.87	14.83	3	0.51	2.24	10.16	4.30	YES
6:15 AM - 6:30 AM	0.50	10.13	3	1.04	15.90	3	0.67	2.89	8.65	4.30	YES
6:30 AM - 6:45 AM	1.07	10.62	4	1.13	16.17	4	0.78	5.98	7.12	2.57	YES
6:45 AM - 7:00 AM	0.56	10.17	5	1.11	15.74	5	0.56	5.89	9.97	2.57	YES
7:00 AM - 7:15 AM	1.01	10.24	10	1.20	16.70	10	0.50	17.50	12.98	2.11	YES
7:15 AM - 7:30 AM	1.07	10.29	12	1.18	16.85	12	0.46	21.81	14.25	2.08	YES
7:30 AM - 7:45 AM	0.74	10.28	5	1.14	15.86	5	0.61	6.88	9.21	2.45	YES
7:45 AM - 8:00 AM	0.89	10.37	9	1.17	17.54	9	0.49	14.90	14.62	2.14	YES
8:00 AM - 8:15 AM	0.98	11.12	10	1.25	17.80	10	0.50	17.02	13.29	2.11	YES
8:15 AM - 8:30 AM	0.93	11.22	12	1.18	17.23	12	0.43	20.92	13.87	2.09	YES
8:30 AM - 8:45 AM	0.81	11.21	12	1.17	17.72	12	0.41	19.59	15.79	2.09	YES
8:45 AM - 9:00 AM	0.81	11.27	15	1.30	17.67	15	0.40	23.53	16.17	2.07	YES
Overall Peak Statistics	0.80	10.54	100	1.15	16.67	100	0.14	177.06	43.82	1.97	YES
							% Null Hypothesis				0.00%

ID	Route 1B (NO INCIDENT)			Route 1A (INCIDENT)			Hypothesis Testing Results				
Route Name	Hume Hwy - Horsley Dr			Cumberland Hwy							
Time (AM Peak)	Std. Dev. (Mins)	Avg. TT (Mins)	N	Std. Dev. (Mins)	Avg. TT (Mins)	N	Std. Error (Mins)	v	t_{stat}	t_{crit}	Reject Null Hypothesis?
6:00 AM - 6:15 AM	0.26	14.94	3	0.86	9.33	3	0.52	2.37	10.79	4.30	YES
6:15 AM - 6:30 AM	0.79	15.47	3	0.95	10.38	3	0.71	3.88	7.16	3.18	YES
6:30 AM - 6:45 AM	1.11	16.09	6	1.01	10.35	6	0.61	9.91	9.33	2.26	YES
6:45 AM - 7:00 AM	1.48	15.85	6	1.02	10.06	6	0.73	8.87	7.90	2.31	YES
7:00 AM - 7:15 AM	1.00	15.85	10	0.95	10.31	10	0.44	17.96	12.73	2.11	YES
7:15 AM - 7:30 AM	1.41	16.32	13	0.97	10.65	13	0.48	21.28	11.91	2.08	YES
7:30 AM - 7:45 AM	0.82	16.50	6	0.93	9.88	6	0.51	9.85	13.07	2.26	YES
7:45 AM - 8:00 AM	1.40	16.81	8	0.99	10.22	8	0.61	12.59	10.89	2.18	YES
8:00 AM - 8:15 AM	0.97	17.44	8	1.09	11.39	8	0.52	13.80	11.73	2.16	YES
8:15 AM - 8:30 AM	1.34	17.61	12	0.96	11.73	12	0.48	19.92	12.36	2.09	YES
8:30 AM - 8:45 AM	1.33	17.82	10	0.94	11.36	10	0.52	16.18	12.52	2.12	YES
8:45 AM - 9:00 AM	1.01	17.66	11	1.03	11.38	11	0.44	20.00	14.44	2.09	YES
Overall Peak Statistics	1.08	16.53	96	0.97	10.59	96	0.15	188.12	40.08	1.97	YES
							% Null Hypothesis				0.00%

PM Peak Results

ID	Route 1A (NO INCIDENT)			Route 1A (INCIDENT)			Hypothesis Testing Results				
Route Name	Cumberland Hwy			Cumberland Hwy							
Time (PM Peak)	Std. Dev. (Mins)	Avg. TT (Mins)	N	Std. Dev. (Mins)	Avg. TT (Mins)	N	Std. Error (Mins)	v	t_{stat}	t_{crit}	Reject Null Hypothesis?
4:00 PM - 4:15 PM	1.17	10.73	311	0.93	10.11	12	0.28	12.39	2.26	2.18	YES
4:15 PM - 4:30 PM	0.67	10.49	308	0.91	10.15	12	0.26	11.47	1.29	2.20	NO
4:30 PM - 4:45 PM	0.93	10.55	309	0.90	10.95	11	0.28	10.77	1.45	2.23	NO
4:45 PM - 5:00 PM	0.64	10.66	294	0.86	11.15	9	0.29	8.28	1.71	2.31	NO
5:00 PM - 5:15 PM	0.87	10.55	260	0.79	10.87	8	0.29	7.53	1.12	2.36	NO
5:15 PM - 5:30 PM	0.96	10.94	272	0.92	11.44	9	0.31	8.59	1.59	2.31	NO
5:30 PM - 5:45 PM	0.54	10.92	252	0.89	11.13	16	0.23	15.70	0.94	2.13	NO
5:45 PM - 6:00 PM	0.60	10.70	270	0.87	10.51	13	0.24	12.56	0.78	2.18	NO
6:00 PM - 6:15 PM	0.43	10.50	254	0.79	10.07	7	0.30	6.10	1.41	2.45	NO
6:15 PM - 6:30 PM	1.00	10.29	248	0.92	10.72	6	0.38	5.29	1.13	2.57	NO
6:30 PM - 6:45 PM	0.24	10.14	219	0.75	10.73	9	0.25	8.07	2.37	2.31	YES
6:45 PM - 7:00 PM	0.98	10.11	200	0.74	9.93	4	0.38	3.21	0.45	3.18	NO
Overall Peak Statistics	0.75	10.55	3197	0.86	10.65	116	0.08	121.56	1.24	1.98	NO
							% Null Hypothesis				83.33%

ID	Route 1B (NO INCIDENT)			Route 1B (INCIDENT)			Hypothesis Testing Results				
Route Name	Hume Hwy - Horsley Dr			Hume Hwy - Horsley Dr							
Time (PM Peak)	Std. Dev. (Mins)	Avg. TT (Mins)	N	Std. Dev. (Mins)	Avg. TT (Mins)	N	Std. Error (Mins)	v	t_{stat}	t_{crit}	Reject Null Hypothesis?
4:00 PM - 4:15 PM	1.22	17.88	364	1.88	17.99	14	0.51	13.42	0.23	2.16	NO
4:15 PM - 4:30 PM	1.10	17.59	359	0.97	18.05	14	0.27	14.33	1.71	2.14	NO
4:30 PM - 4:45 PM	1.15	17.82	365	1.17	17.56	13	0.33	12.84	0.80	2.18	NO
4:45 PM - 5:00 PM	1.08	17.71	354	0.62	17.98	13	0.18	14.79	1.46	2.14	NO
5:00 PM - 5:15 PM	1.14	18.07	355	1.26	17.71	16	0.32	16.12	1.12	2.12	NO
5:15 PM - 5:30 PM	1.17	18.22	346	1.17	18.42	12	0.34	11.78	0.58	2.20	NO
5:30 PM - 5:45 PM	0.98	17.88	331	1.09	17.48	19	0.26	19.70	1.58	2.09	NO
5:45 PM - 6:00 PM	0.94	17.24	313	0.65	17.17	16	0.17	18.36	0.40	2.10	NO
6:00 PM - 6:15 PM	0.77	16.55	324	0.64	16.30	7	0.24	6.39	1.04	2.45	NO
6:15 PM - 6:30 PM	0.72	16.36	312	0.82	16.86	11	0.25	10.55	1.98	2.23	NO
6:30 PM - 6:45 PM	0.76	15.81	295	0.87	16.30	12	0.26	11.69	1.91	2.20	NO
6:45 PM - 7:00 PM	0.72	15.59	268	0.68	15.42	6	0.28	5.25	0.60	2.57	NO
Overall Peak Statistics	0.98	17.23	3986	0.98	17.27	153	0.08	163.72	0.51	1.97	NO
							% Null Hypothesis				100.00%

ID	Route 1A (NO INCIDENT)			Route 1B (NO INCIDENT)			Hypothesis Testing Results				
Route Name	Cumberland Hwy			Hume Hwy - Horsley Dr							
Time (PM Peak)	Std. Dev. (Mins)	Avg. TT (Mins)	N	Std. Dev. (Mins)	Avg. TT (Mins)	N	Std. Error (Mins)	v	t_{stat}	t_{crit}	Reject Null Hypothesis?
4:00 PM - 4:15 PM	1.17	10.72	295	1.21	17.86	295	0.10	587.32	72.90	1.96	YES
4:15 PM - 4:30 PM	0.66	10.45	288	1.09	17.55	288	0.08	473.41	94.08	1.96	YES
4:30 PM - 4:45 PM	0.93	10.46	291	1.15	17.73	291	0.09	555.65	84.22	1.96	YES
4:45 PM - 5:00 PM	0.64	10.56	270	1.07	17.61	270	0.08	438.37	93.14	1.97	YES
5:00 PM - 5:15 PM	0.87	10.52	242	1.13	18.04	242	0.09	451.72	82.19	1.97	YES
5:15 PM - 5:30 PM	0.96	10.93	255	1.16	18.20	255	0.09	489.63	77.23	1.96	YES
5:30 PM - 5:45 PM	0.53	10.90	240	0.97	17.86	240	0.07	370.43	97.40	1.97	YES
5:45 PM - 6:00 PM	0.60	10.67	241	0.94	17.21	241	0.07	406.67	91.12	1.97	YES
6:00 PM - 6:15 PM	0.42	10.47	233	0.77	16.52	233	0.06	360.01	105.71	1.97	YES
6:15 PM - 6:30 PM	1.00	10.29	226	0.72	16.36	226	0.08	408.64	74.27	1.97	YES
6:30 PM - 6:45 PM	0.24	10.10	198	0.76	15.77	198	0.06	235.66	100.02	1.97	YES
6:45 PM - 7:00 PM	0.98	10.05	190	0.72	15.53	190	0.09	346.63	62.02	1.97	YES
Overall Peak Statistics	0.75	10.51	2969	0.97	17.19	2969	0.02	5568.79	296.18	1.96	YES
							% Null Hypothesis				0.00%

ID	Route 1A (NO INCIDENT)			Route 1B (INCIDENT)			Hypothesis Testing Results				
Route Name	Cumberland Hwy			Hume Hwy - Horsley Dr							
Time (PM Peak)	Std. Dev. (Mins)	Avg. TT (Mins)	N	Std. Dev. (Mins)	Avg. TT (Mins)	N	Std. Error (Mins)	v	t_{stat}	t_{crit}	Reject Null Hypothesis?
4:00 PM - 4:15 PM	1.18	10.74	12	1.88	17.99	12	0.64	18.47	11.31	2.10	YES
4:15 PM - 4:30 PM	0.67	10.52	13	0.97	18.03	13	0.33	21.35	23.04	2.08	YES
4:30 PM - 4:45 PM	0.93	10.59	12	1.17	17.53	12	0.43	20.98	16.09	2.09	YES
4:45 PM - 5:00 PM	0.65	10.71	12	0.62	17.95	12	0.26	21.96	28.01	2.08	YES
5:00 PM - 5:15 PM	0.88	10.57	15	1.26	17.70	15	0.40	25.00	18.04	2.06	YES
5:15 PM - 5:30 PM	0.97	10.95	11	1.16	18.41	11	0.46	19.37	16.35	2.09	YES
5:30 PM - 5:45 PM	0.54	10.93	18	1.09	17.47	18	0.29	24.94	22.86	2.06	YES
5:45 PM - 6:00 PM	0.60	10.72	14	0.65	17.16	14	0.24	25.81	27.27	2.06	YES
6:00 PM - 6:15 PM	0.43	10.51	7	0.64	16.29	7	0.29	10.50	19.93	2.23	YES
6:15 PM - 6:30 PM	1.00	10.29	10	0.82	16.86	10	0.41	17.31	15.99	2.11	YES
6:30 PM - 6:45 PM	0.24	10.16	12	0.87	16.29	12	0.26	12.69	23.45	2.18	YES
6:45 PM - 7:00 PM	0.98	10.14	5	0.68	15.40	5	0.53	7.13	9.85	2.36	YES
Overall Peak Statistics	0.76	10.57	141	0.98	17.26	141	0.10	262.55	64.03	1.97	YES
							% Null Hypothesis				0.00%

ID	Route 1B (NO INCIDENT)			Route 1A (INCIDENT)			Hypothesis Testing Results				
Route Name	Hume Hwy - Horsley Dr			Cumberland Hwy							
Time (PM Peak)	Std. Dev. (Mins)	Avg. TT (Mins)	N	Std. Dev. (Mins)	Avg. TT (Mins)	N	Std. Error (Mins)	v	t_{stat}	t_{crit}	Reject Null Hypothesis?
4:00 PM - 4:15 PM	1.22	17.88	11	0.93	10.10	11	0.46	18.69	16.85	2.10	YES
4:15 PM - 4:30 PM	1.10	17.61	12	0.91	10.14	12	0.41	21.23	18.17	2.08	YES
4:30 PM - 4:45 PM	1.15	17.86	10	0.90	10.92	10	0.46	17.01	15.00	2.11	YES
4:45 PM - 5:00 PM	1.08	17.76	9	0.86	11.13	9	0.46	15.23	14.42	2.13	YES
5:00 PM - 5:15 PM	1.14	18.09	7	0.79	10.87	7	0.52	10.70	13.79	2.23	YES
5:15 PM - 5:30 PM	1.18	18.22	8	0.92	11.43	8	0.53	13.21	12.88	2.16	YES
5:30 PM - 5:45 PM	0.98	17.89	15	0.89	11.13	15	0.34	27.74	19.80	2.05	YES
5:45 PM - 6:00 PM	0.94	17.26	12	0.87	10.50	12	0.37	21.85	18.29	2.08	YES
6:00 PM - 6:15 PM	0.77	16.57	6	0.79	10.07	6	0.45	9.99	14.38	2.26	YES
6:15 PM - 6:30 PM	0.72	16.36	5	0.92	10.72	5	0.52	7.59	10.77	2.36	YES
6:30 PM - 6:45 PM	0.76	15.83	8	0.75	10.72	8	0.38	13.99	13.52	2.16	YES
6:45 PM - 7:00 PM	0.72	15.61	3	0.74	9.92	3	0.60	4.00	9.55	3.18	YES
Overall Peak Statistics	0.98	17.25	106	0.85	10.64	106	0.13	206.14	52.30	1.97	YES
							% Null Hypothesis				0.00%

Set 2: Windsor Road Vs Old Windsor Road

AM Peak Results

ID	Route 2A (NO INCIDENT)			Route 2A (INCIDENT)			Hypothesis Testing Results				
Route Name	Windsor Rd			Windsor Rd							
Time (AM Peak)	Std. Dev. (Mins)	Avg. TT (Mins)	N	Std. Dev. (Mins)	Avg. TT (Mins)	N	Std. Error (Mins)	v	t_{stat}	t_{crit}	Reject Null Hypothesis?
6:00 AM - 6:15 AM	0.82	16.51	322	1.15	16.23	3	0.67	2.02	0.42	4.30	NO
6:15 AM - 6:30 AM	0.90	17.02	347	1.71	18.58	5	0.76	4.03	2.05	2.78	NO
6:30 AM - 6:45 AM	0.81	17.83	357	0.76	18.08	5	0.34	4.13	0.70	2.78	NO
6:45 AM - 7:00 AM	0.80	17.44	226	0.47	17.73	7	0.18	7.14	1.56	2.36	NO
7:00 AM - 7:15 AM	1.01	18.70	345	1.50	18.94	12	0.44	11.35	0.55	2.20	NO
7:15 AM - 7:30 AM	1.11	19.42	344	1.65	19.81	12	0.48	11.35	0.80	2.20	NO
7:30 AM - 7:45 AM	0.94	19.50	331	1.20	19.63	17	0.30	17.02	0.46	2.11	NO
7:45 AM - 8:00 AM	1.03	19.69	341	0.80	19.20	11	0.25	11.08	1.99	2.20	NO
8:00 AM - 8:15 AM	1.14	20.10	330	0.74	20.47	19	0.18	23.15	2.07	2.07	YES
8:15 AM - 8:30 AM	1.11	21.33	281	1.40	21.41	67	0.18	86.71	0.39	1.99	NO
8:30 AM - 8:45 AM	1.37	21.34	284	1.27	21.03	67	0.18	105.81	1.76	1.98	NO
8:45 AM - 9:00 AM	1.37	20.87	324	0.99	20.86	43	0.17	65.62	0.03	2.00	NO
Overall Peak Statistics	1.03	19.15	3832	1.14	19.33	268	0.07	298.65	2.58	1.97	YES
							% Null Hypothesis				91.67%

ID	Route 2B (NO INCIDENT)			Route 2B (INCIDENT)			Hypothesis Testing Results				
Route Name	Old Windsor Rd			Old Windsor Rd							
Time (AM Peak)	Std. Dev. (Mins)	Avg. TT (Mins)	N	Std. Dev. (Mins)	Avg. TT (Mins)	N	Std. Error (Mins)	v	t_{stat}	t_{crit}	Reject Null Hypothesis?
6:00 AM - 6:15 AM	1.16	16.54	368	0.71	15.31	3	0.41	2.09	2.96	4.30	NO
6:15 AM - 6:30 AM	1.26	16.84	366	0.92	17.21	5	0.42	4.21	0.89	2.78	NO
6:30 AM - 6:45 AM	1.45	17.78	365	0.82	19.44	5	0.37	4.35	4.48	2.78	YES
6:45 AM - 7:00 AM	1.55	17.68	367	1.80	19.21	7	0.69	6.17	2.23	2.45	NO
7:00 AM - 7:15 AM	1.26	18.82	358	0.93	19.07	13	0.27	13.64	0.93	2.16	NO
7:15 AM - 7:30 AM	1.39	19.55	350	2.22	21.81	12	0.64	11.30	3.51	2.20	YES
7:30 AM - 7:45 AM	1.37	20.32	347	1.63	20.63	16	0.41	15.99	0.76	2.13	NO
7:45 AM - 8:00 AM	1.43	20.47	354	1.42	20.64	11	0.43	10.64	0.41	2.23	NO
8:00 AM - 8:15 AM	1.54	19.90	354	1.81	20.59	20	0.41	20.59	1.67	2.09	NO
8:15 AM - 8:30 AM	1.49	20.99	297	1.62	20.79	76	0.20	109.89	0.94	1.98	NO
8:30 AM - 8:45 AM	1.59	21.53	301	1.55	20.21	72	0.20	110.01	6.49	1.98	YES
8:45 AM - 9:00 AM	1.57	20.07	330	1.66	19.98	45	0.26	55.31	0.31	2.00	NO
Overall Peak Statistics	1.42	19.21	4157	1.42	19.58	285	0.09	324.14	4.25	1.97	YES
							% Null Hypothesis				75.00%

ID	Route 2A (NO INCIDENT)			Route 2B (NO INCIDENT)			Hypothesis Testing Results				
Route Name	Windsor Rd			Old Windsor Rd							
Time (AM Peak)	Std. Dev. (Mins)	Avg. TT (Mins)	N	Std. Dev. (Mins)	Avg. TT (Mins)	N	Std. Error (Mins)	v	t_{stat}	t_{crit}	Reject Null Hypothesis?
6:00 AM - 6:15 AM	0.82	16.43	312	1.15	16.53	312	0.08	562.84	1.27	1.96	NO
6:15 AM - 6:30 AM	0.89	16.94	330	1.26	16.82	330	0.09	593.25	1.38	1.96	NO
6:30 AM - 6:45 AM	0.81	17.77	340	1.44	17.74	340	0.09	533.54	0.35	1.96	NO
6:45 AM - 7:00 AM	0.79	17.44	210	1.55	17.60	210	0.12	312.22	1.30	1.97	NO
7:00 AM - 7:15 AM	1.00	18.69	335	1.24	18.76	335	0.09	639.01	0.70	1.96	NO
7:15 AM - 7:30 AM	1.10	19.39	317	1.38	19.46	317	0.10	601.80	0.65	1.96	NO
7:30 AM - 7:45 AM	0.94	19.47	314	1.35	20.31	314	0.09	557.79	9.12	1.96	YES
7:45 AM - 8:00 AM	1.03	19.68	295	1.42	20.46	295	0.10	536.21	7.68	1.96	YES
8:00 AM - 8:15 AM	1.14	20.03	297	1.52	19.86	297	0.11	548.70	1.55	1.96	NO
8:15 AM - 8:30 AM	1.11	21.34	142	1.48	20.96	142	0.16	261.19	2.45	1.97	YES
8:30 AM - 8:45 AM	1.38	21.31	133	1.59	21.47	133	0.18	258.72	0.90	1.97	NO
8:45 AM - 9:00 AM	1.37	20.85	211	1.56	19.97	211	0.14	413.18	6.14	1.97	YES
Overall Peak Statistics	1.03	19.11	3236	1.41	19.16	3236	0.03	5923.93	1.63	1.96	NO
							% Null Hypothesis				66.67%

ID	Route 2A (NO INCIDENT)			Route 2B (INCIDENT)			Hypothesis Testing Results				
Route Name	Windsor Rd			Old Windsor Rd							
Time (AM Peak)	Std. Dev. (Mins)	Avg. TT (Mins)	N	Std. Dev. (Mins)	Avg. TT (Mins)	N	Std. Error (Mins)	v	t_{stat}	t_{crit}	Reject Null Hypothesis?
6:00 AM - 6:15 AM	0.82	16.51	3	0.70	15.31	3	0.63	3.91	1.92	3.18	NO
6:15 AM - 6:30 AM	0.90	17.03	5	0.92	17.21	5	0.57	7.99	0.31	2.36	NO
6:30 AM - 6:45 AM	0.81	17.85	4	0.81	19.43	4	0.58	6.00	2.75	2.57	YES
6:45 AM - 7:00 AM	0.80	17.48	6	1.80	19.19	6	0.80	6.91	2.12	2.45	NO
7:00 AM - 7:15 AM	1.01	18.73	12	0.93	19.05	12	0.40	21.86	0.80	2.08	NO
7:15 AM - 7:30 AM	1.11	19.46	12	2.21	21.79	12	0.71	16.18	3.25	2.12	YES
7:30 AM - 7:45 AM	0.95	19.50	15	1.63	20.33	15	0.49	22.49	1.71	2.07	NO
7:45 AM - 8:00 AM	1.03	19.69	10	1.42	20.64	10	0.55	16.45	1.71	2.12	NO
8:00 AM - 8:15 AM	1.14	20.12	18	1.81	20.58	18	0.50	28.69	0.92	2.05	NO
8:15 AM - 8:30 AM	1.11	21.35	64	1.62	20.99	64	0.25	111.56	1.46	1.98	NO
8:30 AM - 8:45 AM	1.38	21.37	58	1.54	20.19	58	0.27	112.51	4.35	1.98	YES
8:45 AM - 9:00 AM	1.38	20.91	40	1.66	19.96	40	0.34	75.48	2.80	1.99	YES
Overall Peak Statistics	1.04	19.17	247	1.42	19.56	247	0.11	449.89	3.46	1.97	YES
							% Null Hypothesis				66.67%

ID	Route 2B (NO INCIDENT)			Route 2A (INCIDENT)			Hypothesis Testing Results				
Route Name	Old Windsor Rd			Windsor Rd							
Time (AM Peak)	Std. Dev. (Mins)	Avg. TT (Mins)	N	Std. Dev. (Mins)	Avg. TT (Mins)	N	Std. Error (Mins)	v	t_{stat}	t_{crit}	Reject Null Hypothesis?
6:00 AM - 6:15 AM	1.16	15.74	3	1.15	16.23	3	0.94	4.00	0.52	3.18	NO
6:15 AM - 6:30 AM	1.26	17.46	5	1.71	18.58	5	0.95	7.37	1.18	2.36	NO
6:30 AM - 6:45 AM	1.44	18.59	5	0.76	18.07	5	0.73	6.07	0.73	2.45	NO
6:45 AM - 7:00 AM	1.55	18.92	6	0.47	17.71	6	0.66	5.90	1.83	2.57	NO
7:00 AM - 7:15 AM	1.26	19.11	10	1.50	18.92	10	0.62	17.48	0.30	2.11	NO
7:15 AM - 7:30 AM	1.39	19.89	11	1.65	19.78	11	0.65	19.42	0.17	2.09	NO
7:30 AM - 7:45 AM	1.37	20.33	16	1.20	19.63	16	0.45	29.51	1.53	2.05	NO
7:45 AM - 8:00 AM	1.42	20.47	10	0.80	19.19	10	0.52	14.21	2.46	2.14	YES
8:00 AM - 8:15 AM	1.54	19.92	18	0.74	20.46	18	0.40	24.49	1.36	2.06	NO
8:15 AM - 8:30 AM	1.49	20.20	59	1.40	21.40	59	0.27	115.54	4.51	1.98	YES
8:30 AM - 8:45 AM	1.59	20.26	58	1.27	21.02	58	0.27	108.53	2.83	1.98	YES
8:45 AM - 9:00 AM	1.57	19.82	35	0.99	20.84	35	0.31	57.39	3.26	2.00	YES
Overall Peak Statistics	1.42	19.22	236	1.14	19.32	236	0.12	448.54	0.80	1.97	NO
							% Null Hypothesis				66.67%

PM Peak Results

ID	Route 2A (NO INCIDENT)			Route 2A (INCIDENT)			Hypothesis Testing Results				
Route Name	Windsor Rd			Windsor Rd							
Time (PM Peak)	Std. Dev. (Mins)	Avg. TT (Mins)	N	Std. Dev. (Mins)	Avg. TT (Mins)	N	Std. Error (Mins)	v	t_{stat}	t_{crit}	Reject Null Hypothesis?
4:00 PM - 4:15 PM	0.89	18.34	333	0.93	18.25	13	0.26	12.88	0.34	2.18	NO
4:15 PM - 4:30 PM	0.80	18.12	334	0.88	18.62	13	0.25	12.78	2.02	2.18	NO
4:30 PM - 4:45 PM	1.25	18.61	333	0.94	18.94	7	0.36	6.45	0.90	2.45	NO
4:45 PM - 5:00 PM	0.83	18.91	340	0.95	19.07	6	0.39	5.14	0.43	2.57	NO
5:00 PM - 5:15 PM	0.91	19.26	330	0.92	19.71	12	0.27	11.78	1.68	2.20	NO
5:15 PM - 5:30 PM	1.03	19.56	315	0.95	19.44	14	0.26	14.39	0.43	2.14	NO
5:30 PM - 5:45 PM	0.90	19.75	302	0.95	20.30	9	0.32	8.44	1.71	2.31	NO
5:45 PM - 6:00 PM	0.60	19.33	296	1.03	19.42	14	0.28	13.42	0.31	2.16	NO
6:00 PM - 6:15 PM	0.69	19.37	292	0.96	19.19	9	0.32	8.25	0.57	2.31	NO
6:15 PM - 6:30 PM	0.96	18.57	239	0.92	18.81	8	0.33	7.52	0.73	2.36	NO
6:30 PM - 6:45 PM	0.43	18.05	246	0.88	17.89	7	0.33	6.08	0.48	2.45	NO
6:45 PM - 7:00 PM	0.73	17.44	226	0.80	17.37	8	0.29	7.42	0.25	2.36	NO
Overall Peak Statistics	0.84	18.77	3586	0.93	18.92	120	0.09	125.55	1.66	1.98	NO
							% Null Hypothesis				100.00%

ID	Route 2B (NO INCIDENT)			Route 2B (INCIDENT)			Hypothesis Testing Results				
Route Name	Old Windsor Rd			Old Windsor Rd							
Time (PM Peak)	Std. Dev. (Mins)	Avg. TT (Mins)	N	Std. Dev. (Mins)	Avg. TT (Mins)	N	Std. Error (Mins)	v	t_{stat}	t_{crit}	Reject Null Hypothesis?
4:00 PM - 4:15 PM	0.78	18.32	364	1.40	18.61	13	0.39	12.27	0.74	2.18	NO
4:15 PM - 4:30 PM	1.20	18.22	357	1.49	19.51	13	0.42	12.58	3.08	2.18	YES
4:30 PM - 4:45 PM	0.87	18.73	365	1.33	19.47	9	0.45	8.17	1.65	2.31	NO
4:45 PM - 5:00 PM	0.79	18.80	369	1.27	20.24	6	0.52	5.06	2.76	2.57	YES
5:00 PM - 5:15 PM	1.29	19.34	362	1.53	21.35	13	0.43	12.62	4.68	2.18	YES
5:15 PM - 5:30 PM	1.39	19.74	362	1.46	21.28	15	0.38	15.07	4.01	2.13	YES
5:30 PM - 5:45 PM	1.25	20.72	355	1.28	22.22	12	0.37	11.72	4.00	2.20	YES
5:45 PM - 6:00 PM	1.26	20.80	339	1.30	21.30	16	0.33	16.36	1.50	2.12	NO
6:00 PM - 6:15 PM	1.73	20.30	324	1.36	20.79	7	0.52	6.43	0.94	2.45	NO
6:15 PM - 6:30 PM	0.99	19.26	292	1.27	19.91	10	0.41	9.38	1.59	2.26	NO
6:30 PM - 6:45 PM	0.68	18.14	312	1.23	18.97	7	0.47	6.08	1.77	2.45	NO
6:45 PM - 7:00 PM	0.98	17.56	278	1.05	18.39	7	0.40	6.27	2.06	2.45	NO
Overall Peak Statistics	1.10	19.16	4079	1.33	20.17	128	0.12	132.52	8.47	1.98	YES
							% Null Hypothesis				58.33%

ID	Route 2A (NO INCIDENT)			Route 2B (NO INCIDENT)			Hypothesis Testing Results				
Route Name	Windsor Rd			Old Windsor Rd							
Time (PM Peak)	Std. Dev. (Mins)	Avg. TT (Mins)	N	Std. Dev. (Mins)	Avg. TT (Mins)	N	Std. Error (Mins)	v	t_{stat}	t_{crit}	Reject Null Hypothesis?
4:00 PM - 4:15 PM	0.89	18.26	310	0.78	18.24	310	0.07	608.34	0.27	1.96	NO
4:15 PM - 4:30 PM	0.80	18.02	307	1.20	18.12	307	0.08	533.01	1.28	1.96	NO
4:30 PM - 4:45 PM	1.25	18.52	312	0.86	18.63	312	0.09	552.40	1.39	1.96	NO
4:45 PM - 5:00 PM	0.83	18.85	320	0.79	18.75	320	0.06	636.41	1.59	1.96	NO
5:00 PM - 5:15 PM	0.90	19.20	318	1.28	19.28	318	0.09	566.67	0.93	1.96	NO
5:15 PM - 5:30 PM	1.02	19.47	294	1.38	19.65	294	0.10	539.37	1.86	1.96	NO
5:30 PM - 5:45 PM	0.90	19.71	279	1.24	20.68	279	0.09	506.67	10.56	1.96	YES
5:45 PM - 6:00 PM	0.59	19.31	269	1.26	20.78	269	0.08	381.52	17.26	1.97	YES
6:00 PM - 6:15 PM	0.68	19.28	270	1.73	20.20	270	0.11	350.86	8.16	1.97	YES
6:15 PM - 6:30 PM	0.96	18.56	216	0.99	19.25	216	0.09	429.76	7.44	1.97	YES
6:30 PM - 6:45 PM	0.43	17.97	223	0.68	18.06	223	0.05	374.09	1.69	1.97	NO
6:45 PM - 7:00 PM	0.72	17.35	201	0.98	17.47	201	0.09	368.61	1.42	1.97	NO
Overall Peak Statistics	0.83	18.71	3319	1.10	19.09	3319	0.02	6180.43	16.20	1.96	YES
							% Null Hypothesis				66.67%

ID	Route 2A (NO INCIDENT)			Route 2B (INCIDENT)			Hypothesis Testing Results				
Route Name	Windsor Rd			Old Windsor Rd							
Time (PM Peak)	Std. Dev. (Mins)	Avg. TT (Mins)	N	Std. Dev. (Mins)	Avg. TT (Mins)	N	Std. Error (Mins)	v	t_{stat}	t_{crit}	Reject Null Hypothesis?
4:00 PM - 4:15 PM	0.89	18.38	12	1.40	18.59	12	0.48	18.66	0.44	2.10	NO
4:15 PM - 4:30 PM	0.80	18.17	12	1.49	19.48	12	0.49	16.90	2.70	2.12	YES
4:30 PM - 4:45 PM	1.26	18.66	8	1.33	19.44	8	0.65	13.96	1.21	2.16	NO
4:45 PM - 5:00 PM	0.84	18.93	6	1.27	20.23	6	0.62	8.66	2.08	2.31	NO
5:00 PM - 5:15 PM	0.91	19.28	12	1.53	21.33	12	0.51	17.95	4.00	2.11	YES
5:15 PM - 5:30 PM	1.03	19.60	14	1.46	21.26	14	0.48	23.40	3.47	2.07	YES
5:30 PM - 5:45 PM	0.91	19.77	12	1.27	22.21	12	0.45	19.90	5.38	2.09	YES
5:45 PM - 6:00 PM	0.60	19.34	15	1.30	21.29	15	0.37	19.71	5.27	2.09	YES
6:00 PM - 6:15 PM	0.69	19.42	6	1.36	20.76	6	0.62	7.40	2.16	2.36	NO
6:15 PM - 6:30 PM	0.96	18.57	9	1.27	19.91	9	0.53	14.91	2.52	2.14	YES
6:30 PM - 6:45 PM	0.43	18.09	6	1.23	18.95	6	0.53	6.19	1.61	2.45	NO
6:45 PM - 7:00 PM	0.73	17.49	7	1.05	18.37	7	0.48	10.74	1.82	2.23	NO
Overall Peak Statistics	0.84	18.81	119	1.33	20.15	119	0.14	198.93	9.32	1.97	YES
							% Null Hypothesis				50.00%

ID	Route 2B (NO INCIDENT)			Route 2A (INCIDENT)			Hypothesis Testing Results				
Route Name	Old Windsor Rd			Windsor Rd							
Time (PM Peak)	Std. Dev. (Mins)	Avg. TT (Mins)	N	Std. Dev. (Mins)	Avg. TT (Mins)	N	Std. Error (Mins)	v	t_{stat}	t_{crit}	Reject Null Hypothesis?
4:00 PM - 4:15 PM	0.79	18.36	12	0.93	18.23	13	0.34	22.85	0.39	2.07	NO
4:15 PM - 4:30 PM	1.20	18.27	13	0.88	18.59	13	0.41	22.04	0.78	2.07	NO
4:30 PM - 4:45 PM	0.87	18.78	7	0.94	18.91	7	0.48	11.93	0.27	2.20	NO
4:45 PM - 5:00 PM	0.80	18.83	6	0.95	19.06	6	0.50	9.72	0.45	2.26	NO
5:00 PM - 5:15 PM	1.30	19.36	12	0.92	19.70	12	0.46	19.86	0.72	2.09	NO
5:15 PM - 5:30 PM	1.39	19.79	12	0.95	19.42	14	0.47	18.93	0.78	2.10	NO
5:30 PM - 5:45 PM	1.25	20.74	8	0.95	20.29	9	0.54	13.00	0.83	2.16	NO
5:45 PM - 6:00 PM	1.27	20.81	13	1.03	19.41	14	0.45	23.21	3.12	2.07	YES
6:00 PM - 6:15 PM	1.73	20.35	8	0.96	19.17	9	0.69	10.63	1.71	2.23	NO
6:15 PM - 6:30 PM	0.99	19.27	6	0.92	18.80	8	0.52	10.49	0.90	2.23	NO
6:30 PM - 6:45 PM	0.68	18.18	6	0.88	17.87	7	0.43	10.91	0.72	2.23	NO
6:45 PM - 7:00 PM	0.99	17.61	7	0.80	17.35	8	0.47	11.57	0.56	2.20	NO
Overall Peak Statistics	1.10	19.20	110	0.93	18.90	120	0.13	213.50	2.19	1.97	YES
							% Null Hypothesis				91.67%

***Set 3**: Parramatta Road – St Hillier's Road Vs Centenary Drive – Hume Highway*

AM Peak Results

ID	Route 3A (NO INCIDENT)			Route 3A (INCIDENT)			Hypothesis Testing Results				
Route Name	Parramatta Rd - St Hillier's Rd			Parramatta Rd - St Hillier's Rd							
Time (AM Peak)	Std. Dev. (Mins)	Avg. TT (Mins)	N	Std. Dev. (Mins)	Avg. TT (Mins)	N	Std. Error (Mins)	v	t_{stat}	t_{crit}	Reject Null Hypothesis?
6:00 AM - 6:15 AM	0.66	9.73	356	0.52	9.74	7	0.20	6.38	0.02	2.45	NO
6:15 AM - 6:30 AM	0.71	10.12	358	0.86	10.17	14	0.23	13.70	0.20	2.16	NO
6:30 AM - 6:45 AM	0.74	10.84	351	0.78	11.53	14	0.21	13.95	3.26	2.16	YES
6:45 AM - 7:00 AM	0.71	10.67	357	0.57	10.49	16	0.15	17.16	1.26	2.11	NO
7:00 AM - 7:15 AM	0.77	10.69	359	0.83	10.87	14	0.22	13.89	0.79	2.16	NO
7:15 AM - 7:30 AM	0.76	10.74	355	0.62	10.74	21	0.14	23.75	0.03	2.07	NO
7:30 AM - 7:45 AM	0.83	10.99	354	0.50	10.69	20	0.12	25.25	2.49	2.06	YES
7:45 AM - 8:00 AM	0.83	11.26	356	0.89	11.40	18	0.21	18.52	0.68	2.10	NO
8:00 AM - 8:15 AM	0.79	11.28	353	1.13	11.68	19	0.26	18.97	1.56	2.10	NO
8:15 AM - 8:30 AM	0.85	11.42	354	0.85	11.65	17	0.21	17.55	1.10	2.11	NO
8:30 AM - 8:45 AM	0.80	11.36	346	1.07	11.48	27	0.21	28.28	0.57	2.05	NO
8:45 AM - 9:00 AM	0.83	11.48	354	0.65	11.45	22	0.15	25.47	0.21	2.06	NO
Overall Peak Statistics	0.77	10.88	4253	0.77	10.99	209	0.05	228.93	2.00	1.97	YES
							% Null Hypothesis				83.33%

ID	Route 3B (NO INCIDENT)			Route 3B (INCIDENT)			Hypothesis Testing Results				
Route Name	Centenary Dr - Hume Hwy			Centenary Dr - Hume Hwy							
Time (AM Peak)	Std. Dev. (Mins)	Avg. TT (Mins)	N	Std. Dev. (Mins)	Avg. TT (Mins)	N	Std. Error (Mins)	v	t_{stat}	t_{crit}	Reject Null Hypothesis?
6:00 AM - 6:15 AM	1.02	8.76	359	0.85	9.15	7	0.33	6.34	1.19	2.45	NO
6:15 AM - 6:30 AM	1.29	9.97	359	1.03	10.24	14	0.28	14.62	0.95	2.14	NO
6:30 AM - 6:45 AM	1.05	9.97	360	1.17	9.76	16	0.30	16.09	0.70	2.12	NO
6:45 AM - 7:00 AM	0.69	9.80	360	1.15	9.68	16	0.29	15.48	0.40	2.13	NO
7:00 AM - 7:15 AM	1.06	9.62	363	1.10	9.89	13	0.31	12.82	0.86	2.18	NO
7:15 AM - 7:30 AM	1.04	9.82	356	1.11	10.02	21	0.25	22.12	0.81	2.07	NO
7:30 AM - 7:45 AM	1.02	10.86	359	1.08	10.67	20	0.25	20.93	0.75	2.09	NO
7:45 AM - 8:00 AM	1.13	10.07	358	1.17	10.57	18	0.28	18.64	1.75	2.10	NO
8:00 AM - 8:15 AM	0.56	11.01	353	1.22	9.87	20	0.28	19.45	4.14	2.09	YES
8:15 AM - 8:30 AM	0.95	9.98	354	1.17	10.20	17	0.29	17.02	0.73	2.11	NO
8:30 AM - 8:45 AM	0.90	9.89	350	1.21	9.98	27	0.24	28.24	0.41	2.05	NO
8:45 AM - 9:00 AM	0.93	9.74	353	1.09	9.90	22	0.24	22.93	0.69	2.07	NO
Overall Peak Statistics	0.97	9.96	4284	1.11	9.99	211	0.08	225.97	0.47	1.97	NO
							% Null Hypothesis				91.67%

ID	Route 3A (NO INCIDENT)			Route 3B (NO INCIDENT)			Hypothesis Testing Results				
Route Name	Parramatta Rd - St Hillier's Rd			Centenary Dr - Hume Hwy							
Time (AM Peak)	Std. Dev. (Mins)	Avg. TT (Mins)	N	Std. Dev. (Mins)	Avg. TT (Mins)	N	Std. Error (Mins)	v	t_{stat}	t_{crit}	Reject Null Hypothesis?
6:00 AM - 6:15 AM	0.66	9.63	321	1.02	8.74	321	0.07	548.05	13.19	1.96	YES
6:15 AM - 6:30 AM	0.71	10.04	333	1.29	9.95	333	0.08	517.18	1.18	1.96	NO
6:30 AM - 6:45 AM	0.73	10.07	335	1.04	9.96	335	0.07	599.23	1.65	1.96	NO
6:45 AM - 7:00 AM	0.70	10.65	340	0.69	9.79	340	0.05	677.51	16.07	1.96	YES
7:00 AM - 7:15 AM	0.76	10.65	338	1.05	9.61	338	0.07	611.91	14.68	1.96	YES
7:15 AM - 7:30 AM	0.75	10.70	339	1.04	9.81	339	0.07	617.45	12.87	1.96	YES
7:30 AM - 7:45 AM	0.82	10.92	335	1.01	10.84	335	0.07	640.52	1.11	1.96	NO
7:45 AM - 8:00 AM	0.83	10.16	334	1.13	10.05	334	0.08	609.39	1.43	1.96	NO
8:00 AM - 8:15 AM	0.79	10.95	337	0.55	11.00	337	0.05	603.33	0.83	1.96	NO
8:15 AM - 8:30 AM	0.84	10.34	341	0.94	9.97	341	0.07	671.65	5.51	1.96	YES
8:30 AM - 8:45 AM	0.79	10.32	321	0.89	9.88	321	0.07	631.58	6.70	1.96	YES
8:45 AM - 9:00 AM	0.83	10.44	323	0.92	9.73	323	0.07	636.61	10.34	1.96	YES
Overall Peak Statistics	0.77	10.41	3997	0.96	9.94	3997	0.02	7609.23	23.82	1.96	YES
							% Null Hypothesis				41.67%

ID	Route 3A (NO INCIDENT)			Route 3B (INCIDENT)			Hypothesis Testing Results				
Route Name	Parramatta Rd - St Hillier's Rd			Centenary Dr - Hume Hwy							
Time (AM Peak)	Std. Dev. (Mins)	Avg. TT (Mins)	N	Std. Dev. (Mins)	Avg. TT (Mins)	N	Std. Error (Mins)	v	t_{stat}	t_{crit}	Reject Null Hypothesis?
6:00 AM - 6:15 AM	0.66	9.78	6	0.85	9.12	6	0.44	9.44	1.49	2.26	NO
6:15 AM - 6:30 AM	0.71	10.16	12	1.03	10.22	12	0.36	19.51	0.15	2.09	NO
6:30 AM - 6:45 AM	0.74	10.87	16	1.17	9.75	16	0.35	25.44	3.24	2.06	YES
6:45 AM - 7:00 AM	0.71	10.68	14	1.15	9.68	14	0.36	21.69	2.79	2.08	YES
7:00 AM - 7:15 AM	0.77	10.71	13	1.10	9.88	13	0.37	21.56	2.24	2.08	YES
7:15 AM - 7:30 AM	0.76	10.75	19	1.11	10.01	19	0.31	31.90	2.40	2.04	YES
7:30 AM - 7:45 AM	0.83	11.03	19	1.08	10.65	19	0.31	33.75	1.21	2.03	NO
7:45 AM - 8:00 AM	0.83	11.31	18	1.17	10.54	18	0.34	30.64	2.27	2.04	YES
8:00 AM - 8:15 AM	0.79	11.31	18	1.22	9.85	18	0.34	29.16	4.24	2.05	YES
8:15 AM - 8:30 AM	0.85	11.46	16	1.17	10.18	16	0.36	27.33	3.54	2.05	YES
8:30 AM - 8:45 AM	0.80	11.38	26	1.21	9.97	26	0.28	43.44	4.96	2.02	YES
8:45 AM - 9:00 AM	0.83	11.49	20	1.09	9.89	20	0.31	35.57	5.22	2.03	YES
Overall Peak Statistics	0.77	10.91	197	1.11	9.98	197	0.10	349.99	9.66	1.97	YES
							% Null Hypothesis				25.00%

ID	Route 3B (NO INCIDENT)			Route 3A (INCIDENT)			Hypothesis Testing Results				
Route Name	Centenary Dr - Hume Hwy			Parramatta Rd - St Hillier's Rd							
Time (AM Peak)	Std. Dev. (Mins)	Avg. TT (Mins)	N	Std. Dev. (Mins)	Avg. TT (Mins)	N	Std. Error (Mins)	v	t_{stat}	t_{crit}	Reject Null Hypothesis?
6:00 AM - 6:15 AM	1.02	8.79	7	0.52	9.71	7	0.43	8.94	2.13	2.31	NO
6:15 AM - 6:30 AM	1.29	9.99	12	0.86	10.15	12	0.45	19.18	0.36	2.09	NO
6:30 AM - 6:45 AM	1.05	9.98	13	0.78	11.52	13	0.36	22.11	4.25	2.07	YES
6:45 AM - 7:00 AM	0.69	9.80	15	0.57	10.48	15	0.23	26.98	2.94	2.06	YES
7:00 AM - 7:15 AM	1.07	9.63	14	0.82	10.86	14	0.36	24.45	3.40	2.06	YES
7:15 AM - 7:30 AM	1.04	9.82	19	0.61	10.73	19	0.28	29.13	3.26	2.05	YES
7:30 AM - 7:45 AM	1.02	10.88	18	0.50	10.67	18	0.27	24.73	0.75	2.06	NO
7:45 AM - 8:00 AM	1.13	10.10	16	0.89	11.38	16	0.36	28.40	3.55	2.05	YES
8:00 AM - 8:15 AM	0.56	11.03	17	1.13	11.67	17	0.31	23.43	2.08	2.07	YES
8:15 AM - 8:30 AM	0.95	10.00	17	0.85	11.63	17	0.31	31.64	5.27	2.04	YES
8:30 AM - 8:45 AM	0.90	9.90	25	1.07	11.47	25	0.28	46.54	5.63	2.01	YES
8:45 AM - 9:00 AM	0.93	9.75	20	0.65	11.44	20	0.25	34.03	6.69	2.03	YES
Overall Peak Statistics	0.97	9.97	193	0.77	10.98	193	0.09	365.37	11.25	1.97	YES
							% Null Hypothesis				25.00%

PM Peak Results

ID	Route 3A (NO INCIDENT)			Route 3A (INCIDENT)			Hypothesis Testing Results				
Route Name	Parramatta Rd - St Hillier's Rd			Parramatta Rd - St Hillier's Rd							
Time (PM Peak)	Std. Dev. (Mins)	Avg. TT (Mins)	N	Std. Dev. (Mins)	Avg. TT (Mins)	N	Std. Error (Mins)	v	t_{stat}	t_{crit}	Reject Null Hypothesis?
4:00 PM - 4:15 PM	0.82	11.91	354	0.86	11.80	22	0.19	23.45	0.56	2.07	NO
4:15 PM - 4:30 PM	0.78	11.65	363	1.02	11.83	18	0.24	18.01	0.74	2.10	NO
4:30 PM - 4:45 PM	0.88	11.89	356	0.78	11.77	20	0.18	21.83	0.70	2.08	NO
4:45 PM - 5:00 PM	0.81	11.63	351	0.64	11.66	25	0.13	29.73	0.25	2.05	NO
5:00 PM - 5:15 PM	0.86	12.03	361	0.91	12.04	15	0.24	15.04	0.03	2.13	NO
5:15 PM - 5:30 PM	0.80	11.91	348	0.80	12.11	30	0.15	34.21	1.27	2.03	NO
5:30 PM - 5:45 PM	0.78	11.89	350	0.84	12.14	25	0.17	27.05	1.43	2.05	NO
5:45 PM - 6:00 PM	0.80	11.96	341	0.97	12.00	23	0.21	24.04	0.19	2.06	NO
6:00 PM - 6:15 PM	0.84	11.46	351	0.81	11.62	23	0.18	25.23	0.91	2.06	NO
6:15 PM - 6:30 PM	0.71	11.26	338	0.93	11.18	31	0.17	33.25	0.47	2.03	NO
6:30 PM - 6:45 PM	0.73	10.83	349	0.76	11.07	16	0.20	16.28	1.24	2.12	NO
6:45 PM - 7:00 PM	0.66	10.46	342	0.89	10.43	15	0.23	14.68	0.11	2.14	NO
Overall Peak Statistics	0.79	11.57	4204	0.85	11.64	263	0.05	290.88	1.19	1.97	NO
							% Null Hypothesis				100.00%

ID	Route 3B (NO INCIDENT)			Route 3B (INCIDENT)			Hypothesis Testing Results				
Route Name	Centenary Dr - Hume Hwy			Centenary Dr - Hume Hwy							
Time (PM Peak)	Std. Dev. (Mins)	Avg. TT (Mins)	N	Std. Dev. (Mins)	Avg. TT (Mins)	N	Std. Error (Mins)	v	t_{stat}	t_{crit}	Reject Null Hypothesis?
4:00 PM - 4:15 PM	0.87	10.04	351	1.01	10.28	22	0.22	22.99	1.07	2.07	NO
4:15 PM - 4:30 PM	1.43	10.07	359	0.99	10.53	18	0.25	20.71	1.86	2.09	NO
4:30 PM - 4:45 PM	1.03	10.02	356	1.01	9.94	20	0.23	21.31	0.35	2.08	NO
4:45 PM - 5:00 PM	0.59	9.77	354	0.91	9.88	25	0.18	25.46	0.58	2.06	NO
5:00 PM - 5:15 PM	0.86	9.86	360	0.96	9.91	14	0.26	13.81	0.17	2.16	NO
5:15 PM - 5:30 PM	0.77	9.82	348	0.93	9.76	30	0.17	32.50	0.31	2.04	NO
5:30 PM - 5:45 PM	0.78	9.72	350	0.87	9.91	25	0.18	26.78	1.08	2.06	NO
5:45 PM - 6:00 PM	0.70	9.94	345	0.92	9.90	21	0.21	21.41	0.20	2.08	NO
6:00 PM - 6:15 PM	0.69	9.68	345	0.90	9.40	21	0.20	21.47	1.41	2.08	NO
6:15 PM - 6:30 PM	1.24	9.34	323	0.80	9.82	30	0.16	43.14	2.97	2.02	YES
6:30 PM - 6:45 PM	0.96	9.30	348	0.91	9.53	16	0.23	16.57	0.98	2.12	NO
6:45 PM - 7:00 PM	0.78	9.31	353	0.96	9.24	15	0.25	14.81	0.25	2.14	NO
Overall Peak Statistics	0.89	9.74	4192	0.93	9.84	257	0.06	285.53	1.71	1.97	NO
							% Null Hypothesis				91.67%

ID	Route 3A (NO INCIDENT)			Route 3B (NO INCIDENT)			Hypothesis Testing Results				
Route Name	Parramatta Rd - St Hillier's Rd			Centenary Dr - Hume Hwy							
Time (PM Peak)	Std. Dev. (Mins)	Avg. TT (Mins)	N	Std. Dev. (Mins)	Avg. TT (Mins)	N	Std. Error (Mins)	v	t_{stat}	t_{crit}	Reject Null Hypothesis?
4:00 PM - 4:15 PM	0.81	11.83	305	0.86	9.96	305	0.07	605.89	27.59	1.96	YES
4:15 PM - 4:30 PM	0.78	11.58	326	1.43	10.00	326	0.09	503.43	17.51	1.96	YES
4:30 PM - 4:45 PM	0.87	11.82	314	1.03	9.95	314	0.08	609.90	24.62	1.96	YES
4:45 PM - 5:00 PM	0.80	11.55	297	0.59	9.69	297	0.06	542.48	32.29	1.96	YES
5:00 PM - 5:15 PM	0.85	12.01	330	0.85	9.84	330	0.07	658.00	32.71	1.96	YES
5:15 PM - 5:30 PM	0.79	11.90	277	0.76	9.81	277	0.07	551.21	31.66	1.96	YES
5:30 PM - 5:45 PM	0.78	11.88	296	0.77	9.71	296	0.06	589.94	33.97	1.96	YES
5:45 PM - 6:00 PM	0.79	11.87	293	0.69	9.86	293	0.06	572.93	32.84	1.96	YES
6:00 PM - 6:15 PM	0.84	11.46	303	0.69	9.68	303	0.06	581.52	28.53	1.96	YES
6:15 PM - 6:30 PM	0.71	11.20	262	1.24	9.28	262	0.09	413.62	21.75	1.97	YES
6:30 PM - 6:45 PM	0.73	10.74	301	0.95	9.22	301	0.07	561.05	22.00	1.96	YES
6:45 PM - 7:00 PM	0.66	10.43	309	0.78	9.28	309	0.06	598.80	19.79	1.96	YES
Overall Peak Statistics	0.78	11.52	3613	0.89	9.69	3613	0.02	7118.04	93.03	1.96	YES
							% Null Hypothesis				0.00%

ID	Route 3A (NO INCIDENT)			Route 3B (INCIDENT)			Hypothesis Testing Results				
Route Name	Parramatta Rd - St Hillier's Rd			Centenary Dr - Hume Hwy							
Time (PM Peak)	Std. Dev. (Mins)	Avg. TT (Mins)	N	Std. Dev. (Mins)	Avg. TT (Mins)	N	Std. Error (Mins)	v	t_{stat}	t_{crit}	Reject Null Hypothesis?
4:00 PM - 4:15 PM	0.82	11.95	20	1.01	10.26	20	0.29	36.55	5.82	2.03	YES
4:15 PM - 4:30 PM	0.78	11.69	18	0.99	10.51	18	0.30	32.27	3.96	2.04	YES
4:30 PM - 4:45 PM	0.88	11.93	18	1.01	9.92	18	0.32	33.44	6.35	2.03	YES
4:45 PM - 5:00 PM	0.81	11.67	23	0.91	9.86	23	0.25	43.46	7.13	2.02	YES
5:00 PM - 5:15 PM	0.86	12.04	12	0.96	9.90	12	0.37	21.73	5.75	2.08	YES
5:15 PM - 5:30 PM	0.80	11.92	28	0.93	9.76	28	0.23	52.82	9.34	2.01	YES
5:30 PM - 5:45 PM	0.79	11.89	24	0.87	9.91	24	0.24	45.51	8.24	2.01	YES
5:45 PM - 6:00 PM	0.80	12.00	20	0.92	9.88	20	0.27	37.31	7.72	2.03	YES
6:00 PM - 6:15 PM	0.85	11.47	21	0.90	9.40	21	0.27	39.87	7.66	2.02	YES
6:15 PM - 6:30 PM	0.71	11.30	28	0.80	9.81	28	0.20	53.15	7.34	2.01	YES
6:30 PM - 6:45 PM	0.73	10.87	15	0.91	9.51	15	0.30	26.80	4.53	2.06	YES
6:45 PM - 7:00 PM	0.66	10.47	15	0.96	9.24	15	0.30	24.95	4.11	2.06	YES
Overall Peak Statistics	0.79	11.60	242	0.93	9.83	242	0.08	470.00	22.53	1.97	YES
							% Null Hypothesis				0.00%

ID	Route 3B (NO INCIDENT)			Route 3A (INCIDENT)			Hypothesis Testing Results				
Route Name	Centenary Dr - Hume Hwy			Parramatta Rd - St Hillier's Rd							
Time (PM Peak)	Std. Dev. (Mins)	Avg. TT (Mins)	N	Std. Dev. (Mins)	Avg. TT (Mins)	N	Std. Error (Mins)	v	t_{stat}	t_{crit}	Reject Null Hypothesis?
4:00 PM - 4:15 PM	0.87	10.09	21	0.85	11.78	21	0.27	39.98	6.37	2.02	YES
4:15 PM - 4:30 PM	1.43	10.11	18	1.02	11.81	18	0.41	30.70	4.11	2.04	YES
4:30 PM - 4:45 PM	1.04	10.06	19	0.77	11.75	19	0.30	33.28	5.70	2.03	YES
4:45 PM - 5:00 PM	0.60	9.81	23	0.64	11.64	23	0.18	43.81	10.07	2.02	YES
5:00 PM - 5:15 PM	0.86	9.87	13	0.91	12.03	13	0.35	23.91	6.21	2.07	YES
5:15 PM - 5:30 PM	0.77	9.83	28	0.79	12.10	28	0.21	53.94	10.91	2.01	YES
5:30 PM - 5:45 PM	0.78	9.72	23	0.84	12.13	23	0.24	43.73	10.08	2.02	YES
5:45 PM - 6:00 PM	0.70	9.98	23	0.97	11.98	23	0.25	40.00	7.97	2.02	YES
6:00 PM - 6:15 PM	0.70	9.69	22	0.81	11.62	22	0.23	41.06	8.51	2.02	YES
6:15 PM - 6:30 PM	1.25	9.37	29	0.93	11.17	29	0.29	51.85	6.22	2.01	YES
6:30 PM - 6:45 PM	0.96	9.35	15	0.76	11.05	15	0.32	26.68	5.37	2.06	YES
6:45 PM - 7:00 PM	0.79	9.32	15	0.89	10.42	15	0.31	27.57	3.58	2.05	YES
Overall Peak Statistics	0.89	9.77	249	0.85	11.62	249	0.08	494.75	23.77	1.96	YES
							% Null Hypothesis				0.00%

***Set 4*: Western Distributor Vs Parramatta Road**

AM Peak Results

ID	Route 4A (NO INCIDENT)			Route 4A (INCIDENT)			Hypothesis Testing Results				
Route Name	Western Distributor			Western Distributor							
Time (AM Peak)	Std. Dev. (Mins)	Avg. TT (Mins)	N	Std. Dev. (Mins)	Avg. TT (Mins)	N	Std. Error (Mins)	v	t_{stat}	t_{crit}	Reject Null Hypothesis?
6:00 AM - 6:15 AM	0.69	11.47	367	0.01	11.12	4	0.04	368.74	9.62	1.97	YES
6:15 AM - 6:30 AM	0.67	11.75	369	0.60	11.92	4	0.30	3.08	0.56	3.18	NO
6:30 AM - 6:45 AM	0.76	11.90	367	0.44	12.53	6	0.19	5.49	3.41	2.57	YES
6:45 AM - 7:00 AM	0.81	12.14	361	0.83	12.36	11	0.25	10.60	0.85	2.23	NO
7:00 AM - 7:15 AM	0.78	12.32	361	0.87	13.30	12	0.25	11.59	3.88	2.20	YES
7:15 AM - 7:30 AM	0.83	12.78	363	1.55	13.79	10	0.49	9.14	2.06	2.26	NO
7:30 AM - 7:45 AM	0.92	13.68	360	1.53	14.42	9	0.51	8.15	1.45	2.31	NO
7:45 AM - 8:00 AM	1.02	14.26	353	1.40	14.30	18	0.33	17.93	0.13	2.11	NO
8:00 AM - 8:15 AM	1.17	14.55	359	1.18	16.06	12	0.35	11.74	4.38	2.20	YES
8:15 AM - 8:30 AM	1.19	14.92	350	1.34	15.47	19	0.31	19.56	1.74	2.09	NO
8:30 AM - 8:45 AM	1.19	14.48	356	1.03	13.91	14	0.28	14.40	2.04	2.14	NO
8:45 AM - 9:00 AM	1.17	13.83	356	1.52	14.21	16	0.39	15.81	1.00	2.13	NO
Overall Peak Statistics	0.93	13.17	4322	1.02	13.62	135	0.09	141.04	4.97	1.98	YES
							% Null Hypothesis				66.67%

ID	Route 4B (NO INCIDENT)			Route 4B (INCIDENT)			Hypothesis Testing Results				
Route Name	Parramatta Rd			Parramatta Rd							
Time (AM Peak)	Std. Dev. (Mins)	Avg. TT (Mins)	N	Std. Dev. (Mins)	Avg. TT (Mins)	N	Std. Error (Mins)	v	t_{stat}	t_{crit}	Reject Null Hypothesis?
6:00 AM - 6:15 AM	0.47	11.71	320	0.29	11.43	4	0.15	3.20	1.86	3.18	NO
6:15 AM - 6:30 AM	0.49	12.02	361	0.48	12.50	4	0.24	3.07	1.98	3.18	NO
6:30 AM - 6:45 AM	0.62	12.97	363	0.39	13.97	6	0.16	5.41	6.10	2.57	YES
6:45 AM - 7:00 AM	0.62	12.86	359	0.44	12.71	12	0.13	12.53	1.20	2.18	NO
7:00 AM - 7:15 AM	0.66	13.27	360	0.67	13.41	12	0.20	11.73	0.68	2.20	NO
7:15 AM - 7:30 AM	0.70	13.44	362	0.58	13.61	9	0.20	8.61	0.86	2.31	NO
7:30 AM - 7:45 AM	0.69	13.76	357	0.85	14.16	10	0.27	9.33	1.47	2.26	NO
7:45 AM - 8:00 AM	0.69	14.09	353	0.88	14.40	18	0.21	18.09	1.48	2.10	NO
8:00 AM - 8:15 AM	0.65	14.30	352	0.59	15.36	12	0.17	11.93	6.13	2.20	YES
8:15 AM - 8:30 AM	0.63	14.53	344	0.85	15.22	18	0.20	18.00	3.39	2.11	YES
8:30 AM - 8:45 AM	0.67	14.65	354	0.82	15.06	15	0.21	14.80	1.93	2.14	NO
8:45 AM - 9:00 AM	0.64	14.12	357	0.87	15.03	17	0.21	16.83	4.28	2.12	YES
Overall Peak Statistics	0.63	13.48	4242	0.64	13.90	137	0.06	144.51	7.68	1.98	YES
							% Null Hypothesis				66.67%

ID	Route 4A (NO INCIDENT)			Route 4B (NO INCIDENT)			Hypothesis Testing Results				
Route Name	Western Distributor			Parramatta Rd							
Time (AM Peak)	Std. Dev. (Mins)	Avg. TT (Mins)	N	Std. Dev. (Mins)	Avg. TT (Mins)	N	Std. Error (Mins)	v	t_{stat}	t_{crit}	Reject Null Hypothesis?
6:00 AM - 6:15 AM	0.69	11.43	307	0.47	11.52	307	0.05	539.95	1.89	1.96	NO
6:15 AM - 6:30 AM	0.67	11.82	348	0.49	11.90	348	0.04	634.56	1.87	1.96	NO
6:30 AM - 6:45 AM	0.76	11.87	356	0.61	12.94	356	0.05	680.80	20.70	1.96	YES
6:45 AM - 7:00 AM	0.81	12.14	339	0.62	12.86	339	0.06	631.88	12.95	1.96	YES
7:00 AM - 7:15 AM	0.77	12.28	334	0.66	13.23	334	0.06	650.33	17.18	1.96	YES
7:15 AM - 7:30 AM	0.83	12.74	341	0.70	13.41	341	0.06	662.80	11.34	1.96	YES
7:30 AM - 7:45 AM	0.92	13.65	337	0.69	13.73	337	0.06	621.74	1.23	1.96	NO
7:45 AM - 8:00 AM	1.02	14.22	331	0.69	14.14	331	0.07	580.94	1.08	1.96	NO
8:00 AM - 8:15 AM	1.17	14.52	337	0.65	14.47	337	0.07	523.96	0.66	1.96	NO
8:15 AM - 8:30 AM	1.18	14.62	312	0.63	14.53	312	0.08	473.58	1.21	1.96	NO
8:30 AM - 8:45 AM	1.19	14.44	321	0.66	14.51	321	0.08	502.74	0.90	1.96	NO
8:45 AM - 9:00 AM	1.17	13.89	318	0.63	14.01	318	0.07	488.91	1.60	1.96	NO
Overall Peak Statistics	0.93	13.13	3981	0.63	13.44	3981	0.02	6965.03	17.04	1.96	YES
							% Null Hypothesis				66.67%

ID	Route 4A (NO INCIDENT)			Route 4B (INCIDENT)			Hypothesis Testing Results				
Route Name	Western Distributor			Parramatta Rd							
Time (AM Peak)	Std. Dev. (Mins)	Avg. TT (Mins)	N	Std. Dev. (Mins)	Avg. TT (Mins)	N	Std. Error (Mins)	v	t_{stat}	t_{crit}	Reject Null Hypothesis?
6:00 AM - 6:15 AM	0.70	11.55	4	0.29	11.41	4	0.38	4.02	0.37	2.78	NO
6:15 AM - 6:30 AM	0.67	11.83	4	0.48	12.48	4	0.41	5.44	1.57	2.57	NO
6:30 AM - 6:45 AM	0.76	11.96	5	0.39	13.96	5	0.38	6.00	5.20	2.45	YES
6:45 AM - 7:00 AM	0.82	12.15	11	0.44	12.70	11	0.28	15.25	1.97	2.13	NO
7:00 AM - 7:15 AM	0.78	12.39	12	0.67	13.39	12	0.30	21.50	3.33	2.08	YES
7:15 AM - 7:30 AM	0.83	12.84	8	0.57	13.60	8	0.36	12.45	2.11	2.18	NO
7:30 AM - 7:45 AM	0.92	13.74	9	0.85	14.14	9	0.42	15.90	0.97	2.13	NO
7:45 AM - 8:00 AM	1.02	14.35	16	0.88	14.38	16	0.34	29.36	0.08	2.05	NO
8:00 AM - 8:15 AM	1.17	14.61	10	0.59	15.34	10	0.42	13.23	1.77	2.16	NO
8:15 AM - 8:30 AM	1.19	14.93	16	0.85	15.22	16	0.37	27.06	0.78	2.05	NO
8:30 AM - 8:45 AM	1.19	14.55	15	0.81	15.04	15	0.37	24.74	1.31	2.06	NO
8:45 AM - 9:00 AM	1.17	13.87	16	0.87	15.01	16	0.36	27.57	3.13	2.05	YES
Overall Peak Statistics	0.94	13.23	126	0.64	13.89	126	0.10	221.07	6.50	1.97	YES
							% Null Hypothesis				75.00%

ID	Route 4B (NO INCIDENT)			Route 4A (INCIDENT)			Hypothesis Testing Results				
Route Name	Parramatta Rd			Western Distributor							
Time (AM Peak)	Std. Dev. (Mins)	Avg. TT (Mins)	N	Std. Dev. (Mins)	Avg. TT (Mins)	N	Std. Error (Mins)	v	t_{stat}	t_{crit}	Reject Null Hypothesis?
6:00 AM - 6:15 AM	0.47	11.73	4	0.01	11.10	4	0.24	3.00	2.67	3.18	NO
6:15 AM - 6:30 AM	0.49	12.41	4	0.60	11.90	4	0.39	5.77	1.33	2.57	NO
6:30 AM - 6:45 AM	0.62	12.99	5	0.44	12.52	5	0.34	7.26	1.39	2.36	NO
6:45 AM - 7:00 AM	0.62	12.87	10	0.83	12.36	10	0.33	16.72	1.55	2.12	NO
7:00 AM - 7:15 AM	0.66	13.29	11	0.86	13.28	11	0.33	18.75	0.03	2.10	NO
7:15 AM - 7:30 AM	0.70	13.46	10	1.55	13.77	10	0.54	12.55	0.58	2.18	NO
7:30 AM - 7:45 AM	0.69	13.77	8	1.53	14.41	8	0.59	9.74	1.07	2.26	NO
7:45 AM - 8:00 AM	0.69	14.11	18	1.40	14.28	18	0.37	24.85	0.47	2.06	NO
8:00 AM - 8:15 AM	0.65	14.31	12	1.18	16.05	12	0.39	17.08	4.46	2.11	YES
8:15 AM - 8:30 AM	0.63	14.53	17	1.34	15.47	17	0.36	22.79	2.61	2.07	YES
8:30 AM - 8:45 AM	0.67	14.67	14	1.03	13.89	14	0.33	22.31	2.38	2.07	YES
8:45 AM - 9:00 AM	0.64	14.13	15	1.52	14.20	15	0.43	18.76	0.17	2.10	NO
Overall Peak Statistics	0.63	13.52	128	1.02	13.60	128	0.11	210.70	0.75	1.97	NO
							% Null Hypothesis				75.00%

PM Peak Results

ID	Route 4A (NO INCIDENT)			Route 4A (INCIDENT)			Hypothesis Testing Results				
Route Name	Western Distributor			Western Distributor							
Time (PM Peak)	Std. Dev. (Mins)	Avg. TT (Mins)	N	Std. Dev. (Mins)	Avg. TT (Mins)	N	Std. Error (Mins)	v	t_{stat}	t_{crit}	Reject Null Hypothesis?
4:00 PM - 4:15 PM	0.87	12.09	360	0.83	12.23	20	0.19	21.39	0.75	2.08	NO
4:15 PM - 4:30 PM	0.66	12.40	359	0.77	12.12	18	0.18	18.28	1.51	2.10	NO
4:30 PM - 4:45 PM	0.78	12.38	359	0.93	12.24	15	0.24	14.84	0.59	2.14	NO
4:45 PM - 5:00 PM	0.90	12.32	364	0.92	12.46	13	0.26	12.84	0.54	2.18	NO
5:00 PM - 5:15 PM	0.73	12.46	352	0.89	13.33	19	0.21	19.33	4.17	2.09	YES
5:15 PM - 5:30 PM	0.71	13.19	350	0.90	13.36	15	0.23	14.77	0.71	2.14	NO
5:30 PM - 5:45 PM	0.71	13.84	343	0.95	13.36	15	0.25	14.71	1.95	2.14	NO
5:45 PM - 6:00 PM	0.84	14.21	329	0.85	14.08	14	0.23	14.08	0.56	2.14	NO
6:00 PM - 6:15 PM	0.73	14.08	298	0.92	14.23	20	0.21	20.67	0.75	2.09	NO
6:15 PM - 6:30 PM	0.91	14.16	255	0.84	14.00	21	0.19	24.05	0.85	2.06	NO
6:30 PM - 6:45 PM	0.82	12.90	238	0.86	12.99	21	0.19	23.36	0.42	2.07	NO
6:45 PM - 7:00 PM	0.84	12.12	221	0.76	12.92	13	0.22	13.79	3.65	2.16	YES
Overall Peak Statistics	0.79	13.01	3828	0.87	13.11	204	0.06	221.47	1.56	1.97	NO
							% Null Hypothesis				83.33%

ID	Route 4B (NO INCIDENT)			Route 4B (INCIDENT)			Hypothesis Testing Results				
Route Name	Parramatta Rd			Parramatta Rd							
Time (PM Peak)	Std. Dev. (Mins)	Avg. TT (Mins)	N	Std. Dev. (Mins)	Avg. TT (Mins)	N	Std. Error (Mins)	v	t_{stat}	t_{crit}	Reject Null Hypothesis?
4:00 PM - 4:15 PM	0.58	13.65	344	0.60	13.63	17	0.15	17.50	0.16	2.11	NO
4:15 PM - 4:30 PM	0.59	13.64	354	0.51	13.58	18	0.13	19.38	0.51	2.09	NO
4:30 PM - 4:45 PM	0.52	13.45	356	0.70	13.16	13	0.20	12.49	1.50	2.18	NO
4:45 PM - 5:00 PM	0.53	13.66	342	0.40	13.74	13	0.11	13.64	0.68	2.16	NO
5:00 PM - 5:15 PM	0.55	13.92	339	0.56	13.68	20	0.13	21.22	1.82	2.08	NO
5:15 PM - 5:30 PM	0.54	14.27	347	0.62	14.27	18	0.15	18.37	0.03	2.10	NO
5:30 PM - 5:45 PM	0.59	14.62	344	0.59	14.71	16	0.15	16.47	0.61	2.12	NO
5:45 PM - 6:00 PM	0.63	14.57	357	0.83	14.93	15	0.22	14.68	1.68	2.14	NO
6:00 PM - 6:15 PM	0.64	14.29	337	0.88	14.39	25	0.18	25.91	0.57	2.06	NO
6:15 PM - 6:30 PM	0.57	13.88	330	0.63	13.91	23	0.14	24.55	0.24	2.06	NO
6:30 PM - 6:45 PM	0.55	13.17	277	0.42	13.28	28	0.09	37.09	1.31	2.03	NO
6:45 PM - 7:00 PM	0.41	12.69	240	0.44	12.79	15	0.12	15.59	0.81	2.13	NO
Overall Peak Statistics	0.56	13.82	3967	0.60	13.84	221	0.04	241.89	0.54	1.97	NO
							% Null Hypothesis				100.00%

ID	Route 4A (NO INCIDENT)			Route 4B (NO INCIDENT)			Hypothesis Testing Results				
Route Name	Western Distributor			Parramatta Rd							
Time (PM Peak)	Std. Dev. (Mins)	Avg. TT (Mins)	N	Std. Dev. (Mins)	Avg. TT (Mins)	N	Std. Error (Mins)	v	t_{stat}	t_{crit}	Reject Null Hypothesis?
4:00 PM - 4:15 PM	0.87	12.07	301	0.57	13.64	301	0.06	519.00	26.01	1.96	YES
4:15 PM - 4:30 PM	0.66	12.38	312	0.59	13.63	312	0.05	615.42	24.88	1.96	YES
4:30 PM - 4:45 PM	0.78	12.35	314	0.52	13.42	314	0.05	546.43	20.41	1.96	YES
4:45 PM - 5:00 PM	0.90	12.30	313	0.53	13.64	313	0.06	502.95	22.78	1.96	YES
5:00 PM - 5:15 PM	0.73	12.44	308	0.55	13.89	308	0.05	568.56	27.99	1.96	YES
5:15 PM - 5:30 PM	0.71	13.15	315	0.54	14.22	315	0.05	585.78	21.33	1.96	YES
5:30 PM - 5:45 PM	0.71	13.82	298	0.59	14.60	298	0.05	575.12	14.49	1.96	YES
5:45 PM - 6:00 PM	0.84	14.16	289	0.63	14.22	289	0.06	535.05	0.98	1.96	NO
6:00 PM - 6:15 PM	0.73	14.04	251	0.64	14.15	251	0.06	490.59	1.89	1.96	NO
6:15 PM - 6:30 PM	0.91	14.04	204	0.57	13.96	204	0.08	341.09	1.10	1.97	NO
6:30 PM - 6:45 PM	0.82	12.99	191	0.55	13.05	191	0.07	332.20	0.88	1.97	NO
6:45 PM - 7:00 PM	0.84	12.08	187	0.41	12.65	187	0.07	268.92	8.38	1.97	YES
Overall Peak Statistics	0.79	12.98	3283	0.56	13.76	3283	0.02	5893.43	45.71	1.96	YES
							% Null Hypothesis				33.33%

ID	Route 4A (NO INCIDENT)			Route 4B (INCIDENT)			Hypothesis Testing Results				
Route Name	Western Distributor			Parramatta Rd							
Time (PM Peak)	Std. Dev. (Mins)	Avg. TT (Mins)	N	Std. Dev. (Mins)	Avg. TT (Mins)	N	Std. Error (Mins)	v	t_{stat}	t_{crit}	Reject Null Hypothesis?
4:00 PM - 4:15 PM	0.88	12.12	16	0.60	13.62	16	0.27	26.32	5.65	2.06	YES
4:15 PM - 4:30 PM	0.67	12.43	18	0.51	13.57	18	0.20	31.93	5.78	2.04	YES
4:30 PM - 4:45 PM	0.79	12.44	12	0.70	13.14	12	0.30	21.69	2.30	2.08	YES
4:45 PM - 5:00 PM	0.91	12.36	13	0.40	13.73	13	0.28	16.44	4.96	2.12	YES
5:00 PM - 5:15 PM	0.74	12.52	18	0.56	13.67	18	0.22	31.64	5.31	2.04	YES
5:15 PM - 5:30 PM	0.72	13.29	18	0.62	14.25	18	0.22	33.31	4.32	2.03	YES
5:30 PM - 5:45 PM	0.72	13.88	16	0.58	14.70	16	0.23	28.76	3.52	2.05	YES
5:45 PM - 6:00 PM	0.84	14.29	14	0.83	14.91	14	0.32	26.00	1.96	2.06	NO
6:00 PM - 6:15 PM	0.74	14.16	22	0.88	14.38	22	0.25	40.84	0.89	2.02	NO
6:15 PM - 6:30 PM	0.91	14.21	21	0.63	13.90	21	0.24	35.63	1.27	2.03	NO
6:30 PM - 6:45 PM	0.82	12.93	26	0.42	13.27	26	0.18	37.20	1.88	2.03	NO
6:45 PM - 7:00 PM	0.85	12.22	15	0.43	12.76	15	0.25	20.83	2.21	2.09	YES
Overall Peak Statistics	0.80	13.07	209	0.60	13.83	209	0.07	385.15	10.95	1.97	YES
							% Null Hypothesis				33.33%

ID	Route 4B (NO INCIDENT)			Route 4A (INCIDENT)			Hypothesis Testing Results				
Route Name	Parramatta Rd			Western Distributor							
Time (PM Peak)	Std. Dev. (Mins)	Avg. TT (Mins)	N	Std. Dev. (Mins)	Avg. TT (Mins)	N	Std. Error (Mins)	v	t_{stat}	t_{crit}	Reject Null Hypothesis?
4:00 PM - 4:15 PM	0.58	13.66	20	0.83	12.23	20	0.23	34.01	6.34	2.03	YES
4:15 PM - 4:30 PM	0.60	13.66	18	0.77	12.11	18	0.23	32.09	6.74	2.04	YES
4:30 PM - 4:45 PM	0.53	13.49	14	0.92	12.22	14	0.28	20.65	4.45	2.09	YES
4:45 PM - 5:00 PM	0.53	13.69	12	0.92	12.45	12	0.31	17.63	4.02	2.11	YES
5:00 PM - 5:15 PM	0.55	13.94	18	0.89	13.32	18	0.25	28.30	2.51	2.05	YES
5:15 PM - 5:30 PM	0.54	14.31	15	0.90	13.34	15	0.27	23.07	3.61	2.07	YES
5:30 PM - 5:45 PM	0.60	14.64	15	0.94	13.35	15	0.29	23.69	4.47	2.07	YES
5:45 PM - 6:00 PM	0.63	14.61	14	0.85	14.05	14	0.28	23.93	1.96	2.07	NO
6:00 PM - 6:15 PM	0.64	14.33	18	0.92	14.21	18	0.26	30.47	0.45	2.04	NO
6:15 PM - 6:30 PM	0.57	13.90	20	0.84	13.99	20	0.23	33.53	0.38	2.03	NO
6:30 PM - 6:45 PM	0.55	13.18	20	0.86	12.98	20	0.23	32.47	0.89	2.04	NO
6:45 PM - 7:00 PM	0.42	12.74	12	0.76	12.90	12	0.25	17.09	0.62	2.11	NO
Overall Peak Statistics	0.56	13.85	196	0.87	13.10	196	0.07	334.45	10.18	1.97	YES
							% Null Hypothesis				41.67%

Set 5: Princes Highway Vs Rocky Point Road

AM Peak Results

ID	Route 5A (NO INCIDENT)			Route 5A (INCIDENT)			Hypothesis Testing Results				
Route Name	Princes Hwy			Princes Hwy							
Time (AM Peak)	Std. Dev. (Mins)	Avg. TT (Mins)	N	Std. Dev. (Mins)	Avg. TT (Mins)	N	Std. Error (Mins)	v	t_{stat}	t_{crit}	Reject Null Hypothesis?
6:00 AM - 6:15 AM	0.83	13.78	344	0.71	13.73	16	0.18	16.95	0.24	2.12	NO
6:15 AM - 6:30 AM	0.75	14.21	336	0.73	14.67	11	0.22	10.71	2.08	2.23	NO
6:30 AM - 6:45 AM	0.72	14.82	335	0.70	14.89	22	0.15	24.01	0.42	2.06	NO
6:45 AM - 7:00 AM	0.74	15.10	350	0.89	15.11	19	0.21	19.38	0.05	2.09	NO
7:00 AM - 7:15 AM	0.70	15.42	354	0.86	15.05	11	0.26	10.42	1.43	2.23	NO
7:15 AM - 7:30 AM	1.14	15.95	345	1.07	15.86	23	0.23	25.41	0.37	2.06	NO
7:30 AM - 7:45 AM	1.12	16.25	347	1.18	17.06	25	0.24	27.18	3.30	2.05	YES
7:45 AM - 8:00 AM	1.34	16.63	345	1.21	17.01	27	0.24	31.14	1.54	2.04	NO
8:00 AM - 8:15 AM	1.05	16.92	347	1.07	17.37	27	0.21	30.01	2.12	2.04	YES
8:15 AM - 8:30 AM	0.92	16.86	355	1.18	16.91	21	0.26	21.48	0.16	2.08	NO
8:30 AM - 8:45 AM	1.02	16.66	354	1.14	16.80	22	0.25	23.15	0.57	2.07	NO
8:45 AM - 9:00 AM	1.03	16.52	356	1.08	16.38	19	0.25	19.79	0.55	2.09	NO
Overall Peak Statistics	0.95	15.76	4168	0.99	15.90	243	0.06	268.71	2.20	1.97	YES
							% Null Hypothesis				83.33%

ID	Route 5B (NO INCIDENT)			Route 5B (INCIDENT)			Hypothesis Testing Results				
Route Name	Rocky Point Rd			Rocky Point Rd							
Time (AM Peak)	Std. Dev. (Mins)	Avg. TT (Mins)	N	Std. Dev. (Mins)	Avg. TT (Mins)	N	Std. Error (Mins)	v	t_{stat}	t_{crit}	Reject Null Hypothesis?
6:00 AM - 6:15 AM	0.54	12.37	263	0.83	12.18	12	0.24	11.43	0.78	2.20	NO
6:15 AM - 6:30 AM	1.98	12.04	321	0.88	12.39	11	0.29	13.77	1.23	2.16	NO
6:30 AM - 6:45 AM	1.39	12.32	303	1.22	12.78	19	0.29	21.07	1.57	2.08	NO
6:45 AM - 7:00 AM	0.55	12.97	320	1.25	12.96	14	0.34	13.22	0.02	2.16	NO
7:00 AM - 7:15 AM	1.04	13.25	346	1.22	13.56	11	0.37	10.46	0.82	2.23	NO
7:15 AM - 7:30 AM	2.07	13.81	335	1.58	14.08	23	0.35	27.46	0.76	2.05	NO
7:30 AM - 7:45 AM	1.48	13.18	351	2.58	13.36	25	0.52	25.13	0.33	2.06	NO
7:45 AM - 8:00 AM	1.25	12.60	351	2.27	12.29	27	0.44	27.22	0.69	2.05	NO
8:00 AM - 8:15 AM	1.39	14.03	343	1.75	13.67	27	0.35	28.64	1.03	2.05	NO
8:15 AM - 8:30 AM	1.16	14.37	348	1.57	14.06	21	0.35	21.34	0.91	2.08	NO
8:30 AM - 8:45 AM	1.63	14.38	346	1.55	14.89	22	0.34	24.05	1.51	2.06	NO
8:45 AM - 9:00 AM	2.28	14.08	351	1.15	14.51	17	0.30	22.69	1.41	2.07	NO
Overall Peak Statistics	1.40	13.28	3978	1.49	13.39	229	0.10	251.70	1.09	1.97	NO
							% Null Hypothesis				100.00%

ID	Route 5A (NO INCIDENT)			Route 5B (NO INCIDENT)			Hypothesis Testing Results				
Route Name	Princes Hwy			Rocky Point Rd							
Time (AM Peak)	Std. Dev. (Mins)	Avg. TT (Mins)	N	Std. Dev. (Mins)	Avg. TT (Mins)	N	Std. Error (Mins)	v	t_{stat}	t_{crit}	Reject Null Hypothesis?
6:00 AM - 6:15 AM	0.83	13.77	235	0.54	12.37	235	0.06	402.17	21.86	1.97	YES
6:15 AM - 6:30 AM	0.75	14.19	294	1.98	12.02	294	0.12	375.58	17.62	1.97	YES
6:30 AM - 6:45 AM	0.72	14.81	258	1.39	12.31	258	0.10	385.03	25.59	1.97	YES
6:45 AM - 7:00 AM	0.74	15.08	286	0.55	12.95	286	0.05	526.29	39.22	1.96	YES
7:00 AM - 7:15 AM	0.70	15.40	320	1.03	13.23	320	0.07	559.52	31.18	1.96	YES
7:15 AM - 7:30 AM	1.14	15.90	284	2.07	13.77	284	0.14	438.91	15.21	1.97	YES
7:30 AM - 7:45 AM	1.11	16.24	296	1.47	13.17	296	0.11	549.68	28.57	1.96	YES
7:45 AM - 8:00 AM	1.33	16.60	291	1.25	12.56	291	0.11	577.56	37.67	1.96	YES
8:00 AM - 8:15 AM	1.05	16.88	283	1.39	14.00	283	0.10	524.72	27.86	1.96	YES
8:15 AM - 8:30 AM	0.92	16.83	301	1.15	14.34	301	0.09	571.74	29.27	1.96	YES
8:30 AM - 8:45 AM	1.02	16.66	295	1.63	14.37	295	0.11	493.19	20.41	1.96	YES
8:45 AM - 9:00 AM	1.03	16.48	311	2.28	14.05	311	0.14	430.45	17.21	1.97	YES
Overall Peak Statistics	0.94	15.74	3454	1.39	13.26	3454	0.03	6067.50	86.39	1.96	YES
							% Null Hypothesis				0.00%

ID	Route 5A (NO INCIDENT)			Route 5B (INCIDENT)			Hypothesis Testing Results				
Route Name	Princes Hwy			Rocky Point Rd							
Time (AM Peak)	Std. Dev. (Mins)	Avg. TT (Mins)	N	Std. Dev. (Mins)	Avg. TT (Mins)	N	Std. Error (Mins)	v	t_{stat}	t_{crit}	Reject Null Hypothesis?
6:00 AM - 6:15 AM	0.84	13.79	11	0.83	12.18	11	0.36	20.00	4.53	2.09	YES
6:15 AM - 6:30 AM	0.76	14.24	10	0.88	12.38	10	0.37	17.62	5.08	2.11	YES
6:30 AM - 6:45 AM	0.72	14.86	19	1.22	12.77	19	0.32	29.26	6.42	2.05	YES
6:45 AM - 7:00 AM	0.75	15.14	14	1.25	12.95	14	0.39	21.27	5.61	2.08	YES
7:00 AM - 7:15 AM	0.71	15.47	10	1.22	13.55	10	0.45	14.47	4.31	2.14	YES
7:15 AM - 7:30 AM	1.14	16.04	22	1.58	14.05	22	0.42	38.15	4.78	2.02	YES
7:30 AM - 7:45 AM	1.13	16.28	24	2.57	13.35	24	0.57	31.51	5.11	2.04	YES
7:45 AM - 8:00 AM	1.34	16.71	26	2.27	12.27	26	0.52	40.45	8.57	2.02	YES
8:00 AM - 8:15 AM	1.06	16.98	27	1.75	13.66	27	0.39	42.75	8.44	2.02	YES
8:15 AM - 8:30 AM	0.93	16.92	20	1.57	14.04	20	0.41	30.91	7.07	2.04	YES
8:30 AM - 8:45 AM	1.03	16.67	22	1.55	14.89	22	0.40	36.41	4.48	2.03	YES
8:45 AM - 9:00 AM	1.03	16.60	17	1.15	14.49	17	0.37	31.65	5.64	2.04	YES
Overall Peak Statistics	0.95	15.81	222	1.49	13.38	222	0.12	376.08	20.47	1.97	YES
							% Null Hypothesis				0.00%

ID	Route 5B (NO INCIDENT)			Route 5A (INCIDENT)			Hypothesis Testing Results				
Route Name	Rocky Point Rd			Princes Hwy							
Time (AM Peak)	Std. Dev. (Mins)	Avg. TT (Mins)	N	Std. Dev. (Mins)	Avg. TT (Mins)	N	Std. Error (Mins)	v	t_{stat}	t_{crit}	Reject Null Hypothesis?
6:00 AM - 6:15 AM	0.55	12.38	15	0.71	13.73	15	0.23	26.31	5.82	2.06	YES
6:15 AM - 6:30 AM	1.98	12.07	11	0.73	14.66	11	0.64	12.64	4.07	2.18	YES
6:30 AM - 6:45 AM	1.40	12.36	21	0.70	14.88	21	0.34	29.46	7.40	2.05	YES
6:45 AM - 7:00 AM	0.56	13.01	18	0.89	15.10	18	0.25	28.68	8.46	2.05	YES
7:00 AM - 7:15 AM	1.04	13.30	10	0.86	15.04	10	0.43	17.34	4.07	2.11	YES
7:15 AM - 7:30 AM	2.08	13.91	21	1.07	15.84	21	0.51	29.95	3.78	2.05	YES
7:30 AM - 7:45 AM	1.48	13.21	23	1.18	17.05	23	0.40	41.89	9.69	2.02	YES
7:45 AM - 8:00 AM	1.25	12.67	25	1.21	16.99	25	0.35	47.95	12.39	2.01	YES
8:00 AM - 8:15 AM	1.40	14.10	26	1.07	17.35	26	0.35	46.85	9.40	2.01	YES
8:15 AM - 8:30 AM	1.16	14.43	19	1.18	16.89	19	0.38	36.00	6.48	2.03	YES
8:30 AM - 8:45 AM	1.64	14.38	22	1.14	16.80	22	0.42	37.42	5.69	2.03	YES
8:45 AM - 9:00 AM	2.29	14.16	18	1.07	16.36	18	0.60	24.17	3.70	2.06	YES
Overall Peak Statistics	1.40	13.33	229	0.98	15.89	229	0.11	408.63	22.60	1.97	YES
							% Null Hypothesis				0.00%

PM Peak Results

ID	Route 5A (NO INCIDENT)			Route 5A (INCIDENT)			Hypothesis Testing Results				
Route Name	Princes Hwy			Princes Hwy							
Time (PM Peak)	Std. Dev. (Mins)	Avg. TT (Mins)	N	Std. Dev. (Mins)	Avg. TT (Mins)	N	Std. Error (Mins)	v	t_{stat}	t_{crit}	Reject Null Hypothesis?
4:00 PM - 4:15 PM	1.07	16.64	351	1.79	17.18	26	0.36	26.33	1.52	2.06	NO
4:15 PM - 4:30 PM	0.83	16.53	351	1.01	16.61	26	0.20	27.60	0.43	2.05	NO
4:30 PM - 4:45 PM	0.99	16.80	346	0.94	16.72	29	0.18	33.40	0.44	2.03	NO
4:45 PM - 5:00 PM	0.98	16.29	332	0.93	16.48	37	0.16	45.34	1.22	2.01	NO
5:00 PM - 5:15 PM	1.08	16.63	340	0.94	16.76	28	0.19	33.25	0.68	2.03	NO
5:15 PM - 5:30 PM	0.53	16.84	335	0.91	17.03	23	0.19	23.05	0.99	2.07	NO
5:30 PM - 5:45 PM	0.83	16.51	330	0.90	17.34	26	0.18	28.42	4.56	2.05	YES
5:45 PM - 6:00 PM	0.71	16.19	339	0.84	16.40	18	0.20	18.28	1.02	2.10	NO
6:00 PM - 6:15 PM	0.58	15.63	272	0.80	15.72	20	0.18	20.49	0.51	2.09	NO
6:15 PM - 6:30 PM	0.77	15.24	255	0.72	15.50	17	0.18	18.53	1.40	2.10	NO
6:30 PM - 6:45 PM	0.33	14.96	244	0.66	14.90	9	0.22	8.15	0.28	2.31	NO
6:45 PM - 7:00 PM	0.47	14.91	266	0.70	14.81	13	0.20	12.54	0.50	2.18	NO
Overall Peak Statistics	0.76	16.10	3761	0.93	16.29	272	0.06	298.18	3.30	1.97	YES
							% Null Hypothesis				91.67%

ID	Route 5B (NO INCIDENT)			Route 5B (INCIDENT)			Hypothesis Testing Results				
Route Name	Rocky Point Rd			Rocky Point Rd							
Time (PM Peak)	Std. Dev. (Mins)	Avg. TT (Mins)	N	Std. Dev. (Mins)	Avg. TT (Mins)	N	Std. Error (Mins)	v	t_{stat}	t_{crit}	Reject Null Hypothesis?
4:00 PM - 4:15 PM	2.35	16.69	347	1.96	16.63	25	0.41	29.20	0.14	2.05	NO
4:15 PM - 4:30 PM	1.48	17.91	348	2.03	17.68	26	0.41	27.02	0.56	2.05	NO
4:30 PM - 4:45 PM	2.06	17.87	345	1.96	17.94	29	0.38	33.46	0.18	2.03	NO
4:45 PM - 5:00 PM	1.72	17.28	338	1.75	17.58	37	0.30	43.94	0.99	2.02	NO
5:00 PM - 5:15 PM	1.90	16.60	340	1.92	17.07	27	0.38	30.18	1.21	2.04	NO
5:15 PM - 5:30 PM	1.65	16.62	344	1.74	17.06	24	0.37	25.96	1.18	2.06	NO
5:30 PM - 5:45 PM	1.09	16.42	326	1.88	16.36	26	0.37	26.36	0.16	2.06	NO
5:45 PM - 6:00 PM	1.95	15.48	295	1.47	16.32	17	0.37	19.43	2.26	2.09	YES
6:00 PM - 6:15 PM	1.47	15.31	239	1.48	15.59	18	0.36	19.62	0.76	2.09	NO
6:15 PM - 6:30 PM	1.19	14.41	248	1.30	14.57	18	0.31	19.13	0.51	2.09	NO
6:30 PM - 6:45 PM	1.47	13.84	214	1.23	14.63	10	0.40	10.23	1.96	2.23	NO
6:45 PM - 7:00 PM	1.36	13.66	194	1.34	13.44	9	0.46	8.78	0.47	2.31	NO
Overall Peak Statistics	1.64	16.01	3578	1.67	16.24	266	0.11	304.24	2.18	1.97	YES
							% Null Hypothesis				91.67%

ID	Route 5A (NO INCIDENT)			Route 5B (NO INCIDENT)			Hypothesis Testing Results				
Route Name	Princes Hwy			Rocky Point Rd							
Time (PM Peak)	Std. Dev. (Mins)	Avg. TT (Mins)	N	Std. Dev. (Mins)	Avg. TT (Mins)	N	Std. Error (Mins)	v	t_{stat}	t_{crit}	Reject Null Hypothesis?
4:00 PM - 4:15 PM	1.06	16.62	293	2.35	16.67	293	0.15	406.81	0.32	1.97	NO
4:15 PM - 4:30 PM	0.83	16.49	294	1.48	17.87	294	0.10	461.83	13.90	1.97	YES
4:30 PM - 4:45 PM	0.98	16.77	283	2.06	17.84	283	0.14	403.84	7.88	1.97	YES
4:45 PM - 5:00 PM	0.97	16.27	261	1.71	16.36	261	0.12	412.39	0.76	1.97	NO
5:00 PM - 5:15 PM	1.08	16.59	279	1.89	16.46	279	0.13	441.78	1.00	1.97	NO
5:15 PM - 5:30 PM	0.53	16.80	288	1.65	16.68	288	0.10	345.34	1.18	1.97	NO
5:30 PM - 5:45 PM	0.82	16.47	271	1.08	16.38	271	0.08	502.94	1.10	1.96	NO
5:45 PM - 6:00 PM	0.70	16.19	251	1.95	15.98	251	0.13	313.82	1.59	1.97	NO
6:00 PM - 6:15 PM	0.58	15.51	198	1.47	15.39	198	0.11	256.68	1.03	1.97	NO
6:15 PM - 6:30 PM	0.77	15.22	207	1.19	14.39	207	0.10	353.96	8.45	1.97	YES
6:30 PM - 6:45 PM	0.33	14.92	191	1.46	13.79	191	0.11	209.47	10.38	1.97	YES
6:45 PM - 7:00 PM	0.47	14.87	169	1.35	13.61	169	0.11	207.64	11.40	1.97	YES
Overall Peak Statistics	0.76	16.06	2985	1.64	15.95	2985	0.03	4216.34	3.26	1.96	YES
							% Null Hypothesis				58.33%

ID	Route 5A (NO INCIDENT)			Route 5B (INCIDENT)			Hypothesis Testing Results				
Route Name	Princes Hwy			Rocky Point Rd							
Time (PM Peak)	Std. Dev. (Mins)	Avg. TT (Mins)	N	Std. Dev. (Mins)	Avg. TT (Mins)	N	Std. Error (Mins)	v	t_{stat}	t_{crit}	Reject Null Hypothesis?
4:00 PM - 4:15 PM	1.07	16.69	24	1.96	16.62	24	0.46	35.59	0.14	2.03	NO
4:15 PM - 4:30 PM	0.84	16.61	25	2.03	17.66	25	0.44	31.89	2.39	2.04	YES
4:30 PM - 4:45 PM	0.99	16.87	29	1.95	17.92	29	0.41	41.58	2.59	2.02	YES
4:45 PM - 5:00 PM	0.99	16.32	35	1.75	17.57	35	0.34	53.67	3.67	2.01	YES
5:00 PM - 5:15 PM	1.09	16.72	23	1.92	17.05	23	0.46	34.91	0.72	2.03	NO
5:15 PM - 5:30 PM	0.54	16.93	22	1.74	17.04	22	0.39	24.92	0.29	2.06	NO
5:30 PM - 5:45 PM	0.84	16.59	25	1.87	16.34	25	0.41	33.18	0.63	2.03	NO
5:45 PM - 6:00 PM	0.71	16.20	16	1.46	16.32	16	0.41	21.77	0.30	2.08	NO
6:00 PM - 6:15 PM	0.59	15.67	18	1.48	15.58	18	0.38	22.30	0.26	2.07	NO
6:15 PM - 6:30 PM	0.77	15.30	18	1.29	14.56	18	0.36	27.79	2.07	2.05	YES
6:30 PM - 6:45 PM	0.34	15.06	8	1.23	14.60	8	0.45	8.07	1.01	2.31	NO
6:45 PM - 7:00 PM	0.48	15.00	8	1.34	13.42	8	0.50	8.76	3.13	2.31	YES
Overall Peak Statistics	0.77	16.16	251	1.67	16.22	251	0.12	351.89	0.53	1.97	NO
							% Null Hypothesis				58.33%

ID	Route 5B (NO INCIDENT)			Route 5A (INCIDENT)			Hypothesis Testing Results				
Route Name	Rocky Point Rd			Princes Hwy							
Time (PM Peak)	Std. Dev. (Mins)	Avg. TT (Mins)	N	Std. Dev. (Mins)	Avg. TT (Mins)	N	Std. Error (Mins)	v	t_{stat}	t_{crit}	Reject Null Hypothesis?
4:00 PM - 4:15 PM	2.36	16.73	25	1.79	17.17	25	0.59	44.74	0.74	2.02	NO
4:15 PM - 4:30 PM	1.48	17.99	26	1.01	16.59	26	0.35	44.02	3.96	2.02	YES
4:30 PM - 4:45 PM	2.07	17.94	25	0.94	16.71	25	0.45	33.41	2.71	2.03	YES
4:45 PM - 5:00 PM	1.73	17.32	32	0.93	16.47	32	0.35	47.59	2.43	2.01	YES
5:00 PM - 5:15 PM	1.90	16.69	26	0.93	16.74	26	0.42	36.40	0.13	2.03	NO
5:15 PM - 5:30 PM	1.66	16.70	23	0.91	17.01	23	0.39	34.06	0.78	2.03	NO
5:30 PM - 5:45 PM	1.10	16.50	21	0.90	17.32	21	0.31	38.46	2.63	2.02	YES
5:45 PM - 6:00 PM	1.96	15.49	18	0.84	16.40	18	0.50	23.07	1.80	2.07	NO
6:00 PM - 6:15 PM	1.48	15.36	20	0.80	15.71	20	0.38	29.25	0.94	2.05	NO
6:15 PM - 6:30 PM	1.19	14.47	14	0.72	15.49	14	0.37	21.45	2.75	2.08	YES
6:30 PM - 6:45 PM	1.47	13.93	8	0.66	14.88	8	0.57	9.69	1.67	2.26	NO
6:45 PM - 7:00 PM	1.36	13.74	12	0.70	14.79	12	0.44	16.41	2.38	2.12	YES
Overall Peak Statistics	1.65	16.07	250	0.93	16.27	250	0.12	392.33	1.70	1.97	NO
							% Null Hypothesis				50.00%

APPENDIX C: EXPERIMENT INSTRUCTIONS (CHAPTER 3)

ID:

Welcome to the research study.

Please wait for an assistant to get you started.

ID:

This is a study of decision making in the context of driving. In these tasks you should make any decisions that seem right to you.

The tasks give you the opportunity of earning additional money. Through participating in this experiment you will be given a fixed amount of $5.00 for your participation. In addition, you could earn between $1.00 and $40.00, which on average would earn you about 20 - 25 dollars. How much you earn will depend primarily on your own decisions and partly on chance. The published results of our research will not identify you, or the choice you made in any way. The instructions are simple and you will benefit from following them carefully.

Please raise your hand if you have any questions, and one of us will come to you.

You will be paid in cash today, at the end of the session.

Now, a brief description about today's experiment:

As a driver, you usually have several routes to choose from while driving. The route you choose depends on the travel time and the reliability of travel time on these routes. The following tasks involve you making decisions regarding route choice under different conditions.

The session will proceed in four parts.

In each part, you will be making decisions regarding route choice on your response sheets for monetary consequences. In addition, you will be given a simple questionnaire.

We expect the entire task to take less than 60 minutes. You are free to leave at any time, but if you do not complete all tasks you will not receive your earnings. Your earnings for the tasks could range from a minimum of $1.00 to a maximum of $40.00.

ID:

We would like to know how fast you think you drive as a driver. All drivers do not drive equally fast on the road. We want you to compare your own personal driving speeds to the average speeds of the other vehicles you experience while driving.

In this table we have ranked groups of drivers from the lowest 10 percent to the highest. Please circle the range that you think you belong to.

Where do you place in terms of the speeds you drive at on the road?

Lowest 1-10% 11-20% 21-30% 31-40% 41-50%

51-60% 61-70% 71-80% 81-90% Highest 91-100%

Note: If you consider yourself as driving slower than the average speed of other vehicles, you would belong to lower percentage group (between 1 and 50%, where 1% indicates that you think you drive slower that 99% of drivers). However if you believe that you drive faster than the average speed of other vehicles you would belong to the higher percentage groups (between 50% and 100%, where 100% indicates that you think you drive faster than all drivers on the road.)

Please raise your hand to let the lab staff know you have finished.

ID:

PART 1 INSTRUCTIONS

This task involves making decisions regarding route choice when you have an option between a route which has tolls (motorway) and no tolls (arterial). Your decision sheet on the next page shows ten decisions listed on the left. Each decision is a paired choice between two possible routes you can choose, a Motorway Route "Choice A" and an Arterial Route "Choice B." Each route has two different levels of delay and different probabilities associated to each of the delays.

As mentioned earlier, the choice of route depends on the travel time and the reliability of travel time. The travel delay costs you money. Your value of time in this task is set to $1.00 a minute, i.e. for each minute of delay you lose $1.00 from your wage. Your wage for each commute (i.e. decision row) is $10. Each row represents a separate route choice decision that you need to make while commuting to work. You will make a choice on each row and record these in the final column. There is an additional toll value for the Motorway route, which is provided in the fourth column.

Here is a ten sided die that will be used to determine payoffs. The faces are numbered from 0 to 9, and we will use the 0 face of the die to serve as 10. Look at Decision 1 at the top. Motorway Route (Choice A) has a delay of 5.00 min if the throw of the ten sided die is 1 (i.e. probability of 0.1), and 6.00 min if the throw of the ten sided die is between 2-10 (i.e. probability of 0.9). Arterial Route (Choice B) has a delay of 0.00 min if the throw of the ten sided die is 1 (i.e. probability of 0.1), and 9.75 min if the throw of the ten sided die is between 2-10 (i.e. probability of 0.9). The throw of the dice will determine the delay on the route you choose.

The other decisions are similar, except that as you move down the table, the chances of lower delay for each option increase. In fact, for Decision 10 in the bottom row, the die will not be needed since each option has the lowest delay for sure, so your choice here is between delays of 5.00 min or 0.00 min.

To determine your delay, you will throw this die twice, once to select one of the ten decisions to be used, and a second time to determine what your payoff is for the route you chose, A or B, for the particular decision you selected for that row. Your final monetary payoff will depend on the cost of the delay '***D***' determined by the die roll. Your monetary payoff for this task is calculated as:

$10 – toll - D

A toll is deducted if a motorway route was chosen. The toll for the motorway, in this route choice scenario is $2.00.

Even though you will make ten decisions, only one of these will end up affecting your earnings, but you will not know in advance which decision will be used.

All the delays and payoffs will be determined at the end of the session.

ID:

Please select a choice (Motorway or Arterial) for each decision

Decision	**Motorway Route Choice A**	**Arterial Route Choice B**	**Toll for Motorway Route**	**Your Choice (Circle one)**
1	**5.00** min delay if throw of die is 1 **6.00** min delay if throw of die is 2-10	**0.00** min delay if throw of die is 1 **9.75** min delay if throw of die is 2-10	$2.00	A B
2	**5.00** min delay if throw of die is 1-2 **6.00** min delay if throw of die is 3-10	**0.00** min delay if throw of die is 1-2 **9.75** min delay if throw of die is 3-10	$2.00	A B
3	**5.00** min delay if throw of die is 1-3 **6.00** min delay if throw of die is 4-10	**0.00** min delay if throw of die is 1-3 **9.75** min delay if throw of die is 4-10	$2.00	A B
4	**5.00** min delay if throw of die is 1-4 **6.00** min delay if throw of die is 5-10	**0.00** min delay if throw of die is 1-4 **9.75** min delay if throw of die is 5-10	$2.00	A B
5	**5.00** min delay if throw of die is 1-5 **6.00** min delay if throw of die is 6-10	**0.00** min delay if throw of die is 1-5 **9.75** min delay if throw of die is 6-10	$2.00	A B
6	**5.00** min delay if throw of die is 1-6 **6.00** min delay if throw of die is 7-10	**0.00** min delay if throw of die is 1-6 **9.75** min delay if throw of die is 7-10	$2.00	A B
7	**5.00** min delay if throw of die is 1-7 **6.00** min delay if throw of die is 8-10	**0.00** min delay if throw of die is 1-7 **9.75** min delay if throw of die is 8-10	$2.00	A B
8	**5.00** min delay if throw of die is 1-8 **6.00** min delay if throw of die is 9-10	**0.00** min delay if throw of die is 1-8 **9.75** min delay if throw of die is 9-10	$2.00	A B
9	**5.00** min delay if throw of die is 1-9 **6.00** min delay if throw of die is 10	**0.00** min delay if throw of die is 1-9 **9.75** min delay if throw of die is 10	$2.00	A B
10	**5.00** min delay if throw of die is 1-10	**0.00** min delay if throw of die is 1-10	$2.00	A B

DECISION ROW CHOSEN BY FIRST THROW OF THE DIE: _________

THROW OF THE DIE TO DETERMINE DELAY: ____________

EARNINGS: ________________

ID:

PART 2 INSTRUCTIONS

This route choice scenario is exactly the same as Part 1, except that the toll for taking the Motorway Route is $4.00.

Similar to the earlier task, even though you will make ten decisions, only one of these will end up affecting your earnings, and you will not know in advance which decision will be used. All the delays and payoffs for your choices in this scenario will be determined at the end of the session.

ID:

Please select a choice (Motorway or Arterial) for each decision

Decision	Motorway Route Choice A	Arterial Route Choice B	Toll for Motorway Route	Your Choice (Circle one)
1	**5.00** min delay if throw of die is 1 **6.00** min delay if throw of die is 2-10	**0.00** min delay if throw of die is 1 **9.75** min delay if throw of die is 2-10	$4.00	A B
2	**5.00** min delay if throw of die is 1-2 **6.00** min delay if throw of die is 3-10	**0.00** min delay if throw of die is 1-2 **9.75** min delay if throw of die is 3-10	$4.00	A B
3	**5.00** min delay if throw of die is 1-3 **6.00** min delay if throw of die is 4-10	**0.00** min delay if throw of die is 1-3 **9.75** min delay if throw of die is 4-10	$4.00	A B
4	**5.00** min delay if throw of die is 1-4 **6.00** min delay if throw of die is 5-10	**0.00** min delay if throw of die is 1-4 **9.75** min delay if throw of die is 5-10	$4.00	A B
5	**5.00** min delay if throw of die is 1-5 **6.00** min delay if throw of die is 6-10	**0.00** min delay if throw of die is 1-5 **9.75** min delay if throw of die is 6-10	$4.00	A B
6	**5.00** min delay if throw of die is 1-6 **6.00** min delay if throw of die is 7-10	**0.00** min delay if throw of die is 1-6 **9.75** min delay if throw of die is 7-10	$4.00	A B
7	**5.00** min delay if throw of die is 1-7 **6.00** min delay if throw of die is 8-10	**0.00** min delay if throw of die is 1-7 **9.75** min delay if throw of die is 8-10	$4.00	A B
8	**5.00** min delay if throw of die is 1-8 **6.00** min delay if throw of die is 9-10	**0.00** min delay if throw of die is 1-8 **9.75** min delay if throw of die is 9-10	$4.00	A B
9	**5.00** min delay if throw of die is 1-9 **6.00** min delay if throw of die is 10	**0.00** min delay if throw of die is 1-9 **9.75** min delay if throw of die is 10	$4.00	A B
10	**5.00** min delay if throw of die is 1-10	**0.00** min delay if throw of die is 1-10	$4.00	A B

DECISION ROW CHOSEN BY FIRST THROW OF THE DIE: _________

THROW OF THE DIE TO DETERMINE DELAY: ___________

EARNINGS: _______________

ID:

Some Questions About You

In this survey most of the questions asked are descriptive. We will not be grading your answers and your responses are completely confidential. Please think carefully about each question and give your best answers.

1. What is your AGE? ____________ years

2. What is your sex? (Circle one number.)

01 Male 02 Female

3. What is your major? (Circle one number.)

01 Accounting
02 Economics
03 Finance
04 Business Administration, other than Accounting, Economics, or Finance
05 Education
06 Engineering
07 Health Professions
08 Public Affairs or Social Services
09 Biological Sciences
10 Math, Computer Sciences, or Physical Sciences
11 Social Sciences or History
12 Humanities
13 Psychology
14 Other Fields
15 Does not apply

4. What is your class standing? (Circle one number.)

01 Undergraduate Student
02 Postgraduate Masters Student
03 Postgraduate Doctoral Student
04 Does not apply

5. What is the highest level of education you expect to complete? (Circle one number)

01 Bachelor's degree
02 Master's degree
03 Doctoral degree
04 First professional degree
05 High school diploma or GED
06 Less than high school

ID:

6. What was the highest level of education that your father (or male guardian) completed? (Circle one number)

01 Less than high school
02 GED or High School Equivalency
03 High school
04 Vocational or trade school
05 College or university

7. What was the highest level of education that your mother (or female guardian) completed? (Circle one number)

01 Less than high school
02 GED or High School Equivalency
03 High School
04 Vocational or trade school
05 College or university

8. What is your citizenship status in the Australia?

01 Citizen
02 Permanent Resident
03 Non-Resident
04 Other Status

9. Are you a international student on a Student Visa?
;
01 Yes
02 No

10. Are you currently...

01 Single and never married?
02 Married?
03 Separated, divorced or widowed?

11. What is your current WAM if you are doing a Bachelor's degree, or what was it when you did a Bachelor's degree? This WAM should refer to all of your coursework, not just the current year. Please pick one:

01 Between 85 and 100 WAM (High Distinction)
02 Between 75 and 84 WAM (Distinction)
03 Between 65 and 74 WAM (Credit)
04 Between 55 and 64 WAM (Pass)
05 Between 45 and 54 GPA (Pass Conceded)
08 Have not taken courses for which grades are given.

ID:

12. How many people live in your household? Include yourself, your spouse and any dependents. Do not include your parents or roommates unless you claim them as dependents.

____

13. Please circle the category below that describes the total amount of INCOME earned in 2011 by the people in your household (as "household" is defined in question 13).[Consider all forms of income, including salaries, tips, interest and dividend payments, scholarship support, student loans, parental support, social security, alimony, and child support, and others.]

01 $15,000 or under
02 $15,001 - $25,000
03 $25,001 - $35,000
04 $35,001 - $50,000
05 $50,001 - $65,000
06 $65,001 - $80,000
07 $80,001 - $100,000
08 over $100,000

14. Please circle the category below that describes the total amount of INCOME earned in 2007 by your parents. [Consider all forms of income, including salaries, tips, interest and dividend payments, social security, alimony, and child support, and others.]

01 $15,000 or under
02 $15,001 - $25,000
03 $25,001 - $35,000
04 $35,001 - $50,000
05 $50,001 - $65,000
06 $65,001 - $80,000
07 $80,001 - $100,000
08 over $100,000
09 Don't Know

15. Do you work part time, full time, or neither? (Circle one number.)

01 Part time
02 Full time
03 Neither

16. Before taxes, what do you get paid? (fill in only one)

01 _____ per hour before taxes
02 _____ per week before taxes
03 _____ per month before taxes
04 _____ per year before taxes

ID:

17. Do you currently smoke cigarettes? (Circle one number.)

00 No
01 Yes

If yes, approximately how much do you smoke in one day? ________ packs

18. How frequently do you drive?

01 Almost every day
02 Almost every week
03 Several times a year
04 Very rarely
05 Not at all for more than one year

19. How often do you pay tolls?

01 Almost every day
02 Almost every week
03 Several times a year
04 Very rarely
05 Not at all for more than one year

20. How many speeding tickets have you had in the last 5 years? ____________

21. Do you have an Australian driver's license? ____________

22. How many years have you held your driving license? ____________

Please tell the lab assistant that you have finished with the questionnaire.

ID:

PART 3 INSTRUCTIONS

This task involves making decisions regarding whether you would be willing to pay for information about the delays on each route before making a choice, or not pay for information and choose a route. Your decision sheet on the next page shows ten decisions listed on the left. Each decision is a choice between two possible routes you can choose, Freeway Route "Choice A" and Arterial Route "Choice B", or, pay for Information "Choice C" in which you pay to determine the actual delays on the route prior to your choice. Each route has two different levels of delay and different probabilities associated to each of the delays. In case you choose to purchase information, i.e. Choice C, the actual delays will be determined and provided to you before you make a final choice of route. This information comes at a cost.

As mentioned earlier, the choice of route depends on the travel time and the reliability of travel time. The travel delay costs you money. Your value of time in this task is set to $1.00 a minute, i.e. for each minute of delay you lose $1.00 from your wage. Your wage for each commute (i.e. decision row) is $10. Each row represents a separate route choice decision that you need to make while commuting to work. You will make a choice on each row and record these in the final column. The cost of information is provided in the fourth column.

Here is a ten sided die that will be used to determine delays. The delays and probabilities of delays on each route are similar to earlier parts. Except that in this scenario apart from choosing the routes, you also have a choice to purchase information regarding the delays on the routes.

There can be a maximum of three dice rolls. The first die roll will select one out of the ten decisions.

If you choose Choice A or Choice B the second role of the die will determine the delay on the route you chose.

If you choose Choice C for information, the delay on Freeway Route "Choice A" will be determined by a die roll, and the delay on Arterial route "Choice B" will be determined by a separate independent die roll. After the delays are determined you make the choice of the route. This is analogous to technology that measures delays in real time and transmits it to the user.

Your final monetary payoff will depend on the delay '***D***' determined by the die roll. It is calculated as:

$10-Information Cost-D

The price of information in this task is $2.00.

Even though you will make ten decisions, only one of these will end up affecting your earnings, but you will not know in advance which decision will be used.

All the delays and payoffs for your choices in this scenario will be determined at the end of the session.

ID:

Please select a choice (Freeway, Arterial or Information) for each decision

Decision	**Freeway Route Choice A**	**Arterial Route Choice B**	**Information Choice C**	**Your Choice (Circle one)**
1	**5.00** min delay if throw of die is 1 **6.00** min delay if throw of die is 2-10	**0.00** min delay if throw of die is 1 **9.75** min delay if throw of die is 2-10	$2.00	A B C
2	**5.00** min delay if throw of die is 1-2 **6.00** min delay if throw of die is 3-10	**0.00** min delay if throw of die is 1-2 **9.75** min delay if throw of die is 3-10	$2.00	A B C
3	**5.00** min delay if throw of die is 1-3 **6.00** min delay if throw of die is 4-10	**0.00** min delay if throw of die is 1-3 **9.75** min delay if throw of die is 4-10	$2.00	A B C
4	**5.00** min delay if throw of die is 1-4 **6.00** min delay if throw of die is 5-10	**0.00** min delay if throw of die is 1-4 **9.75** min delay if throw of die is 5-10	$2.00	A B C
5	**5.00** min delay if throw of die is 1-5 **6.00** min delay if throw of die is 6-10	**0.00** min delay if throw of die is 1-5 **9.75** min delay if throw of die is 6-10	$2.00	A B C
6	**5.00** min delay if throw of die is 1-6 **6.00** min delay if throw of die is 7-10	**0.00** min delay if throw of die is 1-6 **9.75** min delay if throw of die is 7-10	$2.00	A B C
7	**5.00** min delay if throw of die is 1-7 **6.00** min delay if throw of die is 8-10	**0.00** min delay if throw of die is 1-7 **9.75** min delay if throw of die is 8-10	$2.00	A B C
8	**5.00** min delay if throw of die is 1-8 **6.00** min delay if throw of die is 9-10	**0.00** min delay if throw of die is 1-8 **9.75** min delay if throw of die is 9-10	$2.00	A B C
9	**5.00** min delay if throw of die is 1-9 **6.00** min delay if throw of die is 10	**0.00** min delay if throw of die is 1-9 **9.75** min delay if throw of die is 10	$2.00	A B C
10	**5.00** min delay if throw of die is 1-10	**0.00** min delay if throw of die is 1-10	$2.00	A B C

DECISION ROW CHOSEN BY FIRST THROW OF THE DIE: _________

IF CHOICE A or CHOICE B, THROW OF THE DIE TO DETERMINE DELAY: ____________

IF CHOICE C, THROW OF THE DIE TO DETERMINE DELAY:

Select FREEWAY DELAY _________ ARTERIAL DELAY ____________

EARNINGS: ________________

ID:

PART 4 INSTRUCTIONS

This task is exactly the same as Part 3, except that the price for information is $4.00.

Similar to the earlier task, even though you will make ten decisions, only one of these will end up affecting your earnings, and you will not know in advance which decision will be used. All the delays and payoffs for your choices in this scenario will be determined at the end of the session.

ID:

Please select a choice (Freeway, Arterial or Information) for each decision

Decision	Freeway Route Choice A	Arterial Route Choice B	Information Choice C	Your Choice (Circle one)
1	**5.00** min delay if throw of die is 1 **6.00** min delay if throw of die is 2-10	**0.00** min delay if throw of die is 1 **9.75** min delay if throw of die is 2-10	$4.00	A B C
2	**5.00** min delay if throw of die is 1-2 **6.00** min delay if throw of die is 3-10	**0.00** min delay if throw of die is 1-2 **9.75** min delay if throw of die is 3-10	$4.00	A B C
3	**5.00** min delay if throw of die is 1-3 **6.00** min delay if throw of die is 4-10	**0.00** min delay if throw of die is 1-3 **9.75** min delay if throw of die is 4-10	$4.00	A B C
4	**5.00** min delay if throw of die is 1-4 **6.00** min delay if throw of die is 5-10	**0.00** min delay if throw of die is 1-4 **9.75** min delay if throw of die is 5-10	$4.00	A B C
5	**5.00** min delay if throw of die is 1-5 **6.00** min delay if throw of die is 6-10	**0.00** min delay if throw of die is 1-5 **9.75** min delay if throw of die is 6-10	$4.00	A B C
6	**5.00** min delay if throw of die is 1-6 **6.00** min delay if throw of die is 7-10	**0.00** min delay if throw of die is 1-6 **9.75** min delay if throw of die is 7-10	$4.00	A B C
7	**5.00** min delay if throw of die is 1-7 **6.00** min delay if throw of die is 8-10	**0.00** min delay if throw of die is 1-7 **9.75** min delay if throw of die is 8-10	$4.00	A B C
8	**5.00** min delay if throw of die is 1-8 **6.00** min delay if throw of die is 9-10	**0.00** min delay if throw of die is 1-8 **9.75** min delay if throw of die is 9-10	$4.00	A B C
9	**5.00** min delay if throw of die is 1-9 **6.00** min delay if throw of die is 10	**0.00** min delay if throw of die is 1-9 **9.75** min delay if throw of die is 10	$4.00	A B C
10	**5.00** min delay if throw of die is 1-10	**0.00** min delay if throw of die is 1-10	$4.00	A B C

DECISION ROW CHOSEN BY FIRST THROW OF THE DIE: _________

IF CHOICE A or CHOICE B, THROW OF THE DIE TO DETERMINE DELAY: ____________

IF CHOICE C, THROW OF THE DIE TO DETERMINE DELAY:

Select FREEWAY DELAY _________ ARTERIAL DELAY ____________

EARNINGS: ________________

APPENDIX D: EXPERIMENT INSTRUCTIONS (CHAPTER 6)

PLEASE DO NOT WRITE ON THESE INSTRUCTIONS

Welcome to the research study.

Please wait for an assistant to get you started.

PLEASE DO NOT WRITE ON THESE INSTRUCTIONS

Welcome and thank you for coming along to this experiment. During this experiment you'll be asked to make decisions a series of three choice tasks. The tasks give you the opportunity to earn money. You will be asked to make these decisions with the objective of maximising your payoff across the three tasks. Your payoff will vary from $0 to as high as $35 and will depend on the decisions you make as well as the decisions made by the other participants. In addition to this payoff, you will receive $5 for your participation throughout the session. You will be paid in cash today at the end of the session. In these tasks you should make decisions that seem right to you. All of your decisions will remain anonymous.

Please read these instructions on the following pages. In case you have any questions or concerns, please raise your hand and the experimenter will come to answer them.

Please note that hereafter communication between the participants is strictly prohibited. If there is any communication with one another in any shape or form, the experiment will be cancelled and no participants will receive any payment.

The session will contain an individual choice task, 2 route choice games and a short questionnaire.

Initially, you will complete an individual choice task where you must select between 2 competing options across 10 varying scenarios. The instructions for this task will be provided to you on the following page.

Within the games, you will be asked to serve as motorists and choose a route to travel from your origin (start) to your destination (finish). The instructions for Game 2 will be presented after completion of Game 1. You will play Game 1 and 2 for 20 identical rounds each.

At the end of the session you will be paid for each task that you complete. The payoff for the individual choice task will be a single round randomly selected for each of the 10 scenarios. Similarly a random round will be selected from the 20 rounds in Game 1 and Game 2 respectively. The payoff units from the 2 games will be multiplied by $0.25 and added to the payoff received in the individual choice task.

PLEASE DO NOT WRITE ON THESE INSTRUCTIONS

Individual Choice Task

The computer screen in front of you presents a table containing 10 choice scenarios. Each choice scenario involves you deciding between 2 options, option A and option B.

The first row indicates that option A gives you a 10% chance of getting \$5 and 90% chance of getting \$4, and that option B gives you a 10% chance of getting \$9.75 and 90% chance of getting \$0.25. Your task is to click on the option you prefer (A or B) for each choice scenario. When you have completed all 10 scenarios choosing between option A and option B, click on "confirm" to register these choices. Your choices can be changed as many times as you wish until you click on the confirmation button.

The payoff for this part will be determined in the following way. The central computer will pick randomly for each participant, one scenario, among the ten scenarios presented to you. Then, depending on the particular scenario selected by the computer, the computer will make an additional drawing lot in determining a number between 1 and 10. This number will finally determine your payoff for the individual choice task.

Let's take an example. Assume that the computer picked randomly for you, choice scenario 3, where you chose option A. In this situation, option A gives you a 30% chance to get \$5 and a 70% chance to get \$4. If the computer randomly chooses a number between 1 and 10 by the computer which is either 1, 2 or 3, you will get \$5 and if the number is 4, 5, 6, 7, 8, 9 or 10, you will get \$4. If for choice scenario 3, you chose option B, you will gain \$9.75 if the number is between 1 and 3 and \$0.25 if the number is between 4 and 10.

The payoff for the individual choice task will be part of your final payoff, as explained before.

Please raise your hand if you are unclear with the instructions.

PLEASE DO NOT WRITE ON THESE INSTRUCTIONS

Please wait for further instructions.

Do NOT turn over the page until instructed to do so.

PLEASE DO NOT WRITE ON THESE INSTRUCTIONS

Game 1

Consider the traffic network presented in the figure below. Each driver is required to choose a route in order to travel from the starting point, denoted by *A*, to the final destination, denoted by *D*. There are three alternative routes and they are represented in the diagram as [*A–B–D*], [*A–C–D*] and [*A-C-B-D*]. The number of drivers selecting each road, in other words the volume of traffic on each road, is denoted by "x_n" where n refers to the relevant road.

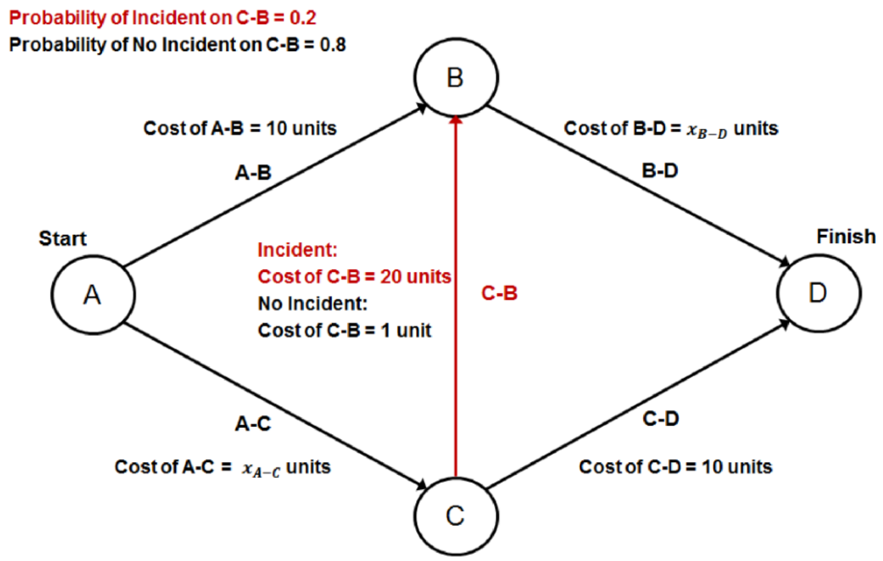


Figure 1 - Traffic Network of Game 1

Travel from an origin to a destination bares a cost for each individual, the cost of time, fuel and any tolls incurred along the route. In addition there are uncertainties when travelling, incidents may arise, weather may create difficulties in driving or there may be an excessive number of vehicles on the network due to peak travel conditions. These types of factors affect the state of the network and the travel costs for each road on the network.

In this particular network, the cost of traveling on each of the road segments (provided in "units") is written near the labels of the road segments. The costs of roads A-B and C-D are fixed at $10, while the cost of A-C and B-D are dependent on number of motorists travelling on the road segments, denoted by x_{A-C} and x_{B-D} respectively. The network describes a scenario where there is a **20% chance of an incident occurring on road segment C-B** which increases the fixed cost of road segment C-B from 1 unit to 20 units as the disruption increases travel time and fuel costs.

Your activity will be to select the route which you think would be the best to travel from node A to node D.

You will NOT know any information about the presence of an incident on C-B prior to making your route selection.

PLEASE DO NOT WRITE ON THESE INSTRUCTIONS

Procedure for Game 1

At the beginning of each round, the computer terminal in front of you will show you the network diagram, presented in Figure 1 on the previous page, containing the three possible routes described before; [*A–B–D*], [*A–C–D*] and [*A-C-B-D*]. The following steps are required to be carried out for each round.

1. You will be asked choose which of the routes you wish to travel on. To choose a route, click the roads related to the route. For an example if you choose route [A-B-D], click on road [A-B] and road [B-D]. Once you click on a specific road segment of a route, that segment will be highlighted in a red colour. If you make an error whilst clicking on a road segment you should either click an alternative road segment or click "Cancel" to restart the selection process. After you have connected origin A and destination D with a feasible route that you would choose to travel on, you will be asked to "Confirm" your route by pressing the "Confirm" pop-up button if you are satisfied with your selection.
2. After confirming your route choice, you will be presented with a message to wait until all other participants have made their decisions.
3. Upon the completion of the task by all participants the computer will present you with the following information;
    a. The traffic conditions of Link C-B: "No Incident on C-B" or "Incident on C-B"
    b. The route you have chosen and the payoff for the round
    c. The number of participants who chose route [*A-B-D*]
    d. The number of participants who chose route [*A-C-D*]
    e. The number of participants who chose route [*A-C-B-D*]
4. You will complete this activity for 20 rounds. At the completion of 20 rounds, the computer will inform you that Game 1 has been completed. A further message will be provided to "Please wait until the experiment continues"

All the decisions will only be made by clicking the "mouse" of the computer; there is no need to type anything whilst participating in the game.

You will receive **45 units** of income for each round. The payoff for each round will be determined by the following equation:

Payoff = (45 – Total Cost of travel) units

All 20 rounds will have the same structure.

At the end of both games (Game 1 and Game 2) you will receive payment for a randomly selected round from each of the games. You will receive **$0.25** for every unit of payoff earnt in the randomly selected rounds of each of the games.

PLEASE DO NOT WRITE ON THESE INSTRUCTIONS

Example of Travel Costs

Let's consider that in the first round you are the only one to choose route [A-C-B-D], 6 participants choose [A-B-D] and 5 participants choose [A-C-D]

- If road **C-B does NOT experience an incident**, the cost of using road A-C is 6 units (5 people using A-C-D and you are using A-C-B-D), the cost of using road C-B is 1 unit and the cost of using road B-D is 7 units (6 people using A-B-D and you are using A-C-B-D). Therefore your total cost will be (6+1+7) = **14 units** for that round. (Figure 2)
- If road **C-B experiences an incident**, the cost of using road A-C is 6 units, the cost of using road C-B is 20 units (fixed cost) and the cost of using road B-D is 7 units (6 people using A-B-D and you are using A-C-B-D). Therefore your total cost will be (6+20+7) = **33 units** for that round. (Figure 3)

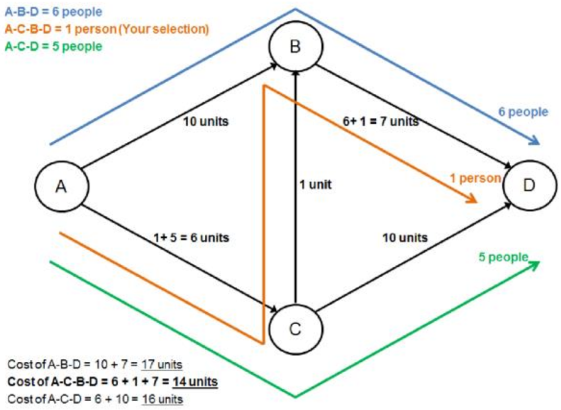


Figure 2 - Costs of Routes (No Incident on C-B), Round 1

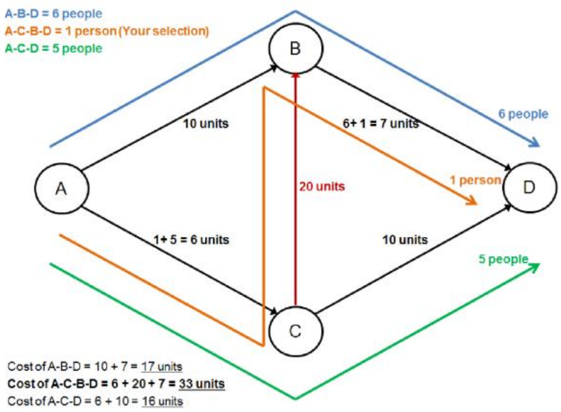


Figure 3 - Costs of Routes (Incident on C-B), Round 1

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Now let's consider that in a subsequent round (Round 2) of the game you and 2 other participants choose route [A-C-B-D], 4 participants choose [A-B-D] and 5 participants choose [A-C-D].

- If road **C-B does NOT experience an incident**, the cost of using road A-C is 8 units (3 people using A-C-B-D and 5 people using A-C-D), the cost of using road C-B is 1 unit and the cost of using road B-D is 7 units (3 people using A-C-B-D and 4 people using A-B-D). Therefore your total cost will be (8+1+7) = **16 units** for that round. (Figure 4)
- If road **C-B experiences an incident**, the cost of using road A-C is 8 units, the cost of using road C-B is 20 (fixed cost) and the cost of using road B-D is 7 units. Therefore your total cost will be (8 + 20 + 7) = **35 units** for that round. (Figure 5)

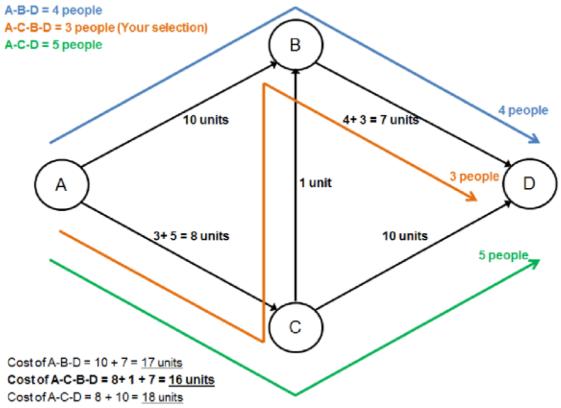

Figure 4 - Costs of Routes (No Incident on C-B), Round 2

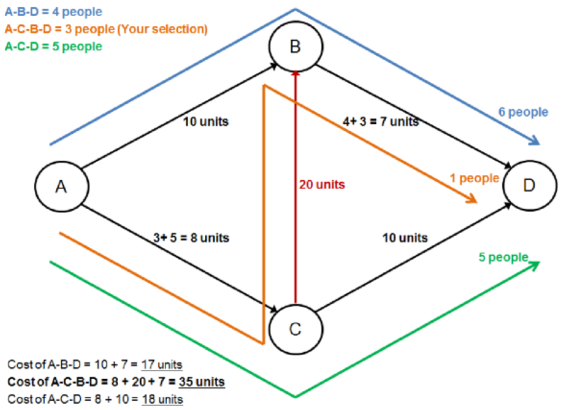

Figure 5- Costs of Routes (Incident on C-B), Round 2

As you can see the cost of travel is dependent on the **presence of the incident on C-B and the number of people selecting the path which you have selected which are both based on chance**.

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Please raise your hand to indicate that you have completed reading these instructions and understood the rules of the game.

Game 1 will begin shortly.

Do NOT turn over the page until instructed to do so.

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Game 2

Similar to Game 1, consider the traffic network presented in the figure below. Each driver is required to choose a route in order to travel from the starting point, denoted by *A*, to the final destination, denoted by *D*. Like before, there are three alternative routes and they are represented in the diagram as: [*A–B–D*], [*A–C–D*] and [*A-C-B-D*]. However the difference with Game 2 is that at node C you will be provided information about the state of Road C-B, analogous to a Variable Message Sign indicating the traffic conditions of the route ahead.

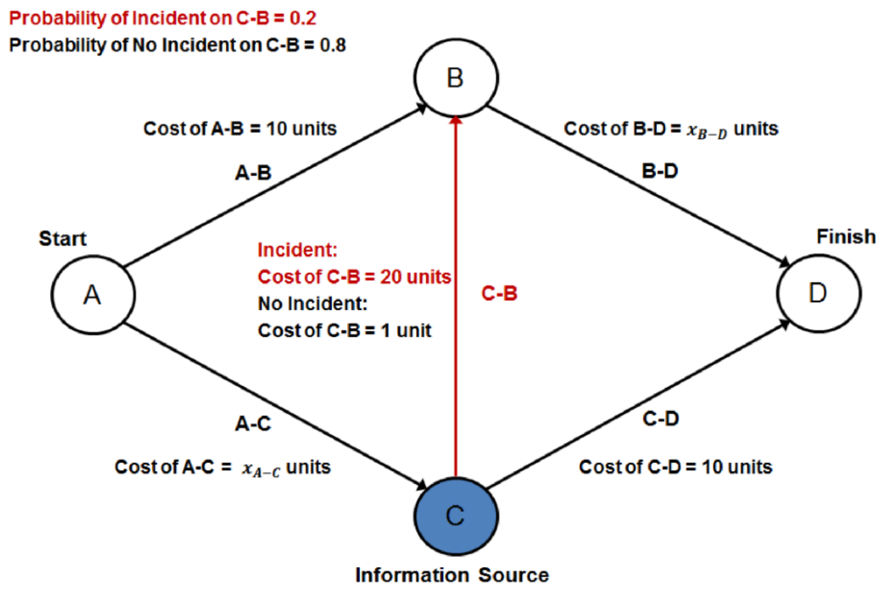

Figure 6 - Traffic Network of Game 2

The travel costs, the likelihood of an incident being present on C-B **(An incident may eventuate 20% of the time)** are identical to what was observed in Game 1. The only difference is that the presence of an incident will be revealed to you at node C if you initially choose road A-C. As with Game 1, please note that the cost charged on roads A-C and B-D of the network depend on the number of motorists choosing them.

Your activity will be to select the route which you think would be the best to travel from node A to node D.

If you travel to node C you will be provided information about the presence of an incident on C-B prior to making your route selection.

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Procedure

At the beginning of each round, the computer terminal in front of you will show you the above network diagram containing the three possible routes described before; [*A–B–D*], [*A–C–D*] and [*A-C-B-D*]. The following steps are then carried out for each round

1. You will be asked to choose which of the routes you wish to travel on a road segment by road segment basis.
    a. Initially you will be asked to select between road A-B and road A-C. Once you select either option you will be asked to confirm by pressing the "Confirm" pop-up button.
    b. If you select A-B, your route is already set as there are no further choices to be made when travelling from A-D and you will be required to select B-D to complete using route [A-B-D].
    c. **If you select A-C, you will be travelling through node C where information will be provided about the state of road C-B. After being provided this information you will be asked to select between road C-B and road C-D. Once you select either option you will be asked to confirm by pressing the "Confirm" pop-up button if you are satisfied with your selection.**
    d. After receiving the information you can select the remainder of the route to reach your destination point, D.
2. After choosing a route, you will be presented with a message to wait until all other participants have made their decisions.
3. Upon the completion of the task by all participants the computer will present you with the following information;
    a. The traffic conditions of Link C-B, "No Incident on C-B" or "Incident on C-B"
    b. The route you have chosen and the payoff for the round
    c. The number of participants who chose route [*A-B-D*]
    d. The number of participants who chose route [*A-C-D*]
    e. The number of participants who chose route [*A-C-B-D*]
4. You will complete this activity for 20 rounds. At the completion of 20 rounds, the computer will inform you that Game 2 has been completed. A further message will be provided to "Please wait until the experiment continues"

All the decisions will only be made by clicking the "mouse" of the computer; there is no need to type anything whilst participating in the game.

You will receive **45 units** of income for each round. The payoff for each round will be determined by the following equation:

Payoff = (45 – Total Cost of travel) units

All 20 rounds will have the same structure.

At the end of both games (Game 1 and Game 2) you will receive payment for a randomly selected round from each of the games. You will receive **$0.25** for every unit of payoff earnt in the randomly selected rounds of each of the games.

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Please raise your hand to indicate that you have completed reading these instructions and understood the rules of the game.

Game 2 will begin shortly.

Do NOT turn over the page until instructed to do so.

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Thank you for completing the tasks of the experiment.

The payment calculation will commence with the central computer selecting a single random scenario from the individual choice task and a random round out of the completed 20 rounds from each game and determining your total payoff. Your final payment will be calculated as follows:

Final Payment= Attendance Fee + Individual Choice Task Payoff + $0.25*Game 1 Payoff+ $0.25*Game 2 Payoff

Your final task is to complete a short questionnaire which will be displayed on your screen shortly following this you will be paid for your participation.

You will be paid in cash for your participation within this research study.

Thank you very much for your participation today.