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Modelling driver experience and its role in influencing diversion behaviour

by

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ABSTRACT

MODELLING DRIVER EXPERIENCE AND ITS ROLE IN INFLUENCING DIVERSION BEHAVIOUR

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Traffic assignment, the process by which vehicle flows are loaded on to paths traversing a road network for the purpose of spatial demand forecasting, has been traditionally approached as a mathematical optimisation problem. However, this assumes typical highway network conditions, yielding 'average day' traffic forecasts only. Such approaches fail to account for time-dependent variability caused by infrequent events such as traffic accidents, vehicle breakdowns or road works which result in sub-optimal network performance. On any day, especially when incidents cause abnormal congestion patterns, drivers can only choose routes and diversion strategies according to the best of their own subjective knowledge and experience which is unique to each traveller. Ensuring that *knowledge*, both within-day and between days, is represented adequately and with realistic assumptions within models is key to forecasting traffic flows in all situations and their resulting network phenomena accurately.

This thesis explores how drivers react under these irregular conditions, termed 'states', with a goal of understanding route choice and consequently advancing demand forecasting techniques. To this end, a simulator based survey is used in order to gain further knowledge of driver learning and diversion behaviour, then an agent based simulation modelling approach is developed using this insight to explore the network and traffic flow effects of drivers reacting to uncertain network conditions by altering their route choices. This work argues that representing driver knowledge and choices from a disaggregate agent based perspective, rather than a traditional aggregate approach, is more appropriate for modelling the impact of variable travel conditions.

Results demonstrate that the possibility of incidents occurring and the potential for diverting can have a significant effect on network characteristics and the decisions of drivers, even on incident-free 'clear' days. Importantly, results show that drivers diverting can temporarily alleviate congestion but ultimately cause more delays and suboptimal network performance. These results have significant implications for demand forecasting practitioners and policy makers who try to minimise disruption through traffic management systems or effective network design.

Contents

List of Figures

List of Tables

Declaration of Authorship

I, James R. Snowdon , declare that the thesis entitled *Modelling driver experience and its role in influencing diversion behaviour* and the work presented in the thesis are both my own, and have been generated by me as the result of my own original research. I confirm that:

- this work was done wholly or mainly while in candidature for a research degree at this University;
- where any part of this thesis has previously been submitted for a degree or any other qualification at this University or any other institution, this has been clearly stated;
- where I have consulted the published work of others, this is always clearly attributed;
- where I have quoted from the work of others, the source is always given. With the exception of such quotations, this thesis is entirely my own work;
- I have acknowledged all main sources of help;
- where the thesis is based on work done by myself jointly with others, I have made clear exactly what was done by others and what I have contributed myself;
- parts of this work have been published as: (Snowdon et al., 2012a), (Snowdon et al., 2012b), (Snowdon, 2013) and (Snowdon and Waterson, 2013)

Signed:...

Date:..

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Chapter 1

Introduction

To begin by setting out the context of this research, the work contained within this thesis is carried out with the Transportation Research Group and with the Institute of Complex Systems Simulation (ICSS) within the University of Southampton, UK. The goal of the institute is to try to better understand and explain the observable trends in a variety of systems characteristics as the result of the interactions between its component parts. Transportation is among the many systems encompassed by this interdisciplinary field including finance, climate and human or animal social systems.

1.1 The importance of understanding travel systems

Travel has become an integral part of our daily lives as commuters travel to and from places of work and centres of education, families and individuals visit places of leisure and retail centres, and nations rely upon international trade and the efficient transportation of goods and services from one location to another. It has been estimated that in 2012 the average person made 954 trips per year (Department for Transport, 2013a). The work presented in this thesis concerns itself with exploring elements of road based travel, which the UK's Department for Transport estimates in 2013 amounted to 303.7 billion vehicle miles driven (Department for Transport, 2014) and accounts for 64% of all trips made (Department for Transport, 2013a).

A road network is utilised by a variety of users with different behaviours, experience, attitudes and goals for undertaking travel. As figure 1.1 shows, presently and historically many road journeys in the UK are made within private cars which must compete for available road space along with other public transport, freight and service vehicles (Department for Transport, 2012b). Competition for road space may be set to increase. The RAC Foundation in 2007 predicted that by 2041 the number of miles driven by private cars will grow by 37% from 2007 levels (Banks and Glaister, 2007, p. 8) and the

Department for Transport more recently predicted that by 2035 road traffic is set to be 44% higher than 2010 levels (Department for Transport, 2012a, p. 5).

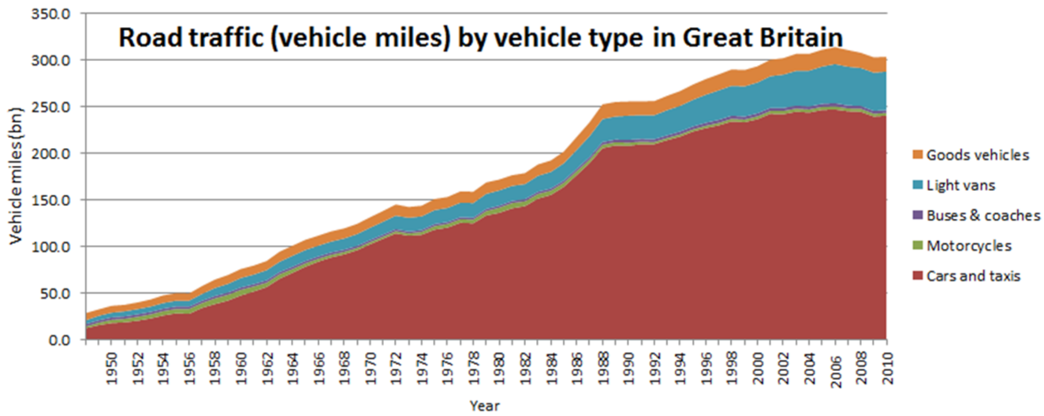


Figure 1.1: Road traffic vehicle type breakdown in Great Britain (Department for Transport, 2012b)

The UK has similar levels of vehicle usage (and congestion) compared with its European neighbours (Banks and Glaister, 2007; TomTom, 2013) and it exhibits a similar percentage of passenger transport by car to countries such as the USA, Germany and Sweden (Department for Transport, 2010). Although this work is based upon general trends and behavioural assumptions, caution must be taken when understanding and generalising the motivations and goals of road users in different nations and cultures around the globe. What motivates travel decisions in a population in one area may not be as important in another.

This thesis concerns itself with understanding congestion causing traffic phenomena and as a result improving our abilities to describe and forecast their impact on highway network experiences. Ortúzar and Willumsen (2001) state that an understanding of traffic phenomena is important for two primary reasons: i) in order to effectively manage the day to day operations of the road transport system, including managing traffic control systems or response to incidents, and ii) to enable strategic planning regarding the future of the road network, which may involve forecasting traffic flows on highways in potential scenarios such as population growth or road network change. These goals, which can be be categorised as short and long term respectively, are not separate in nature - one might expect the long term traveller actions and behaviours to be influenced by successive short term management strategies.

It is important to understand these phenomena because on occasions when performance of the road system, termed the 'supply', falls it can have a negative impact on the economy and environment as well as personal driver experience. Empirical studies have found that this occurs relatively often, as in March 2013 the UK's Department for Transport reported that only 77.1% of journeys managed by the Highways Agency were 'on time', a fall of 7% on the previous year (Department for Transport, 2013b). A study carried out in 2006 claimed that a 5% reduction in travel time for all business and freight travel could generate £2.5 billion of cost savings, which is 0.2% of the UK's GDP, and that if left unchecked the cost of congestion will waste an extra £22bn by 2025 (Eddington, 2006). In The Netherlands it has been found that in 2009 a total of 62 million hours was lost due to sub optimal traffic conditions (8.6% of the total travel time spent on the main road network) (DVS, 2010) and navigations systems developer TomTom recently reported that on average 27% of time spent driving in London is lost in congestion (rising to 55% during the evening peak rush hour) (TomTom, 2013).

In order to mitigate the negative impacts of these road system shortcomings, it is necessary to understand both the factors which cause them to arise and what can be done to reduce their negative effects. The causes of lapses in network performance vary, in the UK the National Audit Office reported that in 2004 approximately 65% of delays experienced by drivers can be attributed to volume of traffic, 25% is accounted for by accidents and incidents and 10% is the presence of road works (National Audit Office, 2004) yet in the USA non volume of traffic related causes have been estimated to account for a total of 60% of congestion (FHWA, 2005) (although the networks are perhaps not comparable due to their size differences). It is important to consider the causes of travel time variability and the impact that they have on system performance when conducting appraisals of the operational abilities of a highway network, rather than only considering the network under 'average conditions' (Hyder Consulting, 2010, p. 110).

As well as the specific cause of delays, such as road blockage or inclement weather, the magnitude of their impact is affected by how drivers respond. Understanding traveller behaviour and what motivates people to make their travel decisions is important in understanding what causes all observed phenomena, not just during incidents and delays. Frejinger (2008) supplies some key general questions relating to travel and aspects of people's travel behaviour which we should attempt to understand. These include 'why do people travel?' and 'where do they go?', 'when is the trip made?' and 'which route was taken?'. The work contained within this thesis focusses on furthering insight regarding the final question - 'which route was taken?', in particular focussing on how variability in travel conditions affects this decision, whether the variability is expected or not, and how aspects of variability itself can be a result of a population's own decisions. The aim of this work is to complement this understanding of travel behaviour by investigating how drivers respond to changing travel environments over time and how their unique experiences both between days and within days causes them to change and adapt their behaviour.

Through understanding traveller learning and reaction to unexpected conditions, transport managers may wish to either plan for or react to its effects. For example by considering the routes which are likely to become popular diversions under incidents and events around the network, such as avoiding a major sporting venue or event arena, additional capacity or traffic management measures such as variable signage can be put in place appropriately by transport planners. Alternatively should an incident arise within a transport network, such as a vehicle breakdown or traffic accident, traffic controllers can provide variable signage, diversion measures and focus resources to best manage the situation.

This thesis asks whether the current level of understanding and in particular forecasting methods of traveller behaviour are sufficient to deal with these issues or, particularly with advances in computational technology and concepts developed within other fields such as social systems modelling, can traveller behaviour be better forecast using other approaches?

1.2 Transportation demand forecasting

Transportation demand forecasting involves predicting the numbers of vehicles traversing roads within a transportation network at some time under a specific scenario such as population growth, residential or commercial development, traffic management schemes and new infrastructure creation, modification or removal. It can also be used to 'stress test' a transport network, forecasting traffic flows under unexpected incidents or events. Useful outputs from transportation demand forecasting, in addition to expectations of accessibility across a region, can be the identification of capacity limiting bottlenecks and areas of extreme congestion which require further investment to manage effectively.

The 'four stage' modelling process, sometimes abbreviated to FSM and originally proposed by Mitchell and Rapkin (1954), has become the standard conceptual framework used to model demand in transportation systems and generate forecasts of flow distribution. It is used in many large scale studies and has become the core component of the wider 'transportation systems analysis' methodology (McNally, 2000). The four stage model deals with demand for all modes of transport based on single trips which are defined as a single unidirectional journey between trip ends. The trip ends are known as the origin and destination respectively, a convention which will be used throughout this work.

An overview of the four stage model is provided by Ortúzar and Willumsen (2001). To summarise, aided by the diagram in figure 1.2, the approach begins with dividing the study region into zones, such as residential areas and retail parks, and subnetworks such as public transport links and road infrastructure. Base-year levels of population are collected for different socioeconomic groups and also levels of economic activity for each zone such as employment, shopping space, educational and recreational activities. This data is used to estimate the total number of trips generated and attracted by each zone of the study area (trip generation). The next step deals with the allocation of these forecast trips from origins to particular destinations, or their distribution over space, providing an origin-destination (OD) matrix. The following stage usually involves the choice of mode for each journey, such as private car, bus or train, which results in the modal split. Finally the last stage in the model requires the assignment of trips by each mode to their corresponding routes and networks. The assignment stage assigns expected numbers of trips to specific routes traversing the road network.

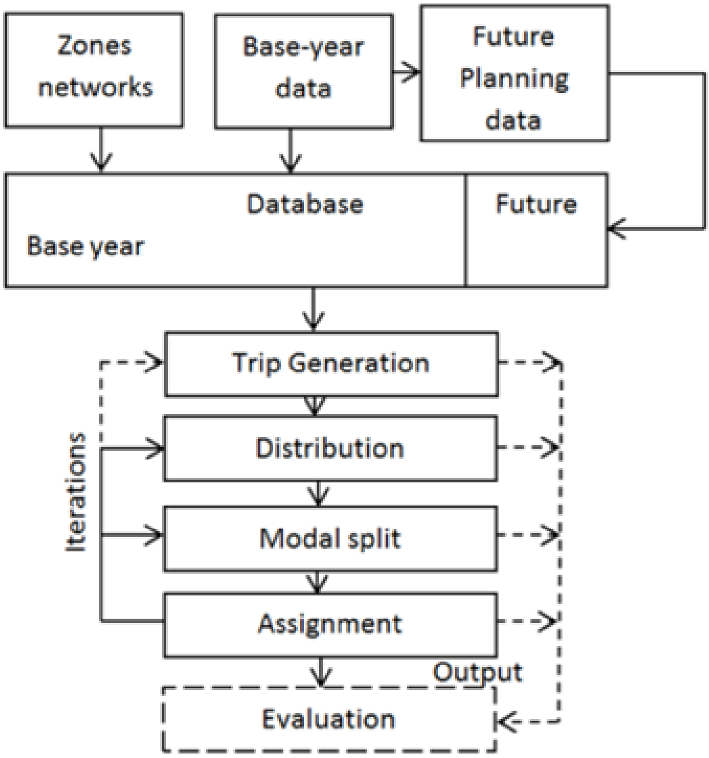


Figure 1.2: The 'four stage' transportation demand forecasting model (Ortúzar and Willumsen, 2001)

By altering system characteristics at one level of the four stage model, travellers may respond by changing their behaviour at another. For example the decision to pedestrianise an urban centre (so altering the network used in the assignment stage) may make roads congested and prompt some travellers to decide to use public transport rather than their private car. For example, a recent bridge collapse in central Minneapolis was expected to increase public transport usage, particularly rail, and decrease private car usage for the period when the road network was altered (although this failed to materialise, perhaps because local residents greatly prefer travel by private car, showing the importance of local calibration of behavioural parameters) (Zhu et al., 2010). Learning effects are accounted for within the four stage model to some degree as feedback mechanisms and iterative processing allow for splits at each level to change based on altered travel environments caused by decisions made at another level.

Despite the prevalence of the four stage methodology, the approach can be criticised (McNally, 2000). These criticisms are usually levelled at the assumed simplifications of human behaviour and the generalisation of population knowledge and decision making abilities which receive attention in this work. However the four stage model itself is a framework rather than a fixed algorithm, and research and techniques are developed within each of the stages, which makes it flexible. Proponents of the alternative 'activity based' approaches towards modelling travel demand behaviour argue that the impact of drivers chaining trips together and altering daily activity patterns can have an important measurable impact which the single trip based four stage approach cannot accommodate (for descriptions see Charypar and Nagel, 2005; Ronald et al., 2010). Since the work in this thesis only concerns itself with the route choice process in the assignment stage of the four stage model, the research and assertions could simply be adapted for use within an alternative methodology.

1.3 Evaluating the competency of demand forecasting

The ability to predict demand levels across a transport network accurately is an important problem and one in which decision makers invest much time and capital. This section aims to examine the predictive accuracy of current techniques in use. Regarding sources of information feeding this critique, Nunez (2007) comments that, perhaps understandably, generally the distribution of errors stated by transport forecasters in industry has a smaller magnitude and smaller variance than those found in academic literature, suggesting that a variety of sources should be consulted in order to reliably evaluate the competency of demand forecasts. Additionally, toll road usage forecasts and statistics appear to be better monitored documented internationally than other schemes, so many evaluated forecasts tend to be regarding toll roads. It is important to remember however that the users and properties of toll roads may not be representative of those using the network as a whole.

In a major review, Flyvberg, Holm and Buhl (2006) compiled details of 210 road and rail infrastructure projects in 14 nations worth a total of (US)$58 billion. The team found that, despite significant financial investment, the predictive ability of the forecasting was lacking when compared against newer demand counts. For 50% of road projects, the difference between actual and forecast long term traffic flows was found to be more than ±20% and for 25% of road projects that difference was larger than ±40%. In transport modelling qualitative trend expectations can be useful, such as in highlighting areas of expected congestion, even if exact results fail to occur.

The accuracy and legitimacy of demand forecasting is not just compromised by predictions which turn out to be inaccurate. Bain (2009) provides figure 1.3 which shows four base case forecasts for a 'well known toll road' which are provided by four 'internationally recognised traffic consultants within months of each other'. As the data was released confidentially, Bain has omitted the vertical axis scale (although it is understood to be linear) but the trend can be seen that over 15 years of operation the difference between highest and lowest predicted traffic flow diverges significantly and the forecast lines do not follow similar trends. Bain does not provide a reason for these differing forecasts, such as whether behavioural assumptions vary in each case (such as population growth) or whether one consultant has access to different sets of data to another (if at all - some values could be assumptions or data from elsewhere), but this example shows that forecasting future behaviour is prone to error and inaccuracies.

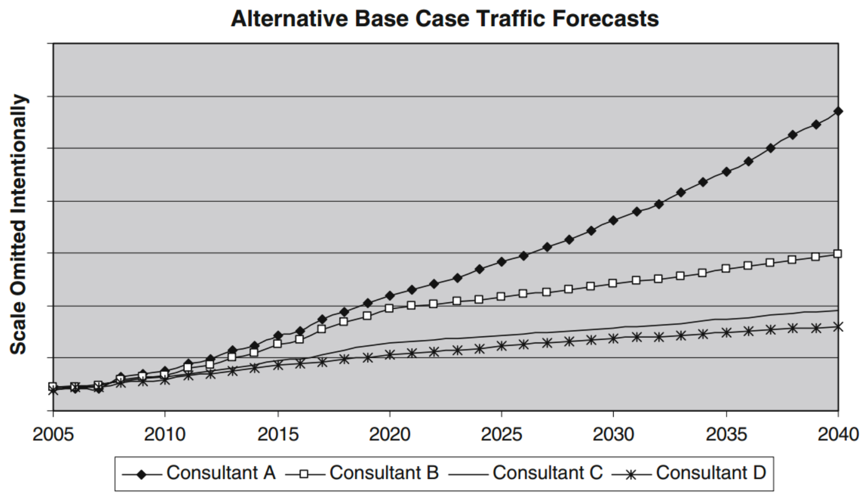


Figure 1.3: Same toll road, different traffic forecasts (Bain, 2009)

It should be admitted that many important problems with the application of transportation demand forecasting techniques are practical rather than methodological, which are not examined in this thesis. For example in the study conducted by Flyvberg, Holm and Buhl (2006) the team suggest, based on interviews with practitioners, that most often a lack of (or incomplete) data regarding local population and inaccurate assumptions regarding land usage is to blame for most forecasting deficiencies. Nunez (2007) considers why predictions of toll road demand differ from actual usage from the perspective of forecasters, project promoters and users separately. He comments that particularly those involved in developing projects are under considerable pressure to positively exaggerate their forecasts. Other studies have also reported that optimism bias appears to be common in traffic flow forecasts by those supporting new schemes (Bain, 2009), for example Flyvberg (2005) reports that Bangkok's $2 billion Skytrain saw passenger forecasts of 2.5 times higher than actual usage which was attributed to optimism bias.

Aside from political and practical reasons regarding why the application of demand forecasting produces such variable results, such as incomplete data, such as optimism or lack of usable data, it remains an interesting and potentially fruitful research question to ask whether methodological change would improve the predictive accuracy of current methodologies. Expanding models to use new techniques can yield more information and insight, and potentially apply in more general settings.

1.3.1 Forecasting behavioural change

Demand forecasts, typically provided as an 'average day' demand for a set of future years under consideration, as seen in figure 1.3, often fail to capture or represent the complex process by which travellers change their habits in the short term over days, weeks or months following system change. Instead they assume that by the first forecast year demand would have settled to a long term steady state without significant variation between typical days.

Flyvberg (2005) describes how disruptive incidents, which can sometimes be found during the first months of an infrastructure alteration, can have a severe negative impact on demand for projects, suggesting that it is therefore common for one year traffic flows to be unrepresentative of long term stability. He cites the example of the Channel Tunnel project which experienced many operational problems within its first year of operations, resulting in lower than expected usage.

Flyvberg comments that it takes time for travellers to effectively discover and make use of new transportation facilities and change their behaviour, even when problems do not arise. Incorporation of an error bar or some form of 'worst case' analysis would go some way towards remedying this issue. Figure 1.4 shows the observed monthly variation in traffic flows following the opening of the M6 toll motorway in the UK (the authors comment that all of which fall short of forecasts) clearly showing how the regular adoption of the new road by travellers is not at all instant and varies considerably over months (ATKINS, 2009). The figure also shows that even when traffic flows are at approximately stable levels there is considerable variation between months. Cairns, Klau and Godwin (1998), also report finding considerable variation in traffic flows in the immediate aftermath of infrastructure change which were not adequately forecast.

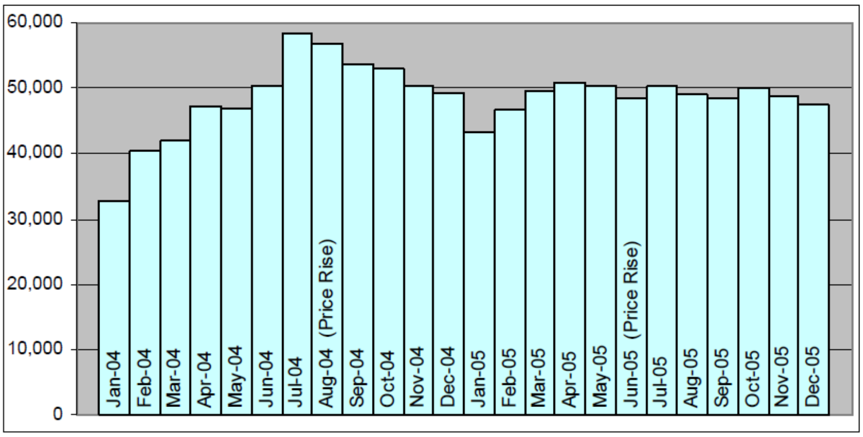


Figure 1.4: Monthly variation in daily total numbers of weekday users of the new M6 toll motorway in the UK (ATKINS, 2009)

A report by the Australian Department of Infrastructure and Transport (2011), focussing on use of toll roads, highlights this regular poor predictive performance in the timespan immediately following toll roads opening, known as the 'ramp up' period, commenting that the shape and duration of the ramp up has been and will remain a challenge for modellers who, when they do comment on it, typically assume fixed properties for each project rather than any modelling output which is specific to the local network. Improving the forecasting of ramp up operations is described as an 'acute' issue in a report by Kriger, Shiu and Naylor (2006) who describe the ramp up period as reflecting the road users' unfamiliarity with the new highway and its benefits (termed the 'information lag'). They describe ramp up forecasts as consisting of three primary dimensions: i) scale of ramp up (the magnitude of difference between current and forecasted traffic) ii) duration of ramp up (from opening day) and iii) the extent of 'catch up' (regarding how much later year traffic flows would need adjusting if early year forecasts were lacking). Both Kriger, Shiu and Naylor (2006) and Meite (2011) find that ramp up periods are regularly ignored during applications of the four stage model.

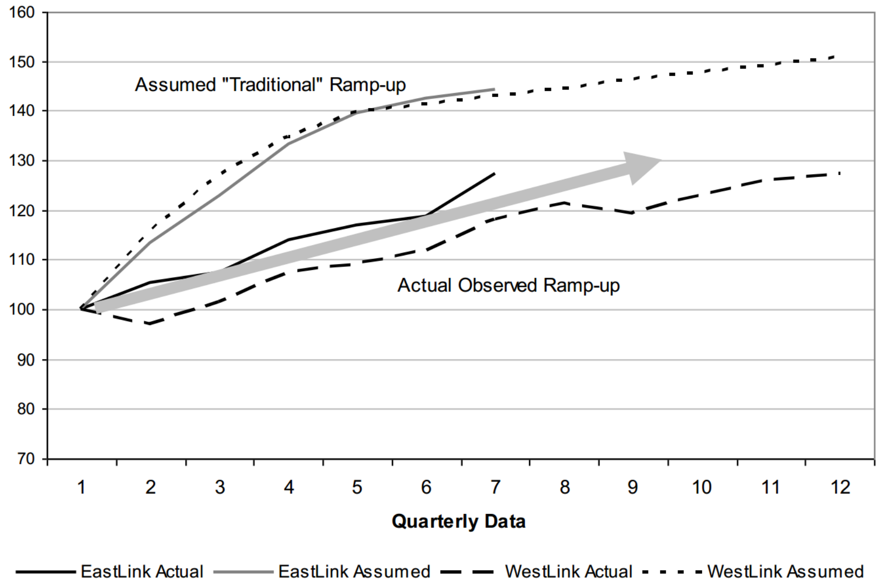


Figure 1.5: 'Traditional' and observed ramp up profiles for new toll road openings (D'Este, 2010)

D'Este (2010) provides the observed flow profiles in figure 1.5 which show forecast 'traditional' and actual behaviour in toll road uptake. D'Este describes forecasting the ramp up period as being determined by 'little science' and instead is based on previous observations which can lead to major differences between forecast and actual ramp up flow profiles, as is shown in figure 1.5. While assuming standard ramp up profiles may be sufficient for some projects, as is currently practised (Kriger et al., 2006), the shape and time span of the ramp up period may indeed vary considerably from project to project.

Sometimes expected special events and their influence on traffic flows can be forecast in the short term (such as Chrobok et al., 2004, who examine overall demand drops due to special events such as football matches). Examples include the detailed traffic forecasts were created for the 2010 Winter Olympic Games (Joshi et al., 2009) and for the

2013 Summer Olympics, held in London UK, which featured models of expected vehicle movements with a focus on Intelligent Transportation Systems planning (Kearns, 2012; Whitaker, 2012). During the London Olympic Games traffic volumes were consistently lower than forecast (Transport for London, 2012) which was attributed primarily to local commuters changing their work habits, so at the trip generation stage of the Four Stage Model. Elsewhere models may be used to forecast the impact of short term road closures or works. However using assumptions usually reserved for forecasting 'steady state' traffic profiles is questionable under infrequent events as drivers do not possess adequate road system knowledge in the short term case (such as the existence of routes) that they would be assumed to have accumulated in the long term case. The suitability of applying techniques to modelling events such as this are under direct consideration in this thesis.

The inability of traffic forecasters to predict properties of the 'ramp up' effect and special events are symptomatic of a wider problem in transport demand forecasting which is the inability for mainstream techniques and practices to capture the important role of the dimension of time. The problems presented above can be summarised as stemming from a viewpoint of the world as a 'static' snapshot at some point in the future and on an 'average' network day. When required to include aspects of variation with time, such as the 'ramp up' situation, it has been shown that ad hoc approaches are most often used instead.

Mahmassani (1990) outlines three principal dimensions of interest related to dynamic (time varying) analysis of driver decisions and associated flow patterns in urban networks - 1) time-dependent flow patterns within a given day, such as build up and dissipation of queues, 2) day-to-day dynamics of decisions, such as how travellers plan their routes, departure times and activity schedules on each successive day and 3) real-time dynamics, such as driver response to information obtained en-route such as diverting.

Expanding further on Mahmassani's second and third points, which are closely coupled with the issue of failing to forecast driver decisions varying with time, is failing to forecast the impact of *driver knowledge* varying. By forecasting on a static 'average day' after the ramp up period has occurred all drivers are, conveniently for the use of modelling under the four stage paradigm, assumed to have knowledge of their available travel options and are able to choose from among them. This is clearly an oversimplification. As Mahmassani points out, knowledge can vary in a variety of situations which are common for a transport network even beyond ramp up periods and special events, such as networks which regularly have large numbers of non-local travellers such as ports, holiday destinations, major cities or even major interurban motorways. Such a situation may exhibit what appears to be an 'average day' but within that participant knowledge of choice options may not be complete. Indeed, a driver's own subjective knowledge may never be 'complete' due to the inability to observe the entire system at one time.

It is not known whether the described lack of representation of temporal aspects of traffic systems, such as ramp up periods and drivers changing habits, is necessarily a *problem* for traffic forecasts, causing predictions to be even more inaccurate, or whether it is simply an aspect of traffic forecasting which can be further probed and insight obtained. The 'average day' assumption is a major limitation of the four stage modelling approach, especially under infrequent events such as inclement weather or strike action (NATS, 2010).

1.3.2 Summary of approaches towards modelling knowledge acquisition over time

Transport forecasts appear to have developed towards the 'snapshot' view of the world for two primary reasons - firstly as a result of their stemming from mathematical solutions to systems optimisation problems, in which time (and knowledge) is an extra dimension to an already complex problem, and secondly because often observations of real world transport systems are themselves 'snapshots' of a day's traffic flows rather than detailed studies of an individual's decisions over time. Work is being undertaken to develop techniques which are capable of including the time dimension in transport forecasts, and this thesis aims to contribute to the development of this field.

Most commonly, forecasts of any system which involve time varying properties require computer based computation or simulation to manage the increased number of calculations and volumes of data. In the context of transport, time varying models can also be challenging to calibrate as one needs knowledge of both the changing decisions and environment in which drivers are making decisions. Mahmassani and Jou (2000) use participants creating 'travel diaries' in order to calibrate a time varying route choice model, recording reported travel and departure times. Other studies have studied this behaviour using interactive computer based surveys (such as Selten et al., 2007; Ben-Elia et al., 2008).

'Day to day' assignment models, as summarised by Bie and Lo (2010) and the team of Smith, Hazelton, Lo, Cantarella and Watling (2013), are potentially capable of capturing ramp up behaviour by explicitly considering time as a series of discrete days over which behaviour change occurs. Traffic flows on routes on each day are a function of flows (and correspondingly travel times) on the preceding day(s), so evolving over time as new network properties are modelled as being 'learned'. Examples of the practical application of these models to explicitly forecasting the ramp up period are limited but a calibrated example is provided by He and Liu (2012) who develop a 'prediction-correction' method of representing drivers updating network beliefs as well as route choices each day. Recent research efforts have focussed on better representing psychological aspects of driver behaviour such as incorporating prospect theory (Zhang and Juan, 2013).

However such day to day approaches may still not provide sufficient detail in knowledge variation among a population to meet the challenges described here, especially in being able to forecast resultant flows under varying network conditions *within* days where each driver has a unique experience during each day. By assuming that the current knowledge level is ‘common’ to all drivers, day to day approaches capture learning at the population level rather than at the individual level. Disaggregate day to day models, or ‘agent based’ approaches, as used by Nagel and Flötteröd (2011) among others, are potentially capable of overcoming this limitation by assuming that each driver in the system has their own impression of system characteristics which is learned over time.

In order to claim that it is essential to include time varying aspects of the road traffic system, it would be necessary to show that ‘average day’ demand is still sensitive to time varying aspects which are currently not being considered by most applications of the four stage model for forecasting purposes. This may include drivers being sensitive to regular severe travel time variations on some routes, whether some routes are often prone to events (such as sporting matches) or traffic accidents, or whether variable Transport Management Systems (such as flow responsive signals) help or hinder traffic flow.

In order to achieve this goal it is important to hold a thorough understanding of how drivers make their travel decisions under varying levels of knowledge. Additionally, a greater understanding of how time varying phenomena arise and their properties is required in order to predict their expected prevalence. These aspects will form the basis of research contained within this thesis. Regardless of whether or not the final prediction of road traffic flows is improved, by incorporating time varying processes in the forecasting process a greater modelling ability of the ‘ramp up’ period may be obtained by predicting and networks under events how traffic flows may vary following network change.

1.4 Thesis aims and goals

1.4.1 Summary of introductory discussion

To summarise the preceding introductory discussion, the following assertions can be made regarding the current state of highway demand forecasting:

- Travel is an integral part of our daily lives. The wider economy, environment and well being of road users depends upon the smooth and efficient operation of the road transportation system. Strategic planning and day to day management of the road system should be based upon accurate and reliable demand forecasts informed by behavioural knowledge of driver decisions.

- Although a selection of practical (i.e. non-methodological) shortcomings in forecasts exist, which practitioners should attempt to overcome, there is scope for statistically improving the demand forecasting accuracy of tools and methods available to transport planners.
- The 'ramp up' period of traffic flow change once an infrastructure alteration occurs is generally not included within applications of demand forecast models. Instead fixed properties are assumed rather than algorithm determined values, causing problems for highway managers failing to adequately manage or anticipate this aspect of a scheme.
- Most long term strategic transport forecasts do not consider day to day causes of variation in transport network conditions and subsequently fail to capture traveller response to this variation, instead providing 'average day' forecasts.
- Traditional approaches towards transport demand forecasting fail to incorporate the dimension of time and consequently the role of variation in knowledge, instead making assumptions of 'common' knowledge across the population.
- The full impacts of how drivers behave in response to variable and unknown travel times, as well as a lack of experience of conditions, is not yet fully understood in order to be implemented within demand forecasting techniques.

1.4.2 Relevant aspects of driver behaviour which we could benefit from understanding

Following the preceding discussion and summary, the following selection of relevant questions could be asked which we could benefit from understanding. These general questions are provided in a similar way to those posed by Frejinger (2008) and Mahmassani (1990), designed to encourage appreciation of the broad research area in which their work is placed. These questions only relate to how drivers choose and amend their routes - there are many other ways, not considered in this work, in which travellers may vary their travel habits, for instance varying departure times, trip frequency (travelling less or more often) or destination (such as using a different retail area). Further, it will fall outside of the scope of this thesis to attempt to provide answers to all of them, but they are nevertheless important issues which demand forecasters could benefit from understanding and accounting for in models. These questions form the basis of the thesis aims and objectives:

Regarding the learning and behaviour adjustment processes of travellers: How do drivers gain knowledge of the typical properties of a road system? How much might a driver seek out information such as on a map or signage? How do they behave when they have absolutely zero knowledge and how does this change as they gain experience?

How much transport network knowledge is based upon assumption or guesses and how much is direct experience?

How a driver responds when they encounter unexpected congestion: How do they decide whether it is beneficial to divert away from their already chosen route or not? How do drivers know if the congestion they encounter isn't always present along their route? Is a potential diversion decision based upon knowledge or experience of the entire road network or is it an estimation of road conditions elsewhere? Do drivers recognise others engaging in diversion behaviour and follow their lead? Is it possible at all to reliably infer network conditions in an unobservable area without external information such as signage? Are there certain types of incidents which are more likely to prompt diversion behaviour among drivers, such as road traffic accidents or inclement weather?

Then, once an incident or form of unexpected congestion has been negotiated: How does the experience feed back into the driver opinion of a route and future decisions, especially when they may still be learning and inexperienced about the characteristics of the road system? Will a driver choose a different route the day after a negative incident experience? Would they be optimistic or pessimistic about encountering congestion on their route?

Given an understanding of each of these points, how do they vary among populations: Road users have different priorities, preferences, and, crucially, experiences. Would all travellers in all regions of the world behave in the same way?

How does congestion behaviour operate at the system level: What are the consequences of many drivers with the knowledge and ability to adjust their route en-route? Are drivers encouraged to engage in diversion behaviour because it actually provides them with any benefit? And perhaps most importantly for planners - does diversion behaviour benefit the system as a whole and therefore how can it be encouraged or discouraged? Given this, is variable signage the most appropriate way of influencing routing behaviour?

As the above points are split, understanding the behaviour of the *individual* is different to understanding the behaviour of the *system*. An observable travel system is the result of many travellers making different decisions individually. However, it would never be sufficient to explore *just* the behaviour of the individual because in a road system containing many travellers the actions of each driver affect the experience of others. Predictive models can be used to translate assumptions regarding individual behaviour into system level trends.

In his paper 'Why Model?' Epstein (2008) explores the reasons for which one might wish to employ modelling, focussing primarily for purposes which are *not* prediction which is often perceived to be the only benefit of modelling. He provides sixteen core reasons other than prediction to build models, a number of which guide the modelling and analysis work contained within this thesis. These include explanation, illumination of core dynamics, discover new questions, bound outcomes of plausible ranges, illuminate core uncertainties, challenge robustness of prevailing theory and to reveal the apparently simple (complex) to be complex (simple). This work employs modelling in these ways, to help understand phenomena that may be taking place within a transport system and guide development of future predictive models.

1.4.3 Thesis aims

This thesis works under the direction of a number of overarching aims and each of the proposed objectives contributes towards the joint research effort dictated by those aims. Those aims are:

- **Aim 1:** *To improve our understanding of the role of incomplete knowledge on route choice decisions.*

This aim focusses on understanding the role of incomplete driver knowledge, relating specifically to highway network properties which impact on expected travel experience. This includes expectations of travel time and the likelihood of encountering congestion on each journey. Variation in knowledge can occur *between days*, as drivers learn those properties from an initial perception, and *within day* as drivers are incapable of forming a complete picture of current road network conditions. This is in contrast to traditional approaches which for convenience assume that all drivers have perfect knowledge of network conditions.

Since this thesis focusses on the development of modelling and forecasting techniques, the aim ultimately seeks to numerically characterise forms of variation between days and algorithmically represent route choice decisions made by individual drivers.

- **Aim 2:** *To improve our understanding of the impact of variable driver knowledge in highway conditions*

The ramp up profile has been provided as an example of a phenomenon which is the result of variation in knowledge between days. This aim seeks to explore further impacts of variation in knowledge on highway networks through the use of modelling techniques, in keeping with Epstein's assertion that modelling can help understand system dynamics (2008).

For this work, this aim includes capturing the ramp up profile itself in a way that can be tailored for a specific scenario and personal travel cost differences as well as extending the approach to model driver behaviour within day. Here a driver may be incapable of forming an impression of current road network conditions without externally provided information, and instead they must rely on their own subjective experience to guide expectations. This is particularly true when incidents occur and traffic flow configurations may not be in their 'usual' state which has been learned by regular travellers.

- **Aim 3:** *To contribute to the debate on suitable modelling techniques which are capable of incorporating driver variation in knowledge.*

This aim relates to the specific methodology which is used to model the impact of learning and incomplete knowledge. Advancement in these fields may come through attempting novel knowledge representation algorithms, implementation with different network representations and improving the computational efficiencies of the techniques.

In particular it seeks to understand whether and how the modelling technique adopted affects the quality of the output forecasts, including the amount of data obtained and the result itself.

1.4.4 Thesis objectives

In order to work towards these overarching aims, a number of specific objectives are proposed:

- **Objective 1:** To assess current understanding of the causes and characterisation of time varying highway phenomenon which give rise to unexpected network conditions and congestion patterns, such as incidents and other events.
- **Objective 2:** To undertake a review of existing knowledge regarding how drivers make decisions under uncertainty and lack of knowledge. Where necessary, this thesis should fill gaps in knowledge relating to this process.
- **Objective 3:** To identify and implement a suitable modelling technique for capturing variation in knowledge among a population of drivers. This should be be capable of representing variation within days as well as between days.
- **Objective 4:** To explore the effect of highway network representation on network phenomena and aspects of driver learning. This includes both representation of incidents and properties of the highway network itself such as queue formation.
- **Objective 5:** To evaluate and, where possible overcome, the technical challenges of modelling individual experience

1.4.5 Scope of this research

Aspects of the Four Stage Model other than route choice and traffic assignment, such as trip generation and mode choice, are not considered in this work. Traffic assignment is assumed to be being undertaken once demand has been established and known numbers of vehicles are expected to travel between origin and destination pairs. Additionally this work does not consider drivers varying their departure time which can feature in traffic assignment applications (such as Ben-Elia et al., 2010; Mahmassani, 1990). While departure time is another important aspect of driver choice, in order to disentangle the impact of the two choice aspects this work focuses on route choice decisions only.

Additionally this work only considers route choice behaviour which is driven by personal experience. A driver may collect information regarding the road traffic network from a variety of sources such as signage, social media or contacts, or satellite navigation systems which will vary in form and effectiveness, but the ways in which drivers interact with these sources is another complex issue which receives its own research efforts (for examples see Hu and Mahmassani, 1997; Lu et al., 2010a).

1.5 Outline of thesis

The flow of work within this thesis is presented in figure 1.6. Each chapter contained within this thesis builds on from the work presented in the last with the aim of progressively exploring more issues, constructing an argument and relaxing assumptions which were previously used in highlighting a result. The general principles of analysis are to vary the number of decision making drivers under analysis from one (in chapters 2 and 3), through hundred in chapter 4, up to thousands in chapters 5 and 6.

This work is broadly separated in to two parts, the first providing an insight in to how drivers behave in reality, the second examining how best to capture this behaviour in forecasting models. As a result the whole literature background and overview is split across two chapters with different topics under consideration. The specific structure and content of this thesis is as follows:

Chapter two expands upon out the research problem under consideration in this work and provides a background of current knowledge regarding how drivers make their route choice decisions in reality. This begins with a discussion of road transportation network properties which feature in route choice decisions.

Chapter three reports the findings of a route choice study undertaken within the University of Southampton to assess how participants choose preferred routes with limited experience of the road network and explore how the opportunity to divert en-route alters initial decisions.

Chapter four introduces existing traffic assignment techniques and examines their ability to represent variation in driver knowledge.

Chapter five develops a simple 'agent based' model representing drivers updating road network perceptions between days and en-route. It studies the application of the model to a simple diversion scenario and how the route choices of agents evolve over time.

Chapter six alters the network representation to that used in chapter five in such a way that travel experience is more dependent on agent decisions. The agent based model of en-route perception updating is also generalised. Within day dynamics receive particular attention in this work.

Chapter seven applies the developed agent model to a larger network representing the city of Sioux Falls, USA. It examines the issues arising from application of perception update models to larger urban networks.

Chapter eight concludes the thesis, providing a discussion of the key issues raised and concluding remarks.

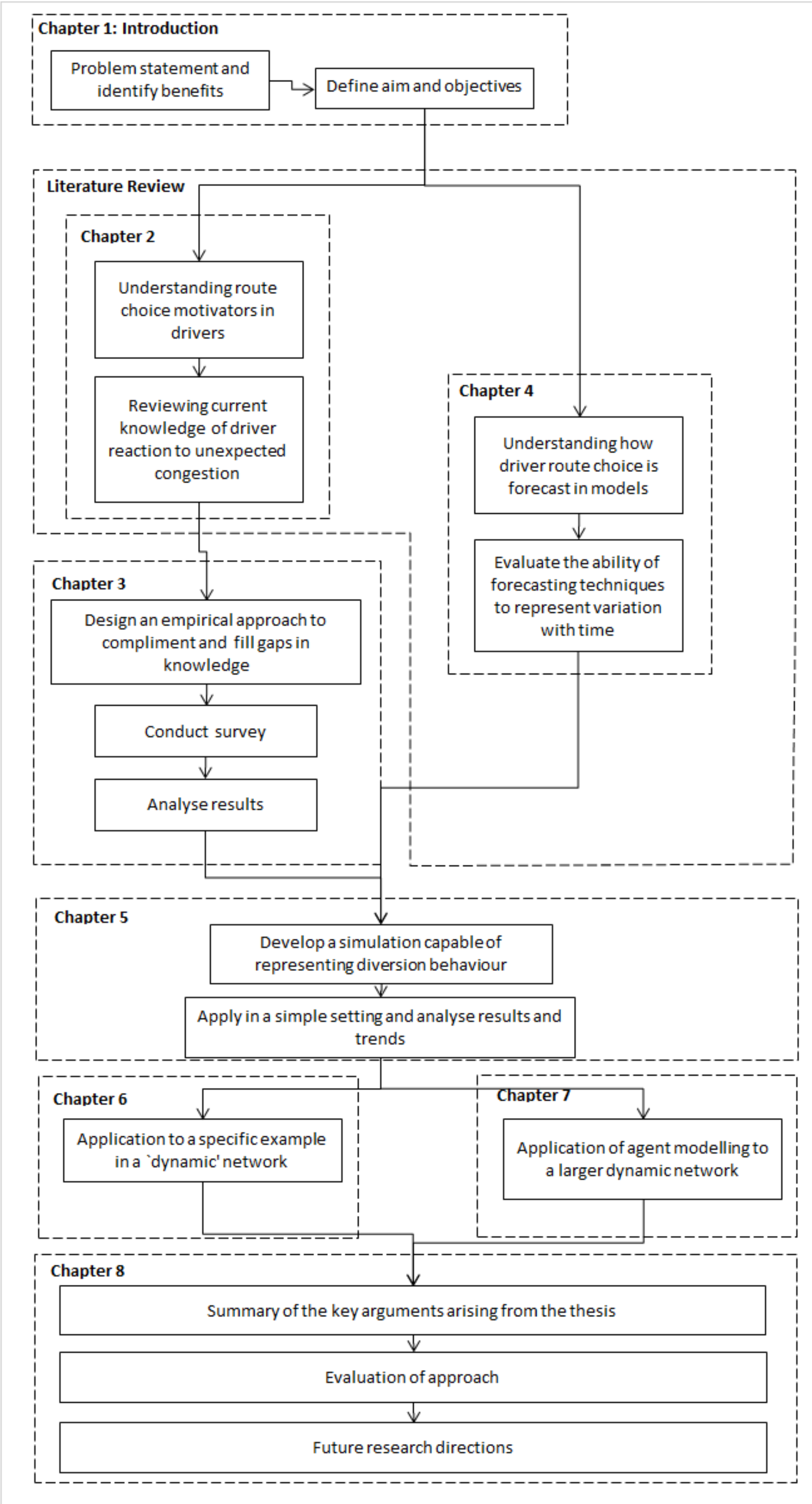


Figure 1.6: Overview of thesis structure and methodology

Chapter 2

Driver route choice and influencing factors over time

This chapter aims to provide a background of how drivers are understood to make route choice decisions, primarily relating to objectives one and two as outlined in section 1.4.4 which concern themselves with not only driver choice but also necessary aspects of network representation in order to forecast that choice. This includes what is understood to be their personal preferences in route attributes, the process of knowledge acquisition and learning, which was highlighted in chapter 1 as being the main focus of this thesis, and a description of relevant properties of the road transport system itself. The chapter concerns itself primarily with how drivers are believed to choose routes in reality and how this compares with modelling assumptions, leading on to an evaluation of the fitness for purpose of current modelling techniques which drives the research contribution of this doctoral work.

Regarding terminology, often the choice dynamics at work in transportation systems can be described using language borrowed from classical economics. Road space can be designated as a finite *resource*, the availability of which forms a *supply* for road users who represent system *demand*. Users form a decision based on the generalised *cost* of supply. A number of conceptual parallels between economic theories and descriptions of transportation systems can be made, such as utilitarianism and equilibrium properties, which will arise in this work. To begin, this chapter addresses a fundamental and often discussed question arising from classical economics applied to social dynamics, 'are drivers rational?'.

2.1 Rational behaviour in route choice

Prior to the second half of the twentieth century, decision theory primarily concerned itself with forecasting the actions of the 'economic man'. Simon (1955) describes the economic man as holding 'voluminous' knowledge regarding relevant aspects of his choice environment and is capable of reaching 'the highest attainable point on his preference scale' without regard for the plausibility of this result.

In the context of transport choices, the manifestation of rational behaviour is an individual always perfectly acting to reduce overall personal travel costs to a minimum level (in time and effort as well as monetary) since travel is (usually) perceived as an entirely negative activity. An individual's travel costs are based on a combination of factors and weighted according to demographic information such as income and age to reflect variation in a population (Bonsall and Palmer, 2004). One of the earliest applications of such 'economic man' thinking in transport was in a study by Kohl in 1846 (described in Ullman, 1941) who assumed that individuals travel between cities along the shortest path alone.

In his work, Simon (1955) outlined an argument for the concept of *bounded rationality* which has 'become firmly associated with Simon's name' and 'time and again, employed to buttress the use of the concept that is being done ... by diverse strands in the field of economic science' (Barros, 2010). In the context of route choice decisions bounded rationality can be summarised as three main principles:

- i) drivers do not know exact travel times on all available route options (lack of knowledge),
- ii) drivers are often required to make decisions in a relatively short space of time and cannot calculate exact overall costs (lack of processing time) and
- iii) drivers are susceptible to biases (such as optimism or pessimism).

Simon closes his paper by commenting that the resulting discrepancies between perfect and bounded rationality 'serve to explain many of the phenomena of organisational behaviour', indicating his belief in the importance of the concept.

Driver decisions can therefore be considered an application of bounded rationality and different methodologies have been developed for incorporating its effect in forecasting a range of driver choices including route, departure time or mode decisions (Di et al., 2013). In their early application of bounded rationality to transport forecasting problems, Mahmassani and Chang (1987) created a departure choice model featuring 'indifference bands' where a choice inertia meant that drivers would not change their decision unless the difference in costs is greater than a threshold, resulting in a 'feasible set' of forecast flows rather than a single fixed outcome were all decision makers 'economic men'. Use of indifference bands has been extended to include route switching over time (Hu and Mahmassani, 1997). Other approaches to replicate bounded rationality have included representations of the extra cost of considering what can be considered alternative or unknown paths (Gao et al., 2011).

The general interpretation of bounded rationality adopted throughout this work is based on the principle that, where a driver is aware of the options available (i.e. point i) above is satisfied), 'better alternatives are chosen more often' (Su, 2007). This accounts for errors in perception and judgement and is in keeping with Simon's assertion that humans generally decide what is 'good enough' for themselves through his exploration of payoff functions in his work (1955). This concept is used in many route choice forecast applications such as Dial's algorithm for algorithmically determining expected demand using logit models (Dial et al., 1979). These models assume that perception and judgement errors from the true value follow a known distribution. It should be remembered that this is quite different to the interpretation adopted by Mahmassani and Chang (1987).

This thesis also places emphasis on the role of subjective personal experience which is another aspect of bounded rationality, mainly stemming from point i) above that drivers do not know the exact properties of all aspects of their choice. This is responsible for the ramp up effect described in chapter 1. Many route choice models provide forecasts on the implicit assumption that all route properties are known to all members of the population, but this is not always true in reality.

As this thesis will demonstrate in what is a recurring theme, there are many aspects of bounded rationality and decision making which could form part of route choice forecasts models, and understanding the key mechanics driving choice and their potential impacts is crucial in forecasting.

2.2 Primary factors in route choice decisions

Many empirical studies have sought to identify the key factors which drivers consider when deciding upon a route from a journey origin to destination. These have been conducted using a combination of GPS based vehicle tracking (Jan et al., 2000; Bekhor et al., 2006; Papinski et al., 2009; Zhu and Levinson, 2010), interviews and travel diaries (Schlich and Axhausen, 2003; Papinski et al., 2009; Zhu et al., 2010) and interactive simulators presenting travel from both a driver's eye view (Bonsall et al., 1997; Bonsall and Palmer, 2004) and from a top down network perspective (Lotan, 1997; Mahmassani and Liu, 1999; Selten et al., 2007; Ben-Elia et al., 2008; Lu et al., 2010a).

By studying the routes which drivers take from a journey origin to destination it has been found that drivers do not generally adopt the shortest path in terms of distance as was assumed by Kohl in the 1800s (Ullman, 1941) (examples of studies using GPS vehicle tracking which observe this behaviour include Jan et al., 2000; Zhu and Levinson, 2010). Instead it is widely believed that travel time is the primary factor which is considered by drivers when formulating route costs. Outram and Thompson (1978) found that a cost function consisting of just travel time and distance accounts for between 60% and 80% of all routes chosen. In a more recent study, Bekhor, Ben-Akiva and Ramming (2006) found that a cost function with travel time alone only accounts for 41% of routes chosen, with free-flow travel time alone performing slightly better (explaining 43% of journeys), suggesting that drivers may usually be optimistic in their impression of network conditions. Similar studies have confirmed that the primary motivations for drivers in choosing routes are time and distance (Prato et al., 2005), minimising congestion levels (Prato et al., 2005; Papinski et al., 2009) and maximising directness (travelling in a straight line to the destination) (Raghubir and Krishna, 1996; Conroy Dalton, 2003; Papinski et al., 2009). The relative importance of these factors will vary by individual so an understanding of the demographics of decision makers is also important (Bonsall and Palmer, 2004; Prato et al., 2005).

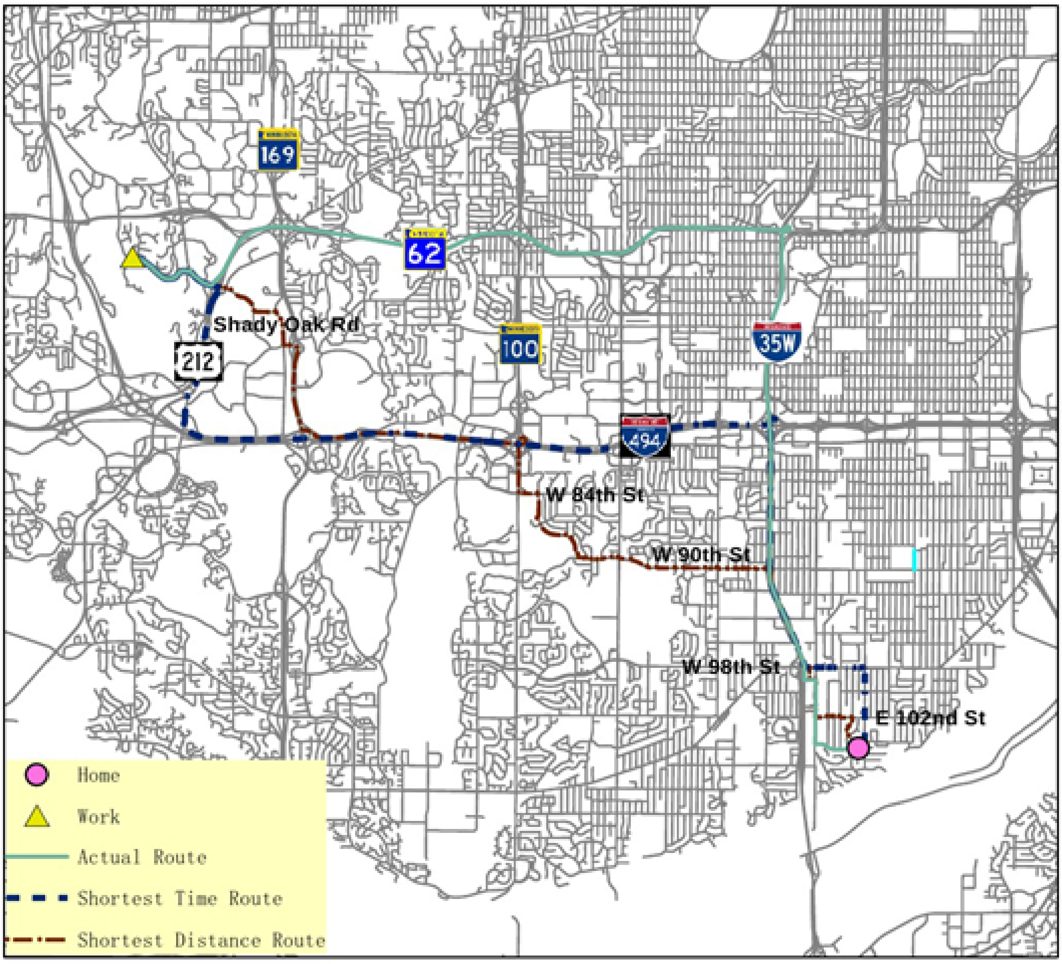


Figure 2.1: Example of commuting route identification and comparison with shortest distance and time routes (Tang and Levinson, 2015)

An example of the potential differences between shortest time, distance and actual route paths is shown in figure 2.1, provided by Tang and Levinson (2015). They found that most travellers from their sample of 278 used routes between home and work which were longer than the shortest path. Instead number of turns and age of driver were among key factors. They also comment that drivers were found to use multiple routes between home and work on different days.

Zhu and Levinson (2010) also used GPS devices in a separate survey to study 657 home to work trips made by 95 subjects in Minneapolis, USA. They found that in most circumstances people choose routes which are less than 5 minutes longer than the shortest time routes and no drivers used the shortest distance path unless it coincided with the shortest travel time path, providing further evidence that travel time is the most important factor in routing decisions.

2.3 Road network attributes featuring in decisions

It is necessary to understand the measurable characteristics of a route which influence driver decisions so that the same principles may be applied in hypothetical locations or scenarios in forecasting.

Many 'attractiveness' variables attributed to a route are usually considered to be independent of levels of vehicular usage, such as distance or the road classification. The exception is travel time, which is often found to be the major factor (Ortúzar and Willumsen, 2001). A road which experiences high levels of demand will at some point become congested as drivers compete for use of the finite road space supply and travel time subsequently increases, originally noted by Greenshields (1935). The point at which vehicular flow is maximum prior to congestion causing traffic to slow down is termed the road's *capacity*.

An example non-linear function used in practice to describe vehicle travel times along carriageways, used within this thesis, is provided by the Bureau of Public Roads (BPR) (1964) which assumes that capacity is reached when the travel time experienced by drivers is 15% higher than it is under free flow conditions. The travel time experienced by a driver traversing a road (t) is be described in terms of flow (q) free flow travel time (t_{ff}) and effective capacity (Q):

$$t(q, t_{\text{ff}}, Q) = t_{\text{ff}}(1 + 0.15\frac{q}{Q}^4) \tag{2.1}$$

Rather than being an entirely physical property, capacity is affected not only affected by road type (such as width, surface and speed limits) but also by local driver behaviour, such as following distances between vehicles and acceleration behaviour (for an example of the derivation of highway capacity values see Knoop et al., 2009). Typical values found in practice for highway capacity include 2000-2800 passenger cars per hour (pc/h) for a two lane carriageway (reported by Harwood et al., 1999; Ahmed, 2009) and 1000-1500 pc/h for a single lane road found in an urban centre (found by Asamer and Reinthaler, 2010).

The effect of capacity and congestion on driver experience is that routes which are popular can become slower than alternative route options, potentially prompting a driver to re-evaluate their route preferences on a their next trip. As drivers gain experience and become more knowledgeable about expected conditions their choices may change a number of times before forming a habitual or preferential choice, causing effects such as the 'ramp up' described in chapter 1.

From a forecasting perspective, capacity and driver experience means that expectations of traffic flow cannot reliably be based on 'free-flow' conditions alone and that the resulting balance between alternative options needs to be considered.

2.3.1 Driver learning of road network attributes and 'ramp up'

As has been established in chapter 1, there is significant empirical evidence that traffic flows do not immediately 'jump' from one stable configuration to another when an aspect of the road network changes and drivers change their daily travel patterns. It takes network users time to explore new options and adjust their behaviour, resulting in a 'ramp up' period of traffic flows converging a new long term stable level.

Kriger, Shiu and Naylor (2006) claim that an inverse relationship between time savings and ramp-up has been observed, such that greater time savings appeared to correlate with a shorter ramp up. This is plausibly explained by the accumulation of experience as one might assume that as knowledge accumulates the value of each new day's experience decreases in comparison to the preceding set of days. Provided that no further major network change occurs, eventually drivers are aware sufficiently aware of system attributes to make repeated decisions.

As a practical example, a large amount of research has been undertaken regarding travellers changing their behavioural patterns following the collapse of the I-35W bridge in central Minneapolis (Zhu and Levinson, 2010; Zhu et al., 2010; He and Liu, 2012, are of particular relevance to this work). The studies use a combination of inductive loop data (counting numbers of vehicles passing fixed points on roads) and travel diaries to assess route and activity choices and traffic numbers. In this situation many drivers had to find alternative routes for their trips and re-engage in network exploration. The most common responses to the bridge collapse were for travellers to change departure times and change routes, however a significant number of trips using the bridge prior to the collapse no longer crossed the river, indicating that travellers also changed their destination and activity habits. Following the disruption, traffic flows took approximately two months to settle down to regular patterns like those before the incident. Figure 2.2 shows traffic flows through a number of closed cordons around the bridge area in the days following the collapse (He, 2010), however since this graph shows total flows through cordons it should be remembered that it does not show route changes but instead changes to other aspects of travel behaviour such as destination, mode or trip frequency change, i.e. drivers are making fewer trips by car into those cordons.

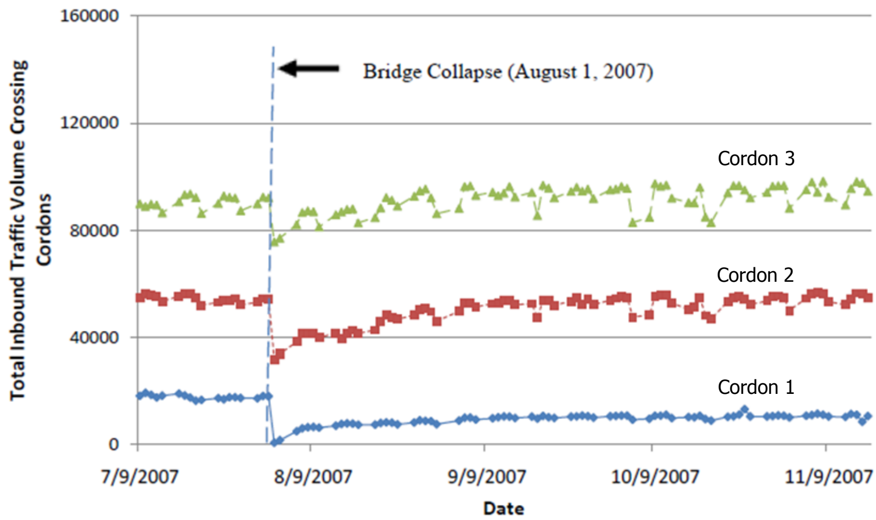


Figure 2.2: Daily traffic flows following a major bridge collapse event (note that dates are given in an American format) (He, 2010)

As evidence to support the learning and knowledge acquisition assertion, drivers who can be considered familiar with the road network have been found to make their route choices differently to those who are inexperienced. Lotan (1997) conducted a route choice study using a driving simulator and groups of ‘informed’ and ‘uninformed’ drivers. The subjects were found to be more likely to seek out new routes and information when they have limited knowledge of the system (compared to when drivers have good knowledge of the system and are less likely to seek out information). Uninformed drivers also appeared to pay more attention to information regarding, and subsequently switch to, routes which are well known to them.

As an experiment representing the entire ramp up process, Selten, Chmura, Pitz and Schreckenberg (2007) devised a lab experiment with multiple participants choosing routes for a number of repeated journeys in a hypothetical two route system. In their experimental set up, the travel time on each route is proportional to the number of participants choosing the route, imitating usual forms of congestion due to volumes of traffic. The participants received feedback of the travel time only on the route on which they travelled. Over time participants became more likely to use a ‘habitual route’ and were less likely to pick a different route option on the next day. Similar studies have observed learning processes and habit formation in individuals choosing from a set of routes under variable travel times (Katsikopoulos et al., 2002; Ben-Elia et al., 2008).

A number of studies of vehicle routes have suggested that habit is the strongest factor in whether to use a particular route, even when the habitual route does not rate highly in comparison to others using the route choice factors (Schlich and Axhausen, 2003). Drivers are also considerably less likely to acquire and heed information relating to changing routes on 'habitual' journeys, such as on weekdays, than during 'non-daily recreation trips' which is when drivers are more willing to engage in more exploration (Van der Horst and Ettema, 2005). Habits may be broken during situations where the habitual alternative performs very badly such as during road works or incidents (Fujii et al., 2001). Drivers are also considerably more likely to explore the network and switch routes in the evening commute rather than the morning commute when arrival time is more flexible (Petrella and Lappin, 2004).

The evidence explored here has suggested that once drivers have found a preferable route they are likely to repeatedly choose that route again in future. This may be expected in response to congestion caused by regular volume of traffic alone but when unexpected incidents arise, drivers may abandon their initial route choices in favour of an alternative with expected lower travel costs. It is necessary to understand the likelihood of diversion behaviour occurring and its relation to initial route choices in order to incorporate the effect of non recurrent congestion into demand forecasting.

2.4 Temporal variation in travel conditions

The preceding section has suggested that drivers will over time learn the properties of a transport system and determine which route option is the most attractive to themselves. This behaviour would account for a 'ramp up' in traffic flows from scheme opening to a stable flow on each road within the network. For forecasting purposes, such as within the four stage model, an assumption of 'average conditions' is often used which assumes that this process has already occurred for all users and all route possibilities. The 'average conditions' assumption is therefore not just limited to route choice but applies to all travel decisions.

In reality highway travel times are not necessarily similar for journeys on the same routes and at the same time of day for a variety of reasons. As an illustration of the actual variation in driver travel time experiences, figure 2.3 shows the distribution of travel times on one unidirectional route between Amersfoort and Amsterdam in The Netherlands during weekdays in 2002 (AVV, 2004) when demand would not be expected to vary significantly between most days. It is clearly noticeable that the morning peak period experiences a higher travel time than the evening peak period and that the mean journey takes more than twice as long as the route free flow travel time (48 versus 22 minutes). On 15% of weekdays the travel time during the morning peak is slightly higher than free flow travel time and on others it can reach five times as high. Similar figures are also created by Van Lint, van Zuylen and Tu (2008) and other studies (AVV, 2004) who critically compare empirically measured travel time variability against model forecasts.

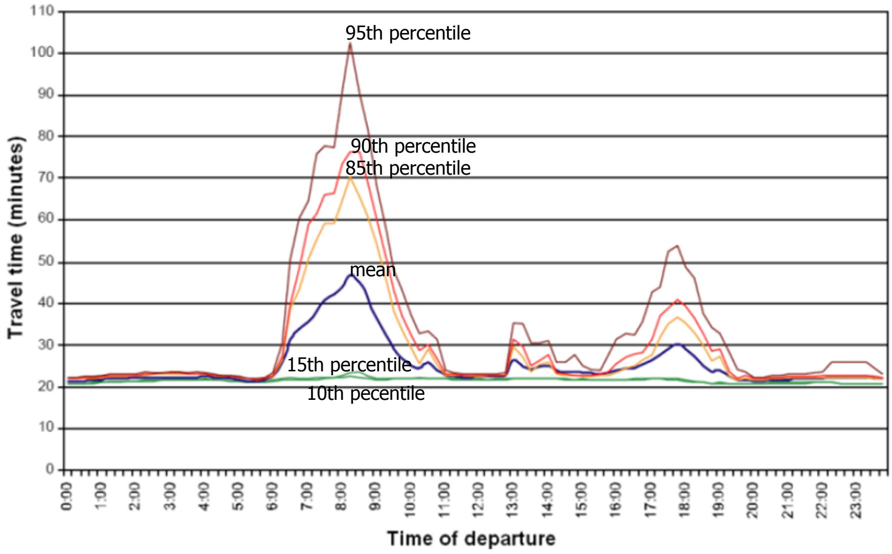


Figure 2.3: Travel time distribution on a single route from Amersfoort to Amsterdam during weekdays in 2002 (AVV, 2004)

A trend emerges from such empirical studies that driver experience can be largely similar on a day to day basis except for the presence of some form of 'incident' occurring, which usually results in a severely reduced network performance and increase in driver travel time. Although 'average days' may fall within one distribution of travel times experienced by travellers, 'incident days' may fall within another.

Meite (2011) provides a detailed exploration of a range of possible 'incidents' or sources of temporal variation in driver experience which are of relevance to this work. Table 2.1 classifies the various sources of variability in travel time according to a number of criteria: whether they are continuously present (left column) or can be considered a single event/ disturbance (right column), whether they are sources of regular (top row) or irregular (bottom row) variations and whether they spatially impact an entire network *(N)*, a local area *(L)* or 'in between local and network areas' *(B)*. The traditional Four Stage Model, which assumes that average conditions occur allowing travellers to form travel preferences over time, sits firmly in the top left cell of table 2.1.

To explain some of the decisions prompting the classifications in table 2.1, 'weather' is included as both a source of supply and demand variation because it can not only affect road conditions (such as local flooding and surface water in the presence of rain) but it can also alter the behaviour of road users (such as causing them to drive slow in rain).

The actions of traffic control and demand management systems are also completely omitted from table 2.1 despite having a large impact on driver experience. This is because

		Time span	
		Continuously present	Event/ Disturbance
Degree of regularity	Sources of regular variations	**Demand sources** Regular pattern of travel behaviour over the day *(N)* Regular pattern of travel behaviour over the days of the week *(N)* Regular pattern of travel behaviour over periods of the year *(N)* **Supply sources** Variation in vehicle population *(N)* Variation in driver population *(N)*	**Demand sources** Public holidays *(N)* **Supply sources** Darkness *(N)*
	Sources of irregular variations	**Demand sources** Unexplained variations in human travel behaviour *(B)* **Supply sources** Variation in vehicle population *(B)* Variation in driver population *(B)* Variation in human behaviour *(L)*	**Demand sources** Varying weather *(N/B)* Road works *(B)* Events *(B)* Strike actions *(N/B)* Emergencies *(N/B)* **Supply sources** Incidents *(L)* Demonstrations *(L)* Emergencies *(N/B/L)* Varying weather *(N/B/L)* Road works *(L/B)*

Table 2.1: Classifications of various sources for variations in traffic supply and demand (compiled by Meite, 2011). Letter labels indicate whether the effect is felt across the entire network *(N)*, a local area *(L)* or 'in between local and network areas' *(B)*

various forms of traffic control can be assigned to each of the categories, for example signalised intersections act on a continuous basis, yet specific control plans or ramp metering operations may only operate for short amounts of time. Some control schemes may further be traffic responsive (therefore irregular) or fixed time only (thus regular).

The sources of experience variation in table 2.1 can be broadly summarised as expected so deterministic (regular variations) and unexpected so stochastic (irregular variations) in nature. This important distinction leads to a fundamental difference in consideration of these factors and subsequent predictive modelling:

Recurrent variations are caused by deterministic sources. Congestion here primarily occurs during rush hour periods or other 'busy' times of day, usually caused by volume of traffic (demand outstripping supply) and is unrelated to a special or infrequent event. Demand on days considered to be 'similar' may be sufficient to forecast with accuracy, for example demand on weekdays may be similar to other weekdays but different to weekends. Weijermars and Van Berkum (2005) carried out a cluster analysis to assess the similarity of traffic profiles in a number of locations on many days and find that, among working days, Mondays and Fridays are two distinct separate clusters and separate from a single cluster containing Tuesdays, Wednesdays and Thursdays. Non-working days are less straight forward, the pair finding that although most Saturdays fall into a single cluster (also containing Sundays in January), Sundays at other times of year fall under a variety of other clusters. This could be explained by travellers varying seasonal activities dependent upon climate or national holidays.

Non recurrent congestion and variation, caused by stochastic sources, is sometimes referred to as road system 'perturbations' (such as by Gao et al., 2008). Emmerink, Axhausen, Nijkamp and Rietveld (1995) define sources of non-recurrent congestion as being either endogenous shocks to the system, such as traffic accidents, or exogenous shocks such as inclement weather. These are the forms of congestion which are neglected by transport demand forecasting methodologies so fall under the temporal phenomena under consideration in this work.

From a forecasting perspective, increased variation in driver experience may be have a number of consequences: drivers may take longer to form an accurate impression of expected conditions (if at all), and other psychological processes besides learning may act where a route choice decision is more of a risk associated gamble. The impact of either of these effects could change expectations of traffic behaviour beyond the 'average conditions' assumption.

2.4.1 Characterising non recurrent congestion for modelling purposes

In order to examine the impact of incidents and non recurrent congestion on driver route choice, particularly for forecasting and modelling purposes, it is necessary to characterise the forms of experience to drivers that non recurrent congestion may have.

As figure 2.4 shows, Skabardonis, Varaiya and Petty (2002) find that under non recurrent congestion travel times tend to be higher and more variable although this depends upon the exact cause of the delay. They conducted a study of the prevalence of non-recurrent congestion along two stretches of an interstate corridor in California, finding that incident related delay is the cause of 13% to 30% of total congestion delay during peak periods. As the team note, this is lower than other quoted values, an example being 50% reported by Schrank and Lomax (2009). However a stretch of road which never experiences recurrent congestion will experience 100% non-recurrent congestion by this measure so it is perhaps flawed and unsuitable for comparisons. In the UK 45% of overall vehicle delay is attributed to non recurrent sources (National Audit Office, 2004) and the US Federal Highways Administration has described this figure as 60% (FHWA, 2005).

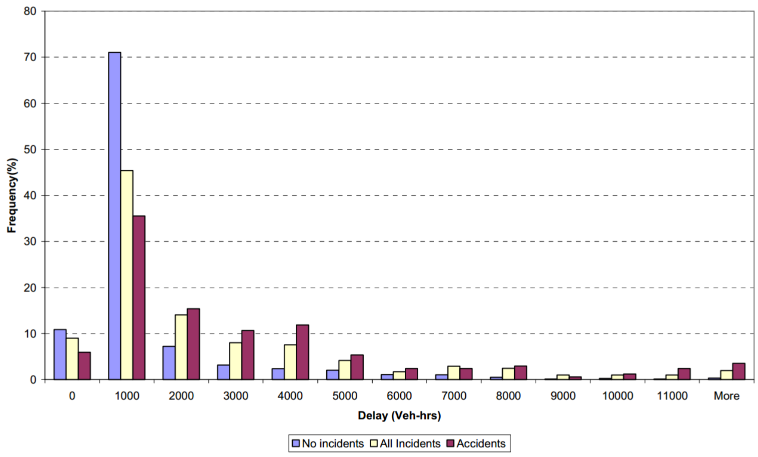


Figure 2.4: Delay distribution on the I-210 (Skabardonis et al., 2002)

Regarding the frequency and duration of incidents as a form of non-recurrent congestion, Immers, Bleukx, Stada, Tampère and Yperman (2004) quote a value of 0.171 incidents on average per 100,000 car kilometres (cited from Cullison et al., 1997). Ceder and Livneh (1982) also derive relationships between hourly traffic flow and the probability of types of traffic accidents occurring. It is unknown whether these relationships are sufficient for forecasting highway incident levels which may depend on other local factors such as junction or road types or road conditions.

To illustrate the impact of incidents on highway capacity, referring back to the description in section 2.3, Knoop, Hoogendoorn and Adams (2009) measured the capacity reduction effects of 90 incidents on Dutch carriageways which blocked various lane configurations (shoulder, one out of three lanes, two out of three lanes and 'rubbernecking' traffic slowing in the other direction on the opposite side of the carriageway). The results are reported in table 2.2. The 'efficiency of lane use' field is related to driver behaviour, describing the proportion of queue discharge rate existing following on remaining lanes unaffected by the incident.

Type of blocking	**Shoulder**	**1 out of 3**	**2 out of 3**	**Other direction**
Mean capacity proportion	0.72	0.36	0.18	0.69
Standard deviation	0.09	0.14	0.12	0.08
Efficiency of lane use	0.72	0.54	0.54	0.69

Table 2.2: Measured impacts on traffic flow on highways following various incidents (Knoop et al., 2009)

The team also report effective capacities following incidents in other locations, ranging from an optimistic: (0.84 - shoulder, 0.53 - one of three lanes blocked and 0.22 - two of three lanes blocked) (Blumentritt et al., 1981) to a relatively pessimistic: (0.37 - one of three lanes blocked, 0.27 - two of three lanes blocked) (Smith et al., 2003). A greater understanding of the effects of different types of incidents is almost certainly required however, much like the study of incident probabilities, before they can be sufficiently incorporated within demand forecasts. The ability to discretise capacities and travel conditions based on stochastic events leads to the introduction of representing travel conditions as a 'state'.

2.4.2 Travel conditions as 'states'

The works presented in this section have suggested that a sensible representation of transport conditions is as belonging to one of a number of discrete 'states' which is a terminology adopted by this thesis.

A discrete transport system state can be defined as a specific combination of any road transport attributes - whether the properties are quantifiable such as available capacity, free flow speed and available road width or more qualitative such as weather conditions and general driver attitudes. That is, the network with which drivers are interacting in one state is fundamentally different to when the network is in a different state. Obvious examples of distinct states include 'usual' operating conditions, varying degrees of 'incidents' as outlined in the preceding section or demand fluctuations such as from public holidays.

Since state changes can be driven by what Emmerink, Axhausen, Nijkamp and Rietveld (1995) name 'shocks' as in the manner described by the table 2.1 presented by Miete (2011), states do not overlap so are not considered continuous in nature. However the range of conditions within a state are certainly continuous in nature - for example a fast journey through an incident may be faster than a slow journey through usual conditions. But they remain different states because the properties of the road transport system with which they are interacting are different.

From a modelling and forecasting perspective, the consideration of states is useful because they divide up the range of possible driver experiences. As was noted regarding table 2.1, the four stage model firmly forecasts conditions under a single state. Representing the road network in models in this way has been applied before in a range of applications (Gao, 2002; Kwon and Murphy, 2000; He et al., 2006) but examining how states impact with driver learning and modelling that impact yields unanswered and important questions. Such questions include how does the potential presence of states impact on route flows and, whether driver behaviour in each state uninfluenced by the possible presence of other states?

2.5 Driver expectation of states of variable travel conditions

The preceding sections of this chapter have discussed actual variability in highway conditions. These cause drivers to have a detrimental experience on some occasions so, given rationally bounded assumptions of behaviour, drivers would be expected to tend to avoid them if they believe they could occur.

This section sets out to explore the ways in which states of non-recurrent congestion can be predicted by drivers based on personal experience alone. In reality information regarding non-recurrent congestion is often propagated by media such as radio or variable signage but this work examines the situation when these are not available.

In particular a driver may use an expectation of non-recurrent congestion in one of two ways: either to modify their route choice en-route, diverting to avoid an expected incident or in an adjustment of their initial route choice to entirely avoid an incident affected area.

Travellers can adopt a number of strategies in response to the presence of incidents, both pre-trip and en-route, such as divert, seek out additional information, revise travel objectives, delay travel, substitute routes, substitute destinations or re-order scheduled activities (Golledge and Garling, 2001). Whether or not the possibility of incidents occurring affects the initial route choice decisions of drivers, regardless of whether or not they receive information pre trip, appears to have received little research attention.

2.5.1 Driver reaction to forms of non-recurrent congestion

It has been found that drivers are more likely to seek out information on network performance if they expect conditions to be poor, such as when road works are expected or regular sporting events, usually in order to depart at a later time (Abdel-Aty and Jovanis, 1994). It might be expected that a route which is prone to relatively frequent accidents, flooding or event traffic may be consistently less popular among travellers although existing studies of traveller reaction to travel time reliability suggests that drivers tend to favour risk taking in their routing decisions (Katsikopoulos et al., 2002) so the possibility of accidents may not be a consideration for travellers. The issues of optimism and risk taking play a large part in how a traveller sees diverting opportunities across the road network.

Papinski, Scott and Doherty (2009) conducted a survey evaluating planned versus realised route choices with GPS tracking and questionnaire based surveys. The results of this study showed that 20% of the 21 vehicle based trips analysed involved a deviation from their initially planned route (which was on average 44% of the total trip distance), and of these diverting journeys the longest was 7.1km which is shorter than the average trip distance of 13.9km - indicating that drivers are more likely to divert on local journeys where perhaps they are more confident in their expectation assessments. The reasons for diverting, provided by drivers, vary from 'exploring a new route to shorten travel time' (although this is more likely in situations where arrival time is flexible) to 'minor changes due to convenience' (which one may conclude is to avoid non recurrent delays).

Often the study of characterising incidents is undertaken in order to mitigate their negative impacts, in particular examining how Advanced Traveller Information Systems can be utilised in order to divert vehicles on to other routes (Abdel-Aty and Jovanis, 1994; Chorus et al., 2006). The use of information from en-route (and pre trip) sources varies considerably by age and gender (Chatterjee and McDonald, 2004) and the format of information and situation has a role in whether drivers utilise the advice (Khattak et al., 1995; Chorus et al., 2006). Drivers may also use experience of within day network conditions, such as congestion locations, in order to infer conditions of other routes should they have sufficient experience and knowledge of the network.

Knowledge of network structure and conditions plays a large part in driver diversion decisions as drivers are known to almost exclusively only divert on to familiar routes (Khattak et al., 1995) either pre-trip or very close to the trip origin (Chen and Mahmassani, 1999). Drivers can choose to divert after assessing levels of traffic on their current route and considering the availability of alternate routes (Mannering, 1987). Often drivers exhibit a congestion tolerance, which acts as a barrier to them changing their route choice so hindering the performance of information provision. Haselkorn, Spyridakis, Conquest and Barfield (1989) found that only 20% of commuters would frequently change routes if they experienced an average of 13 minutes delay, 23% of commuters would never change routes and other drivers would change routes if they experienced an average 27 minute delay.

Travellers will also be more likely to divert (and seek out travel information) when they expect the performance of a road network to be poor (whether that be due to congestion during peak hours, poor weather or the presence of incidents) (Chatterjee and McDonald, 2004). Peirce and Lappin (2004) conducted a study of travellers in the Seattle area and found that few (10%) actually consult information prior to departure and fewer (1%) change plans based on this information.

A lab based route choice experiment, similar to that of Selten, Chmura, Pitz and Schreckenberg (2007), was conducted by Lu, Gao and Ben-Elia (2010a). This multi participant experiment allowed a portion of travellers to switch from their initially planned routes once information from a variable message sign had been obtained. The experiment was also multi-participant meaning that determining individual responses to specific situations is challenging. However the team found evidence that some travellers will actually make their initial route choices with the intention of passing the variable message sign and potentially adapting their route. Drivers have elsewhere been to found to prefer to usually seek the majority of information pre trip (with an intention of changing departure time) (Abdel-Aty and Jovanis, 1994).

When drivers consider diverting they must weigh up the benefits of remaining on a route, which is likely to be habitual and with a known range of travel times, against diverting on to a different route about which they know less. One might expect that the decision to divert en-route (in the absence of any additional information beyond personal experience) could be influenced by psychological trends such as the 'gamblers fallacy' and 'the illusion of control' (Camerer, 2002) where subjects tend to believe their initial choice was the 'correct' one to pick even though it has been clearly explained to them that the variable they are picking is random. Comparisons of route choice with gambling behaviour would also potentially explain why Bekhor, Ben-Akiva and Ramming (2006) found that comparing free flow travel time explains more route choice decisions than comparing actual travel time. Also of possible relevance is the 'nonrational escalation of commitment' (Bazerman and Neale, 1992) in which subjects feel reluctant to change initial choices due to the feeling of persistence as a virtue.

A prominent area of research is driver reactions to variable travel times, introducing a 'risk' that an alternative route could hold lower travel costs. Much work in this field has focused on the potential application of the concept of prospect theory (Kahneman and Tversky, 1979), which is often applied and considered within transportation networks where payoffs are quantifiable, such as by Katsikopoulos, Fisher, Duse-Anthony and Duffy (2002) and more recently by Zhang and Juan (2013). It is also examined in experiment by Ben-Elia, Erev and Shiftan (2008) and further in Ben-Elia and Shiftan (2010). Prospect theory focuses on the natural asymmetry between reward/ losses among subjects - put simply, losses hurt more than gains of equal value feel good. This leads to risk seeking behaviour in the loss domain (risking the chance of a potentially lower travel time, even though it's more likely to be higher, rather than a guaranteed travel time between the two) and risk aversion in the reward domain (preferring to hold on to a guaranteed prize rather than likely losing it all to win a greater prize).

Ben-Elia, Erev and Shiftan (2008) also found evidence for the presence of the 'hot stove effect' (Denrell, 2007) which suggests that travellers are unlikely to revisit a route choice option for some time after a negative experience.

It is difficult to numerically assess and generalise travel decisions based on 'real world' survey data, such as collected by GPS or travel diaries, when only the decision maker's actions are being monitored. This is because a range of situation specific factors such as road traffic conditions are unobservable, leading to results being more 'anecdotal' in nature. Lab based experiments can be more useful for developing algorithms to represent driver decisions for forecast purposes because the full experience of the decision maker are known.

2.6 Network structure in road conditions for personal predictive purposes

Drivers moving through a road transport network may be affected by an incident not just because it occurs along the stretch of road upon which they are travelling. Should any form of congestion occur, whether from a recurrent or non-recurrent source, its impacts may be felt not just along a single stretch of carriageway. Such phenomena could signal to drivers that other parts of the network are in a negative incident affected state.

A number of studies have reported that strong relationships exist between nearby road links when travel times are unusually high (or low) as a result of traffic queueing along multiple roads. This may be caused by network structure, such as the existence of a single 'bottle neck', or routes which experience high demand compared to their capacity. He, Kornhauser and Yelinek (2006) present a study from Princeton, New Jersey, which uses GPS route traces to examine the relationships between road link travel times. An example of raw data provided by their study is shown in figure 2.5 where the travel time on link 10 only increases when the travel time on link 11 is more than 60 seconds, suggesting that for this link a 'tipping point' exists at this level of congestion as congestion blocks back on to other links. They find that strong spatial correlations exist on stretches of road within the examined network and that overall path travel time distributions are best described using a combination of linear normal distributions dependent upon traffic conditions, suggesting that driver experience is linked to sources of network variation.

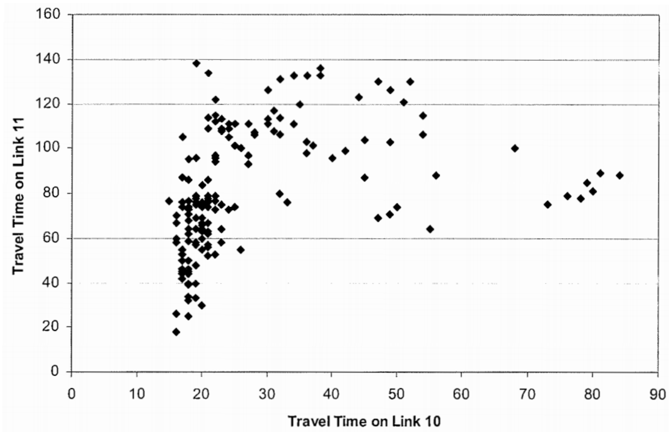


Figure 2.5: Travel times found on two connected road links (measured in seconds) (He et al., 2006)

Meite (2011) provides the diagrams in figures 2.6 and 2.7 which illustrate how the intersections between road links can cause relationships between road traffic states and resulting relationships in travel times. In particular the figures highlight how drivers not themselves passing an incident can still be affected by their presence.

Figure 2.6 describes the potential impact of an incident occurring on a single lane of a three lane highway. Immediately after the incident occurs (at $t = t_0$), flow passing the location is restricted resulting in a travel time delay for vehicles with a destination beyond the incident and thereby reducing flows on the carriageway downstream of the incident. At a later time ($t = t_0 + \Delta t$), as the queue grows back up the carriageway, the queue blocks access to an off ramp, increasing travel times for drivers on routes using this off ramp. This phenomena is known as 'blocking back'.

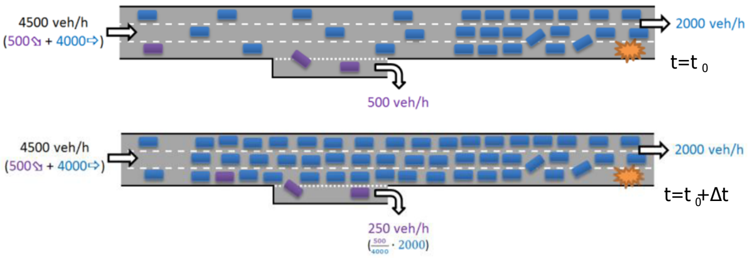


Figure 2.6: Non recurrent congestion blocking an upstream off ramp (Meite, 2011)

Blocking back does not necessarily impact traffic on only one stretch of road. Figure 2.7 illustrates an incident on a major east-west road causing traffic to back up on to a minor north-south road by $t = t_0 + \Delta t$, increasing travel time for drivers on routes which do not utilise the major road. In this case congestion on the north-south route is entirely caused by the route choice decisions of drivers joining the east-west route, suggesting that drivers diverting from this original route choice (perhaps prompted through personal experience or use of signage) may alleviate the problem.

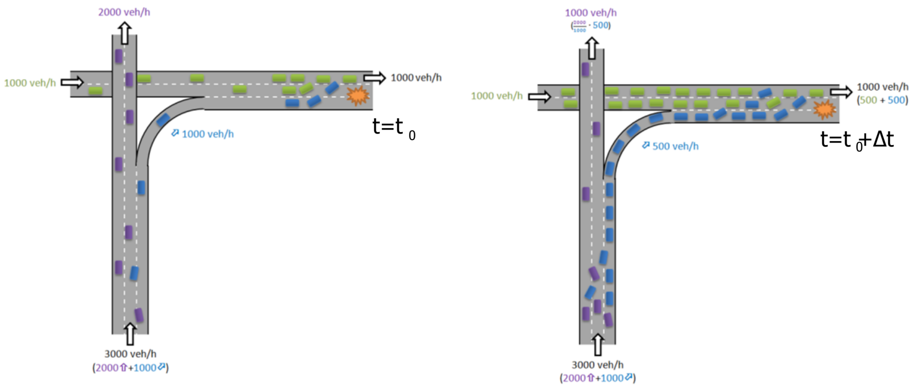


Figure 2.7: Non recurrent congestion blocking another connected carriageway (Meite, 2011)

Figure 2.8, presented by Xing and Zhou (2011), examines correlation coefficients between road link travel times along a 6 mile (presumably single direction) continuous segment of the Bayshore Freeway between Mountain View and San Jose, California. Along the X and Y axis are link numbers and the Z axis provides an empirically determined correlation coefficient for travel times in a fixed period. Figure 2.8 shows stronger spatial dependency on connected and nearby links, which is intuitive and further, 'regions' of closely correlated links can be observed potentially describing network structure although the authors themselves do not comment on the observed patterns. A similar figure is also produced in simulation by Corthout, Tampère and Immers (2009). The impact of clustering road links by states is recently explored by Han and Moutarde (2013) who report positively on a new technique utilising simulation data.

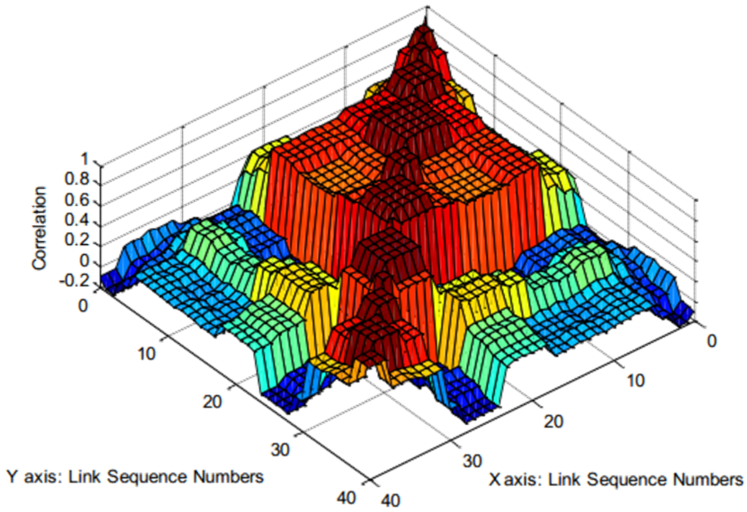


Figure 2.8: Road link travel time correlation coefficients on the Bayshore Freeway, California (Xing and Zhou, 2011)

The issue of correlation versus spatial distance is also examined by Bernard, Hackney and Axhausen (2006). They use GPS sensors in vehicles to determine correlation coefficients along straight sections of a variety of roads including motorways, trunk roads and 'collector roads' in Zurich, Germany, with some roads incorporating intersections (which are investigated separately). They find that for all road types strong correlations exist for short distances away from a reference point (up to 0.8 for 500m distance during off peak times) but that the correlation coefficients usually drop to 0.0 at 2500m. They conclude, and report in a subsequent paper fitting a predictive model to the data (Hackney et al., 2007), that neglecting correlation from analysis of road travel times 'are not only poorly designed but the results of those models are likely to be even wrong'. Cheng, Haworth and Wang (2012) focus on spatial-temporal relationships in London, UK. However travel time correlations are not always present in practice, and a study in Stockholm, Sweden found that travel times could in their case be considered independent on each road link (Jenelius et al., 2012).

Spatial relationships between road travel times are useful in predicting unknown travel conditions based on incomplete sensing data, so travel time forecasting and reliability models such as STARMA (Spatio-Temporal Auto-Regressive Moving Average) and similar models (Herring et al., 2010; Min and Wynter, 2011) incorporate these effects.

2.7 Summary and underdeveloped areas of understanding regarding driver routing

The preceding literature overview has sought to examine available theories and empirical studies regarding how drivers make their routing decisions. The focus has been on identifying the aspects of behaviour which should be applied to forecast situations in new locations or scenarios in line with thesis aim 1 and objectives 1 and 2.

Most fundamentally it showed that overall drivers act in a manner which can be described as 'boundedly' rational where, although the specific interpretation and form of its application is debated, generally routes are chosen with the intention of minimising perceived generalised costs to themselves in a satisfactory manner. Drivers are never realistically expected to make perfect decisions (due to biases and errors in judgement and a lack of complete knowledge of options) but uncertainty of network characteristics would decrease over time as experience accumulates into knowledge. The result of this process is an expected approximate 'steady state' system of route choices after an initial 'ramp up', as is forecast by traditional applications of the four stage model.

This chapter has advocated placing emphasis on studying and appreciating the environment in which drivers are making their decisions, and its 'live' impact on en-route routing decisions within a trip. It introduced the concept of the road system being in one of a number of discrete possible 'states' where road network attributes are fundamentally different to another state. Although in most trips drivers may be unaffected by negative and randomly occurring 'incident' states, such events can occur and have a negative impact when they do, suggesting a boundedly rational individual would attempt to avoid their impact if they are able.

Towards meeting the thesis objectives in section 1.4.4, this chapter has contributed towards meeting objectives one, regarding understanding causes and characteristics of of time varying phenomena, and two, examining how drivers are understood to make routing decisions in reality.

The overarching hypothesis of this thesis is that temporal variation in travel conditions within-day has some impact on the learning process and driver route choices, making it an important aspect to include in models which could affect end forecasts. Research regarding how drivers behave in response to their presence (in terms of route choice) has previously focussed on reactions to signage and information, but has found evidence that expectation of incidents can affect start of day route choice.

Finally, this literature overview has put forward the new and plausible suggestion that drivers could add knowledge of congestion relationships to their learned experience of the system and use this in their route choice decision making process. This is presently an underdeveloped area of understanding both in how drivers learn network congestion structure and how to best forecast their impact into the future.

Chapter 3

Evaluating Route Choices Under Varying Network States Using a Stated Preference Travel Simulator Survey

An early analysis of the work contained within this chapter was presented at the second Student Conference on Complexity Science 2012.

3.1 Motivation and goals of this study

The previous chapter has sought to identify the main attributes which drivers consider when determining route choices. Evidence of these attributes have been found using both 'real world' behavioural observations and lab experiments in a controlled environment where participants are asked what their decision would be in a situation. It has been suggested that an underdeveloped area of understanding concerns how drivers react to the presence of negative 'states' of non-recurrent congestion which have a detrimental impact on experience.

The preceding chapter put forward the hypothesis that drivers might be capable of learning, through network structure, relationships between individual road states which went some way towards meeting objective two of this thesis. The experience of this phenomena to the driver would be that the current observable travel conditions on one road gives indications of current travel conditions on another unobservable road. The goal of this study is ultimately to attempt to test this assertion and better understand the factors which contribute to en-route diversion decisions and initial route choice decisions, filling the gap in knowledge and providing an empirical base for modelling work.

While a benefit of an interactive 'travel simulator' study is that choices can be observed in a completely known environment, as pointed out by Mahmassani (1990), much insight can be found by taking the opportunity to engage in speaking with drivers about whether and how much they believe that they adopt such strategies in reality.

In stated preference surveys respondents are asked to specify which behaviour they would adopt were they in the scenario presented. Not only can the choice set be entirely determined by the assessor but also the level of information given to participants can be controlled. A main benefit of this approach in transportation studies, particularly those regarding route choice, is that choices are made given an entirely known knowledge set and experience history of the choice environment. This is impossible to determine from GPS or travel diary monitoring alone.

3.1.1 Trends and findings from related studies

A number of relevant lab experiments have sought to determine how drivers react to variability in experienced travel conditions when choosing preferred routes in hypothetical scenarios (relevant examples include Selten et al., 2007; Ben-Elia et al., 2008; Ben-Elia and Shiftan, 2010; Avineri and Prashker, 2003; Bogers and Hoogendoorn, 2005; Iida and Uchida, 1992; Lu et al., 2010a; Mahmassani and Liu, 1999). These have all examined how study participants said they would behave in terms of route choice given a variable travel time environment over a number of repeated 'days', so common themes include learning of system properties and attitude to risk.

The studies by Selten, Chmura, Pitz and Schreckenberg (2007), Mahmassani and Liu (1999) and Iida, Akiyama and Uchida (1992) deal with participants making routing decisions in environments where they are in competition with other participants, so congestion is modelled such that travel time on routes become longer as more participants choose them. In game theoretic analysis, such a competition is described as a 'coordination game' (McAdams, 2008) where the best solution is to coordinate ones actions with other participants. In these studies there is some evidence that over time participants form habitual routes and the number of route changes between days decreases, for example Iida, Akiyama and Uchida present four groupings of individuals dependent on their frequency of between day route switches (the most populous grouping is labelled 'switch infrequently').

The other cited studies all examine situations where the travel experience fluctuation is applied externally, so participants are not in direct competition and their individual actions in response to a fixed choice are assessed. A common finding regarding route choice is what Avineri and Prashker (2003) term the *payoff variability effect* where high payoff (travel time) variability encourages random behaviour and participants spend a longer time finding an optimal choice (Ben-Elia et al., 2008; Bogers and Hoogendoorn, 2005). In each of these tests there is also evidence of learning and habit formation, with Bogers, Viti and Hoogendorn (2005) asserting that, when calibrating a predictive model, the number of times a route was chosen previously contributes to the perceived utility of that route.

Usually in these studies travel time variability is applied as a wider distribution of potentially experienced travel times (Ben-Elia and Shiftan, 2010). A study by Lu, Gao and Ben-Elia applied the concept of states described in the previous chapter where a stretch of road would adopt a different travel time distribution were an incident present (Lu et al., 2010a). It is unknown whether this change in representation altered route attractiveness to participants which is explored further in this study.

Further, the primary novel contribution from this experiment stems from including an en-route diversion opportunity *without* signage or external information. In reality it is highly unlikely that a driver would be 'locked in' to their route choice decision along its entire length and when a driver realises that they have adopted a sub-optimal choice they may try to divert. It is tested here whether the diversion opportunity may affect route attractiveness, even when en-route travel information is not available and a driver may not be as confident in their perception of the network.

En-route diverting is examined in a similar fashion in the studies of Lu, Gao and Ben-Elia (Lu et al., 2010a) and by Mahmassani and Liu (1999) but in the context of information provision with a goal of evaluating the effectiveness of varying information forms. These both found that travellers heed information provided en-route and will divert, particularly when the time between planned and advised arrival time is high. Instead this study investigates whether network structure and queue formation itself can provide sufficient information for drivers to choose to divert.

3.2 Methodology

The analysis presented here is based on an interactive survey conducted at the University of Southampton, UK. During the experiment, participants are asked to choose what they believe to be the fastest route through a given road transport network presented to them as a top down map over a number of repeated 'days', each occurring consecutively with one trip made each day. Participants receive choice feedback information in the form of travel time on their chosen route, drawn from a set of distributions representing the travel time on each road link.

On some 'days' within the survey incidents may impact a number of road links, causing the travel time distribution to change such that they have a higher average travel time. Participants are informed of when an incident is affecting a road on which they are currently travelling alone. Importantly, it may happen either because an incident occurred on the road itself or because congestion has spilled back from a connected road through one of the mechanisms described in section 2.6. A probabilistic congestion structure exists such that, on any simulated day, if an incident occurs then connected links may themselves become delayed with a higher probability, thus allowing participants to change their expectation of other incident affected road links, representing the network properties as described in section 2.6. The road links potentially enabling diversion behaviour between routes are framed in such a way that using them would not constitute a feasible route unless when adopting diversion behaviour.

The interactive survey is split into three scenarios, which are completed consecutively with thirteen simulated days on each:

Scenario 1: No incidents, no diverting ability: No road links are delayed due to incidents and participants make whole route choices at the start of each simulated day. This is in keeping with a number of existing route choice studies (Selten et al., 2007; Ben-Elia et al., 2008).

Scenario 2: With incidents, no diverting ability: Participants also make whole route decisions in this scenario but road links may be affected negatively by the presence of incidents.

Scenario 3: With incidents, with diverting ability: Participants begin a journey by making a whole route decision. They receive travel time feedback up until a diversion opportunity and at this point are asked whether they wish to divert on to a different available path. Incidents may affect road links in this scenario with the same probabilities as in scenario 2.

The rationale for using this series of scenarios is that participants have the opportunity to learn unchanging network attributes as they progress through the experiment: in scenario one the range of travel times on routes under non incident conditions, in scenario two how and when incidents occur, and their impacts on travel time, and in scenario three how to exploit the opportunity to divert. The three scenarios split these three main aspects of participant learning into separate tasks with the intention of allowing for easier analysis of results.

The number of simulated days in each test is limited to thirteen on each of the three scenarios (39 in total). The number of 'days' in other experiments have included 25 (Bogers and Hoogendoorn, 2005), 41 (Iida and Uchida, 1992), 100 (Avineri and Prashker, 2003) and 300 (Ben-Elia and Shiftan, 2010). Bogers, Viti and Hoogendorn (2005) describe the number of iterations as an important aspect of obtaining accurate results, as too many can lead to 'fatigue and bad responding'.

3.2.1 Network description

The road network, used in this experiment is shown in figure 3.1 along with associated link travel time distributions. Where links are labelled as holding a travel time drawn from one of two distributions, that with the higher mean is the ‘incident affected’ travel time state profile and the lower is the ‘standard’ state profile. Participants are made aware during the experiment whether the roads they are currently traversing are in the incident afflicted state. They do not receive information regarding the state of any other.

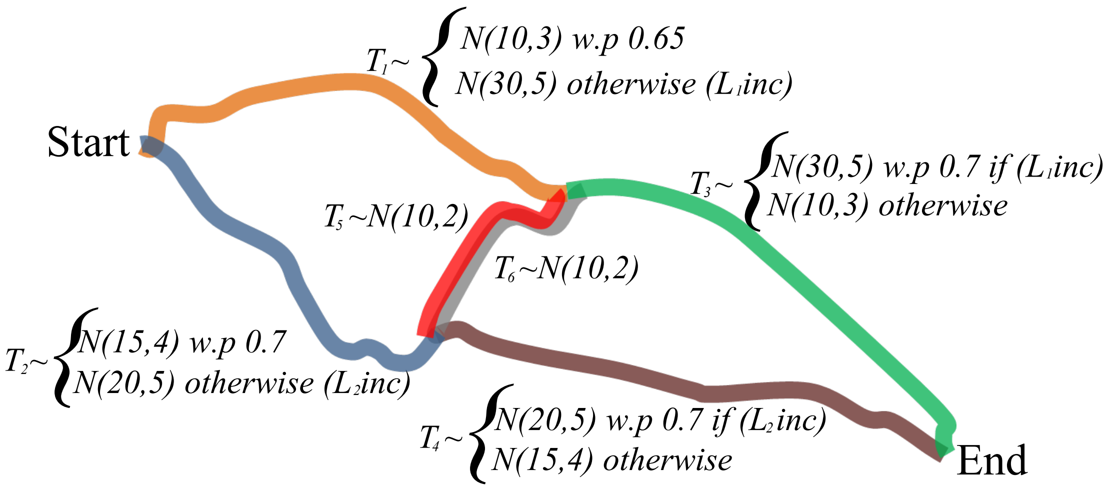


Figure 3.1: Network description showing distribution of link travel times in minutes.

Links 1 and 3 are designated as generally faster ‘highway’ links, links 2 and 4 are slower ‘town’ links and links 5 and 6 can be considered ‘connector’ links joining the highway and town routes. The four routes available through the example network are therefore: entirely travelling on the highway (route 1), beginning on the highway then moving to the town (route 2), entirely travelling through the town (route 3) or beginning in town and then transferring to the highway (route 4). On each simulated day, if incidents are possible in the scenario, a new incident configuration is determined randomly and without influence from other day’s conditions. ‘Upstream’ links 1 and 2 may be affected by incidents with a fixed probability but ‘downstream’ links 3 and 4 are only affected (with a fixed probability) if their corresponding upstream link is affected that day. Allowing downstream links to be in the incident profile without upstream links being so, a plausible situation in reality, would have no expected effect on diversion decisions, since subjects cannot use the information en-route, so is excluded here. Average route travel times with delays possible and without are given in table 3.1.

Route	**Name**	**Links**	**Average travel time *without* incidents (mins)**	**Average travel time *with* incidents (mins)**
1	All highway	R1, R3	20.0	42.1
2	Highway to town	R1, R5, R4	35.0	49.2
3	All town	R2, R4	30.0	32.7
4	Town to Highway	R2, R6, R3	35.0	45.6

Table 3.1: Average travel times of routes traversing the network shown in figure 3.1

3.2.2 Implementation details

The study was conducted at the University of Southampton over a 4 week period. The game interface, shown in figures 3.2 and 3.3, was left unattended and running in the entrance area of the main engineering building within the university during opening hours and passers-by were invited to participate through on screen information while the simulator was idle. Since the space is frequented by staff, visitors and students of all disciplines using lecturing facilities, it was expected that this would provide a sufficient spectrum of subject characteristics. Demographic data relating to age, gender and driving frequency was collected voluntarily from the subjects.

As the survey was left unsupervised for periods of time it is possible that either some participants began the study without fully understanding the objectives, or that others interacted with the experiment with the intention of not providing sensible responses. In an attempt to reduce the effect, only participants who completed the full first scenario's responses were used in the analysis, and evaluation of the aggregate results includes sense checking that participants generally understood what was being asked of them. This is another reason why the first scenario is intentionally simple.

The experimental network is laid over a map of the town of Maidstone, UK, since the road structure of the town closely matches that which is of interest here although travel time distributions used in the experiment are not taken from the location. Participants were asked about their familiarity with the town but previous surveys which have been modelled on both real world locations (Wardman et al., 1997) and networks not existent in reality (Lu et al., 2010a) have suggested that obtained results are not influenced by this factor (Katsikopoulos et al., 2002). The use of a real world network location is not expected to provide any additional motivational information for route choice beyond what is presented by categorising links as 'highway' and 'town'.

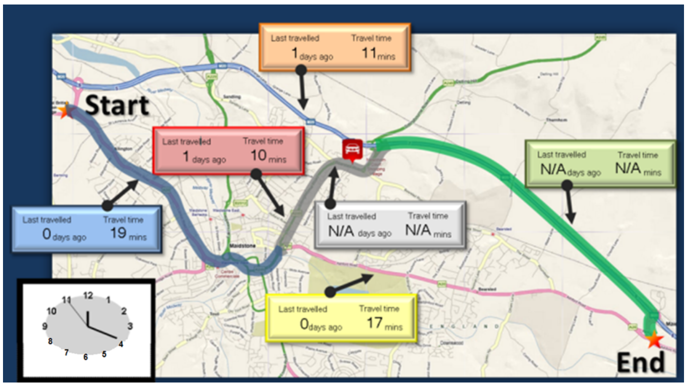


Figure 3.2: TV wall screen

Figure 3.3: Touch screen interface

The survey interface consists of two devices: a 3x3 screen TV wall, displaying the majority of information and visual feedback of participant's decisions, and a touch screen display through which participants make their choices and enter information. After pressing to begin the experiment, subjects are presented with an overview of study objectives and asked for demographic data before beginning the experiment itself.

Since subjects participated in the unattended experiment voluntarily there was no obligation to remain through to the end of the experiment. Accordingly if no button presses are registered for a 10 minute period the game resets to the unattended idle screen after a 30 second on screen count down. Data provided by those who did leave the experiment early was stored and used in aspects of the analysis. An investigator also attended some randomly chosen trials and was able to speak to a number of participants about their thoughts and decision making processes during the experiment.

The experiment interface, coded in C#, stores participant response data as individual comma separated value (csv) files inside of a secure, passworded directory which are then probed for analysis using scripts written in Python. Random numbers, determining experienced travel times and delay structures, are seeded from the system clock so participant experiences are different in each trial although they follow the distributions shown in figure 3.1.

3.2.3 Sample properties

Over the 4 week period 123 participants took part in the travel simulator experiment. Participants were also offered the option to not specify responses to each demographic question asked. 80% of participants specified that they were male and 16% that they were female. 42% of the sample was aged 17-22, 27% were aged 23-30, 21% were aged 31-50 and 5% were over 50 years old. 52% of the sample specified that they drove weekly and 42% said that they did not. Additionally 10% of the sample said that they had driven in Maidstone within the past year and 85% had not.

The participants who finished all three scenarios took on average 10 minutes to complete the experiment from pressing the idle screen to completion. All 123 subjects who provided data used in analysis completed scenario 1, 85 subjects (69% of the original sample) completed scenario 2 and 74 subjects (60% of the original sample) completed scenario 3.

3.3 Results and Discussion

Figures 3.5, 3.6 and 3.7 show the 'daily' route splits from the sample during scenarios 1 (without incidents, without diverting), 2 (with incidents, without diverting) and 3 (with incidents, with diverting) respectively. This is aided by figure 3.4 which shows the proportion of participants making a different choice on each day compared to what they chose on the previous day (smoothed using a moving average with window size 3). Table 3.2 contains the mean and standard deviation of route proportion splits for the last 8 days of each experiment scenario and table 3.3 further splits decisions made in the last 8 days of each experiment scenario by subject demographic data.

Since the study scenarios are purposefully incremental, the complete analysis and discussion of results is here presented in a similar fashion.

3.3.1 Scenario 1: No incidents, no diverting ability

Figure 3.5 shows the choice splits for the 123 participants during scenario 1. Here route 1 (all highway) is on average the fastest (as in table 3.1) but participants must try other routes in order to form an impression of overall road network travel times. Despite having no prior knowledge of travel times, just of road class, almost all participants initially choose route 1 (all highway) then on the following day 66% of participants tried a different route. In a concave shaped curve close to that found in a similar experiment

	Route 1		**Route 2**		**Route 3**		**Route 4**	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Scenario 1 (no incidents, no diverting)	0.80	0.04	0.06	0.02	0.08	0.03	0.07	0.03
Scenario 2 (incidents, no diverting)	0.36	0.04	0.09	0.03	0.44	0.04	0.12	0.03
Scenario 3 (incidents, diverting)	0.46	0.04	0.03	0.02	0.49	0.05	0.02	0.01

Table 3.2: Mean and standard deviation of route splits for days 5-13 of each experiment scenario

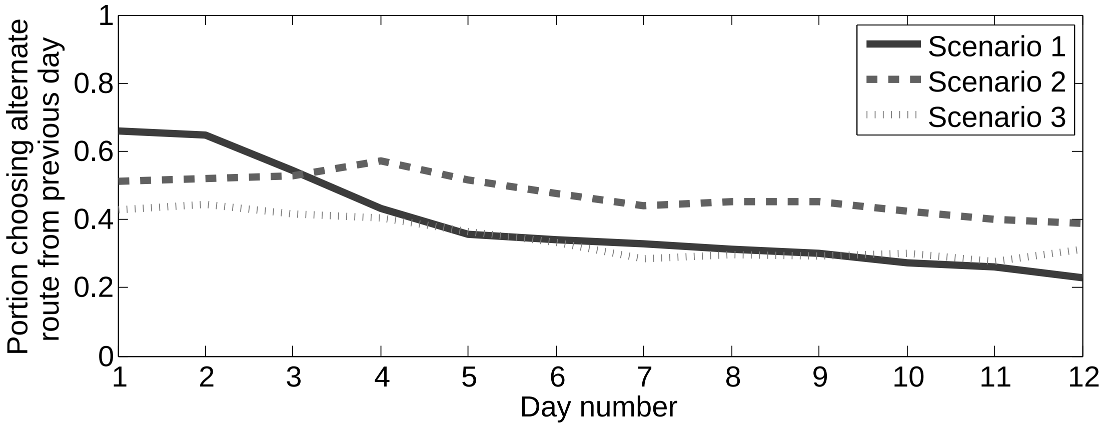


Figure 3.4: Portion of participants choosing a route which is different to that chosen on the previous day

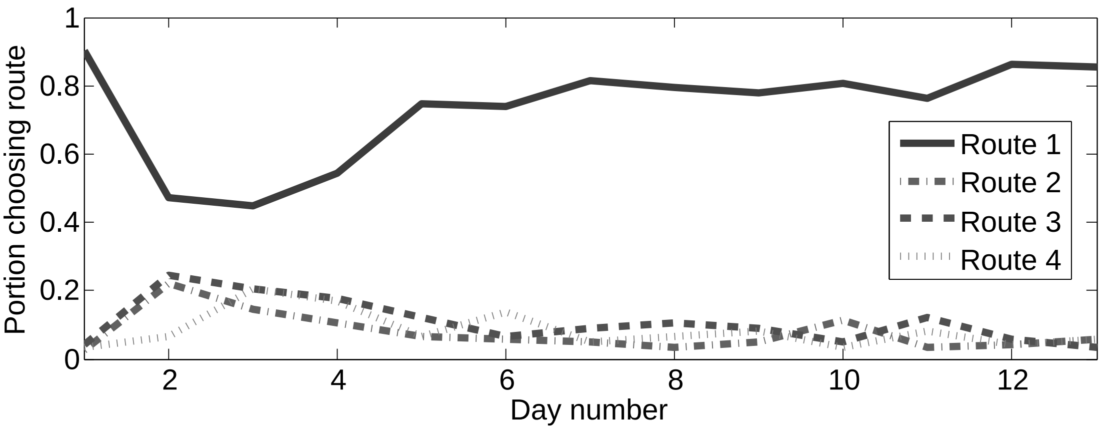


Figure 3.5: Proportional route splits in scenario 1 (no incidents, no diverting ability)

carried out by Ben-Elia, Erev and Shiftan (2008) and resembling the shape of 'ramp up' or 'information lag' trend described in chapter 1, participants successfully identify and

	Gender		**Age range**				**Regular driver?**		**Familiar with Maidstone?**	
	Male	Female	17-22	23-30	31-50	50+	Y	N	Y	N
Scenario 1										
Route 1	0.81	0.75	0.79	0.83	0.81	0.66	0.79	0.81	0.81	0.88
Route 2	0.05	0.05	0.06	0.04	0.05	0.08	0.05	0.05	0.02	0.06
Route 3	0.07	0.11	0.09	0.07	0.08	0.06	0.07	0.08	0.07	0.08
Route 4	0.06	0.09	0.08	0.04	0.06	0.19	0.08	0.06	0.09	0.07
Scenario 2										
Route 1	0.36	0.30	0.32	0.39	0.38	0.28	0.35	0.35	0.45	0.34
Route 2	0.10	0.08	0.10	0.05	0.13	0.13	0.11	0.08	0.09	0.09
Route 3	0.42	0.56	0.43	0.49	0.39	0.48	0.44	0.45	0.35	0.46
Route 4	0.12	0.05	0.15	0.07	0.09	0.13	0.10	0.13	0.09	0.11
Scenario 3										
Route 1	0.48	0.40	0.36	0.54	0.53	0.53	0.54	0.35	0.46	0.46
Route 2	0.03	0.02	0.02	0.03	0.06	0.00	0.05	0.01	0.04	0.03
Route 3	0.48	0.53	0.60	0.43	0.39	0.44	0.39	0.62	0.44	0.49
Route 4	0.01	0.05	0.02	0.01	0.02	0.03	0.02	0.02	0.06	0.02
Scenario 3 - incident encountered										
Diverts	0.45	0.38	0.64	0.36	0.30	0.38	0.42	0.48	0.28	0.46
Does not divert	0.55	0.62	0.36	0.64	0.70	0.62	0.58	0.52	0.72	0.54
Scenario 3 no incident encountered										
Diverts	0.06	0.13	0.08	0.07	0.06	0.06	0.10	0.04	0.26	0.06
Does not divert	0.94	0.87	0.93	0.93	0.94	0.94	0.90	0.96	0.74	0.94

Table 3.3: Demographic splits for decisions made in the last 8 days of each experiment scenario

develop a tendency to use the fastest all highway route. Evidence for the formation of habit and confidence in choice is further suggested by the fact that 45% of participants chose the same route on the last 4 days of the scenario and 33% made the same choice for the last 6 days of the experiment. This observed behaviour in this relatively straight forward scenario suggests that participants understand the aims and objectives of the experiment and replicates some of the findings of other studies such as that by Ben-Elia, Erev and Shiftan (2008).

In conversation with participants during this scenario, the assessor found that many initially tended to hold strong preconceptions of relative road travel times prior to their first trip, providing rationalisations for day one decisions such as 'I'll choose the highway as that should be fastest' and 'I don't know the local roads so I'd pick the highway on day one'. Previous work has also found that in networks where travellers hold no information they tend to choose 'major' routes or those with the lowest perceived free flow travel time even when they are aware that congestion can occur (Selten et al., 2007). As the scenario progressed participants replaced their preconceptions with acquired network knowledge, for example commenting 'I know the highway route is fastest so why would I choose any other?'. Other routes were chosen occasionally as 'variety seeking' or as a 'check' that route 1 was still fastest, but none of the interviewed participants believed any route other than 1 was the choice with lowest travel time overall.

Demographic data for this scenario, found in table 3.3, suggests noticeable differences in behaviour and attitudes between gender and age range. Women and older participants (over the age of 50) are less likely to choose route 1 than males and younger subjects. In this experiment, where no factors other than travel time are considered in route choices, these groups may either take longer to determine the fastest route, are less confident in their decisions or are more likely to seek out variety. Kaplan and Prato (2012) describe males as exhibiting 'higher mnemonic capability, higher level of familiarity with the choice and environment and better spatial and time saving skills' suggesting that males may be expected to outperform females in this scenario.

3.3.2 Scenario 2: With incidents, no diverting ability

Figure 3.6 shows choices for the 85 participants who completed scenario 2 where on average route 3 (all town) is fastest due to the presence of incidents in the network but route 1 remains fastest on incident free days. Once again the majority of participants initially choose route 1, possibly because during scenario 1 they formed a preference for this choice, but the portion of subjects choosing route 1 decreases quickly to a distribution where route 3 takes a higher average share of decisions.

The route choice distributions in days 5-13 of scenario 2 and scenario 1 are compared using a Chi-squared test for homogeneity, rejecting the null hypothesis that distributions

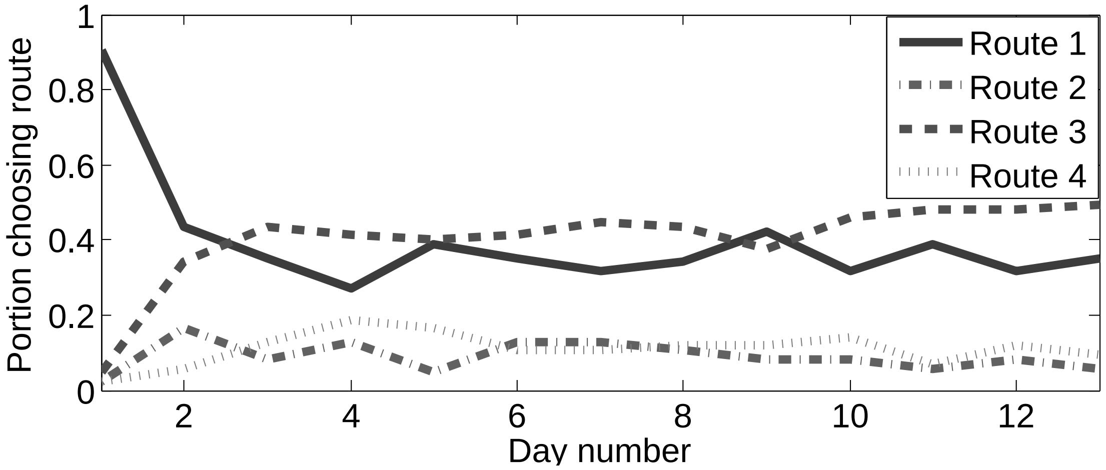


Figure 3.6: Proportional route splits in scenario 2 (with incidents, no diverting ability)

are identical at a 1% confidence interval. It is clear that the potential for incidents to occur does have an effect on initial route choice decisions as participants become less likely to choose the riskier route 1. Ben-Elia, Erev and Shiftan (2010) report that an increase in variability of travel times 'moves behaviour in the direction of random choice' and also that as experience of a road system grows, drivers tend to favour routes with less travel time variability.

Supporting this, during this scenario interviewed participants reported that they generally felt less in control of their experienced travel times, prompting them to hold less of a preference for any particular route. This is further evidenced in figure 3.4 which shows that in this scenario the portion of subjects changing routes from one day to the next remains relatively high throughout compared with other scenarios.

Many participants appeared to note that the highway route was more likely to be affected by incidents and were more likely use a different route immediately after a negative experience. From the data 65% of participants chose a different route on the day after experiencing an incident in the last 8 days of this scenario, yet only 28% of participants chose different routes after no incidents during the last 8 days. Ben-Elia, Erev and Shiftan (2010) describe how this phenomena, termed the 'hot stove effect' can contribute towards drivers choosing lower variability routes which may further explain the higher proportion of participants choosing route 3.

All demographic groups tend to predominantly use route 3 yet, among alternatives, males are more likely than females to use route 1. Studies have reported that men are more willing to take travel time risks than women (Khattak et al., 1995) which may explain this behaviour.

3.3.3 Scenario 3: With incidents, with diverting ability

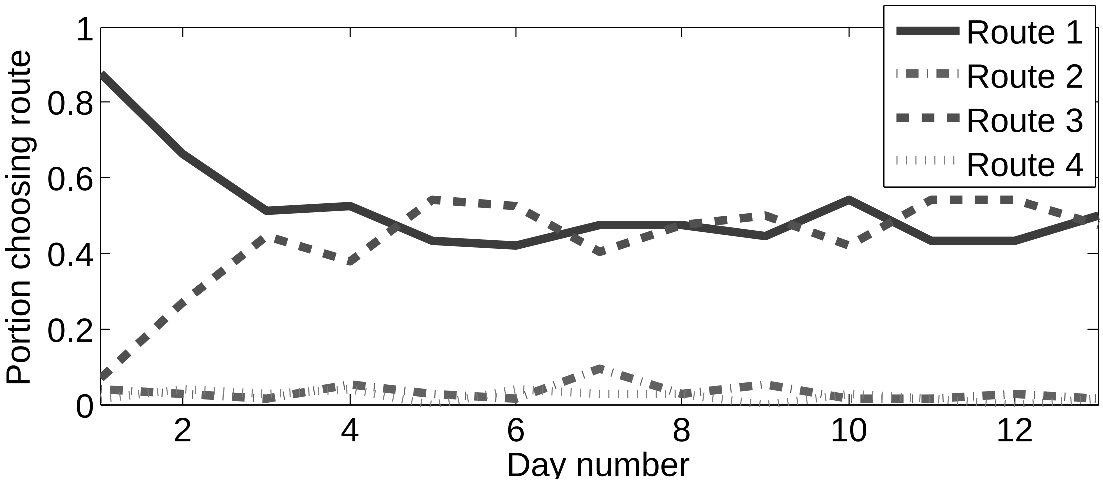


Figure 3.7: Proportional route splits in scenario 3 (with incidents, with diverting ability)

In scenario 3 travel times and incident probabilities are the same as in scenario 2 but participants are aware that they are able to divert en-route on to a different path should they change their belief of which route is fastest. Once again subjects almost exclusively choose route 1 on day one and then form a distribution which is closer to that of scenario 2 but with a greater tendency to initially choose route 1 again. In this scenario, as is reported in table 3.2, the relative difference between proportions of participants choosing route 1 and 3 decreases and the proportions of participants choosing routes 2 and 4 is less than in scenario 2. Comparing scenario 3 against scenarios 1 and 2 using a Chi-squared test for homogeneity the null hypothesis is rejected at a 1% confidence interval, suggesting that participants are behaving in a different manner during those scenarios.

During this scenario participants reported that they felt more in control of their eventual travel time and that their decisions were being made less randomly. This is reflected in the lower proportion of participants changing routes between day in figure 3.4.

Demographic data in table 3.3 shows that older, male participants are more likely to risk the potentially faster route 1 in this scenario than younger, female participants who favour route 3. This agrees with the finding in scenario 2 that men display a higher risk seeking tendency than women. Also regular drivers seem more likely to choose route 1 than irregular drivers.

Regarding how participants react to within day conditions, figure 3.8 plots whether participants remain on their originally chosen path or divert and whether they have experienced an incident effect on upstream links 1 and 3. The distributions remain approximately equal throughout the scenario, showing that around half of experiment subjects will divert in this experiment when encountering incident affected road links.

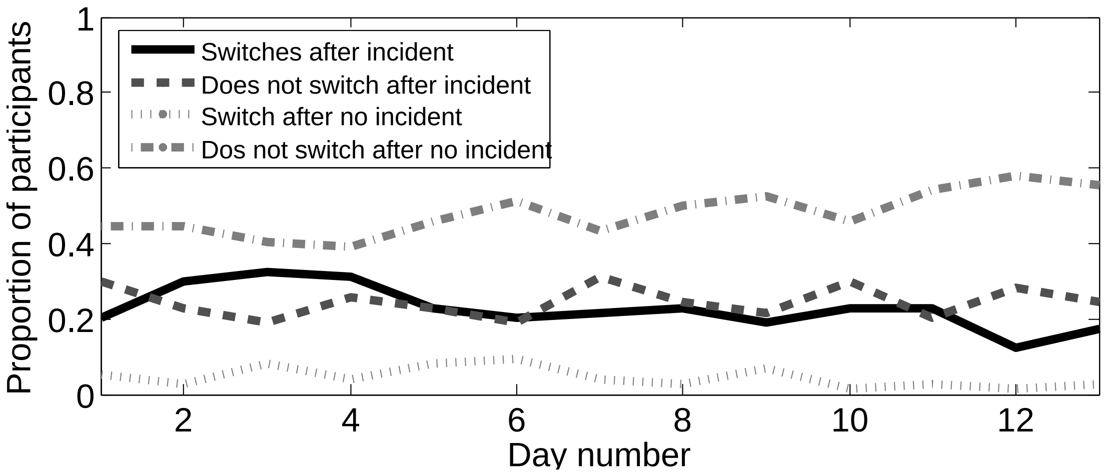


Figure 3.8: Participants reaction to within day conditions during scenario 3 (with incidents, with diverting ability)

Demographic data from table 3.3 suggests that when encountering an incident men and younger drivers are more likely to divert which agrees with the findings of other studies (Khattak et al., 1995).

3.4 Summary and Conclusions

This study has sought to identify how travellers perceive the possibility of non-recurrent congestion occurring, and whether potential opportunity for diverting affects route choice even without the provision of information from an external source. This is an important area of research as it regards expectations of driver behaviour in a general setting yet has received little academic attention thus far.

The study was intentionally structured in such a way that initially subjects were allowed to operate in an environment which had previously been explored within available literature, where decisions were made without the opportunity for diversions. That assumption was then relaxed to create what is arguably a more plausible choice environment. One may wish to further examine whether the ordering of scenarios plays a part in the final outcome as an extension to this work, since in scenario 1 the Route 1 option was demonstrated as being superior in clear conditions.

As a way to compare the final route choice distributions on each of the three scenarios, highlighting the key results in a new graphical format, figure 3.9 plots a ‘point cloud’ of participant decisions in each of the final eight surveyed days in each scenario. This approach is adopted here because it represents the complete choices made on one day as a single point rather than four. It is considered acceptable to group routes 2 and 4 for this comparison since relatively few participants chose them on any day. As a result it is considerably easier to compare different days and scenarios, particularly for the later modelling work presented in this thesis.

Two new variables are created to implement the point cloud: $g_1 = f_1 - (f_2 + f_4)$ and $g_2 = f_1 - f_3$ where f_1, f_2, f_3, f_4 are the daily proportional choices on routes 1, 2, 3 and 4 respectively. Points on the two dimensional state space are referred to using (g_1, g_2). The route flow state space therefore falls within the triangle defined by $(1, 1)$,$(-1, 0)$ and $(0, -1)$, representing 'all adopt route 1', 'all adopt route 2 or 4' and 'all adopt route 3' respectively, as seen in figure 3.9.

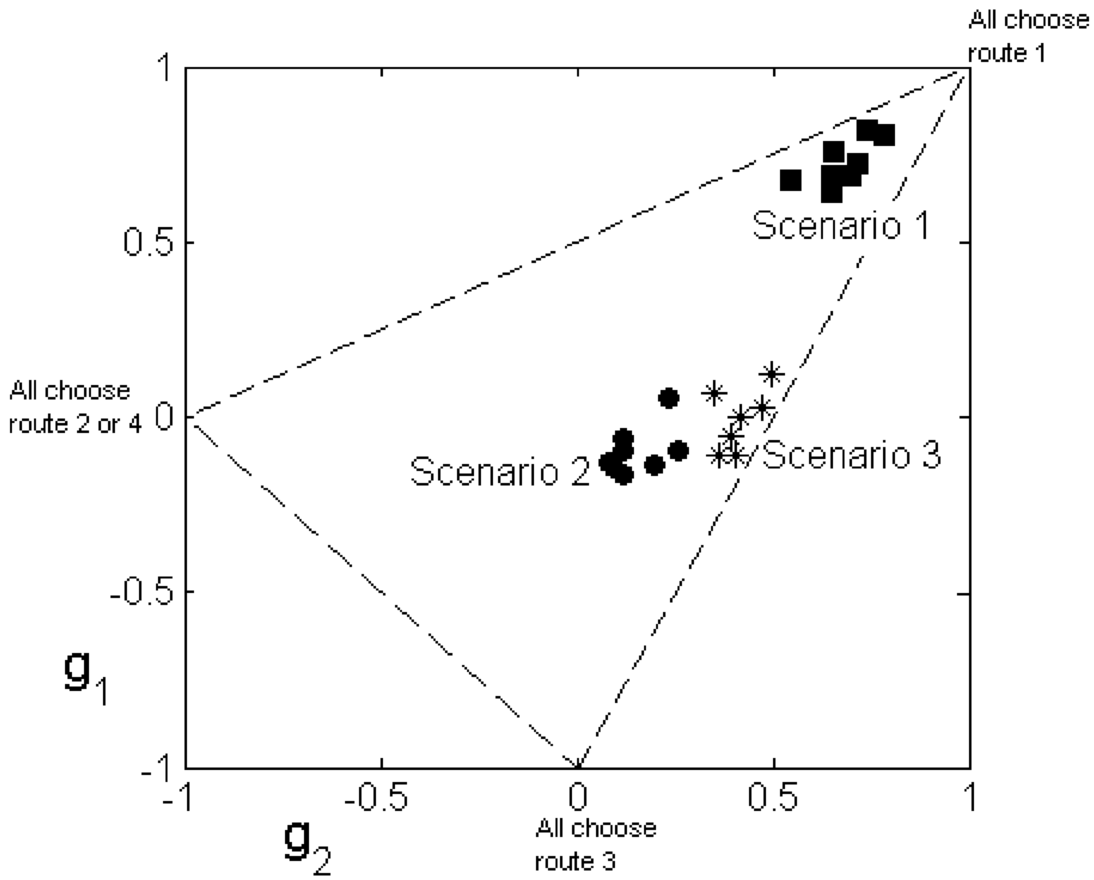


Figure 3.9: Point cloud of participant choices in the final eight surveyed days of the experiment in the three scenarios

Figure 3.9 appears to validate many of the assertions that have already been made and provides a useful comparison of the magnitude of the differences between the experiment scenarios. It shows that each scenario produces a distinct choice result distribution and also the effect that the scenario 3 choice structure has on participant decisions where the final result is closer to 'all choose route 1' than 'all choose route 3'.

The tendency is therefore shown for participants in scenario 3 to move away from choosing inefficient routes 2 or 4 like they may have done in scenario 2, and instead initially choose one of the major route options - allowing participants to 'take a chance' on a more favourable option in the knowledge that they can potentially divert. The point cloud appears to be more concentrated in scenario 3 than scenario 2, suggesting that at an aggregate level choices are similar between days and would display less variation in flows.

3.4.1 Findings supporting other studies

A number of the findings of this study support other observations within the available literature. This adds credibility to the sample and experimental procedure adopted here and adds further evidence to the assertions from elsewhere:

- Habit formation appears to be a major force in route choices and over time the probability of choosing an alternative route on the following day decreases (Selten et al., 2007; Iida and Uchida, 1992). Participants are more likely to choose a route if they have chosen it before.
- The attractiveness of a route option is affected negatively by the possibility of travel time increasing incidents randomly occurring on any day. Higher variance in travel times push drivers towards more random behaviour and lower preference for one route over another, termed the *payoff variability effect* (Ben-Elia and Shiftan, 2010; Avineri and Prashker, 2003).
- When participants hold no information of travel time distributions they rely on other sources of information such as route labels in this study, often prompting them to choose the highway route in each scenario on the first day (Lu et al., 2010a).

It appears that in this study participants are able to determine their preferred routes sooner than in others where more iterations were required (Ben-Elia and Shiftan, 2010). This is possibly because labelling the routes gives participants strong clues about properties (which are valued more than direct experience) or because travel time distributions are more distinct, resulting in faster routes more clearly being faster.

Some of these points would benefit from further follow up studies, such as the noted emphasis placed on route labels. The experiment seemed to show a strong bias towards the 'all highway' route in every scenario regardless of performance. In reality this would likely vary with experience and potentially drivers learn to disregard labels over longer time periods.

3.4.2 Novel findings and implications for diversion forecasting

Further to the findings previously which are in line with other reported studies, a number of novel contributions from this work exist:

- The attractiveness of a 'risky but potentially faster' route option has been found to increase by the opportunity to divert en-route

- The fraction found to switch routes when encountering an incident occurs is higher than that which have been found 'real world' in studies where information is provided en-route to travellers (Chatterjee and McDonald, 2004). This may be because participants have learned that downstream links are highly likely to be affected in the scenarios presented. One could conclude in this experiment that, upon encountering an incident the decision to divert is random since an approximately equal proportion switch as do not. However it is likely that some form of strategy is at play because when an incident does not occur the vast majority of participants choose not to switch.

- Demographic factors such as age and gender appear to play a large role in driver routing decisions regarding incidents in this experiment. Males appear to exhibit a higher overall tendency to take risks, favouring routes which have a chance of being faster should incidents fail to occur, especially when they are aware that they can divert en-route. Regular drivers also seem to be more risk taking. In comparison women are cautious in their decisions, choosing routes with less variation in travel times and being less likely to form a habitual route.

Regarding the applicability of these findings to the generation of traffic flow forecasts, it is not sufficient to make forecasts based on the assumed actions of individual travellers alone. This is because each decision maker affects the actual network state themselves through their own choices (survey work incorporating this effect includes Selten et al., 2007; Iida and Uchida, 1992). It is therefore necessary to understand the *implications* of drivers adopting the routing strategies suggested by this work, which is a benefit of modelling, and working towards meeting thesis objective three.

Chapter 4

Demand forecasting and modelling behaviour change

Having explored aspects of how individual travellers make their route choice decisions in reality, both from studies within the available literature in chapter 2 and through the survey experiment undertaken in chapter 3, it is useful for forecasting purposes (and a host of other reasons as explored by Epstein's work 'Why model?' (2008)) to translate these trends and findings into algorithmic models. These provide estimates of how a population would behave in any general travel situation.

In particular this chapter focusses on introducing and critiquing common modelling algorithms and their inherent assumptions. Such critiques regard already discussed concepts such as assumptions of rationality (in section 2.1), learning (in section 2.3.1) and reaction to a change in network conditions such as states (in section 2.5.1). The previous chapter showed how the possible occurrence of states can have an impact on the learning process and resultant route preferences.

The core challenge posed here is that the situation is being examined where drivers have no externally provided information and must rely on their previous experience to guide perception updates within day as well as between days. This goal drives the innovation of this study into how best to represent incomplete knowledge, regarding thesis objective 3.

This chapter starts by presenting an overview of knowledge relating to modelling route choices and demand forecasting, then the system consequences of route choice decisions and decisions changing with time, then finally explores disaggregate intelligence (or 'agent based') approaches to modelling route choice systems. This works towards the thesis aims of better representing driver reactions to time varying phenomena within traffic forecasting models.

4.1 Modelling route choice behaviour in a single network state

The transport forecasts considered in this work are mathematical in nature and provide numerical solutions based on functions and algorithms. For the initial part of this chapter the state of a route can be assumed to be fixed over time, in keeping with the traditional approach towards demand forecasting as per the four stage model of section 1.2 and the top left portion of Meite's table 2.1 (2011). The discussion in this section primarily focusses on how drivers choose routes in an unchanging environment to give an overview of existing models.

Mathematically, in such a system the role of route choice algorithms is to determine a route flow vector, $\mathbf{f}$ by translating a route cost vector, $\mathbf{C}$ (which is generated by the transport network under consideration in its current state), into a proportional flow split through a function, p, and multiplying by overall system demand, $\mathbf{F}$, which is assumed to come from a higher stage of the Four Stage Modelling approach discussed in chapter 1.

$$\mathbf{f} = \mathbf{F}p(\mathbf{C}) \tag{4.1}$$

Chapter 2 opened with a discussion regarding assumptions of rationality in choice modelling, describing the conflict modelling between what Simon (1955) describes as an 'economic man' (capable of making perfect decisions with full knowledge of his or her options) and a more realistic 'boundedly rational' man (prone to random errors in judgement, perception and only holding limited knowledge of available options). As was stated in section 2.1, the interpretation of bounded rationality used in this thesis is that among known choices 'better alternatives are chosen more often' (Su, 2007) which is believed to fit with Simon's core argument.

4.1.1 Route choice of the 'economic man'

The route choice of Simon's 'economic man' (1955) is entirely deterministic and would be known to a forecaster who possesses full knowledge of available options.

Supposing here that drivers act in such a way as to strictly minimise their generalised costs of travel, the corresponding route choice model is deterministic least costs path (sometimes referred to as 'all or nothing' or an application of Dijkstra's algorithm (1959)) where all drivers travelling from an origin to destination only traverse the path which incurs the least generalised costs to themselves.

Although the pure concept of an 'economic man' is a simplification of knowledge and decision making abilities, all or nothing assignment may be useful when little computation is a requirement or differences between route costs are large. An example might be such as a choice between an uncongested highway or a minor road where flows would be heavily in favour of one choice.

4.1.2 Stochastic route choice and algorithms

Stochastic route choice models allow for elements of bounded rationality to be incorporated into the decision making algorithm. To capture perception errors for individuals choosing among discrete alternatives (in many applications of modelling) the multinomial logit (MNL) model is often adopted. This still assumes that drivers are adopting the least cost path but adds a random mathematical perception component ε to the deterministic utility ($c_r = V_r + \varepsilon$) of an option, and so spreads driver decisions across different alternative options in a manner following a describable distribution. In the MNL model, the random component ε is Gumbel distributed, resulting in a choice equation of the form

$$P(r) = \frac{\exp(-\beta c_r)}{\sum_{j \in \mathbf{R}_i} \exp(-\beta c_j)} \tag{4.2}$$

where $P(r)$ is the probability of an individual choosing route r (or, from an aggregate perspective, the proportion of trips using route r) and β is a calibrated spread parameter. As an example, figure 4.1 shows a three route network with given deterministic costs (i.e. independent of vehicular flow) given in the form V_r^n where V is the deterministic cost, r is the route number and n is the day (which is at this stage general and unchanging across days). Table 4.1 shows how all or nothing and MNL route choice models would proportionately split demand across the three routes.

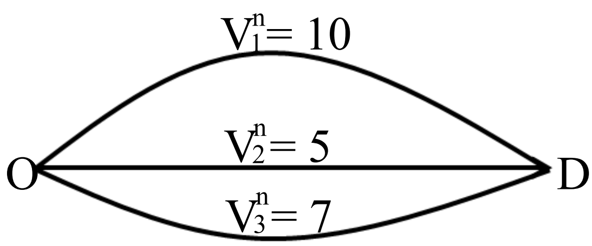


Figure 4.1: Route costs on an illustrative 3 route system

Route	All or nothing	MNL			
		$\beta = 10$	$\beta = 1$	$\beta = 0.1$	$\beta = 0.001$
r_1	0.0	0.0	0.01	0.25	0.33
r_2	1.0	1.0	0.88	0.41	0.33
r_3	0.0	0.0	0.11	0.34	0.33

Table 4.1: Proportional route flows for the network in figure 4.1 according to all or nothing and MNL choice models

Algorithms such as that provided by Dial (1979) (sometimes known as the STOCH algorithm - a useful practical overview of which is provided by Sheffi (1984)) can be used to load flows on to networks with overlapping routes. However, the MNL form described here is based on the assumption that error terms for each option are identically and independently distributed (i.i.d) and, although this is satisfied for the network in figure 4.1 where the routes do not interact, for most real world networks the presence of overlapping route paths prohibit the accurate use of the standard MNL model.

A number of extensions to the MNL have been suggested to overcome this limitation and capture route flow relationships such as including a deterministic Commonality Factor (CF) in route cost formulations, in addition to the random error component, which is equal to the proportion of overlap with other routes in the choice set, as originally proposed by Cascetta, Nuzzolo, Russo and Vitetta (1996).

The original C-logit formulation provided no theoretical justification and limited practical application, prompting Ben-Akiva and Bierlaire (1999) to propose the Path Sized Logit model which adds a Path Size (PS) attribute to route costs which is derived from discrete choice theory for aggregate alternatives, thus making the cost of a route $c_r = V_r + \beta_{\mathrm{PS}} \ln \mathrm{PS}_r + \varepsilon$ where β_{PS} is a calibrated parameter.

Ramming (2001) extended the model provided by Ben-Akiva and Bierlaire (1999), incorporating a parameter γ (≥ 0) to decrease the impact of unrealistically long paths in the choice set (setting $\gamma = 0$ corresponds to the original PS model where only the *number* of overlapping links are considered to negatively affect route utility). This formulation of the MNL choice function is used within the route choice models in this work.

$$\mathrm{PS}_r = \sum_{a \in \Gamma_r} (\frac{l_a}{L_i}) \frac{1}{\sum_{j \in \mathbf{R}_i} (\frac{L_i}{L_i})^{\gamma} \delta_{aj}} \tag{4.3}$$

Bekhor, Ben-Akiva and Ramming (2001) find that the PS-Logit model outperforms the C-Logit approach by explaining a greater number observed driver routing decisions within their Boston data set.

As an alternative to MNL models, Probit-based models were first used in route choice by Daganzo (1977) and do not suffer from the path overlapping issue since these adopt a multivariate normal error distribution which use an arbitrary covariance structure. However in practice this requires Monte Carlo based simulation to determine choice probabilities, whereas logit-based approaches can be written an analytical form as in equation 4.2. A practical application of a probit-based model is provided by Yai, Iwakura and Moricihi (1997).

The other main class of route choice models is Multivarirate Extreme Value (MEV) which include for example Cross-Nested Logit (CNL) models (as described and compared within Bekhor et al., 2006) which allow options to belong to a number of structured 'nest' sets. However this requires many parameters to be determined which Ben-Akiva, Bekhor and Ramming (2006) find limit its accuracy in forecasting flows.

For these reasons the path-size logit model is employed throughout the discrete choice aspects of this work, based upon a driver's knowledge of available options.

Discrete choice models need not only be used to provide feasible route splits given actual travel costs. In the context of a learning process these discrete choice models would provide a routing split 'given a set of *perceived* network costs' to drivers, rather than *actual* costs. This is also in line with the first principle of Simon's bounded rationality (1955) in section 2.1. For example in a 'day one' situation, when no driver is aware of the actual travel costs on any route, the perception may be that routes have equal costs (which may well not be the case when drivers experience the routes). In fact, the experiment conducted in chapter 3 suggested that travellers consider the categorisation of a route (such as main highway or small road), possibly related to speed or free flow travel time expectations, in their initial route choices.

4.2 Behaviour change and long term equilibrium

The example road network in figure 4.1 is a simplification of reality since, as was described in section 2.3, the travel time (so generalised cost) experienced by travellers is affected by the volume of vehicular traffic traversing a stretch of road. As Sheffi (1984) describes at the opening of his work, the traffic system will undergo a feedback process over time of drivers making route choice decisions in order to minimise the generalised costs of travel, but those costs varying with numbers of drivers choosing a route.

Considering only 'rational' deterministic route choice models in a single typical state at this stage, where each driver strictly traverses the route of least cost to themselves (or, using an MNL model with spread parameter $\beta = \infty$), a game theoretic Nash equilibrium is eventually reached, denoted as User Equilibrium (UE) based upon Wardrop's first principle of equilibrium (Wardrop, 1952) (the precise definition and meaning of which is discussed below). At UE, traffic flows are arranged such that each used route from each origin to destination pair has generalised costs which are minimal and equal to any other, providing no incentives for a driver to use a different route on the next journey. Mathematically this can be written as formulated by Smith (1979):

$$f_r > 0 \Rightarrow c_r(\mathbf{f}) \leq c_s(\mathbf{f}) \quad \forall_{r,s} \in \mathbf{R}_i, r \neq s, i = 1, 2, \ldots, N \tag{4.4}$$

Beckmann, McGuire and Winston (1956a) first showed that finding the Deterministic User Equilibrium was equivalent to solving the non linear minimisation problem:

$$\min\ z(\mathbf{q}) = \sum_{a \in \mathcal{L}} \int_0^{q_a} c_a(\omega) d\omega \tag{4.5}$$

$$\text{s.t.} \quad \sum_{r \in \mathbf{R}_i} f_r = d_i \tag{4.6}$$

$$f_r \geq 0 \quad r \in \mathbf{R}_N \tag{4.7}$$

$$q_a = \sum_{r \in \mathbf{R}_i} f_r \delta_{a,r} \quad \forall a, \forall i = 1, 2, \ldots, N \tag{4.8}$$

Although properties such as existence, uniqueness and optimality conditions of the Beckmann formulation have been analysed (Beckman et al. (1956b) summarised within Sheffi (1984)), Smith (1979) points out that this formulation only applies to 'symmetric' traffic assignment problems where link travel costs are only the result of the flows traversing them, so cannot consider link flow interactions such as intersections or the 'blocking back' creating congestion structure described in section 2.6.

To solve the Beckmann formulation, techniques such as the method of convex combinations or Franke-Wolfe Algorithm (LeBlanc et al., 1975) and the Method of Successive Averages (MSA) are most commonly applied (a description is given within Sheffi (1984)). These are both used to solve general nonlinear optimisation problems, the Franke-Wolfe approach splitting the problem into a successive combination of two steps: linear 'direction finding' (finding a feasible solution to improve the objective function) and nonlinear 'line search' steps (determining weights to combine average the direction finding solution with previous results to obtain a new minimum of the objective function), and the MSA method instead using predetermined fixed weights in the line search step thus making it simpler to program but potentially longer to find a solution. Sheffi (1984) also provides details of how these approaches can be extended to determine an stochastic user equilibrium solution.

As an example of finding equilibrium in congested systems, suppose that the network shown in figure 4.1 features routes with generalised costs V as per the Bureau of Public Roads (BPR) travel time function (Bureau of Public Roads, 1964):

$$V_1 = 10(1 + 0.15 \frac{q}{50}^4) \tag{4.9}$$

$$V_2 = 5(1 + 0.15\frac{q}{200}^4) \tag{4.10}$$

$$V_3 = 7(1 + 0.15\frac{q}{100}^4) \tag{4.11}$$

Table 4.2 provides the result of Dial's algorithm for SUE (implemented in Excel) and the UE result (found using a non-linear equation solver within the mathematical processing software Mathematica) for assignment across these three routes. A higher β produces flows which are closer to the UE solution and by decreasing β route choices become more random as drivers are assumed to hold less preference for the fastest route (such as one might wish to do to represent travel times in minutes rather than hours and a travel time saving of one minute is considered less important than a travel time saving of one hour).

Route	**UE**	**MSA with Dial's algorithm**			
		$\beta = 10$	$\beta = 1$	$\beta = 0.001$	$\beta = 0.00001$
r_1	124	136	149	226	327
r_2	602	592	579	418	337
r_3	274	271	271	357	336

Table 4.2: Equilibrium route flows for the network in figure 4.1 assuming 1000 drivers and travel time profiles from equations 4.9, 4.10 and 4.11

Dial's algorithm (and non-linear equation solvers) simply provides the expected flow set at system equilibria (defined as satisfying Wadrop's first principle) and provides no suggestion of how flows would arrive there over time from any initial starting conditions, as is the 'ramp up' period. In this case one would need to explore how cost *perception* to drivers varies with time, rather than actual travel costs.

Although it is not explored within this work, another often used 'solution' to traffic flow forecasting worthy of mention here is the System Optimal (SO) formulation. Under SO conditions, the average travel time is to be minimised rather than each individual travellers own journey time, suggesting that drivers behave cooperatively. As Sheffi (Sheffi, 1984) comments, the value of the SO objective function may serve as a 'yard stick' by which different flow patterns can be measured under different scenarios. Traffic managers may try to use traffic management systems and techniques to attain as close as possible to SO flows. Transport planners may be interested in the system optimal solution as a new scheme may attempt to move expected route flows closer to that value.

It is further important to remember that the preceding discussion on route choice models only consider a network in a single state, where the complete cost definition can be described in a single set of equations. Although this can be give a useful indication of expected traffic flows given such state assumptions, the preceding chapters of this work have shown the sensitivity of route choice decisions to network states.

4.3 Equilibrium by fixed routing or routing preference?

Wardrop's first principle of transport equilibrium (1952) states:

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.

A common interpretation could suggest that drivers are expected to hold a single route which they would traverse and, once equilibrium was found would never try any other route. This would be in keeping with the assumption that drivers adopt a habitual route and then never choose any other. Were this the case, when a network change occurs, such as a change in speed limit or the opening of a new road, drivers would *never* think to engage in network exploration and discover that the network change had occurred (resulting in a non-equilibrium system).

A perhaps more plausible interpretation in line with the direction of this thesis, which still adheres to Wadrop's first principle, is based on the El Farol bar problem presented by Arthur (1994). This concerns a bar in Santa Fe where, should less than 60% of the town's population attend in an evening, they would have a better time than had they remained at home. If more than 60% of the town's population attends they would have a worse time than if they remained at home. To translate the problem into a route choice perspective, consider two route system (representing 'the bar' and 'staying in') where the performance of 'the bar' option becomes progressively worse until a threshold is reached and then the alternative route (representing staying at home) is more desirable.

Should the entire population within the El Farol Bar problem adopt a single 'pure preference' strategy (attend the bar or not) then some members of the population would lose out on every night. Instead, the equilibrium falls in a 'mixed strategy' where individuals possess a *probability* of choosing whether to go to the bar or not on a given night. Should a system property change (such as the capacity of the venue increasing, increasing the occupancy under which a negative experience is had) then this form of equilibrium can adapt to accommodate that change.

This interpretation lends itself well to transport equilibrium where equilibrium routing is based on preference rather than fixed choice. In a congested network routes which hold a lower capacity, so are more likely to become congested, would be lower down a driver's preference than one with a higher capacity which can accommodate many vehicles. But they may occasionally still be chosen.

Routing preferences do understate the role of personal habit. In the El Farol bar problem, it is likely that in reality some individuals will develop a tendency to either 'mostly attend' or 'mostly not attend' and the population will not play the same strategy each night. The same is true of transport systems, where some users will have stronger tendencies than others to choose a particular route.

This thesis has presented evidence of routing being a preference rather than a fixed choice (albeit with evidence of habit), where the strength of preference is related to the relative benefit obtained. In chapter 3, and supported by further empirical studies (Ben-Elia et al., 2008; Li et al., 2004) drivers were shown to be willing to try a different route on any given day, even if they had experience that it was not optimal and had already chosen a different route which could be regarded as ‘habitual’. In the route choice survey presented in this work in chapter 3, some participants regarded this choice as a ‘check’ that other travel properties on unobserved routes had not changed.

In many ways the concept of routing preference is incompatible with the interpretation of bounded rationality adopted by Mahmassani (Mahmassani and Jou, 2000; Hu and Mahmassani, 1997; Mahmassani, 1990; Chen and Mahmassani, 1999) where ‘indifference bands’ dictate that an adjustment would not occur unless driver experience fell outside of the tolerable level, replicating human desire for habit. Mahmassani points out that indifference bands vary over time, such as widening after repeated unsuccessful days of experience falling within them, but if network experience remains the same then individuals would not explore for the sake of exploration, creating a fixed routing equilibrium. Mahmassani uses network disruption such as planned engineering works to provide a trigger for drivers to change their routing preferences (Mahmassani, 1990).

4.4 Day to day ‘common intelligence’ route choice adjustment models

Day to day route choice models are a class of traffic assignment techniques which *do* consider the adjustment of flows progressively towards an equilibrium, capturing the ramp up profile. These can sometimes be referred to as ‘disequilibrium’ models which forecast route choice behaviour outside of the equilibrium rather than other techniques, such as the Method of Successive averages, which only provide fixed equilibrium solutions.

In day to day models, modelled drivers are assigned to routes on a given ‘day’ (which is an iteration of the process) based on a function of previous travel times on each route. Bie and Lo (2010) describe day to day models using the form where y is a function which translates the previous day’s route flows, $\mathbf{f}^{n-1}$ into a new set $\mathbf{f}^n$. $\mathbf{f}$ can be referred to as the system state:

$$\mathbf{f}^n = y(\mathbf{f}^{n-1}) \tag{4.12}$$

Cantarella and Cascetta (1995) refer to these functions y as ‘filters’ and take various forms. If the filter function, sometimes called the ‘transition function’, is deterministic then the resulting future states are also deterministic:

$$\mathbf{f}^n = y(y(\ldots(\mathbf{f}^{n-1})\ldots)) = y^n(\mathbf{f}^n) \tag{4.13}$$

This transition process can also be described as an 'evolution' of model state. The definition of equilibrium in this methodology is therefore:

$$\mathbf{f}^n = y(\mathbf{f}^n) \tag{4.14}$$

i.e. a route flow system which re-generates its own route flow system on the next 'day' of the day to day model.

Some day to day models further incorporate 'memory length' (e.g. as described by Horowitz (1984), Cantarella and Cascetta, (1995) and Watling (1999)). In the context of route choice, 'memory' means that the costs of a route on day n are not only influenced by the previous day's travel costs (determined by route flows) but also by the *perceived* route cost on the previous day(s), $\mathbf{C}^{n-1}$.

$$\mathbf{f}^n = y(\mathbf{f}^{n-1}, \mathbf{C}^{n-1}) \tag{4.15}$$

$$\mathbf{C}^n = z(\mathbf{f}^{n-1}, \mathbf{C}^{n-1}) \tag{4.16}$$

The perceived cost updates according to its own function (in this example $z(\mathbf{f}^{n-1}, \mathbf{C}^{n-1})$), often a moving average. The memory updating process is described as the application of learning and perceptions changing over time. In 'common intelligence' models, this perceived cost is assumed to be shared by the entire population making route choice decisions.

From an aggregate perspective an 'evolving' day to day route choice system can be described as a Markov chain whereby future system states (where a state is a unique flow configuration) are dependent upon the system's history (Daganzo and Sheffi (1977) were among the first to use this terminology).

To summarise how day to day models may be applied in transport models, figure 4.2 illustrates the general approach taken towards day to day route choice modelling, replicated from Jha, Madanat and Peeta, (1998) who propose a Bayesian updating model which accounts for variation in travel time distributions. An initial perception of possible routes and travel times is set externally to the model, such as travel time at free flow speeds. This is potentially combined with external forms of information (such as provided by the media or word of mouth) during a pre-trip perception updating stage. The specific attributes relating to a route being perceived by drivers vary but usually for modelling purposes, as elsewhere in this section, only travel time is considered.

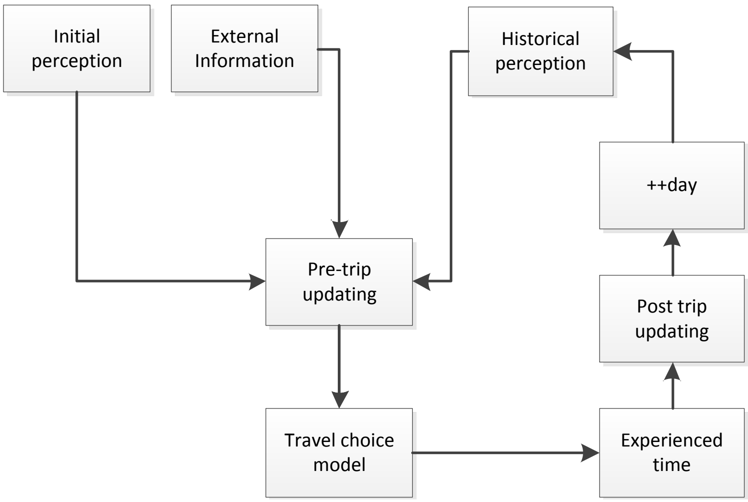


Figure 4.2: Individual decision making framework, (adapted from Jha et al., 1998)

4.4.1 Examples of the application of common intelligence day to day assignment techniques

Horowitz (1984) was one of the first researchers to examine day to day models of system evolution. He defines the two route system, in keeping with the descriptions above for days $r, k = 1, 2, \ldots$:

$$\begin{cases} \mathbf{f}_1^n = F(\mathbf{C}_2^n - \mathbf{C}_1^n) \\ \mathbf{f}_2^2 = (1 - \mathbf{f}_1^n) \\ \mathbf{C}_r^n = \alpha c_r^n + (1-\alpha)\mathbf{C}_r^n \end{cases} \tag{4.17}$$

A demand of 1 unit is assumed on the single origin-destination pair. $c_r(f_r)$ is the cost-flow relationship for routes 1 and 2. α is a learning parameter $\in [0, 1]$ and $F(\mathbf{C}_2^n - \mathbf{C}_1^n)$ describes the proportion of travellers choosing route 1 when the predicted route costs are $(\mathbf{C}_2^n, \mathbf{C}_1^n)$. This discrete choice is applied using a logit model.

Horowitz's model is used to show how a simple travel cost update and network loading mechanism can allow the convergence of route flows towards a single global stable equilibrium. The model also demonstrates how parameter settings (implying learning rates and sensitivity to travel time differences) may lead to unstable behaviour which does not evolve towards a stable equilibrium. Horowitz's model was expanded and explored further by Cantarella (1993) who classified system behaviour and its relationship upon learning rates and Cantarella and Cascetta (1995) who link the long term system behaviour with the Jacobian matrix of the cost transition function.

The solution to stochastic day to day models can be computed using simulation where travel times are drawn from microsimulation (models featuring detailed traffic interaction) rather than fixed flow dependent performance profiles such as the BPR function. A number of traffic microsimulators have been used with this approach to assign route flows such as DRACULA (Liu et al., 1995, 2006) and Vissim (Fellendorf and Vortisch, 2010).

As an example showing the usefulness of day to day models, particularly in the context of providing estimates of 'ramp up' behaviour, Bie and Lo (2010) illustrate the 'basins of attraction' of a three route system by exploring flow trajectories graphically. For example figure 4.3 uses the network defined by Watling (1999) with one OD pair connected by three routes, a fixed demand of two units and cost functions defined as:

$$\begin{cases} c_1 = \mathbf{f}_1 + 3\mathbf{f}_2 + 1 \\ c_2 = 2\mathbf{f}_1 + \mathbf{f}_2 + 2 \\ c_3 = \mathbf{f}_3 + 6 \end{cases} \tag{4.18}$$

Demand in the fixed system has just 2 degrees of freedom so Bie and Lo show that the unique system state, $\mathbf{f}$, can be fully described by two variables: $(g_1, g_2) = (c_1 - c_2, c_1 - c_3)$ which can be plotted converging to equilibrium from initial positions. This representation also inspired the point cloud formulation of figure 3.9 in section 3.4, showing how a survey sample distributes its choices on a single surveyed 'day's' decision, and is revisited later in this thesis. Since in this network route costs are asymmetric (route flows are a function of other route's flows as well as their own) the network has three equilibrium configurations, two which are stable and one which is unstable.

Route choices are not the only variable in transport systems which can be evolved in this fashion. As an example Mahmassani and Chang (1986) evolve driver departure times in 200 users in an urban environment, where travel time is dependent upon departure time. This model operates in a similar manner to route choice posed above ((dis)benefits are related to the number of users making similar situations) and converges to an equilibrium solution. Mahmassani and Jou (2000) also calibrate a day to day model of decision switching (both route and departure time), although this is based on single individual's preferences and does not consider resulting network flows.

The one known example of successfully developing an adequately validated model explicitly exploring flow system evolution is that developed for analysing traffic flows following the I35 bridge collapse in Minneapolis, Minnesota (He, 2010). The reason for this is that day to day models of the form described in the examples presented previously are too simple to capture the dynamics of actual route choice adjustments successfully. In the work of He, a prediction-correction framework was used to capture the effect of updating network perception (travellers are assumed to 'predict' other route flows prior to departure, affecting their own routing choice). One of the main benefits of the day to day

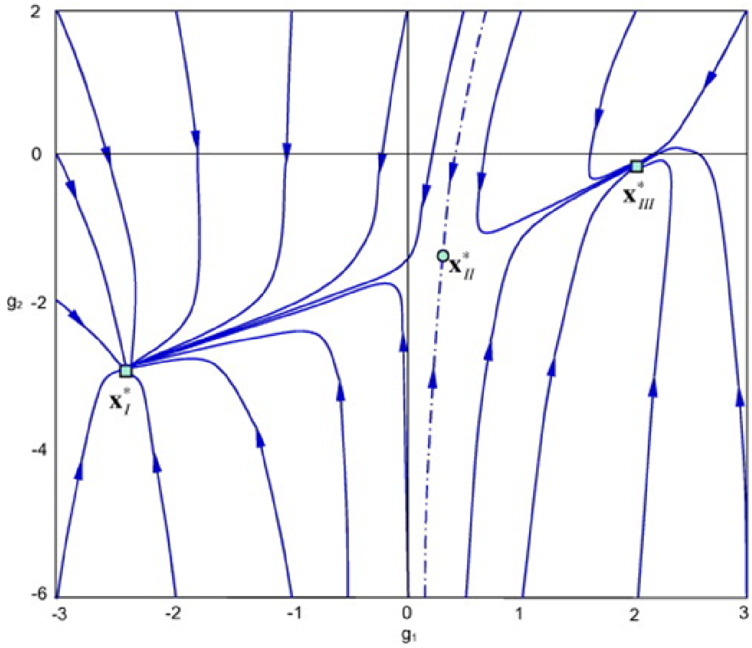


Figure 4.3: Route flow trajectories for the network evaluated by Bie and Lo (2010)

approach is that modelling learning processes can be more intuitive and (potentially) have greater psychological grounding than direct equilibrium calculation such as by the Method of Successive Averages.

4.4.2 Stochastic variables in day to day models

Cantarella and Cascetta (1995) along with Watling and Hazelton (2003) would describe the day to day route choice models presented above as being deterministic in nature even when the daily route choice modelling uses a logit model, which utilises distribution theory and provides a result traditionally known as Stochastic User Equilibrium flow set. They instead use the term 'stochastic day to day' for models explicitly using random variables which explicitly use stochasticity to compute flow trajectories. They show that a benefit of using truly stochastic variables is that variation in flows between days is captured, whereas deterministic processes tend towards a single fixed point equilibrium attractor solution.

In systems with computer generated random variables it is important to remember that the impression of stochasticity is given by the random number generator seed. If two identically structured algorithmic random number generators are initialised with the same seed then they will produce the exact same series of pseudo-random numbers. For example, an average over parallel simulations may in fact be over identical runs if the same seed is used. In many common programming languages the seed is by default initialised by the system clock unless stated otherwise, so repeated runs (launched consecutively) would not suffer from this problem. Further, Watling (Watling, 2002) provides examples of unexpected and implausible behaviour in day to day variances in flows caused by the specific stochastic assignment process adopted.

Expanding on the use of random variables, Cantarella and Cascetta also introduce a third type of learning model which is distinct in behaviour from the deterministic and stochastic 'common intelligence' models examined in this section. This new class is a 'stochastic process with disaggregate memory' where each member of the simulated population holds their own unique perception of the system. For the purposes of this thesis, each member of the population in such models are termed 'agents' which are examined in the next section.

4.5 Disaggregate 'agent based' models of route choice with learning

In reality only drivers who have personal experience of traversing a road are actually aware of what its exact travel time might be in the absence of external information, and, as was shown in chapter 2 on any day the experience may be vastly different to any other. As such, two drivers who have traversed the same road at the same time of day on two different days may hold a different perception of expected conditions on the road.

The goal of agent based models is to disaggregate the cost perception, c_r^n, distributing it among individual agents who *each* hold their own unique perception driven by their own experience - $\gamma_r^{z,n}$ is the perceived cost of route r by agent z on day n (for simplicity the z term will be omitted from here forward). This is illustrated in figure 4.4.

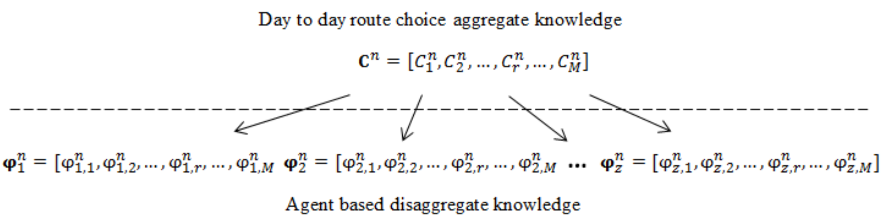


Figure 4.4: Knowledge conversion from day to day modelling to agent based

Nagel and Flötteröd (2011) and Bazzan and Kluegl (2013) provide field overviews of the use in agent based models in transport. This is not limited to assignment and route choice - agent based models have been used in traffic control and modelling traffic flow. Raney and Nagel (2006a) describe agent based transportation models as being the recent merger of two different disciplines: i) complex adaptive systems and ii) distributed artificial intelligence. Complex adaptive systems is a topic which examines the system level behaviour of many independently acting sub-entities. In many such situations, the system state is dependent upon each individual's actions and each individual's actions are dependent upon system state. A commonly cited example of complex behaviour is witnessed in ant colonies where ants adopting apparently simple 'rule based' behaviour are capable of exhibiting sophisticated behavioural patterns such as efficient search for food and resources (Resnick, 1997). Artificial intelligence deals with generating cognitive models capable of processing information and determining courses of actions. Raney and Nagel (2003) summarise Multi Agent Simulations (MAS) as: 'a combination of complex adaptive systems and distributed artificial intelligence, concentrating on the interaction of many, somewhat complicated agents.'

A research based simulation tool, MATSim, has been produced for implementing agent based choice models which Bazzan and Kluegl (2013) describe as being a 'step in the right direction' towards a usable modelling tool. This has been applied to real transportation networks including Tel Aviv (Bekhor et al., 2011) and Switzerland (Meister et al., 2010) - which remains the largest agent based transportation model created to date. Agent based approaches are typically computationally intensive, for example the Switzerland model features 10^6 individual agents in a network consisting of 10^6 road links and simulation runs can take days to complete. In such a system the representation of agents and computational memory requirements become an important limiting factor in model size.

The multi agent modelling approach does however lend itself well to parallelisation and distributed computing where groups of agents decisions can be formulated as separate processes on multiple processors. Nagel and Marchal (2006b) provide a discussion of computational techniques when working with agent based traffic simulation models. Agent based models can require large amounts of computing memory in order to store the beliefs of thousands or millions of individuals, especially when the network size is large.

Although not under direct consideration in this work (although it implicitly applies to the conceptual development of agent based models in general) a popular methodology for designing agent based models is the 'Belief, Desire, Intention' framework, a description is provided by Dia (2002) and Rossetti, Bordini, Bazzan, Bampi, Liu and Van Vliet (2002). This posits that each travelling agent holds a belief or current knowledge relating to the system, in the case of Tiang, Liang and Hiu's model described above this is simply the travel time on each route, an desire or objective which the agent wants to attain such as 'travel with the minimum journey costs', and an intention which is what the agent will do to reach their desire, such as pick the route choice with minimum costs to themselves.

Other agent based models used in the literature include those developed by Rossetti and Liu (2005) which include departure time choice and a lateness of arrival preference for drivers, and much of the work by Arentze (such as Arentze and Timmermans, (2005), Ronald et al., (2010)) who explores themes such as the impacts of modelling drivers gaining information relating to network structure, the role of social networks informing information levels and the application of activity models. Additionally evacuation models of urban environments are sometimes created using agent based methodologies (such as Chen and Zhan (2006)).

For this work only the factors influencing route choice are under consideration, since it is within the domain of traffic assignment. It would be expected that principles relating to knowledge acquisition and choice are equally applicable within other aspects of the four stage model.

4.5.1 Algorithmic details of agent based models and defining equilibrium

Nagel and Flötteröd (2011) provide the algorithm presented below to describe the process by which traffic assignment can be performed with multi agent simulations (which is similar to the framework in figure 4.2 provided by Jha, Madanat and Peeta (1998)). When dealing with choices made by individual agents, random variables are often used making the simulation 'Monte Carlo' in nature.

Algorithm 1: Route assignment based on Nagel and Flötteröd (2011).

1. **Initial conditions:** Compute some initial routing (e.g. best path on empty network for every agent or best perceived path given certain initial perception conditions)
2. **Iterations:** repeat until convergence criteria are met
   (a) **Network loading:** Load all agents on to the network, let them follow their routes and experience network conditions.:
   (b) **Choice set generation:** On the next day, compute new route options based on experienced network delays
   (c) **Choice:** Assign every agent to a route based on a discrete choice preference model

An example of the application of a simple agent based learning model extending day to day models as described, which the agent based models in this work build upon, is provided by Liu and Huang (2007) and expanded by Tiang, Liang and Hiu (2010). This features an agent model where perceived path travel time, φ_r^n is the only route cost considered when forming a route choice decision. Agents choose a route through a logit model so this is a 'routing preference' model. At the end of a discrete 'day', the exponentially weighted moving average update rule is applied with $\alpha \in [0, 1]$:

$$\varphi_r^{n+1} = \alpha(c_r^n) + (1 - \alpha)\varphi_r^n \tag{4.19}$$

In this update mechanism α is a parameter which represents how much weight is placed on previous experience. Due to the form of this equation, in earlier 'days' a greater weight is placed on initial perceptions than in later days when there is a longer history to base expectation on. This is in line with how one might expect knowledge of a road transport system to accumulate in reality. Generally, agent based models lend themselves well to replicating human decision making processes due to the individual focus on decision making and store of knowledge.

Figure 4.5 shows a simulation result provided by reimplementing the model used by Tiang, Liang and Hiu (2010) showing 700 agents choosing routes on a two route system defined with BPR travel time functions (1964) with a higher capacity 'major route' ($t_{\rm ff} = 20$, $Q = 600$) and a lower capacity 'minor route' ($t_{\rm ff} = 60$, $Q = 200$). Other parameters are $\alpha = 0.5$, $\beta = 0.05$ and initial travel time perception on both routes = 30 time units. Also shown is the MSA solution of route paths (Route 1 flow = 606.2, Route 2 flow = 93.8).

As figure 4.5 shows, on day one agents have no perception of which route would hold the lowest travel time, so the logit model application splits agents approximately equally. As a consequence of this, those on the minor route experience relatively high travel times and those on the major route receive relatively low travel times. The route flow system then appears to converge to what visually appears to be a (noisy) equilibrium distribution. The figure makes it clear that agent based models are similar to day to day representations but include stochasticity (noise) in route choice decisions since agents are computing probabilities of adopting routes, thus demand fluctuates.

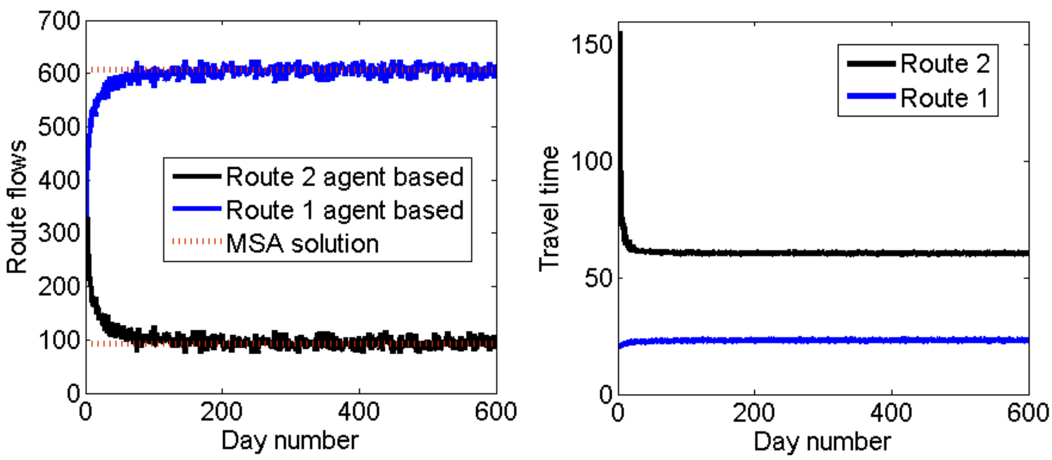


Figure 4.5: Result of simulating the network evolution process using a multi agent simulation, reimplemented based on the model by Tiang Liang and Hiu (2010)

Although one may determine visually from figure 4.5 that the system has tended towards an equilibrium distribution containing stochastic 'noise', defining mathematically whether the system has actually converged to an equilibrium is challenging. In the context of 'stochastic' day to day route choice systems, Cantarella and Cascetta describe that to their knowledge there is no formal technique to relate attractors of deterministic processes to their corresponding stochastic processes. Instead, they cite Davis and Nihan (1993) who showed that as a stochastic process converges, for large enough numbers of users, the distribution tends to the sum of a deterministic non-linear process and Gaussian white noise. They therefore summarise that the equilibrium link or path flows of a deterministic system 'become closer to the corresponding *average* values obtained through a stochastic process model'. Watling (2002) comments that this is a common justification for conventional equilibrium in stochastic conditions, although many applications in fine zoning systems do not meet the 'large enough numbers of users' criteria.

To this end, and as per a recommendation by Watling and Hazelton (2003), figure 4.6 examines the effect of running the simulation in figure 4.5 multiple times in parallel from different starting seeds (defined by the system clock) and taking the average route flow for each day. It shows that, as one would expect by averaging normally distributed results, the variance decreases and the mean appears to tend to fixed equilibrium solution also provided by MSA (= 93.8).

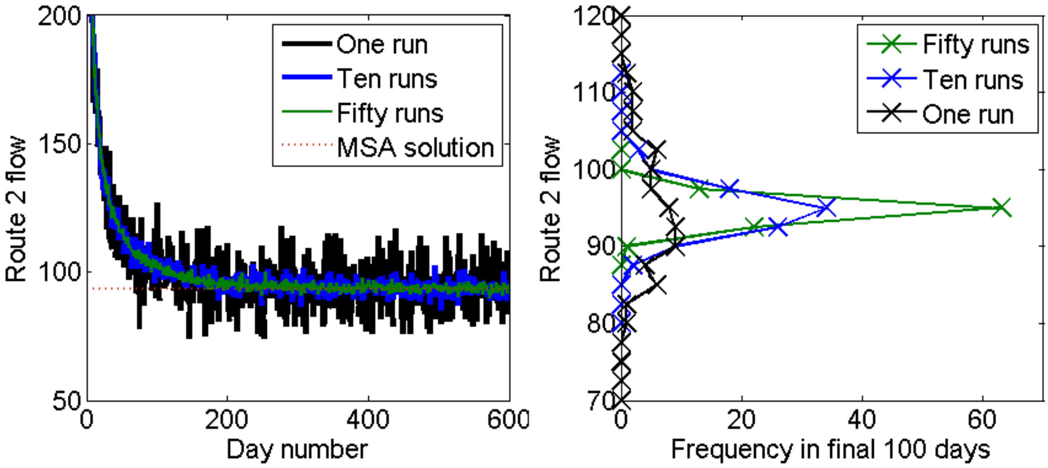


Figure 4.6: Effect of averaging over multiple simulation runs (left) and histogram of choices in the final 100 days in the system in figure 4.5

Watling and Hazelton (2003) mention that assignment techniques involving stochastic variables may yield flow sets which vary more than may be seen in reality because they do not include elements of habit, which should be noted. A possible extension to this work which may overcome this limitation may be adopting Mahmassani's interpretation of 'bounded rationality' where agents only change path on the next day if their believed payoff is greater than a threshold level (1997). However, despite this limitation, it will be shown that there are further benefits of adopting agent based approaches over traditional 'single solution' methods.

4.6 Agent based models versus 'common intelligence' models

Deterministic day to day models which do not utilise agents, such as those explored by Bie and Lo (2010), feature a form of 'common intelligence' meaning whenever a route is completed the travel time expectation for this route is updated for all drivers. Routing decisions are then made by dividing up the demand using a discrete choice model. As figure 4.7 shows, these systems evolve to the same solution as agent based methods and in these situations the resultant travel costs expectation is the same for all agents, which is the same as that found by day to day models.

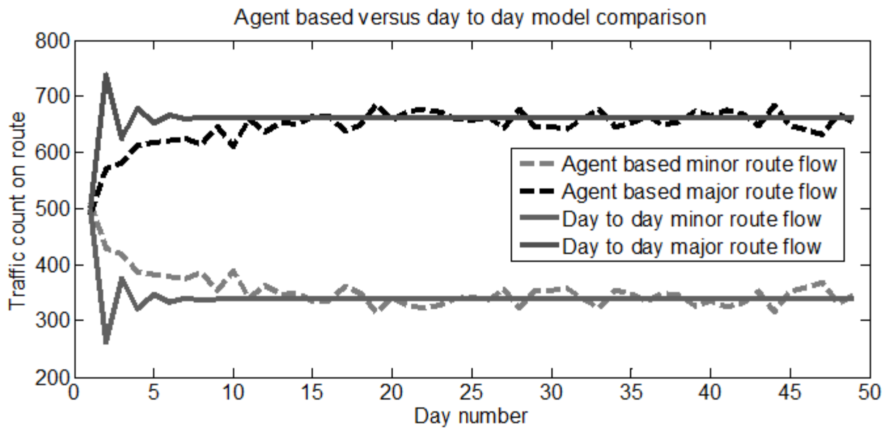


Figure 4.7: Deterministic 'common intelligence' route choice model evolution versus agent based approach

As a further comparison, Cantarella and Cascetta (1995) examine the differences in flow evolution and equilibrium in figure 4.8 between deterministic (as per the examples in section 4.4, stochastic aggregate (as per the description of 'common intelligence' models with stochastic variables in section 4.4.2) and stochastic disaggregate (as per the agent based models in section 4.5). They also include the equilibrium flows as computed by the Method of Successive Averages. They observe similar trends seen in figure 4.7, where the agent based technique evolves to the same (average) equilibrium distribution as the Method of Successive averages predicts. They also find that agent based techniques are more 'dampened' in their movements than common intelligence models. This effect is particularly noticeable when the common intelligence method finds itself in a periodic equilibrium pattern, repeating the same flows over a period of four simulated days and the agent based solution does not.

As well as producing an apparently more 'plausible' flow evolution trace visible in figure 4.7, the benefits of agent based simulation models are therefore found most when differences between agents and their attributes are important. These include multi class

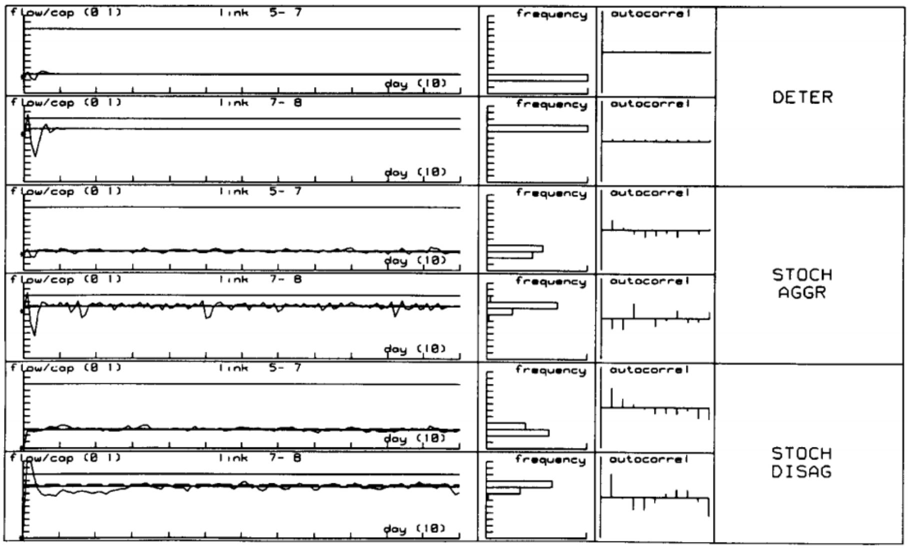


Figure 4.8: Comparison of deterministic, stochastic aggregate and stochastic disaggregate flow evolution from (Cantarella and Cascetta, 1995)

simulations, such as how microsimulation tools suppose that some drivers are more 'aggressive' than others and occasions where some agents receive more network state information than others (such as through route guidance and other in car navigation systems) (Sykes, 2010).

To be critical of agent based approaches, they are are more computationally intense and have larger memory requirements than equivalent common intelligence models. Each of the calculations carried out for each driver agent in figure 4.7 are carried out once for the entire population in the common intelligence model. The development of more sophisticated agent intelligence representations therefore can encounter longer run times and require more resources than a simpler model. This issue is further exacerbated by any need to launch multiple parallel simulations with full agent populations to average over.

Agent based models can also difficult to calibrate to observed data, since they contain many parameters relevant for each individual modelled. An example of successful calibration is provided by Mahmassani and Jou (2000) whose day to day choice model features 'indifference bands' to replicate habit as per their interpretation of bounded rationality. Although they do not apply their models to a complete agent based network as described here, the calibrated parameters provide insight into the relative preferences of individuals, such as the finding that departure time changes are more likely due to small variations in travel time than route choice changes, which can be triggered by larger variation.

4.7 Incorporating states into route choice models

This chapter has described methods for route choice and demand forecasting, beginning with the very simple 'assume that all drivers choose the least costs path' and eventually providing techniques whereby stochasticity causes between day variation in flows and plausible learning processes over time.

However in each of the algorithms and techniques provided the network to which demand is being assigned is unchanging other than flow dependent travel times. Therefore there is no consideration of varying network states between days and non-recurrent congestion which has been described in preceding chapters as being an important aspect of forecasting flows.

The work of Mahmassani (1990) includes a number of highly comparable conceptual elements to the work presented in this thesis such as bounded rationality and disaggregate preference building. In Mahmassani's work a 'planned disruption' state acts as a trigger for modelled drivers (which act as agents with disaggregate preferences, experiences and decisions) to reconsider their present whole route and departure time habitual choices on the next day. A day to day adjustment model evolves individual preferences until the system reaches a new equilibrium, defined as all agents choosing route and departure time combinations which fall within their current 'indifference bands' so a fixed and unchanging flow set. Since the 'planned disruption' acts for a number of days within the simulation, the agents do not explicitly consider them as being in a different 'incident afflicted' state, but are rather adapt their routing preferences in response to the network change in the same manner as the 'ramp up period' and day to day models would.

Mahmassani extends the indifference band model to include within day reaction to Advanced Traveller Information Systems (ATIS), including providing agents with the ability to engage in en-route diverting if a route is described by the ATIS source as currently being faster, based on participant response in laboratory experiments with varying reliability of information provision (Chen and Mahmassani, 1999). The focus of the analysis presented in this study is insight obtained from the value of calibrated parameters themselves and implications on design of information systems.Instead it is the mechanism of plausible en-route perception updating without ATIS, and its implication on routing decisions, is the focus of this thesis.

In a similar manner, Unnikrishnan, Boyles and Waller (2009) introduce the concept of 'recourse' where travellers are modelled receiving up to date network state information as they traverse the network. Some traffic microsimulation tools also incorporate within trip re-routing based upon information and familiarity, such as DynaMIT (Ben-Akiva et al., 2000) (calibrated with empirical data in Florian et al., (2006)) and PARAMICS (2010) although these models do not incorporate learning processes but rather posit that some travellers have prior experience of network conditions so hold a more accurate impression of network travel times, which is one of the benefits of agent based modelling. A model produced by Dobler (2013) also includes agents making en-route reaction to states but in this case also agents are made aware of travel times on links which they cannot observe, much like a source of ATIS.

Gao (2002) introduces a 'routing policy' approach for modelling strategic driver behaviour (extensions include Gao, Frejinger and Ben-Akiva, (2008) and Gao, Frejinger and Ben-Akiva, (2010)) which, although aggregate in nature rather than agent based, is believed to be the most appropriate current form of representing diversion behaviour although has thus far been limited to small network sizes (and applications to larger networks may be challenging). A routing policy is defined as 'a mapping from network states to choices of the next link'. The resulting rule based 'if - then' formulation specifies the individual link choices if links are found to be in any state. This approach does not consider the travel time on each link, but rather a policy choice is determined through a 'policy size logit model' which is combined with overall travel time factors.

The routing policy approach has not yet been applied (or calibrated) on larger networks beyond six links in size and it is likely that, as network size increases, the numbers of routing policies necessary to represent all possible choices and re-routing options soon becomes unmanageable (applying nested logit models of route choice to real world networks also become unmanageable in practice for the same reasons).

4.8 Summary and lessons learned for simulating network states varying with time

This chapter has sought to provide and assess a number of relevant techniques for forecasting traffic flows with particular focus on their capability in forecasting driver reaction to varying network states between days and within day. An overview comparison of the methodologies presented is provided in table 4.3.

This chapter has shown how each of the methodologies presented in table 4.3 builds on the previous set of techniques, incorporating their algorithms and assumptions into more general and behaviourally sound tools. For example the agent based approaches as described use day to day update mechanisms, as initially explored by Horowitz (1984) and summarised in the work of Bie and Lo (2010) but with the innovation that perception of network properties are disaggregate rather than assumed to be common to all users. Day to day algorithms themselves use discrete choice models but with the innovation that perceptions of network costs are allowed to change over a number of iterations, representing time, rather than being known by the choice algorithm.

It has been shown that agent based assignment models can provide the same solution as other techniques which are less computationally intensive and require fewer calibrated

Table 4.3: Description of the choice and perception updating models described in this chapter

Methodology	**Section described**	**Purely/ boundedly rational**	**Includes learning across time**	**Allows varying network state**	**Allows individual knowledge within day**
Deterministic least costs	4.1.1	Purely	No	No	No
Logit based choice models	4.1.2	Boundedly	No	No	No
Day to day common intelligence without stochastic variables	4.4	Boundedly	Yes	No	No
Day to day common intelligence with stochastic variables	4.4.2	Boundedly	Yes	Yes	No
Agent based	4.5	Boundedly	Yes	Yes	Yes

parameters. This is because under the 'routing preference' interpretation of equilibrium all agents hold a non zero probability of choosing any route available, so eventually at equilibrium all agents *do* have identical network property expectations, as per the assumptions made in other models.

The primary potential for agent based models to provide insight is in forecasting *within day* dynamics, which makes them suitable to evaluate behaviour under varying network states and incidents causing non-recurrent congestion. Within day it is highly implausible for a real world driver to observe conditions on every road link yet if drivers are capable of inferring network conditions based on personal experience then they may choose to divert. In order to meet thesis objective three, identifying a suitable modelling technique capable of capturing variable knowledge within a population, it is recommended that agent based techniques stand alone in their potential usefulness in this area.

Throughout this chapter a number of parallels have been drawn against the work of Mahmassani (1990) who investigates agent based models where drivers are assumed to hold an 'indifference band' in their decisions representing habit, and negative experiences (or, expectations of negative experiences provided by information systems whilst en-route (Chen and Mahmassani, 1999)) can force an agent to alter their choices. The modelling approach adopted in this thesis is similar except for two main differences, firstly that the assumption of bounded rationality is based on a routing preference rather than fixed routing as per section 4.3 and 2.1 and secondly that an agent will explicitly store previous experience in 'states', appreciating that conditions may only be temporary and other links may be affected.

A methodology compatible with states would, as per the argument in section 2.6, allow for agents to hold perceptions of *different* conditions on each route, varying by expected state. The expected state would then update en-route, either by the relationships suggested in section 2.6 or perhaps through signage The next chapter attempts to apply this direction to a novel agent based model, based upon the forms presented in section 4.5.

Chapter 5

An agent based model incorporating within-day reaction to states

An earlier version of this work was presented at the 4th International Symposium on Dynamic Traffic Assignment 2012 as (Snowdon et al., 2012c) and at the 45th Annual Conference of the Universities' Transport Study Group (UTSG) as (Snowdon, 2013)

5.1 Motivation and goals of this study

The preceding chapters have identified the potential benefits of forecasting driver behaviour in time varying 'non-recurrent' network conditions, both within day and between day, which are in this thesis termed 'states' as per the discussion in section 2.5.1. A distinct state is defined as a period of time when the network has measurably different properties such as lower free flow speed and/ or lower capacity. Changes in states may be caused by exogenous or endogenous events such as inclement weather, road traffic accidents and the clearing of road traffic accidents (Emmerink and Rietveld, 1995). A distinct state may last for a few minutes or hours at a time but is not what would be considered 'usual' operation.

Section 2.6 put forward the hypothesis that boundedly rational drivers (as per the interpretation presented in section 2.1) are capable of personally predicting, with varying degrees of success usually dependent on experience, the state of a network link without directly observing it whilst en-route to their destination. This is most likely caused by relationships between link conditions such as irregular congestion patterns providing 'clues' regarding network performance elsewhere. Chapter 3 described a route choice survey which was undertaken as part of this thesis to suggest whether and to what degree drivers themselves do actually draw these conclusions and act on their behaviour. It showed that in the presented scenario participants would not only divert from their initially chosen path when network performance was expected to be poor, but the ability to divert from their path altered their initial perception of which route was best to choose also.

The primary purpose of this chapter is to devise and examine a simple model where the learning and en-route switching behaviour displayed in chapter 3 is allowed. This goes some way towards meeting thesis objective three, the implementation of a model featuring variation in knowledge among a population, and five, to describe and overcome associated technical challenges, as defined in section 1.4.4.

The preceding chapter explored the ability for modelling and forecasting techniques to capture the influence of states on network demand as required by the aims of this thesis. It found that the majority of techniques are designed to forecast traffic flows in 'average' network conditions which are unsuitable. Agent based techniques were determined to be the most potentially useful for modelling driver reaction to states, where variation in knowledge both between day and within day can be incorporated.

The purpose of the model presented in this chapter is to explore a scenario whereby agents, representing plausible drivers, must utilise their experience of network conditions (congestion structure) on previous days to update their perception of road network attributes while en-route. The aim is to show, by means of a simple model, how incorporating past personal (i.e. incomplete) experience within an agent's perception of network conditions can affect traffic flows and provide evidence of the impact that including such behaviour would have within traffic forecast models. The presented agent based model and specific network structure, including representation of incidents themselves, is heavily inspired by the dynamics found in chapter 3 where next day decisions for agents are based on previous experience.

5.2 Capturing non-recurrent congestion in an example road network model

The simple road network considered within this model is structurally persistent across the entire set of simulated days during which a fixed population of agents makes repeated daily trips between a single origin and destination pair. As per algorithm provided in section 4.5.1 by Nagel and Flötteröd (2011), once all agents have chosen their routes a travel time is computed for each link and agents experience the travel times on links forming their chosen route, as used by others including Tian, Liang and Liu (2010). To represent recurrent congestion, all link performance functions adopt the Bureau of Public Roads (1964) travel time function where link travel time, t is a function of variable link flow q, constant free flow travel time t_f and effective capacity Q:

$$t(q, t_f, Q) = t_f(1 + 0.15(q/Q)^4) \tag{5.1}$$

On the majority of simulated days, road links can be considered to be in their 'normal' state of operation where only recurrent congestion can occur, which is caused by volume of traffic. This can be considered to be the 'average day' profile for which the majority of traffic forecasts are typically generated.

However, on a relatively small portion of days, road links may be negatively affected by non recurrent congestion, resulting in them being in what is here described as a 'perturbed' state and taking longer to traverse for the same amount of vehicular demand. This free flow travel time increase is coupled with a capacity decrease in keeping with observations in reality by researchers including Knoop, Hoogendoorn and Adams (2009) in table 2.2. For example a vehicle blocking one lane of a three lane highway would both require other drivers to slow down in order to avoid it (increasing free flow travel time) and reduces the road's capacity as one lane is out of operation (and cars are travelling slower in the remaining lanes).

The emphasis of this model is to examine variable agent knowledge within day and the result of agents learning congestion structure which can cause them to adapt their intended path en-route (as opposed to whole route average travel times). For this purpose an external probabilistic relationship between road link profiles is also applied, as inspired by the method adopted by Gao (2002). In reality many congestion patterns are the emergent result of every driver's routing decisions themselves (as discussed in chapter 2), which is a valid extension to this work and examined later in this thesis, but for the purposes of this simple model a congestion structure is externally applied - mimicking instead perhaps physical (i.e. non demand dependent) network attributes such as severe bottlenecks and rights of way structures.

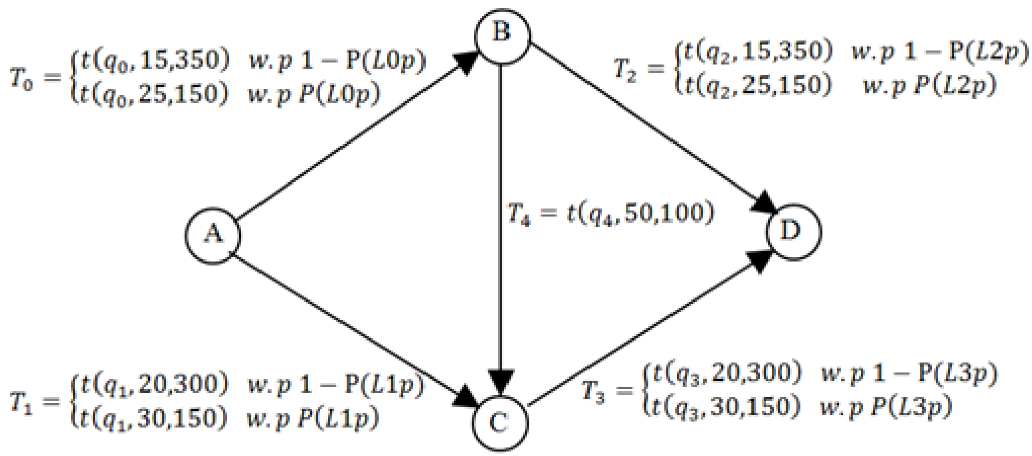


Figure 5.1: Example network under consideration.

Route number	**Flow count**	**Route description**	**Node path**	**Link path**
1	f_1	'Major route'	A→B→D	0→2
2	f_2	'Major to minor route'	A→B→C→D	0→4→3
3	f_3	'Minor route'	A→C→D	1→3

Table 5.1: Routes through the network shown in figure 4

The three routes which traverse the network in figure 5.1 are defined in table 5.1. The node path A→B→D (consisting of links 0→2) is characterized as the 'major route' which in the 'normal' state can accommodate more traffic with a lower travel time than the path A→C→D (links 1→3) which is termed the 'minor route'. However, for sufficiently high demand on the major route, agents using the minor route find themselves benefiting from a shorter travel time. Therefore at an equilibrium flow configuration, assuming zero non-recurrent congestion, traffic would be spread across the major and minor routes. A connector link, 4, holds both a relatively high free-flow travel time and a low capacity such that it incurs a high travel time penalty to agents.

Links 0, 1, 2 and 3 are capable of being in the perturbed incident afflicted state on each simulated day which results in them adopting a relatively poor performance profile. The probability of this occurring ($P(Llp)$ for a link l, where p is used to denote the presence of a perturbation causing event) is given as:

$$P(L0p) = 0.4 \tag{5.2}$$

$$P(L1p) = 0.15 \tag{5.3}$$

$$P(L2p) = \begin{cases} 0.95 & \text{if L0 affected by incident} \\ 0 & \text{otherwise} \end{cases} \tag{5.4}$$

$$P(L3p) = \begin{cases} 0.9 & \text{if L1 affected by incident} \\ 0 & \text{otherwise} \end{cases} \tag{5.5}$$

Imagine a driver experiencing this road network in the real world. Having initially chosen route 1, once arriving at node B they have a choice - either to continue on link 2 whose state is unknown or switch to link 4, potentially incurring an increased travel time cost by using the low capacity connector link and further links in unknown states. Clearly a traveller arriving at node B who is aware of the probabilistic relationships in network performance structure can use their within day en-route knowledge to infer a new expectation of unobservable network link states and amend their perception of available route travel times. This behaviour guides the development of a 'strategic' adaptive route switching agent model which is explored in the context of route choice on this network. To most clearly illustrate the effect of allowing learning of within-day conditions, a 'naïve' behaviour model is also used where agents are incapable of re-evaluating travel times en-route.

5.3 Two approaches to modelling driver route choice behaviour

Central to the representation of driver knowledge in the routing models examined here is the expectation of travel time on a route r held by each agent: φ^r. Models which only consider recurrent congestion use a single variable to denote travel time (or generalised cost), such as those in the work of Bie and Lo (2010), but here the expectation of travel time is a combination of travel time expectations under incident and no incident conditions (γ and ω respectively) weighted by expectation:

$$\varphi^r = \sum_{l \in \Gamma_r} [E\{P(Llp)\}\gamma_l + (1 - E\{P(Llp)\})\omega_l] \tag{5.6}$$

This relationship may not take this exact form in reality but is sufficient for this model. As noted in section 2.5.1, drivers combine positive and negative experiences into a single travel time expectation in complex ways, for example as is described by Prospect theory (Kahneman and Tversky, 1979). Other researchers have begun to formulate travel time expectations using experience and prospect theory (Xu et al., 2011) which could be considered an extension to this work.

Exactly how equation 5.6 is updated and used depends upon the behaviour model adopted: 'strategic' or 'naïve' which forms the focus of this study - allowing within day knowledge variation to play a part in agent route choice decisions.

5.3.1 Naïve behaviour model

A 'naïve' model of agent routing behaviour is here one in which the expectation of a link being affected by an incident and falling into the perturbed state is simply based on an agent's previous experience of that link's conditions. It does not consider within day relationships with any other link states. Using such a formulation it is impossible to use within day acquired network state information to infer an updated impression of the state of any other link.

At the start of an agent's journey a route is planned using route costs derived from equation 5.6, using the agent's own stored perceptions of link attributes.

At the end of the trip, agent knowledge is updated by the following exponential moving average model where c_l^n indicates the actual travel time on link l on day n and α ($\in [0, 1]$)

is a learning rate parameter and q_l now represents the expectation of link l being in its perturbed incident affected state - $E\{P(Llp)\}$ in equation 5.6.

$$\gamma_l^{n+1} = \alpha c_l^n + (1-\alpha)\gamma_l^n \quad \text{if link } l \text{ is perturbed} \tag{5.7}$$

$$\omega l^{n+1} = \alpha c_l^n + (1-\alpha)\omega l^n \quad \text{if link } l \text{ is clear} \tag{5.8}$$

$$q_l^{n+1} = \alpha \cdot (1) + (1-\alpha) q_l^n \quad \text{if link } l \text{ is perturbed} \tag{5.9}$$

$$q_l^{n+1} = \alpha \cdot (0) + (1-\alpha) q_l^n \quad \text{if link } l \text{ is clear} \tag{5.10}$$

The initial beliefs held by agents at the start of the simulated set of days is varied in the exploration of this model as a parameter sweep. The result of the naïve model is that agents learn the average experienced travel time on the whole route considered, which is in keeping with assignment methodologies which only consider recurrent forms of congestion.

5.3.2 Strategic behaviour model

In contrast, a strategic routing model facilitating ‘adaptive route switching’ allows for the expectation of link state to change en-route if the agent receives other link state information en-route. In reality this may be provided by signage or other forms of media but this work only considers the role of prior experience.

In this model, each agent learns an expectation of each link being perturbed without considering its relationship with other links as in the naïve model q_l. This informs route choices at the start of each simulated day when the agent contains no within day knowledge:

$$q_l^{n+1} = \alpha \cdot (1) + (1-\alpha) q_l^n \quad \text{if link } l \text{ is perturbed} \tag{5.11}$$

$$q_l^{n+1} = \alpha \cdot (0) + (1-\alpha) q_l^n \quad \text{if link } l \text{ is clear} \tag{5.12}$$

To facilitate the strategic behaviour, each agent also holds two further knowledge matrices. One informs the expectation of link i being in the perturbed incident affected state based on the state of link j, $\mathbf{C}$. Each cell in the matrix $\mathbf{C}$ indicates the current learned probability of link i being perturbed and link j being clear. Another matrix $\mathbf{D}$ indicates the learned probability of link i being perturbed and link j being perturbed.

By storing this link relationship information the agent can alter $\mathrm{E}\{P(Llp)^n\}$ in equation 5.6 en-route and so change their impression of ω_k^n. Both matrices are initialised to zero, indicating that agents have no prior knowledge of link relationships.

Upon completing a trip on each simulated day, experiences are incorporated within the matrices in a similar exponentially weighted moving average model:

$$d_{i,j}^{n+1} = \alpha \cdot (1) + (1-\alpha) d_{i,j}^{n} \quad \text{if } i \text{ perturbed and } j \text{ perturbed} \tag{5.13}$$

$$d_{i,j}^{n+1} = \alpha \cdot (0) + (1-\alpha) d_{i,j}^{n} \quad \text{if } i \text{ clear and } j \text{ perturbed} \tag{5.14}$$

$$c_{i,j}^{n+1} = \alpha \cdot (1) + (1-\alpha) c_{i,j}^{n} \quad \text{if } i \text{ perturbed and } j \text{ clear} \tag{5.15}$$

$$c_{i,j}^{n+1} = \alpha \cdot (0) + (1-\alpha) c_{i,j}^{n} \quad \text{if } i \text{ clear and } j \text{ clear} \tag{5.16}$$

At the start of a daily trip, the expectation of travel time on network links is the same as the naïve model, using q_l to represent the expectation of link l being in the perturbed incident affected state, since agents do not hold any knowledge of the current day's network state.

Whilst en-route an agent updates the probability of link i being perturbed with experience gained from each link j traversed:

$$\mathrm{E}P(Lip) = c_{i,j} \cdot (0) + d_{i,j} \cdot (1) \quad \text{if link } j \text{ experienced perturbed} \tag{5.17}$$

$$\mathrm{E}P(Lip) = c_{i,j} \cdot (1) + d_{i,j} \cdot (0) \quad \text{if link } j \text{ experienced clear} \tag{5.18}$$

This model will facilitate agents reconsidering their travel options en-route and potentially diverting on to a different route should incidents occur which affect upstream links. The modelling question of interest here arises in the consideration of whether the strategic methodology alters expected route flows over time compared with the naïve methodology when no perturbations arise.

5.3.3 Day to day assignment process

The agent based assignment technique used in this work is founded upon the general approach as described by Nagel and Flötteröd (2011) and outlined in section 4.5.1. A Monte Carlo simulation approach is used to generate random system behaviour on each day and random agent choices. Agent behavioural parameters used throughout the simulations presented here are $\alpha = 0.01$, $\sigma = 0.01$ and $\theta = 0.05$.

As discussed in section 4.4.2, there is not believed to be a direct way to determine whether an equilibrium flow set has been obtained from an agent based learning model since stochastic variables within the simulation provide day to day noise. Instead, as mentioned by Cantarella and Cascetta (1995) citing Davis and Nihan (1993), for sufficiently large populations the distribution of day to day flows tends towards a zero-mean Gaussian distribution.

	Equilibrium route flows		
	f_1	f_2	f_3
Initial route choice	381	3	316
Final route choice - L0 perturbed	336	48	316
Final route choice - L0 clear	381	3	316

Table 5.2: Equilibrium route flows for the strategic behaviour model under the equilibrium definition described in section 5.3.3

The analysis provided below is therefore based on fifty model simulation runs with different random number generated seeds (from the system clock). 9000 simulated days was visually determined to be the length of time taken for the system to reach a steady state. A single equilibrium point was taken as the average flows of the final 100 (averaged) simulated days. This is a long learning time frame which may not be plausible in reality, but for this study these parameters were chosen to highlight the end result and learning processes. Other simulations, such as those in section 4.5.1, have shown that agent based models can converge within more realistic time periods.

5.4 Simulation results

5.4.1 Equilibrium properties

The naïve routing model converges to an equilibrium which is the same as in the static assignment case considering average link travel times confirmed through application of the method of successive averages with average travel times used (as in Sheffi, 1984)

$$f_1 = 317, \quad f_2 = 22, \quad f_3 = 361 \tag{5.19}$$

For the strategic model the system reaches a point where two flow sets exist dependent upon whether upstream link 0 is perturbed and whether agents choose to switch routes, as shown in table 5.2.

As well as flows reflecting agents choosing to divert under the strategic route choice model, at equilibrium the initial 'start of trip' flows for the naïve and strategic routing models are quite different. Equilibrium route flow configurations under strategic routing suggest a higher proportion of travellers using the major route in this case and a lower proportion initially using the 'major to minor' route option. Even though the system is the same under both behaviour model situations, the two knowledge representations have not only produced different 'end of day' behaviour, as might be expected, but have produced different 'start of day' route choices.

It is an important and unexpected finding that by allowing knowledge to vary within day, the agents themselves generate a different highway network on which to travel than if the behaviour was not permitted. Mechanistically this is because when an 'upstream' link 0 or 1 is in an incident afflicted state, the act of some agents diverting results in the corresponding 'downstream' links 2 or 3 to be not as congested than if none had diverted. Due to this mechanism, agents can effectively 'take a chance' on the more attractive route at the start of the day and are more likely to benefit from it.

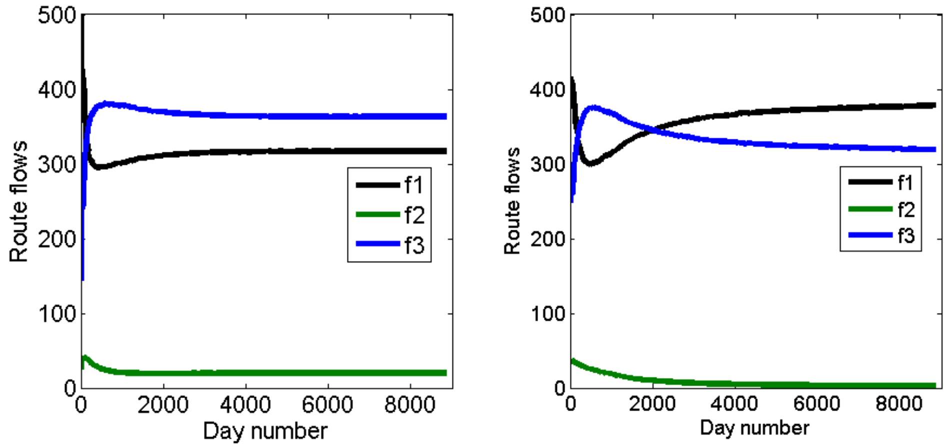


Figure 5.2: Evolution of route flows with naïve model (left) and strategic model (right)

Figure 5.2 plots the trajectories of the two behaviour models from initial starting points, in the same manner as earlier presented figures 4.5 and 4.7 showing agent based simulation route flow evolution over time. It should be remembered that these are the average daily flows of fifty simulation runs in order to reduce noise as shown in figure 4.6. It clearly shows the presence of the two learning mechanisms in the strategic model over two timescales, one which acts in a similar way to the naïve model, just learning link travel times favouring route 3, then learning state relationships eventually favouring route 1.

5.4.2 System evolution behaviour

As Bie and Lo (2010) show, one of the benefits of any form of day to day route choice modelling is that the model's basins of attraction for each equilibrium flow configuration can be explored. This provides details of how traffic flows would be expected to move from an initial set towards a long term stable equilibrium (if one exists within the system) and, if multiple equilibria exist, what the likelihood of reaching each equilibrium will be from any starting flow set configuration. This models the 'ramp up' behaviour described in empirical studies in section 1.3.1. The 'search by sampling' technique proposed by Bie and Lo involves initialising a number of simulations around the flow configuration state space and monitoring their evolution which is adopted here.

The graphical convention in figure 5.3 is used to explore the flow configuration state space of the models under exploration, the same which was used in figure 3.9 in section 3.4 to clearly illustrate the differences in choice behaviour by survey experiment participants making choices in a similar network representation.

Since the three route system used in the analysis of this simple model has a fixed demand of 700 vehicles, the model only contains two degrees of freedom and thus the complete route flow configuration can be plotted on to a point on a two dimensional state space. As was used in figure 3.9, two new variables are created: $g_1 = f_1 - f_2$ and $g_2 = f_1 - f_3$ which create a state space within the triangle $(700, 700)$,$(-700, 0)$ and $(0, -700)$, representing 'all adopt route 1', 'all adopt route 2' and 'all adopt route 3' respectively. This graphical representation only visualises flow state rather than the complete system which includes agent knowledge. As a consequence multiple agent knowledge configurations can create the same point on the figure 5.3.

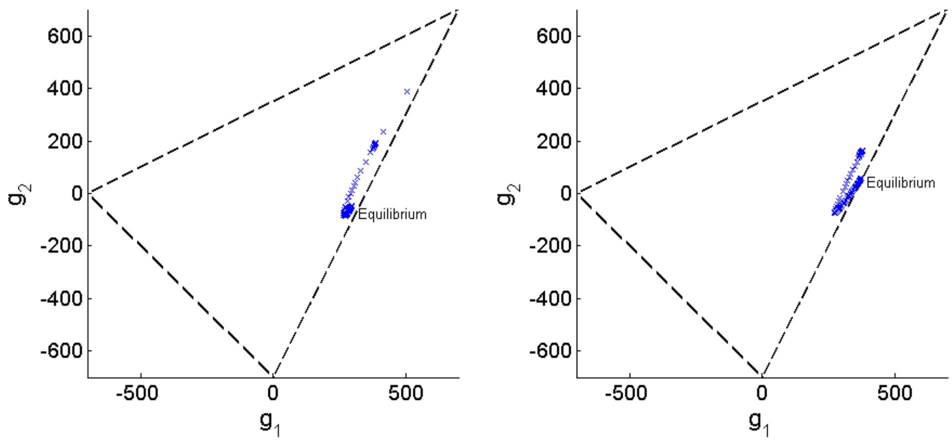


Figure 5.3: Figure 5.2 plotted in the new state space where the points $(700, 700)$,$(-700, 0)$ and $(0, -700)$ represent 'all adopt route 1', 'all adopt route 2' and 'all adopt route 3' respectively

Figure 5.3 illustrates how the three route flow time varying plot in figure 5.3 maps into a single trajectory on the state space. Although the state space visualisation approach fails to include any indication of time progression, one can clearly observe how the system evolves and reaches a steady state.

As an exploration of the parameter space as per Bie and Lo's 'search by sampling' technique (2010), the figures included in table 5.3 plot the evolution of flows of a number of different runs initialised around the state space by altering initial link journey time beliefs. Of particular interest is the way in which the system evolution behaves near to the long term equilibrium point. The strategic behaviour model is initially drawn towards the same equilibrium configuration as in the whole route choice case ($g_1 = 295, g_2 = -45$) with $P(L0p) = 0.4$ but then as drivers learn state relationship properties which the naïve model is incapable of, the equilibrium drifts towards the different and final flow configuration ($g_1 = 378, g_2 = 65$). This is also visible in figure 5.2.

Figure 5.4 plots the final asymptotic equilibrium produced under the two methodologies by averaging the last 100 days of simulated initial route choices, enlarging part of the system state space and still showing its edge. The equilibrium locations are shown for varying P(L0p). Intuitively, as P(L0p) increases, the attractiveness of the major route decreases and drivers instead favour the minor route, which occurs under both routing methodologies. This is in keeping with the findings of the survey in chapter 3 as similar travel times lead to less preference between the two options.

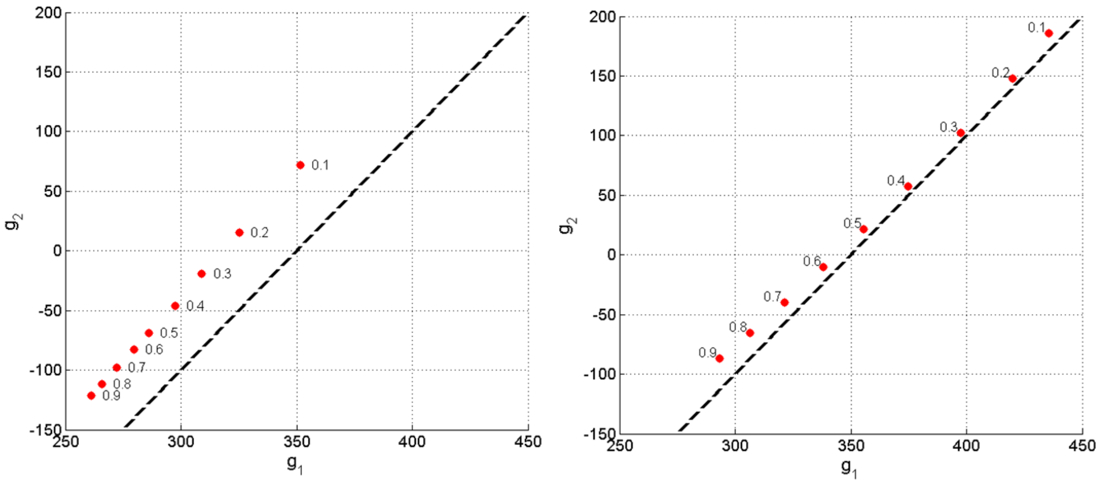


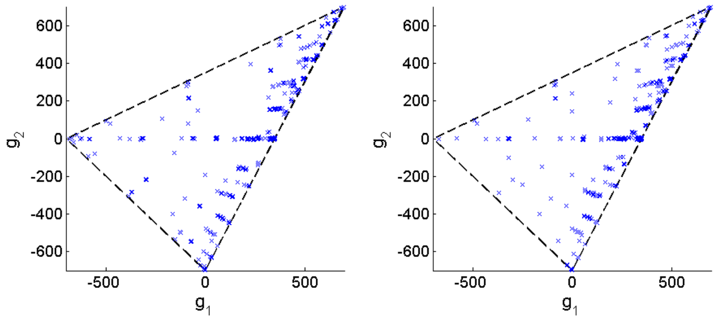
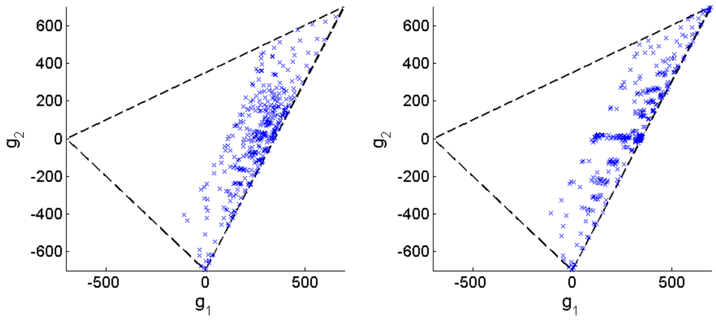
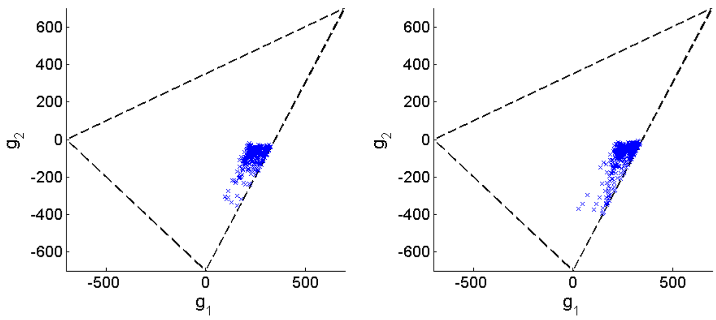
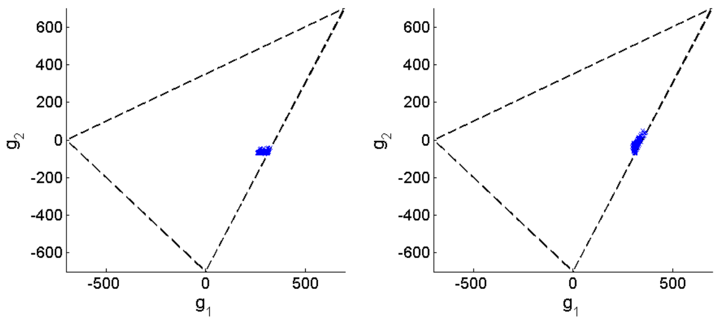
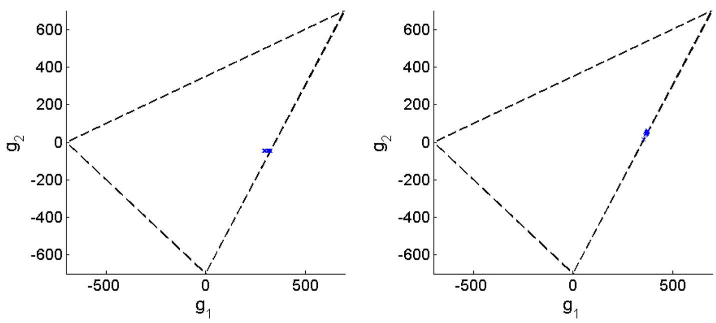
Figure 5.4: Final equilibrium initial route choice flows location for varying P(L0p) with the naïve behaviour model (left) and strategic behaviour model (right)

5.5 Conclusions resulting from this work

The primary aim of this simple model has been to examine the impact which including plausible within day reaction to states has on route flows. An agent based approach was chosen for this goal since it was determined in chapter 4 that these stand apart from other approaches in its ability to model variation in knowledge across a population. In this example it is found that it is the variation in knowledge *within day* which gives rise to system dynamics which lead route flows to a different equilibrium than were a different choice modelling approach adopted.

This is an important result as it demonstrates both the importance of including variable network conditions within day, which drivers may in reality attempt to divert away from en-route, which can alter the travel costs around the network and change expectations of route flows.

Table 5.3: Showing the evolution of a number of simulations initialised around the state space

Day number	Daily flow profile (left - naïve model, right - strategic model)
1	
125	
235	
1,245	
8,145	

The agent based model shows that initially the route flow configuration may converge to the same equilibrium as a 'naïve' behaviour model which does not consider within day travel time perception updating strategies. However the equilibrium 'drifts' towards a different flow set as agents learn further network characteristics such as correlations between link states which may exist in reality. The equilibrium can be thought of as 'resultant flow patterns with available information' which drifts as drivers learn more information about congestion structures around the network and can each make routing decisions which are more likely provide them with benefits.

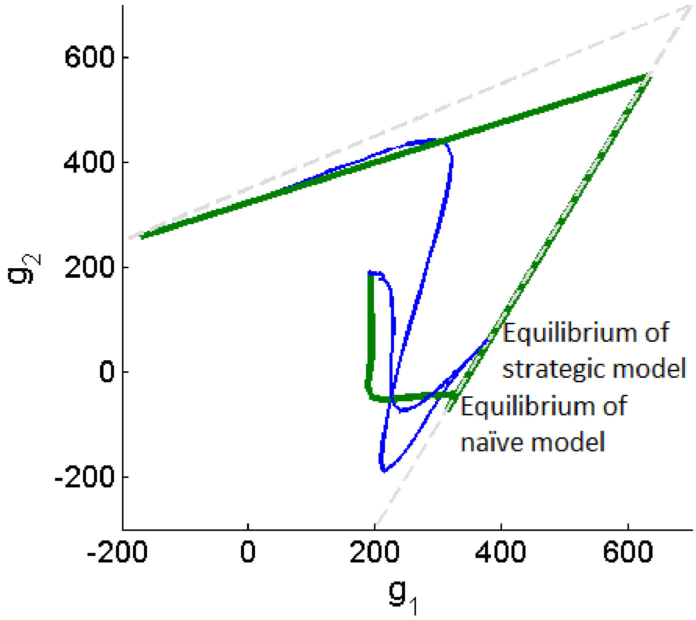


Figure 5.5: Flow trajectories under the agent based strategic behaviour model (blue) and under 'common intelligence' (green) behaviour models

In addition to the main result, figure 5.5 illustrates that the shape of the ramp up profiles from a starting position to the final equilibrium are found to be different under 'common intelligence' and agent based approaches to the same assignment problem. This is a similar finding to that shown in figure 4.7, that agent based disaggregate learning approaches produce a distinctly 'smoother' and more plausibly shaped ramp up profile like those seen in reality in figure 1.5.

It should be stressed that the network representation and manifestation of link relationships used in this work are a simplification of reality used to isolate and demonstrate the effect in action. Section 2.6 showed a number of scenarios where link state relationships may occur, such as traffic backing up on to other links and impeding traffic flows through network bottlenecks. As in these real world situations, in reality it is the choices of individual drivers in their original routing decisions and how they react to non-recurrent congestion states which creates the relationships between links. This issue is further explored in the remainder of the thesis as well as generalising the learning behaviour for more general networks.

Chapter 6

A model of reaction to states in a dynamic network with queuing

A version of this work was presented at the 12th European Conference on Artificial Life as (Snowdon and Waterson, 2013).

6.1 Motivation and goals of this study

Chapter 5 examined the behaviours of agents, each representing single drivers, which are capable of learning the experienced relationships between congestion 'states' causing travel time increasing disturbances occurring on network links. This was inspired by the behaviour witnessed among participants in the route choice survey experiment conducted in chapter 3.

In the preceding chapter's network representation, the relationships between which links were affected by disturbances was applied externally, suggesting that delay causing queues 'block back' along a fixed path of links regardless of traffic flow behaviour itself. In reality, if a queue forms and flow on links joining the queue is sufficiently small then the queue may dissipate. Or, if network flows change (possibly in reaction to the presence of queuing traffic) then the queue may back up along a different set of links than it would at a different moment in time. The issue of which interconnected links are likely to be affected and why is discussed in section 2.6 of this work.

This is not to say that the work presented in the previous chapter is wrong or requires additional consideration before being accepted, just that further insight can be obtained in a more general setting by relaxing these previously held assumptions. Using 'static' speed and flow relationships is a suitable indicator of average conditions and the externally enforced link state relationships could occur on real network links.

The work presented in this chapter incorporates two new features in the traffic assignment process in order to capture both the effect of spatial congestion structure and of incomplete network information as has been described:

- The first is the use of a Cell Transmission Model, which captures vehicle movements within day *dynamically* along sections of road links (known as cells) and the resulting build up of queues in parts of the network. This represents agents moving and interacting with other agents in a spatial environment to form queues as a result of all agent decisions.
- The second is the definition of a spatial learning mechanism, inspired by a coupled hidden markov model representation, given to agents traversing the simulated network. This is a more general form of the relationship matrices which were incorporated in the previous chapter's knowledge model.

6.1.1 The role of simulation environments

Using a within day 'dynamic' cell transmission model allows the resultant link states and their relationships to become an *emergent* property of the within day simulation, rather than relying on them being externally imposed to occur. The fact that the process occurs in this way is important because, as section 2.6 argued, the relationships observed in reality are themselves a result of driver decisions.

A number of papers have argued the importance of including appropriate within day phenomena to capture between day routing behaviour. These are mainly from perspective that in order to accurately model the impact of within day phenomena, day to day dynamics should be considered. These works include studies by Liu, Van Vliet and Watling (2006) and Mahmassani and Hu (1997) who examine the role of traffic responsive control systems (such as signal timings). They highlight that the choice of within day processes included in the modelling approach does have an impact on modelled driver experience and the resulting long term equilibrium is different than if they were ignored or represented in a different way.

A number of microsimulation tools exist which would be suitable for representing the environment in this modelling work, such as PARAMICS or AIMSUN (Sykes, 2010). These capture aspects of road based travel within-day such as traffic signals, lane changing and priority turns. Although none of these effects are included within the CTM, this approach was chosen because it replicates queuing and blocking back in a simple manner, so will create the required link relationships as described in section 2.6.

The agent based choice model and knowledge representation adopted in this work would be applicable to any other simulation environment which includes the queuing and blocking back, such as the CTM tool. It is not felt that the key results or conclusions would be affected by this choice, but using a full microsimulation environment would be a suitable way to study other processes acting such as adaptive traffic control.

6.2 A cell transmission model of road traffic interactions and congestion propagation

The CTM used here is a reimplementation of previous works (Long et al., 2008, 2011), extended from Daganzo's original CTM (1994).

The novel CTM implementation is created specifically for this study and in a general manner such that any network structure can be modelled. 'Simulation manager' code, which is technically external to the operation of the CTM itself, allows for the CTM simulation to be manipulated, such as injecting agents with persistent day to day knowledge and by altering network characteristics representing incident delays and states.

In this formulation a network features a set of nodes N, a set of links A and a set of centroids C which are each attached to a single node $n \in N$. In contrast to the previous model presented in chapter 5, a CTM explicitly models time acting within-day. In the CTM each link is discretised into homogeneous cells and time is partitioned into intervals such that the cell length is equal to the distance travelled by free-flow traffic in one time interval δ. For example, here $\delta = 5$s and free flow vehicle speed (v) is 15m/s so cell length is 75m. A time variable, t, advances by 5s at each simulation time step. Each cell also has a fixed capacity of vehicles which can reside inside it at each time step. The units traversing the cell transmission model are implemented as agents which each hold their own driver behaviour model.

Figure 6.1 shows a single link created within the CTM, showing cell occupancy as a percentage of full. An 'incident' is modelled as a cell capacity reduction which results in queuing, as with the approach used in chapter 5 and noted empirically in chapter 2. In this chapter there is no free flow speed change associated with passing through incident affected cell.

At each time step, as well as advancing agents on to their next cells and links, a number of agents are drawn from the population 'pool' (imagined to be sat outside of the CTM) and may be entered into the simulation at centroids specified by the agents. Should an agent be unable to join the link connected to n they will join a centroid waiting queue and attempt to enter the network at each time step onwards. Each simulated day agents are injected into the simulation in the same order but the number of agents entering at each time step is randomly chosen (up to a limit of 5 per origin).

Unlike in previous implementations of the CTM, which are usually used to replicate traffic dynamics for the purposes of determining travel times, in this system each modelled agent

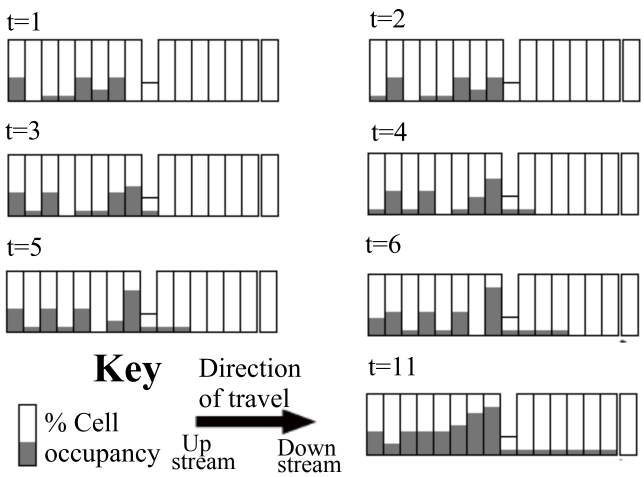


Figure 6.1: Cell transmission model output showing a stream of vehicles encountering a cell of lower capacity, resulting in the formation of an upstream queue.

holds a unique identity persistent between days (within the 'population pool' area) and attached behaviour model. This is the first known implementation of an agent based knowledge system within a CTM. Prior to arriving at a node, agents are interrogated for their turning intention and next link choice. The simulated day only comes to an end when all vehicles have left the network. The 'burn in' period (before any agent has left the network) and 'burn out period' (while agents are only leaving the network) are noted and excluded from results analysis.

All junctions within the CTMs in this work are implemented as fair four-way signals. Approaching arms take it in turns to act out the waiting agent's turning movements, regardless of when those agents arrived at the junction. There are no priorities in these modelled junctions.

6.3 Modelling a driver agent's network knowledge using a coupled hidden markov model

Previous work has reported positively on describing a period of observed road link conditions as belonging to a set of states including 'free flow', 'mildly congested' and 'highly congested' travel time distributions (Kwon and Murphy, 2000; He et al., 2006). In reality link states exhibit an often predictable spatial structure around the road network as queues propagate from a single starting point such as a busy junction or incident location and affect other regions, as was shown in section 2.6 by a number of studies. These correlations have been used as a basis for developing reliable travel time predicting algorithms (Min and Wynter, 2011).

Choosing the right number of states to represent road link performance and capture travel time variation sufficiently is not a trivial task. The appropriate set of states may vary by location and time of day under consideration. In their work, Kwon and Murphy (2000) use two states, free flow and congested, but this work uses three states to emphasise the distinction between minor and severe congestion. In reality drivers may experience any state regardless of its cause, but non-recurrent congestion may result in an unusual state set around the network being experienced compared to under 'usual' recurrent congestion. This is seen in reality within travel time distributions across different days such as shown in section 2.4. States as used here only depend upon travel times alone:

Free flow Travel time on link is less than or equal to $1.3\times$(Free flow travel time on link)

Moderate congestion Travel time on link is less than or equal to $2.0\times$(Free flow travel time on link) and greater than $1.3 \times$ '(Free flow travel time on link)

Heavy congestion Travel time on link is greater than $2.0\times$(Free flow travel time on link)

The driver behaviour model proposed here focusses on allowing driver agents to learn link state structures through the use of a mechanism inspired by a Coupled Hidden Markov Model (CHMM), a more general extension to the use of relationship matrices in chapter 5. By learning link state structures drivers can re-evaluate the expectation of congestion elsewhere in the network based on that day's experience. Traffic systems have previously been represented successfully as CHMMs for predictive purposes (Kwon and Murphy, 2000; Herring et al., 2010) but have yet to be explored as the basis of an agent based driver knowledge representation.

6.3.1 Model overview

A Hidden Markov Model (HMM) considers time as discrete and at each step can be in one of a number of unobservable (hidden) states, S. At each time step the model emits one of a number of externally observable symbols, V, with a given probability in each internal state, $B = \{b_j(k)\}$ $j \in S, k \in V$. A transition probability distribution describes the state which the model will be in at the next step given the current state, $C = \{c_{ij}\}$ $i, j \in S$. The probability of the model being in any initial state is given by a distribution, $\pi = \{\pi_i\}, i \in S$.

This work implements an extension to HMMs inspired by the work of Zhong and Ghosh (2001) which is shown in figure 6.2 and allows for the consideration a network of *coupled* hidden markov models. The state of each HMM in the next time step is influenced not only by itself but also by the (hidden) states of other connected HMMs. Here the CHMM is achieved by extending both the system transition matrix to describe the influencing

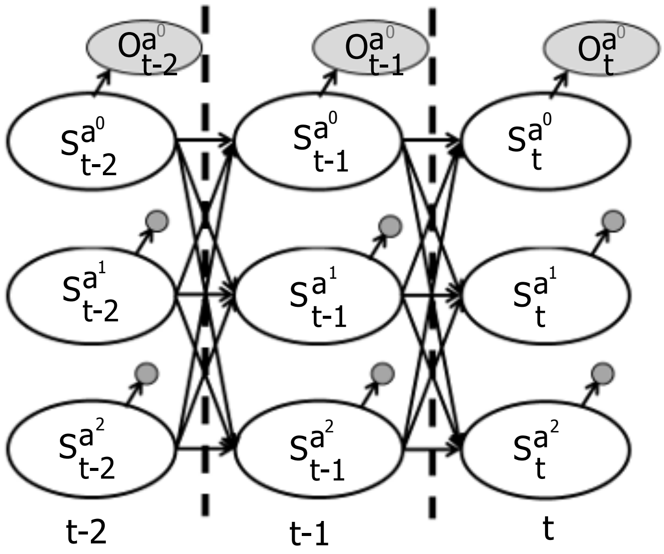


Figure 6.2: Overview of the structure of the Coupled Hidden Markov Model in this work. At time t each HMM a contains an internal state s and externally observable state o. The internal state of each HMM is dependent on each other HMM at the preceding time $t-1$

effect of model a' on model a, $C = \{c_{ij}^{(a',a)}\}$, initial probability distributions, $\pi = \{\pi_i^a\}$, and also introducing a coupling matrix $\Theta = \{\theta_{a',a}\}$ which defines how the set of HMMs are connected.

6.3.2 Implementation details

Each driver agent is equipped with a single CHMM as described which is unique to the agent, where each HMM represents a single road link in the network. The goal of the model is to determine an expectation of travel time for a link a, φ^a, both at the start of each simulated day and en-route once the state of other links elsewhere in the network has been observed. For this implementation the CHMM belonging to each driver agent is considered fully connected ($\Theta = J_{|L|}$) although in their work Kwon and Murphy (2000) only connect HMMs considered connected in the road network (which simplifies the representation). The relationships between nearby link states are not fully understood yet limiting the interconnectedness of the CHMM would save on computations and memory use required by the simulation.

Driver agents also store an associated expected travel time (in simulation steps, i.e. multiples of 5 seconds) for each state of each link, $\Gamma = \{\gamma_j^a\}, j \in S, a \in A$, which is adjusted by daily experience using the exponentially weighted moving average model where r^a is the experienced travel time on link a and α is an externally set learning parameter (0.01 in this implementation):

$$\gamma^a = \alpha r^a + (1-\alpha)\gamma^a \tag{6.1}$$

Once a driver agent has traversed a link a they observe the link's state exactly (i.e. each state is tied to only one observation, $B = I_{|S|}$) so only the state in question's expected travel time is updated. The initial state distribution, π^a, is then updated directly as the average experienced proportion of occasions that the link was in state s. At the start of the simulation the probability of any link being in any state is equal and each state's expected travel time, γ_j^a =free flow travel time on link.

The expectation of travel time on network links at the start of any simulated day can then be simply found as $\varphi = \Gamma\pi$.

This model would be sufficient to ignore within day effects and determine an equilibrium set of route flows based on initial route choices alone, as per the naÃŕve behaviour model of the previous chapter. However this work sets out to incorporate the possibility of agents changing the expectation of a link's state en-route based on information relating to the state of other links obtained on the trip, within day.

The system transition matrix is updated at the end of each simulated trip, $C = \{c_{ij}^{(a',a)}\}$, as the experienced proportion of occasions that link relationships occurred. That is, for the HMM associated with link a, the state probability distribution describes the probability of link a' being in state j given that link a was in state i.

As an agent travels through the network, experience is accumulated in two sets which are re-initialised as empty at the start of each day; $L = \{a\}$, which stores the identifiers of experienced links, and $O = \{o^a\}$ which stores the corresponding set of observed link states. This information is used to update the expected probability to that agent that link a will be in state i, $P(o_i^a)$ as the average expected state of link a given its relationships with each of the traversed links in the set L:

$$P(o_i^a) = \frac{\sum_{(a' \in L)} c_{a',a}^{o^{a'},a}}{|L|} \tag{6.2}$$

Due to this mechanism each agent will form their own subjective impression of relationship between flows, in the same way as in the preceding chapter. Thus the single expected travel time on link a can be re-evaluated en-route as:

$$\varphi^a = \sum_{i \in S} P(o_i^a) \times \varphi_i^a \tag{6.3}$$

To inform the choice model, the final utility of a route is given as $\varphi \times -0.1$ (negative since travel time is a disutility). Although not explicitly calibrated to real world data, this parameter choice was chosen to produce the plausible behaviour of interest within the model. That is, based on reasonable journey time differences agents will prefer the faster route to an acceptable degree. Not setting this parameter appropriately can cause the model not to converge because either the probability of choosing a slower route is so low or too high. The discrete choice model used to determine the probability of an agent choosing a route is a path sized logit model (with calibrated parameter = 0.1) which takes into account the overlap between route options as well as utility (Bekhor et al., 2006).

In this application of a CHMM the re-evaluation of HMM states occurs when the agent receives any new information about current link states, such as when leaving a link. The result of this is that the CHMM does not operate in fixed time steps which would create unnecessary computations or information not being considered in network re-evaluations.

6.4 A simulation of driver reaction to network incidents

As an illustration of the effects of incorporating the general CHMM agent knowledge representation, the proposed day to day traffic assignment method is performed on the network shown in figure 6.3 featuring a fixed vehicular demand of 7500 vehicles on each simulated day. The network consists of 13 links, 13 nodes and one origin to destination pair O0-D0. Each link is divided into 10 cells with a capacity of 10 vehicles with two exceptions: link 6, which is divided into 16 cells, and link 5, which is divided into 3 cells.

The probability of all network cells being affected by incidents on each day is 0 except cell 9 on link 6, whose capacity drops from 10 to 3 when an incident occurs. This has the same effect as is shown in figure 6.1 which describes how congestion behaves in the CTM. On any simulated day there is a 30% chance that link 9 cell 6 is perturbed in this way. All other constants are set as in the model definition.

There are two routes through the network here forward named as the 'major route' and 'diversion route' which consist of links $[1, 2, 3, 4, 5, 6, 13]$ and $[1, 2, 3, 4, 5, 7, 8, 9, 10, 11, 12, 13]$ respectively. The free flow travel times on the two routes are therefore 345 seconds on the major route (5.2km) and 565 seconds on the diversion route (8.5km).

Although the CHMM knowledge model presented here suggests that all agents should re-evaluate their decision en-route, in reality not all drivers will be able to do so either due to personal reluctance or lack of knowledge regarding the area and alternative route options, as was discussed in chapter 2. Accordingly, each agent holds the CHMM behaviour model as described except for the following key differences: ***switchers*** will re-evaluate their route choices en-route and may choose to divert (although it is important to remember that not all will, the discrete choice model only provides a likelihood of choosing a route rather than a decision) and ***stayers*** who will not re-evaluate any system perceptions

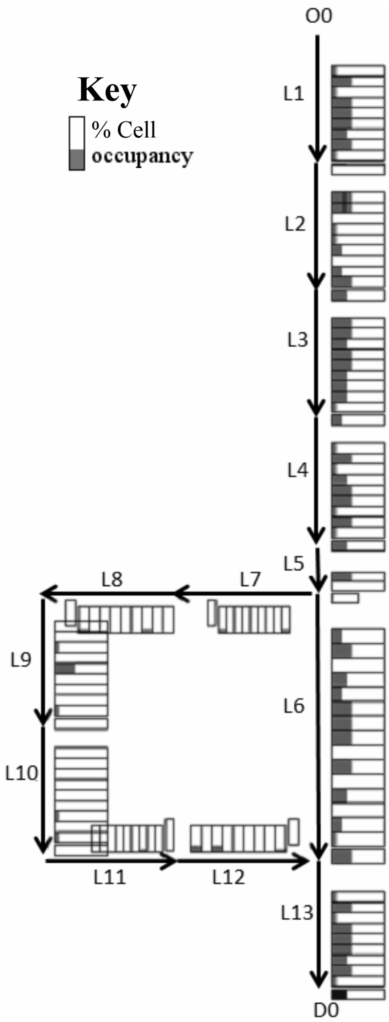


Figure 6.3: The network structure under examination, also showing the cells associated with links and vehicles traversing the network in a non incident affected day.

en-route. As described in the literature overview, the vast majority of transportation forecasting models do not consider that agents will process information en-route, thus consist of a population of 100% stayers (0% switchers).

Figure 6.4 shows the day to day initial route choices of 7500 agents traversing the network in figure 6.3 over a period of 30 days. The population consisting of 100% switchers is capable of moving to an equilibrium probability distribution which features fewer agents initially choosing the diversion route. This can be considered modelling the ability for switchers to 'take a chance' on the preferable major route and stayers being forced to consider average network performance in their routing decisions so more often initially choosing the diversion route.

The previous chapter modelled route flow evolution averaged over a number of parallel iterations to reduce noise, identifying an equilibrium mean point. That method was not felt to be necessary for this result where the network choice is simpler and contains less

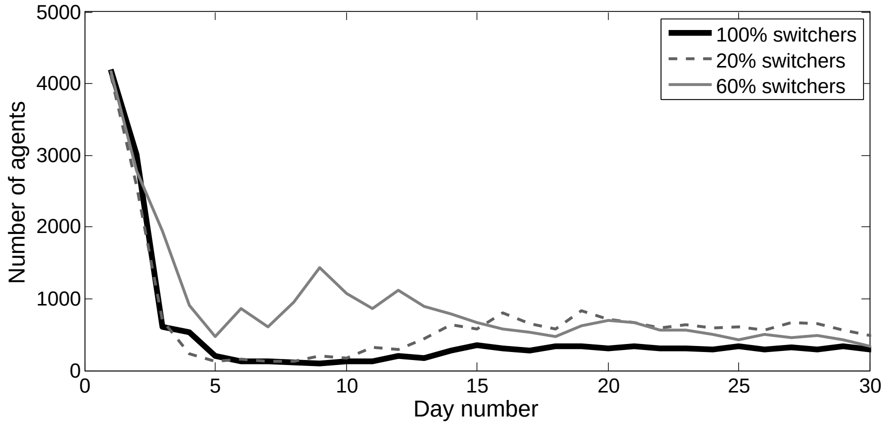


Figure 6.4: Numbers of agents choosing the diversion route as their initial route choice against simulation day.

recurrent congestion on links, meaning that journey times are less dependent on link flows. By simulation day 30 all agents in the network are understood to be aware of travel times and relationship distributions.

As an analysis of within-day system behaviour, figure 6.5 shows the proportion of the agent population engaged in switching against time during a single incident affected day once route flows reached equilibrium (beyond day 50). The diverting proportion is calculated as the number of agents which have chosen to switch routes and are present on links 7, 8, 9, 10, 11 and 12 (the diversion section) against the number of agents present on links 6, 7, 8, 9, 10, 11 and 12 (the combination of the diverting section and incident affected link). As figure 6.5 shows, the 7500 agents take between 15000 seconds (≈4 hours) and 30000 seconds (≈8 hours) to pass through the network for the strategy mixtures examined.

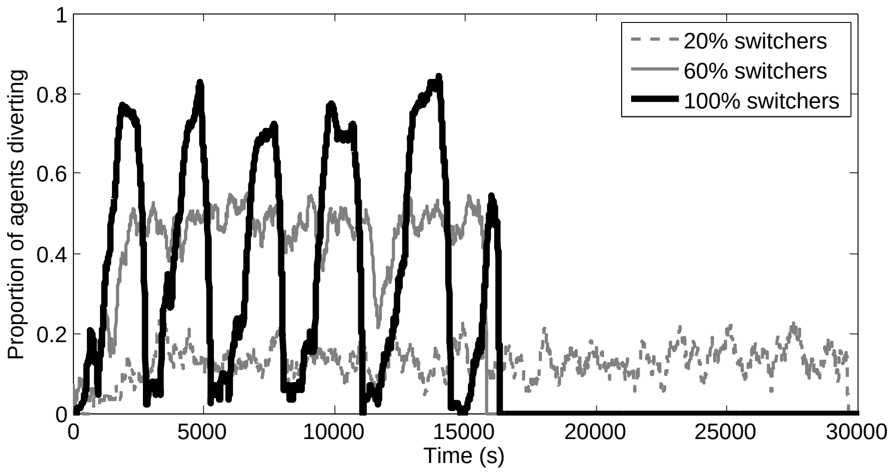


Figure 6.5: Proportion of agents engaged in diverting throughout an incident affected simulated day at equilibrium.

As would be expected, for lower percentages of switchers present in the population the proportion of agents engaged in switching is capped by that percentage. It is logical that if few switchers exist in the population each will engage in diverting, enjoying a reduced travel time of close to free flow conditions on the diversion route. Due to the 'boundedly rational' nature of the discrete choice models assumed in this thesis in section 2.1, if an agent predicts that link 6 has a higher travel time than at the start of their journey, it only becomes *more likely* that it will divert (according to the parameters of the logit function), hence not every switcher agent chooses to divert.

The trend of 'maximum numbers of switching agents divert' would not be expected to continue with increasing the proportion of switchers in the population. If a population of 100% switchers exists and the maximum number divert then the major incident affected route would hold a close to free flow travel time and thus be faster than the diversion route.

Figure 6.6 summarises and extends figure 6.5, showing the proportion of only the switching agents engaged in diverting during a 12500 second portion (≈3.5 hours) of the simulated day for varying proportions of switchers. This time frame was chosen to exclude the 'burn in' and 'burn out' periods where either no vehicles have yet left or no vehicles are left to arrive respectively. Below 60% switcher populations, the mean proportion of switchers engaged in diverting reaches 0.77, with the standard deviation decreasing to 0.09. Beyond 60% a clear system change appears in both figures 6.5 and 6.6 as the average proportion of agents diverting falls. There are two reasons for this; first the mechanism as described above suggests that some switching agents will choose not to divert - although this is few as figure 6.5 shows that the maximum proportion of agents diverting in a population of 100% switchers is close to 0.77. Secondly, the periodic 'wave' like diversion behaviour visible in figure 6.5 appears and at 100% switchers the proportion of agents switching is rarely steady as diversion behaviour regularly breaks down.

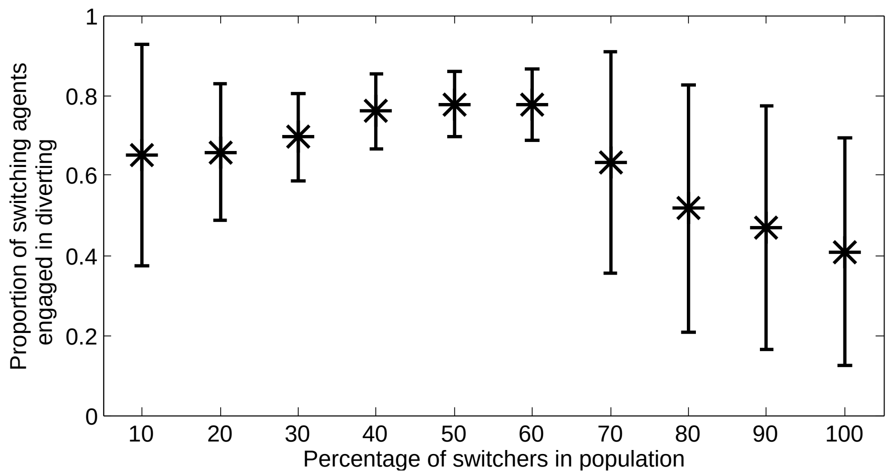


Figure 6.6: Mean and standard deviation of proportion of switching agents engaged in diverting between $t = 2500$s and $t = 15000$s.

To understand the impact of these trends on agent experience, figure 6.7 charts the average travel times between the route divergence point at the end of link 5 and route merge point at the beginning of link 13 (the same region examined by figure 6.5) experienced by switcher, stayer and *all* agents on an incident affected equilibrium day. This shows the (average) benefit to agents of adopting the two strategies. As has been discussed, below to 60% switchers within the population, switcher agents enjoy a lower average travel time as stayer agents traverse the incident affected major route. Above 60%, the value of this benefit to switchers decreases even though in every simulation it is on average better for agents to adopt the switcher behaviour.

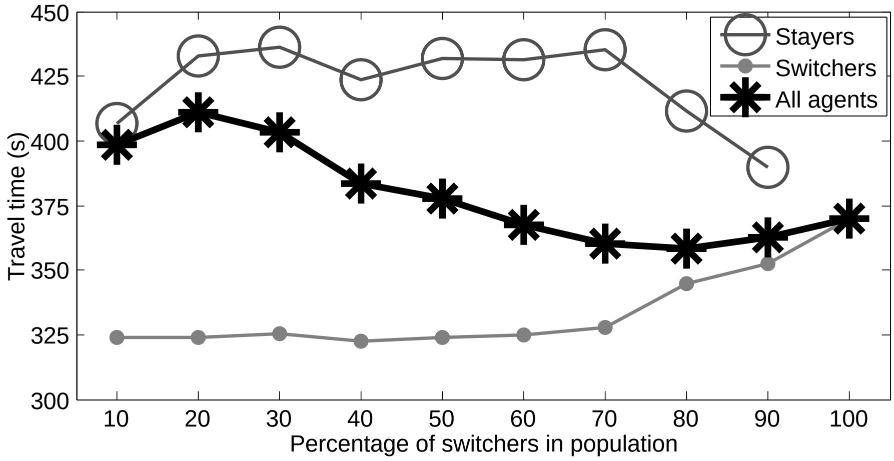


Figure 6.7: Mean of travel times between diverging and merging points experienced by switcher, stayer and all agents during a single incident affected equilibrium day for varying proportions of switchers in the population, for the same time frame as figure 6.6.

To examine the effect of varying population proportions on system performance, figure 6.8 charts the time required for all 7500 agents to pass through the network. As the proportion of switching agents in the population increases, up to around 70-80% switchers, the amount of time required falls, suggesting that the system can be considered to be acting in a *more* optimal fashion. Beyond 80% switchers in the population, despite the simulation consisting of more agents capable of making en-route diverting decisions in the hope of decreasing overall travel time, the time taken for all agents to traverse the network *increases*.

The graph in figure 6.8 also shows the 'optimal' time required to complete an incident affected day from a simulation where the likelihood of link 6 being affected by incidents is certain. This simulation length is lower because uncertainty is removed from the system and network attributes do not change in the day to day model. Agents can each optimise their initial route choices through the evolutionary route adaptation process and at equilibrium do not need to alter route choices within day. Consequently the negative diversion breakdown does not occur.

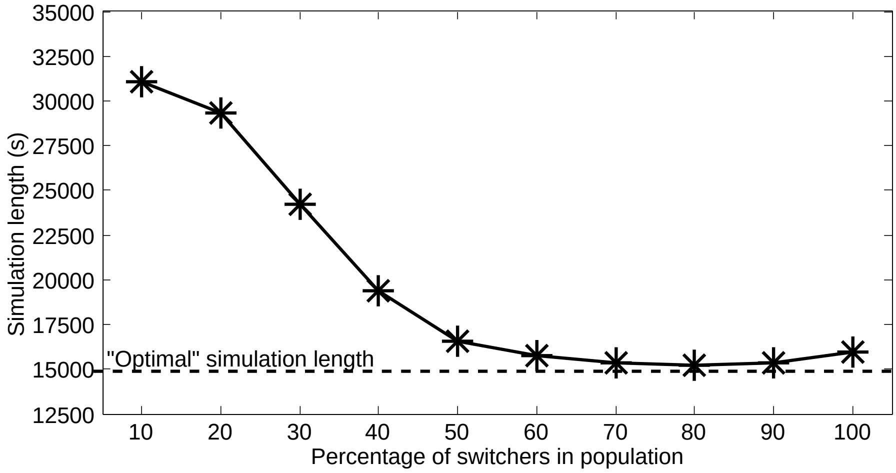


Figure 6.8: Time required to complete the movement of 7500 agents at equilibrium on an incident affected day. Also shown is the 'optimal' time required when the probability of an incident on link 6 cell 9 is 1.0.

6.4.1 Diversion breakdown and the role of subjective information accumulated by agents

The simulation result in figure 6.5 has shown how, for higher proportions of switching agents existing within the population, when an incident arises the number of agents engaging in diverting rises and falls in a wave like motion which has a negative impact on overall network performance.

To demonstrate how this trend arises, figure 8.1.3 shows a series of simulation outputs at six time steps on an incident afflicted day (as shown by the capacity decrease on link 6). In a) ($t = 1755$s) agents are joining the network and, due to the existence of congestion on the links leading up to the route diverging point, perceive link 6 to be in a highly congested state. At this early point in the simulation the upstream queue is still forming and few agents are diverting. In b) ($t = 3990$s) the congestion stretches up the network but due to a larger number of agents engaging in diverting the size of the queue in each cell decreases - as in the peaks in figure 6.5. By c) ($t = 5040$s) the reduced congestion on preceding links means that agents are no longer capable of considering link 6 to be in a highly congested state even though link 6 remains affected by the incident. At d) ($t = 5530$s) few agents are engaged in diverting and most agents join link 6 believing it to be clear as in the troughs from figure 6.5. In e) ($t = 5930$s) queues re-form on links preceding link 6 and by f) ($t = 6490$s) agents once again perceive that link 6 is in the heavily congested state and again engage in diverting as in the peaks in figure 6.5.

The simulation has shown how, when an incident occurs, agents anticipate its presence and more agents which are capable of diverting do so, the queue on preceding links decreases and agents joining the simulation receive no information about any queues occurring ahead, so are unable to predict that link 6 is in a highly congested state.

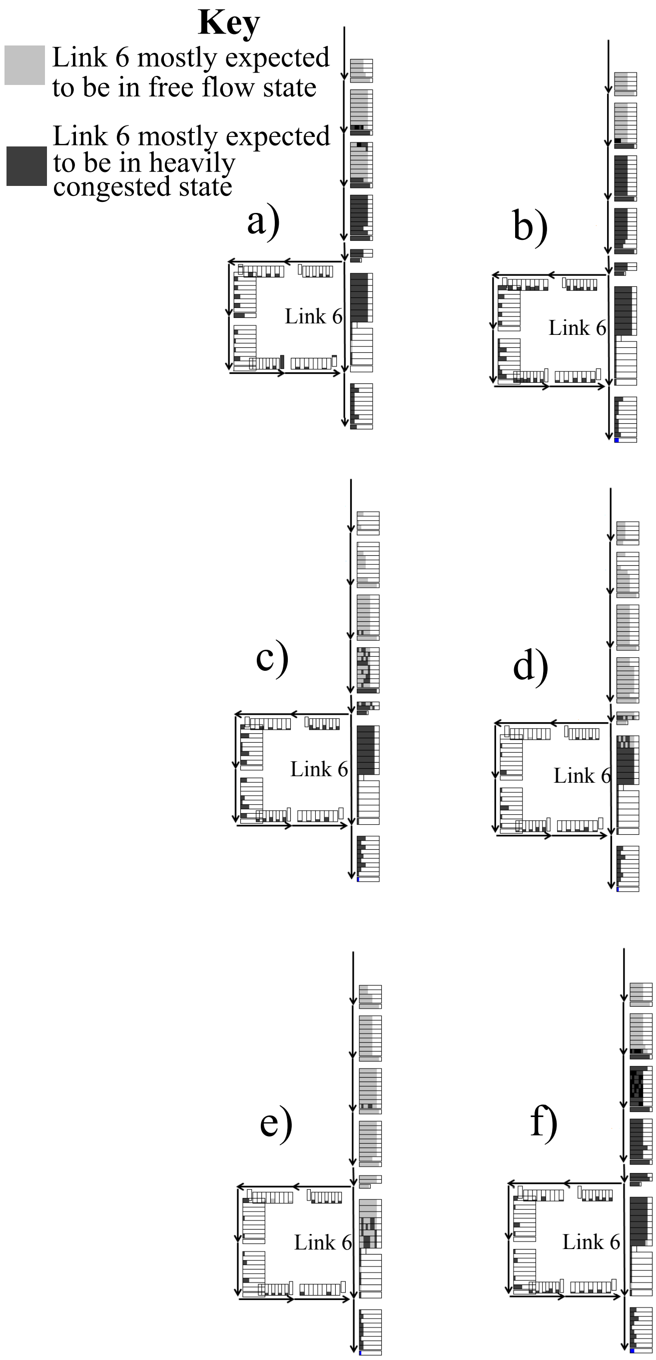


Figure 6.9: Simulation outputs at a number of time steps exploring system behaviour on an incident affected day at equilibrium with a 100% switchers population. Agents occupying each cell are coloured according to their belief of the current state of link 6.

Thus all incoming agents naively remain on the major route believing it clear, eventually creating more queues which then back up the carriageway restarting the cycle.

Diversion breakdown has the result of decreasing network performance despite being caused by agents trying to decrease their own travel times, suggesting that in this simulation some level of queueing on upstream links can be seen as positive to the network as a whole (and presumably a traffic manager). In order to reduce average travel times in a network without information provided, some drivers are required to wait in congestion so that others can benefit from observing the presence of queues.

6.5 Impact on other flows and 'knock on' diversion behaviour

The previous test network showed how diversion behaviour can occur when an incident reduces capacity along a stretch of road causing queues to block back up along preceding links. Using this small exploratory extension to the network structure it is also theoretically possible that delays and diversion behaviour may occur which is caused by traffic already in the act of diverting.

Figure 6.10 shows a simple extension to the network shown in figure 6.3 where a second OD pair is added on a second route which for a stretch utilises the diversion route of the first. Additionally the capacity of the shared links is reduced from 10 to 4 vehicles.

The test in this extended network is run under the same conditions as the previous single OD pair test but equal demand of 2500 vehicles is run between Origin 0- Destination 0 and Origin 1 - Destination 1. The network is left to converge for 30 simulated days.

At equilibrium the flow distribution on days not affected by incidents the majority of traffic barely interacts. As figure 6.11 shows, when an incident occurs on the original route the diverting traffic must interact with traffic on the other route, both increasing the cost of diverting (as the traffic joining the new route must queue to do so) and increasing the travel time to travellers in the new network section. This drives fewer vehicles on the original to engage in diverting at all who might not be better off.

From a system optimality viewpoint, this shows that often it can be better for the transport system for traffic *not* to divert, despite the findings of the previous work in this chapter. Clearly diversions should only be encouraged or suggested when other network routes are capable of handling the extra volumes of traffic.

6.6 Conclusions

This model has demonstrated a plausible road traffic phenomena in the form of diversion breakdown which is created in simulation by incorporating within the model both inter-vehicle interactions and a subjective driver knowledge representation which focuses on experience gathered within trip and relationships between anticipated link states. This effect could not be witnessed without the use of both the Cell Transmission Model and

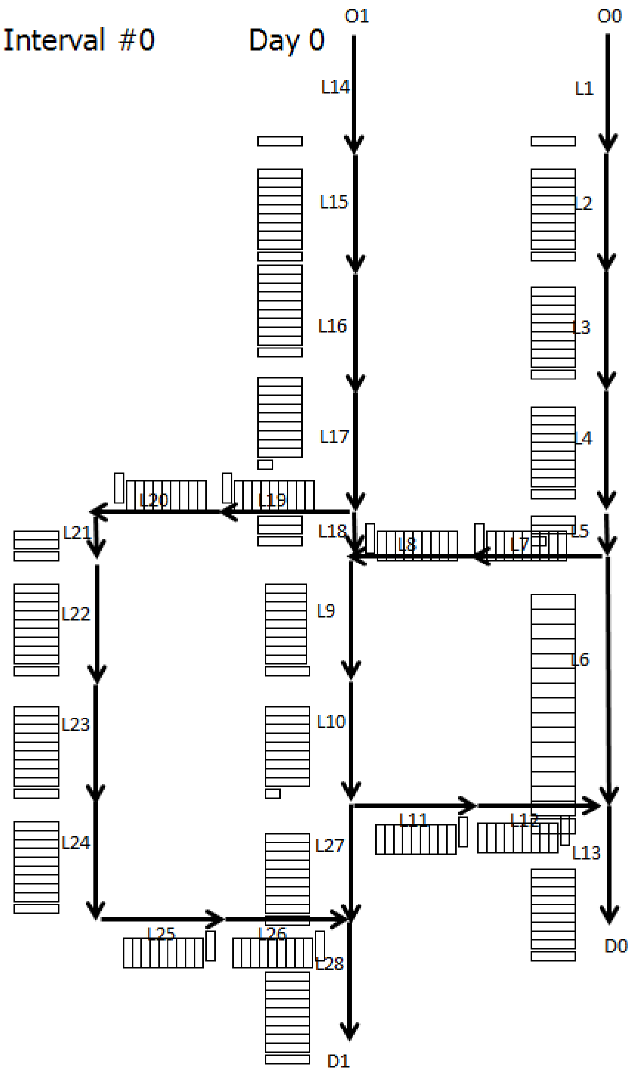


Figure 6.10: Exploratory extension to the network shown in figure 6.3 where the network is extended with a second OD pair and route

the Coupled Hidden Markov Model style subjective knowledge representation, neither of which was present in the simple model presented in chapter 5. This works towards meeting thesis objective four as defined in section 1.4.4, illustrating that 'diversion breakdown' dynamics are not possible to observe without the network representation used here.

In addition to the 'diversion breakdown' dynamic, this chapter has further shown the link between diversion behaviour and state relationships where each can influence the other in a dynamic network representation as used here. In order to fully capture the resulting route flows it is essential to incorporate both of these aspects within the simulation. This is in agreement with Liu, Van Vliet and Watling (2006) and Mahmassani and Hu (1997) who stress the link between suitably modelling within day dynamics and between day traffic assignment.

For highway network designers, network structure will play a key role in whether and

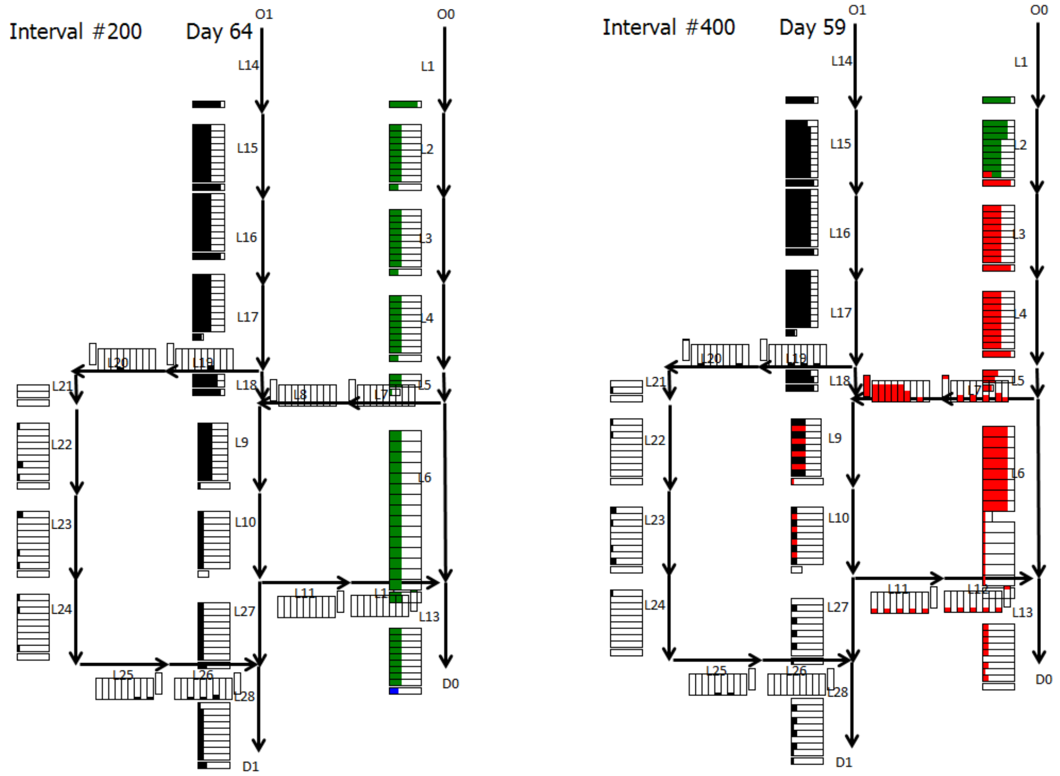


Figure 6.11: (Left): Network flow snapshot on a non-incident affected day. (Right): Network flow snapshot on a day affected by an incident.

when diversion breakdown occurs and there may be multiple opportunities for drivers to divert. Overall network performance is only improved if the diversion route can accommodate increased volumes of traffic which is uncertain, even unlikely, in most real world traffic networks.

From a technical viewpoint, it should be noted that much of the analysis and observations undertaken in this chapter are within a single Monte Carlo draw and would not necessarily occur in the same manner given a different random number seed. The preceding chapter reduced the impact of this effect by averaging over multiple simulation runs. However such an approach was not suitable here where the interest is on dynamics within a typical 'average equilibrium day'.

Chapter 7

Simulating adaptive route choice across a larger urban region

7.1 Motivation and goals of this study

The preceding work has sought to examine the benefits of using agent based models of driver route choice in simple networks with limited numbers of routes available for use. This study seeks to relax the assumption of a simple two or three route system with one OD pair and try to expose additional issues and insight involved with utilising the behaviour model and associated principles in a more realistic urban environment.

As the previous tests and literature have shown, it is likely that in an urban environment road links are affected by incidents even though none of the vehicles themselves are passing the incident site (such as in figure 2.7 provided by Meite (2011)). In addition, within an urban environment it is likely that recurrent forms of congestion will exist alongside recurrent forms which are attributable to volumes of traffic alone, such as common at junctions. Drivers in reality must distinguish 'unexpected' delay and its implications on road network conditions elsewhere when choosing to remain on their initially chosen route path.

Accordingly, the purpose of this test is to examine how diversion behaviour affects a network more closely matching one in reality where many route paths interact and other network users are impacted by driver diverting. There are a number of necessary extensions and additional considerations required in this model which were not factors in the preceding chapters yet affect diverting in reality.

7.2 Choice set generation

The first issue to consider in using a more general network structure is the inclusion of an automated choice set generation process. Choice set generation involves determining an appropriate set of possible routes from which drivers make their choices. This was not necessary to include in the previous work, where the number of potential routes to an agent was at most three, but in a larger urban region between each origin and destination there may be large numbers of potential routes (and infinite if loops exist in the network). Drivers may not be aware that some or many of these routes exist or would reasonably consider them to be options.

In practical applications, choice set generation algorithms are evaluated by their *coverage* which is a measure of the percentage of observed routes which overlap algorithm generated routes in a proportion higher than a threshold amount. For the purposes of this model it is sufficient that a choice set generation process simply provides a feasible set of route options for agents traversing the network.

An example of the evaluation of a number of choice set generation algorithms against real world data is provided by Bekhor, Ben-Akiva and Ramming (2006). The majority of techniques are deterministic, such as link elimination (Azevedo et al., 1993) where once the shortest path has been found parts of it are removed and the shortest path in the new network are discovered, or link penalty approach (Barra et al., 1993) where costs are added to the shortest path after identification. For the purposes of this model a simple link elimination technique is added to the implementation when agents are initialised and forming route choice sets.

7.3 Sioux Falls network and demand profile

The network used in this study is one representing the city of Sioux Falls located within South Dakota, USA. This network structure, first presented by LeBlanc (1975), has been used on a number of occasions to demonstrate route choice and traffic assignment techniques (Han, 2003; Watling, 2002).

The network shape can be seen in figure 7.1 and is defined in table 7.2. The origin and destination pairs are defined in table 7.1 and visible diagramatically in figure 7.2.

The demand entry profile used in this network is shown in figure 7.3, showing the cumulative number of agents which have been added to the system at each time step (not the total number of agents in the system). An equal number of agents moving between each origin and destination pair (shown in table 7.1) is added at each adding event. Unlike in previous works, this demand profile is fixed and follows a 'ramp up' and 'ramp down' pattern.

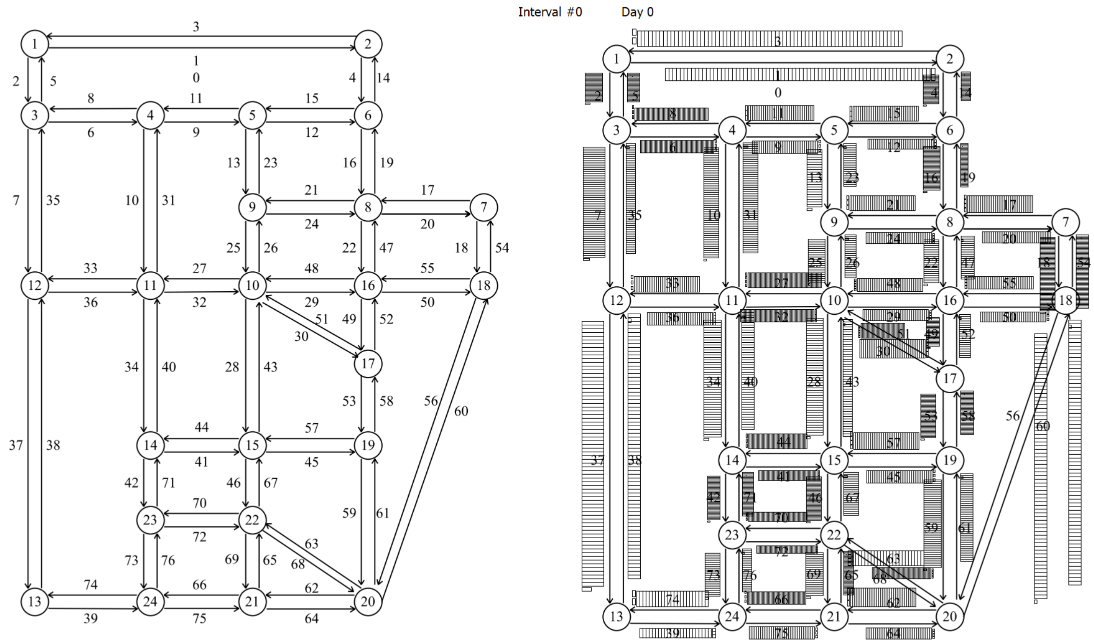


Figure 7.1: (Left): Sioux Falls network, adapted from the image used by Han, 2003. (Right): CTM implementation of network

Origin node	**Destination node**
1	10
4	19
6	15
7	15
12	19
13	10
14	8
18	5
20	9
22	8
2	15
3	16

Table 7.1: Origin and destination pairs, taken from Han, 2003. Shown visually in figure 7.2

7.4 Extending the representation of an incident and link states

Two issues arise with directly using the model presented in chapter 6 in this more complex network. These are both due to the fact that in this network recurrent congestion can arise at junctions (which, as mentioned previously, are all coded as fair four way signals

Link	A node	B node	No. of cells		Link	A node	B node	No. of cells		Link	A node	B node	No. of cells
1	1	2	65		26	10	9	45		51	17	10	45
2	1	3	55		27	10	11	50		52	17	16	45
3	2	1	65		28	10	15	45		53	17	19	45
4	2	6	60		29	10	16	40		54	18	7	50
5	3	1	55		30	10	17	45		55	18	16	55
6	3	4	60		31	11	4	55		56	18	20	55
7	3	12	60		32	11	10	50		57	19	15	40
8	4	3	60		33	11	12	60		58	19	17	45
9	4	5	50		34	11	14	50		59	19	20	50
10	4	11	55		35	12	3	60		60	20	18	55
11	5	4	50		36	12	11	60		61	20	19	50
12	5	6	50		37	12	13	65		62	20	21	40
13	5	9	50		38	13	12	65		63	20	22	45
14	6	2	30		39	13	24	60		64	21	20	40
15	6	5	50		40	14	11	60		65	21	22	50
16	6	8	45		41	14	15	50		66	21	24	50
17	7	8	40		42	14	23	50		67	22	15	45
18	7	18	50		43	15	10	40		68	22	20	45
19	8	6	45		44	15	14	45		69	22	21	50
20	8	7	40		45	15	19	50		70	22	23	40
21	8	9	45		46	15	22	40		71	23	14	40
22	8	16	45		47	16	8	45		72	23	22	40
23	9	5	50		48	16	10	40		73	23	24	60
24	9	8	45		49	16	17	45		74	24	13	50
25	9	10	45		50	16	18	55		75	24	21	40
										76	24	23	x

Table 7.2: Structure of the Sioux falls network, adapted from Han, 2003. Each cell has capacity of 4 unts.

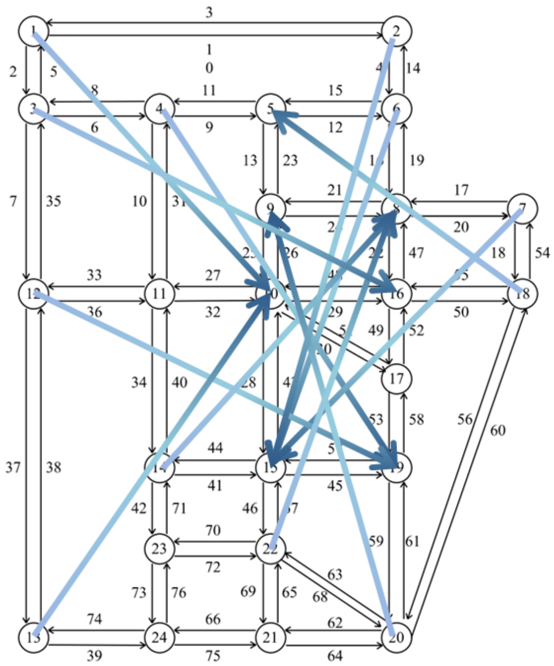


Figure 7.2: Visual representation of OD movements within the Sioux falls network

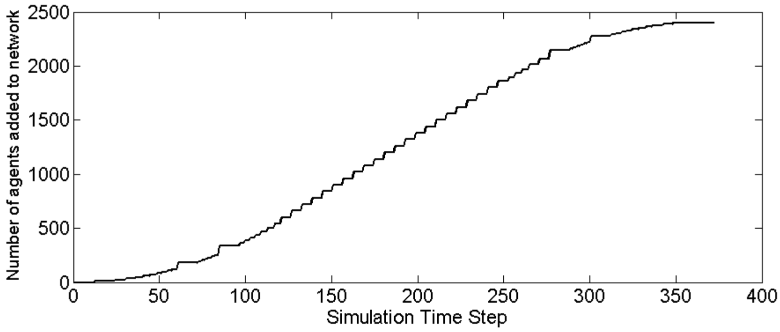


Figure 7.3: Number of agents having been added to the network against time, showing the arrival profile

where one arm takes a 'turn' to release agents each time step). This recurrent congestion is visible in figure 7.4, showing agents within the network on a non-incident affected simulated day.

Firstly, representing incidents is more challenging than simply using a cell capacity reduction as in the previous chapter 6. Often the natural recurrent queue from the junction occupies space on the link as far back as the incident, especially in early simulated days and central links are more congested. When the incident occurs within recurrent congestion its effects are not felt as vehicular flow is already restricted by the recurrent congestion. This is also a consequence of incidents occurring on relatively short network links with signalised junctions at either end. Such a situation can also arise in urban environments with short stretches of road and high levels of vehicular demand.

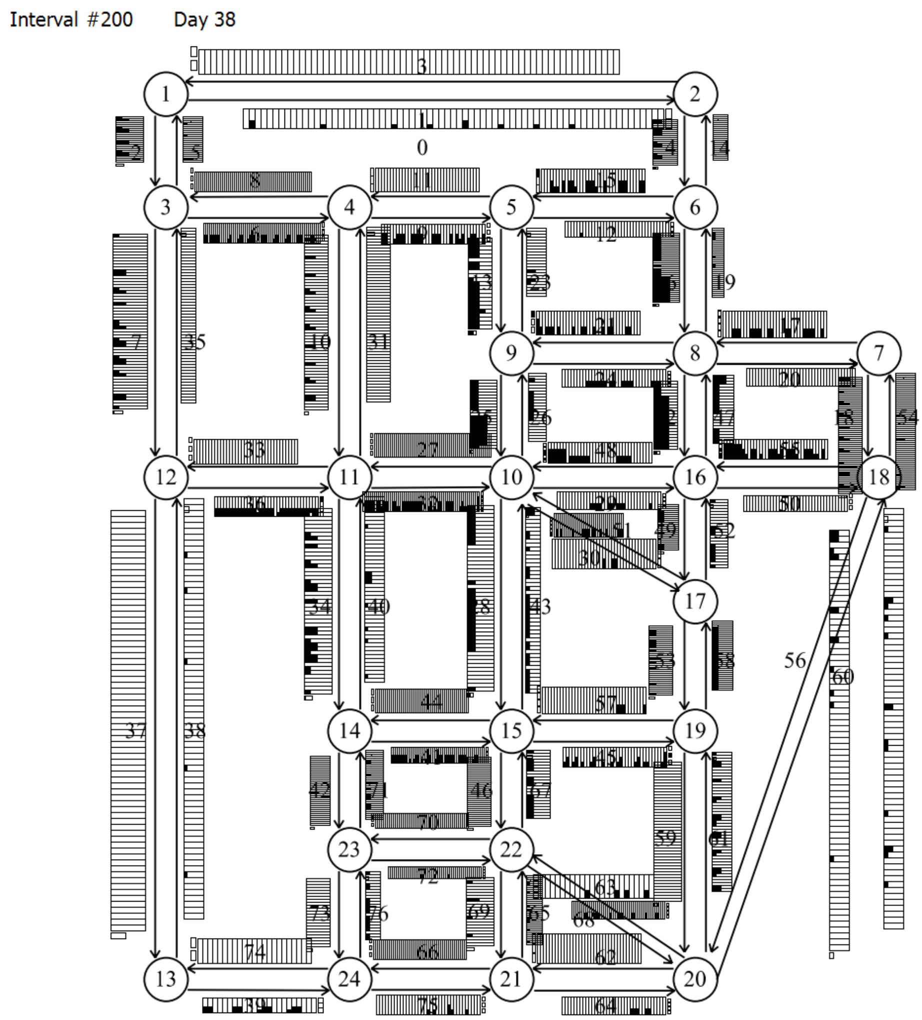


Figure 7.4: Showing a typical time period on a simulated day

Since the model functions on individuals subjectively distinguishing 'unexpected' system behaviour, this would have more of an impact in usually clear networks.

In response to the first issue, the representation of an incident has been extended for this study. In addition to a capacity reduction, from 4 to 1 agents capable of residing in the affected cell in each simulation time step, a free flow travel time penalty also applies, much like in the form adopted in chapters 3 and 5. This is modelled as a rule that an agent can pass only every one in four time steps.

The second issue relates to the definition of link states. The previous chapter 6 defined link states as being linear functions of free flow travel time where 'uncongested' less than 1.3× free flow travel time and 'heavily congested' is more than 2× free flow travel time. In this urban network links which feature heavy recurrent congestion may be likely to have a travel time greater than 1.3× free flow time under normal recurrent conditions, so distinguishing abnormally high amounts of congestion would also be difficult.

To alleviate this problem in this work, the definition has been shifted such that anything less than 2.5× free flow time is 'uncongested' and greater than 4× free flow time is 'heavily congested'. An extension to this work would allow the parameters of each state to be fully dependent on the network and its properties. In their original work from which this state representation is inspired, Kwon and Murphy (2000) allow for the mean of each state to vary as part of the learning process, although they report that only using 2 states is inadequate. As noted in the preceding chapters, further analysis of the suitable number of states required for a stretch of road should be considered in order to extend this work.

7.5 Results

Motivated primarily by figure 7.2 and by observing flows in the non-incident affected network, it was decided that for the analysis presented here the incident should affect link 22 (cell number 15) and link 32 (cell number 18). These two links were chosen because even though they are central to the network, link 22 is surrounded by relatively shorter links than 32 - the anticipated effect being that a link 22 incident will block back on to more other routes than a link 32 incident. Two simulations are run separately with one incident affected link in each. The link cell in question can be in its incident state on 20% of simulated days.

Figure 7.5 shows the link flow evolution over time on when the two separate links 22 and 32 are affected by incidents on 20% of simulated days. As well as noting that the two systems appear to evolve towards two quite different steady equilibrium distributions, the observation can be made that flows on links which are closer to the incident affected links (such as link 10) vary by more in the two tests than ones which are further away (such as links 61 and 75). This is intuitive, since the closer links to the incident sites are severely negatively affected due to queues blocking back as well as the incident site itself.

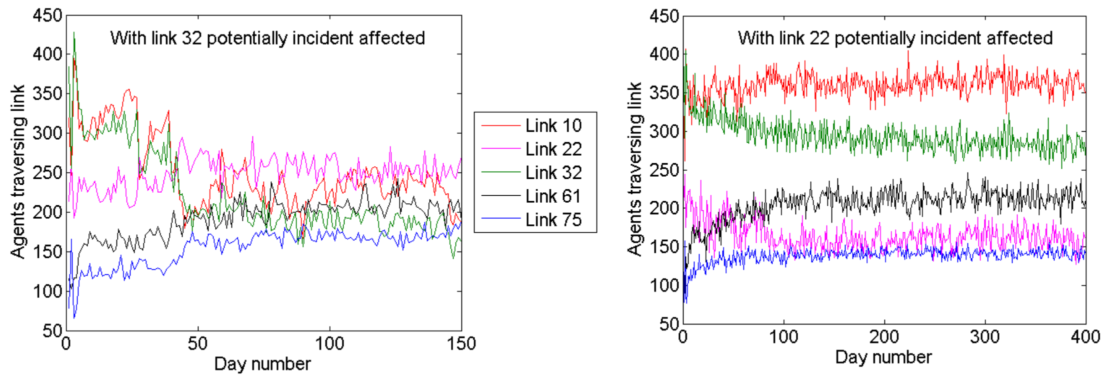


Figure 7.5: Evolution of day to day link flows using the same behaviour model under two different potentially perturbed links

Examining diversion behaviour also highlights differences between the two incident affected link locations. Figure 7.6 shows link 22 being affected by an incident and some agents appearing to travel to link 10 via link 9 rather than 22 because they perceive link 22 to be in the incident affected state. This only occurs with certainty at the end of the simulated day (figure 7.6 shows timestep number 653 - after all agents have been added to the network) once the network is much less congested. Before this point link 25 in particular is very highly congested, suggesting that there is no benefit to be had for agents arriving earlier to engage in diverting.

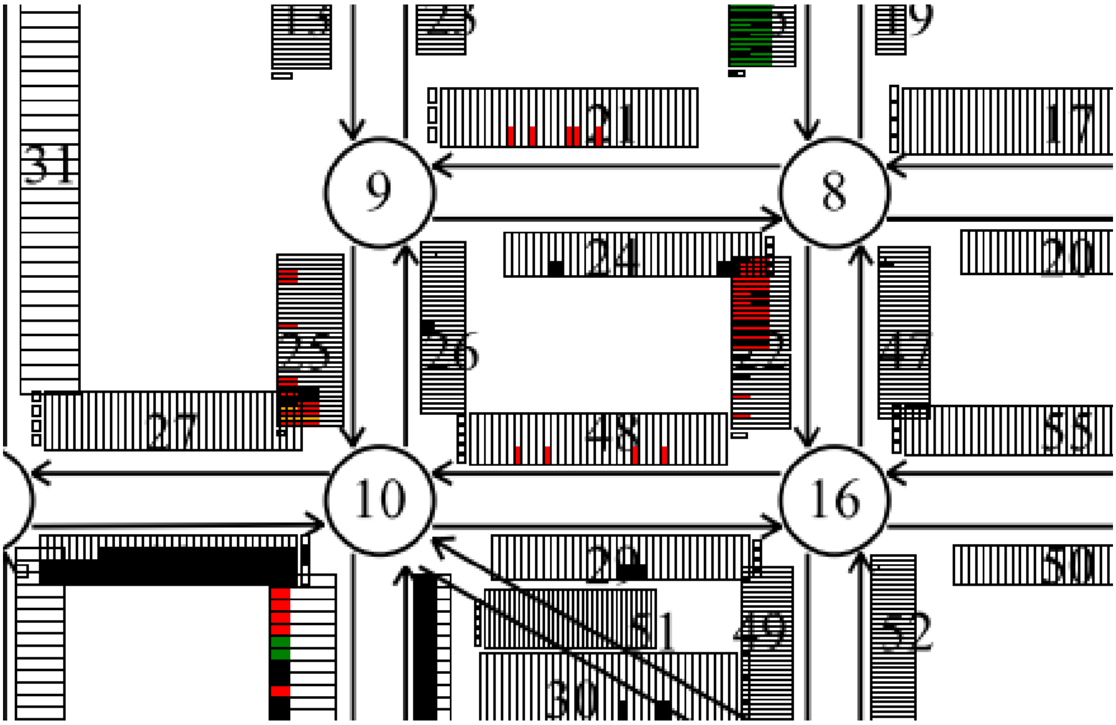


Figure 7.6: Showing detail of diverting vehicles around link 22 at time step 693 on day number 393

Figure 7.7 shows the network level comparison for the situation when link 32 is in the incident affected state. When an incident occurs, congestion from this link primarily blocks back along link 10 but since this link is relatively long it can accommodate the queuing vehicles, resulting in no visible diversion behaviour taking place.

7.6 Summary and key findings

The purpose of this work has been to relax the assumptions made in the preceding chapter 6 that diversion situations could arise on a road void of any other road users on trips between different origins and destinations. It also set out to demonstrate the impact of other traffic flows on driver diversion behaviour and the impact of diversion behaviour on other traffic flows.

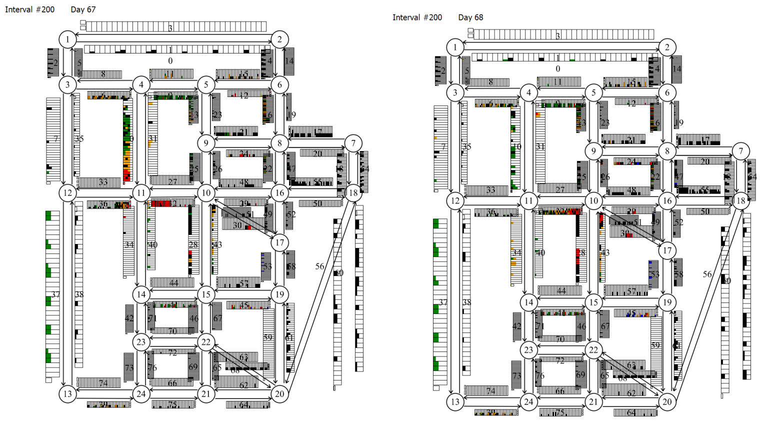


Figure 7.7: Showing the network level comparison between a link 32 incident affected day (left) and a non-incident affected day (right)

It has been found that two relaxations are required to the model presented in chapter 6 in order to create reasonable results, firstly that incidents slow down traffic and secondly that highly congested states hold a higher travel time. Both of these are a consequence of the model being applied in a congested urban environment where a real world driver would find it difficult to determine what can be considered unexpected non-recurrent congestion. This is important to the modelling of diversion behaviour, and suggests that further studies may reveal how drivers divert in different networks.

Regarding the model application process, Watling (2002) utilises an alternative second order 'Generalised Stochastic User Equilibrium' applied to the Sioux Falls network which attempts to resolve a number of fundamental issues arising with other forms of stochastic process models, named SP1 and SP2 (of which the model presented in this work more closely resembles SP1). These issues include equilibrium behaviour which 'could not reasonably be viewed as the plausible day-to-day operation of a network'. An extension to this work would be examining these issues and potentially applying other assignment techniques to the network in order to compare their impacts.

It has been shown that in an urban environment the assumptions and method of using the Coupled Hidden Markov Model are reasonable for representing general forms of congestion and their effects. Extensions to this work would include varying the network representation to include other properties of an urban environment, such as different junction types and traffic control systems which may be demand responsive such as in the work of Mahmassani and Hu (1997).

Chapter 8

Conclusions and Discussion

This thesis has primarily sought to address the issue of how individual, subjective, driver experience is represented in traffic flow forecasting models featuring driver route choice, applying both within day and between days. This has focussed on two main areas in its application to route choice decisions - learning of expectations of network properties between days and inferring network conditions in unobservable locations based on prior experience. Both are similar topics where one regards drivers determining what perceived conditions are given zero within day knowledge, and the regards drivers determining what perceived conditions are given some within day knowledge. At the end of the day drivers can combine that days experience with their prior beliefs and understanding of network properties.

Regarding the justification of this research, the question of 'how previous experience of congestion patterns feeds in to driver route choice decisions' is an important area of research because it drives demand expectations around a highway network. If one considers just behaviour within days, this traditionally has implications on traffic management and network design (Ortúzar and Willumsen, 2001).

As was addressed in chapter 1, forecasting events and incidents has implications in traffic management because highway managers may wish to understand where queues could be expected (which may be expected in some areas more than others) or general 'worst case scenarios' and stress tests. Managers may wish to provide targeted variable signage or other forms of information and influence behaviour in these locations where diverting may be common. It has implications in network design in that either drivers may seek out diversion routes (which may not be able to cope with additional demand) or the proposed locations of signage and information should be best known.

Additional to the traditional importance of understanding pure diversion behaviour as described, this thesis has suggested that drivers adopting strategic diversion behaviour (as a direct response to within day knowledge acquisition) can fundamentally change a drivers perception of the transport network and change expectations of route flows even in clear conditions not requiring diversions. Appreciating the causes and implications of this result, and how to capture its scale within forecasts, are a key reason for modelling within day variation in network conditions and flows.

Chapter 1 introduced the potential usefulness to practitioners of adopting some form of time varying ‘day to day’ assignment models to capture system ‘ramp up’ behaviour. This is based on the premise that after a sudden network change traffic flows take time to adjust to new long term ‘stable’ levels and currently most models do not forecast this with any numerical algorithm. Although ‘day to day’ mathematical models exist it is argued in this thesis that they do not necessarily allow for the variation in knowledge within day which can drive important dynamics in transport systems. The ability to illuminate and explain core dynamics which can be witnessed in reality, along with challenging the robustness of prevailing theory, is what Epstein (2008) points out and are the benefits of developing modelling techniques and is among the broader aims of this thesis.

This chapter revisits the key arguments of the thesis, which are the primary research contributions and merit further research, then examines the degree to which specific aims and objectives have been met. The chapter closes with recommendations for further research.

8.1 Key arguments of this thesis which contribute towards aims

This thesis has put forward a number of key arguments on which the research and main assertions are founded. These arguments are the primary novel contributions towards meeting the thesis aims in section 1.4.3. It is not believed that the effects of these arguments have been linked previously hence they drive the innovation in the thesis. They are: that highway network conditions be described as discrete ‘states’; that drivers behave in a boundedly rational manner which is different to interpretations in other transport applications; and that adequately capturing variation in knowledge among a population of drivers is essential to capturing key dynamics.

8.1.1 State based link representation

Section 2.4.2 introduced a definition of a link state as ‘a specific combination of any road transport attributes - whether the properties are quantifiable such as capacity, free flow speed and available road width or more qualitative such as weather conditions and general driver attitudes’. State changes are driven by what Emmerink, Axhausen, Nijkamp and Rietveld (1995) term ‘shocks’. Examples of shocks are shown in table 2.1 presented by Miete (2011).

The concept of states applying within day is not new in demand forecasting and form the basis of Gao's network representation for the routing policy choice models (Gao, 2002; Gao et al., 2008). However these only consider static networks where any relationship between link states is externally applied, in the same manner as in the network models applied in chapters 3 and 5. In reality, as argued in section 2.6, it is likely that relationships exist between link states as queues block back and create a congestion structure around the network which is in some way predictable. A number of spatial network performance forecasting tools have been developed which exploit this property (Min and Wynter, 2011; Kwon and Murphy, 2000).

Chapter 6 utilised a Cell Transmission Model to generate queuing as an emergent property of agent decisions in order to capture state relationships as exist in reality, demonstrating that the learning of link state relationships is a plausible possibility. The implementation presented here also highlighted how the relationship between link states themselves is dependent on agent actions, as when more agents diverted the congestion structure disappeared severe queues reformed in a wave like motion causing 'diversion breakdown'.

This key argument contributes primarily towards aim number 3, suggesting that it could be a key part of modelling driver perception of within day conditions which impacts upon simulation results.

8.1.2 Interpretation of bounded rationality

As outlined in section 2.1, the first discussion of bounded rationality in forecast models was provided by Simon (1955). This was based on the principles that (applied to route choice systems) i) drivers do not know exact travel times on all available route options (lack of knowledge), ii) drivers are often required to make decisions in a relatively short space of time and cannot calculate exact overall costs (lack of processing time) and iii) drivers are susceptible to biases (such as optimism or pessimism).

A number of key results in this thesis are founded on the specific interpretation and implementation of bounded rationality. This can be summarised as firstly that individual drivers are only able to form judgements based upon their own subjective experience and secondly that drivers are prone to their own errors in judgement although 'better alternatives are chosen more often' (Su, 2007). It is acknowledged that this interpretation is different to others, such as the work of Mahmassani (1987). An extension to this work could be to further incorporate principles adopted by Mahmassani in to the models presented, such as habit formation, although currently Mahmassani's method is not believed to include an appreciation of non-recurrent congestion or structure of states which is carried across days.

Chapters 5, 6 and 7 have shown that agent based modelling approaches, which Cantarella and Cascetta (1995) term 'disaggregate stochastic day to day models', stand alone in their ability to capture all of these aspects of bounded rationality which lead to a number of insights which are unique to the approach.

8.1.3 The importance of capturing variation in knowledge

This argument relates to the findings in chapters 3, 5 and 6 that there are found to be reasons why participants in transport systems would behave differently when one assumes that they do not have perfect knowledge and will act to the best of their subjective knowledge in a boundedly rational manner. Most importantly this difference manifests itself in initial routing decisions which would alter route flows even in clear and usual conditions without incidents.

In chapter 3 this meant, as summarised in figure 3.9, that when 'real world' participants had the option of acting on their incomplete knowledge whilst en-route by diverting, they were observed to change their initial choices in order to 'take a chance' on the faster option under clear conditions.

Chapter 5 showed how, under an agent based model of variation in knowledge within day, the action of other agents themselves diverting can fundamentally change properties of the highway network in that 'incident afflicted' links are not as severely congested as they would be were no agents capable of diverting. This alters the initial route choices of agents who form routing decisions based on their expected average travel times, shown in figure 5.2.

Chapter 6 further showed how the ability for agents to divert en-route can considerably change network conditions within a single day. The result was shown in figure that congestion could dissipate and cause agents entering the environment to no longer perceive the need to divert.

8.2 Success in meeting thesis objectives

The following discusses the degrees to which the individual thesis objectives have been met, as set out in section 1.4.4.

- **Objective 1:** To assess current understanding of the causes and characterisation of time varying highway phenomenon which give rise to unexpected network conditions and congestion patterns, such as incidents and other events.

It was established in chapters 1, 2 and 4 that generally transport demand forecasts do not cater for the impacts of travel time uncertainty due to day to day variation or infrequent incidents. Instead traditional techniques forecast 'average day' conditions for a number of reasons including the development of mathematical forecast techniques and secondly the tendency for models to be calibrated based on 'snapshot' views of the network rather than considering how flows vary over time. Novel models are being developed to provide tools to evaluate non-recurrent congestion, incidents and driver diverting behaviour. Arguments exist regarding which approach offers the most potential for best modelling such situations.

Regarding how best to represent non-recurrent congestion and delays themselves, this thesis has sought out examples of their characteristics in available literature and looked at how they are represented by others. It found that this is generally through decreases in capacity and increases in free flow travel times (which may only act for a portion of a simulated day). Examples of empirically measured changes are can be seen in table 2.2. Although significant work needs to be done in understanding the *causes* of incidents to truly capture them in models it is believed that their representation is satisfactory to model the effects.

Most importantly in meeting this objective, this thesis has adopted a methodology whereby time varying highway phenomenon can be included in modelling forecast techniques. This is where models allow for road capacity and free flow travel times to be adjusted in line with empirical impacts. Since this has been achieved it is felt that this objective has been met.

- **Objective 2:** To undertake a review of existing knowledge regarding how drivers make decisions under uncertainty and lack of knowledge. Where necessary, this thesis should fill gaps in knowledge relating to this process.

This objective focussed on our ability to understand how drivers make their routing and diversion decisions in real world traffic networks. It was observed in this thesis that experience and diversion behaviour had not received much attention which could contribute towards a numerical algorithm for predictive forecasting purposes. Instead much research of the research on diversion behaviour is based on travellers providing their account of what they did, rather than actually being monitored in scenarios in any way.

Chapter 3 conducted a route choice simulator based survey with the intention of proving to some degree a link between diversion behaviour, network familiarity and making assumptions about conditions in unknown network areas. Many of the findings of the study agreed with findings in previous literature, relating to tendencies to behave more randomly when cost distributions are similar and learning behaviour. The study was also able to provide insight in to how gender and age appears to affect risk perception. The key finding of this study however was that it appeared to show among human participants a link between the known possibility of diverting and start of day routing decisions. Useful insight was also taken from this route choice survey to develop a novel agent based driver behaviour model. This aim is therefore considered to be met.

- **Objective 3:** To identify and implement a suitable modelling technique for capturing variation in knowledge among a population of drivers. This should be be capable of representing variation within days as well as between days.

This objective sought to aide our methodological ability to represent incidents and time varying travel conditions within models of forecasting spatial transport demand around a highway network.

Regarding the representation of individuals and general modelling approach, the concepts behind day to day route choice models have been identified as a useful modelling approach to capture learning and daily variation in flows. They are capable of generating outputs such as expected flow trajectories and can provide the stability of fixed basins of equilibria. Although these models are being augmented with better behavioural representation, such as implementation of prospect theory (Zhang and Juan, 2013), it is argued as a result of this doctoral work that to *best* represent plausible learning and route flow trajectories *disaggregate* day to day models, or agent based models, stand apart as being best able to suitably capture traffic dynamics.

Regarding the ramp up effect introduced in section 1.3.1, it has been found in all of the models in this work that often the effect of drivers with no correct knowledge of system attributes (such as after a network change) is likely to be negative for the system as a whole, as usually more drivers attempt to travel on routes which then become congested. It should be pointed out however that this may not be the case in reality as He (2010) found that flows following network change were better represented using a mechanism whereby drivers make assumptions of the choices of others. This result also highlights the importance of supplying information and advice to travellers which was not a primary concern in this work.

In addition to modelling learning and route choice evolution, this argument for the adoption of agent based models is far strengthened by the consideration of modelling diversion behaviour. Chapters 5, 6 and 7 have all examined plausible behaviour models with varying degrees of simplifying assumptions and the result has been found in each case that the within day variation in individual knowledge drives the overall system behaviour, even on days when the incidents do not occur.

In conclusion it is felt that this aim has been met, although there is certainly still scope for further research in this area as is discussed below it is hoped that these thoughts and assertions will inspire others to take up research in this emerging field.

- **Objective 4:** To explore the effect of highway network representation on network phenomena and aspects of driver learning. This includes both representation of incidents and properties of the highway network itself such as queue formation.

Perhaps the most important finding is in chapter 5 that, supposing route choices impact on resulting route travel times and experience then guides future route choices, in a network with potential for non-recurrent congestion, having groups of drivers who are able to divert creates a more favourable route option for themselves on the original route when they 'taking a chance' on the potentially perturbed (but unknown when the decision is made) option.

Chapter 6 suggests that this result may only be true to a point however, as having too many drivers willing to divert away from their original choice of route path has a negative impact on the system as a whole. In the behaviour models presented in chapters 6 and 7 the decision to divert is only informed by the decisions of other travellers (in the form of dynamic queues) so if the queue recedes then future drivers are unable to gain the knowledge that a diversion may be in their best interests. This was termed 'diversion breakdown'.

Chapter 7 focussed on how non-recurrent congestion and its effects interact with other network traffic, going some way to meeting objective 3.4. In this exploratory study it was found that diverting behaviour appeared to happen little due to network structure - in one case that no diversion routes were available and in another that no diversion route had a satisfactory travel time until the network was empty. This model did suggest however that the impact of non-recurrent congestion is felt in a wider area than where drivers may engage in diverting as queues block back along links. This significantly alters system behaviour and the equilibrium which arises.

Chapter 7 also raised that effective diversion behaviour was ineffective because according to this behaviour model agents had no way of knowing that an upcoming link was congested until it was no longer possible to divert. This is probably a rationale for effective information dissemination, advising travellers in advance of upcoming link conditions. A promising study has suggested that in reality drivers may even adapt their routes to obtain the benefit of passing by signage (Lu et al., 2010b).

In line with the arguments put forward by Liu, Van Vliet and Watling (2006) and Mahmassani and Hu (1997), it is clear that representing the highway network within day appropriately is key to faithfully forecasting flows. It is felt that this thesis has evidenced this and the objective is considered to be met.

- **Objective 5:** *To evaluate and, where possible overcome, the technical challenges of modelling individual experience*

This objective refers to managing the technical differences and difficulties arising between implementing agent based models and traditional analytical approaches to determining traffic assignment with equilibrium solutions, such as the techniques outlined within the work of Sheffi (1984).

The general technical requirements and subsequent challenges involved in implementing agent based models are well known, as discussed by Nagel and Marchal (2006b). Storing many large parameters and arrays of data relating to each individual agent within the simulation requires significant memory requirements. Bazzan and Klugl (2013) refer to this problem as one with *scalability* and they comment that none of the more sophisticated agent based representations have yet been implemented on as large a scale as traditional approaches.

Assuming a fixed computational memory resource, a technological trade off exists between 1) the number of disaggregate intelligences used within the model and 2) the sophistication of that intelligence. The agent based models presented in chapter 4 are simple in nature as they only require one matrix to be stored per agent, φ_r being the expectation of route travel times. Those presented in subsequent chapters store more variables per agent, although steps must be taken to ensure that these can be replicated among thousands of agents.

In particular, in the work presented here only variables which inform routing decisions are stored by agents. The exact agent decision and experience histories are not stored within the simulation, instead parameters which update through learning algorithms, such as link travel times, are used. Also, in the CHMM work, agents only form a hidden markov model with an associated network link they have already traversed so none are ever created for links outside of the agent's choice set.

Although not explored by this work there is scope for simplification of the models presented in this thesis. For example one of the main features of these models is that agents learn relationships between all link states, yet it is reasonable to assume from empirical studies that beyond a certain distance link states are usually uncorrelated (Bernard et al., 2006; Cheng et al., 2012) so would not need to be represented within this model. Alternatively, research has found that in many networks clusters may exist of links with related travel times which would not require learning individually (Krichene, 2010; Xing and Zhou, 2011). This too may be a fruitful future research direction.

As a final comment about representation of agents it may also be useful and less memory intensive to explore whether it is possible to use 'packets' of agent intelligence. Rather than one intelligence assigned to each agent, one intelligence could guide the decisions of three or four agents traversing a network. Each of their experience would then affect this group intelligence. This may prove to be an effective trade off to capture aspects of behaviour, particularly diversion based or anything more sophisticated, not able to be represented by day to day models.

8.3 Future research directions

The technological challenges have already been discussed in the preceding section, describing how disaggregate simulation based models are entirely limited by the computational power available. Although this limitation may ease with time as computational resources become cheaper, one should keep in mind when designing and building agent based models to be smart with keeping memory footprints per individual as small as possible.

Regarding the modelling approach, disaggregate models - particularly those with sophisticated behaviour mechanisms - are notoriously hard to calibrate for a population. There are typically many parameters which drive individual preferences and sensitivities, and within the model there are feedback effects and subtleties which produces chaotic behaviour. This is especially true for detailed transport modelling like in chapter 7 where one link being blocked can dramatically influence the future flows across a broad selection of others.

One could imagine that in the future a 'unifying theory' of transport modelling may occur where all steps of the four stage modelling approach are integrated seamlessly as every aspect of a populations travel patterns are completely simulated including trip chaining and having distinct work and leisure trips carried out at different times of day. This would be open to more parameters, sensitivities and chaotic results than just simulating traffic moving across an urban environment with fixed departure times.

Accordingly moving towards developing a single model of transport is likely not to be the sensible way to proceed and keeping models split in to capturing different aspects of travel can be more powerful overall - such as the reasons for modelling other than prediction provided by Epstein (2008).

An area which does not appear to have received any research attention is *how* to integrate incidents and events within transport models. Within every found example of a diversion model in the literature (and in this work) incidents are supplied externally rather than being an emergent property of the model. The description of sources of variation provided by Meite (2011) in table 2.1 shows that some events truly are external, such as weather, but it could be reasonable to assume that traffic accidents are a function of link flow. In section 2.4.1 a figure of 0.171 incidents are reported on average per 100,000 car kilometres (Cullison et al., 1997) but it is likely that local area aspects also play a part such as poor visibility.

8.4 Concluding remarks

It is likely that the future of transport modelling will move towards higher detail simulations in order to capture the effect of more traffic flow influencing processes. This includes not only drivers learning more detailed network properties over time, arising from more detailed network representations capable of capturing link flow relationships, but also the impact of Intelligent Transportation Systems (ITS) including responsive traffic signals, Advanced Traveller Information Systems (ATIS) including variable signage, and the role of individual travellers possessing live traffic information on internet connected devices such as smart phones.

In order to model driver behaviour in more detail is important to understand driver behaviour in as much detail. Many of the detailed empirical studies presented in this work have been undertaken in controlled laboratory environments where the choice environment is fully known to the observer. It is far more challenging to resolve a driver's knowledge level and network perception based on the gps traces of single vehicles or even travel diaries. Large sources of 'big data', such as for example mobile phones location data, may provide insight in to how larger populations fully react to infrastructure change and events in the real world.

Fundamentally, related back to the goals of transport modelling in section 1.2, it is important that practitioners are aware of the assumptions which exist in the modelling techniques that they use and the impact that these assumptions can have on their forecasts. This thesis has shown how traffic flow forecasts can vary significantly based on input assumptions regarding both driver knowledge and how the highway network operates.

References

Abdel-Aty, M. A., K. R. and Jovanis, P. P. (1994). Using stated preference data for studying the effect of advanced traffic information on drivers' route choice. *Transportation Research Part C: Emerging Technologies*, 50(1):39–50.

Ahmed, U. (2009). Passenger car equivalent factors for level freeway segments operating under moderate and congested conditions. Master's thesis, Marquette University.

Arentze, T. A. and Timmermans, H. J. P. (2005). Information gain, novelty seeking and travel: a model of dynamic activity-travel behavior under conditons of uncertainty. *Transportation Research A: Policy and Practice*, 39(2):125–145.

Arthur, W. B. (1994). Inductive reasoning and bounded rationality. *American Economic Review*, 84:406–411.

Asamer, J. and Reinthaler, M. (2010). Estimation of road capacity and free flow speed for urban roads under adverse weather conditions. In *13th International IEEE Annual Conference on Intelligent Transportation Systems*.

ATKINS (2009). M6 toll traffic monitoring study: Post opening evaluation. Technical report, Highways Agency.

Avineri, E. and Prashker, J. N. (2003). The impact of travel time information on travellers' learning under uncertainty. *10th International Conference on Travel Behaviour Research*.

AVV (2004). Ontwikkelingen verkeer en vervoer 1990/ 2020, probleemverkenning voor de nota mobiliteit. Technical report, Adviesdienst Verkeer en Vervoer.

Azevedo, J., Santos-Costa, M. E. O., Silvetre-Madeira, J. J. E. R., and Veira-Martins, E. Q. (1993). An algorithm for ranking of shortest paths. *European Journal of Operational Research*, 69(1):97–106.

Bain, R. (2009). Error and optimism bias in toll road traffic forecasts. *Transportation*, 36:469–482.

Banks, B. and Glaister (2007). Motoring towards 2050. Technical report, RAC Foundation.

Barra, T., Perez, B., and Anez, J. (1993). Multidimensional path search and assignment. *Proceedings of the 21st PTRC Summer Meeting 363*, pages 307–319.

Barros, G. (2010). Herbet a. simon and the concept of rationality: Boundaries and procedures. *Brazilian Journal of Political Economy*, 30(3 (119)):455–472.

Bazerman, M. and Neale, M. (1992). On rational escalation of commitment in negotiation. *European Management Journal*, 10(2):163–168.

Bazzan, A. L. C. and Klugl, F. (2013). A review on agent-based technology for traffic and transportation. *Knowledge Eng. Review*.

Beckmann, M. J., McGuire, C. B., and Winston, C. B. (1956a). *Studies in the Economics of Transportation*. Yale University Press, New Haven, Conn.

Beckmann, M. J., McGuire, C. B., and Winston, C. B. (1956b). *Studies in the Economics of Transportation*. Cowles Commision Monograph, Yale University Press, New Haven, Conn.

Bekhor, S., Ben-Akiva, M., and Ramming, S. (2006). Evaluation of choice set generation algorithms for route choice models. *Annals of Operations Research*, 144(1):235–247.

Bekhor, S., Dobler, C., and Axhausen, K. W. (2011). Integration of activity-based with agent-based models: an example from the tel aviv model and matsim. *90th Annual Meeting of the Transport Reseaerch Board*.

Ben-Akiva, M. and Bierlaire, M. (1999). *Handbook of Transportation Science*, chapter Discrete choice methods and their applications to short-term travel decisions, pages 5–34. Kluewer.

Ben-Akiva, M., Bierlaire, M., Burton, D., Koutsopoulos, H., and Mishalani, R. (2000). Simulated-based tools for dynamic traffic assignment: Dynamit and applications. *Proceedings of ITS America 10th annual meeting*.

Ben-Elia, E., Bierlaire, M., and Ettema, D. (2010). A model of departure time choice with latent classes and peak-hour avoidance rewarding. In *12th World Conference of Transportation Research, Lisbon, Portugal*.

Ben-Elia, E., Erev, I., and Shiftan, Y. (2008). The combined effect of information and experience on drivers' behavior. *Transporation*, 35(2):165–177.

Ben-Elia, E. and Shiftan, Y. (2010). Which road do i take? a learning-based model of route-choice behavior with real-time information. *Transportation Research Part A: Policy and Practice*, 44(4):249–264.

Bernard, M., Hackney, J., and Axhausen, K. (2006). Correlation of link travel speeds. In *6th Swiss Transport Research Conference*.

Bie, J. and Lo, H. K. (2010). Stability and attraction domains of traffic equilibria in a day-to-day dynamic system formulation. *Transportation Research Part B*, 44(2):163–168.

Blumentritt, C. W., Ross, D. W., Glazer, J., Pinnell, C., and McCasland, W. R. (1981). Guidelines for selection of ramp control systems. Technical Report 232, Transportation Research Board.

Bogers, E. A. I., V. F. and Hoogendoorn, S. P. (2005). Joint modeling of atis, habit and learning impacts on route choice by laboratory simulator experiments. *84th Annual Meeting of the Transportation Research Board*.

Bonsall, P., Firmin, P., Anderson, M., Palmer, I., and Balmforth, P. (1997). Validating the results of a route choice simulator. *Transportation Research Part C: Emerging Technologies*, 5(6):371–387.

Bonsall, P. W. and Palmer, I. (2004). Modelling drivers' car parking behaviour using data from a travel choice simulator. *Transportation Research Part C: Emerging Technologies*, 12(5):321–347.

Bureau of Public Roads (1964). *Traffic assignment manual*. Bureau of Public Roads, Urban Planning Division, US Department of Commerce.

Cairns, S., Klau, C. H., , and Goodwin, P. (1998). *Traffic Impact of Highway Capacity Reductions: Assessment of the Evidence*. Landor Publishing.

Camerer, C. F. (2002). *Behavioral game theory: Experiments on strategic interaction*. Princeton University Press.

Cantarella, G. E. (1993). Day-to-day dynamics in transportation networks: Stability and limits of equilibrium in a two link network. *Sistemi Urbani*, I:27–50.

Cantarella, G. E. and Cascetta, E. (1995). Dynamic processes and equilibrium transportation networks: Towards a unifying theory. *Transportation Science*, 29(4):305–329.

Cascetta, E., Nuzzolo, A., Russo, F., and Vitetta, A. (1996). A modified logit route choice model overcoming path overlapping problems. specification and some calibration results for interurban networks. In *Proceedings of the 13th International Symposium on Transportation and Traffic Theory, Lyon, France*.

Ceder, A. and Livneh, M. (1982). Relationships between road accidents and hourly traffic flow - analyses and interpretation. *Accident Analysis & Prevention*, 14(1):19–34.

Charypar, D. and Nagel, K. (2005). Generating complete all-day activity plans with genetic algorithms. *Transportation: Planning, Policy, Research, Practice*, 32(4):369–397.

Chatterjee, K. and McDonald, M. (2004). Effectiveness of using variable message signs to disseminate dynamic traffic information: Evidence from field trails in european cities. *Transport Reviews: A Transnational Transdisciplinary Journal*, 24(5):559–585.

Chen, P. S. and Mahmassani, H. S. (1999). Dynamics of urban commuter behavior under real-time traffic information. Technical Report SWUTC/99/472840-00066-1, Southwest Region University Transportation Center.

Chen, X., Meaker, J. W., and Zhan, F. B. (2006). Agent-based modelling and analysis of hurricane evacuation procedures for the florida keys. *Natural Hazards*, 38(3):321–338.

Cheng, T., Haworth, J., and Wang, J. (2012). Spatio-temporal autocorrelation of road network data. *Journal of Geographical Systems*, 14:389–413.

Chorus, C. G., Molin, E. J., and Van Wee, B. (2006). Travel information as an instrument to change car drivers travel cchoice: a literature review. *EJTIR*, 6(4):335–364.

Chrobok, R., Kaumann, O., Wahle, J., and M., S. (2004). Different methods of traffic forecast based on real data. *European Journal of Operational Research*, 155:558–568.

Conroy Dalton, R. (2003). The scecret is to follow your nose: route path selection and angularity. *Environment and Behavior*, 35(1):107–131.

Courthout, R., Tampère, C. M. J., and Immers, L. H. (2009). Marginal incident computation: An efficient algorithm to determine congestion spillback due to incidents. *Transportation Research Record*, 2099:22–29.

Cullison, J. T., Nowlin, R. L., Fitzpatrick, K., and Ogden, M. A. (1997). Incident management in the united states: a state-of-the practice review. Technical report, Texas Transportation Institute, College Station, Texas.

Daganzo, C. and Sheffi, Y. (1977). On stochastic models of traffic assignment. *Transportation Science*, 11(3).

Daganzo, C. F. (1977). Multinomial probit and qualitative choice: A computationally efficient algorithm. *Transportation Science*, 11:338–358.

Daganzo, C. F. (1994). The cell transmission model: a simple dynamic representation of highway traffic. *Transportation Research Part B*, 28(4):269–287.

Davis, G. and Nihan, N. (1993). Large population approximations of a general stochastic traffic assignment model. *Operation Research*, 41(1):169–178.

Denrell, J. (2007). Adaptive learning and risk taking. *Psychological Review*, 114:117–187.

Department for Transport (2010). Transport statistics great britain: 2010: International comparisons. Technical report, Department for Transport.

Department for Transport (2012a). Road transport forecasts 2011: Results from the department for transport's national transport model. Technical report, Department for Transport.

Department for Transport (2012b). Tra0101 (also tsgb0701) road traffic (vehicle miles) by vehicle type in great britain, annual from 1941.

Department for Transport (2013a). National travel survey 2012: Statistical release. Technical report, Department for Transport.

Department for Transport (2013b). Reliability of journeys on highways agencyŠs motorway and ŚaŠ road network, england: March 2013. Technical report, Department for Transport.

Department for Transport (2014). Annual road traffic estimates: Great britain 2013. Technical report, Department for Transport.

Department of Infrastructure and Transport (2011). Review of traffic forecasting performance toll roads. Technical report, Australian Government Department of Infrastructure and Transport.

D'Este, G. (2010). What happens to toll road ramp-up profile when there is an initial toll-free period, and the broader implications for demand forecasting. In *Australasian Transport Research Forum 2010 Proceedings*.

Di, X., Liu, H. X., Pang, J., and X., B. (2013). Boundedly rational user equilibria (brue): Mathematical formulation and solution sets. *Procedia - Social and Behavioral Sciences*, 80:231–248.

Dia, H. (2002). An agent based approach to modelling driver route choice under the influence of real-time information. *Transportation Research C*, 10:331–349.

Dial, R. B., Glover, F., Karney, D., and Klingman, D. (1979). A computational analysis of alternative algorithms and labeling techniques for finding shortest path trees. *Networks*, 9.

Dijkstra, E. W. (1959). Note on two problems in connection with graphs. *Numerical Mathematics*, 1:269–271.

Dobler, C. (2013). Travel behaviour modelling for scenarios with exceptional events - methods and implementations. Master's thesis, ETH Zurich.

DVS (2010). Kwartaalmonitor bereikbaarheidsontwikkeling hoofdwegennet, 4e kwartaal 2009, 1 oktober Ű 31 december 2009. Technical report, Dienst Verkeer en Scheepvaart (DVS).

Eddington, R. (2006). The eddington transport study. Technical report, HM Treasury.

Emmerink, R. H. M., A. K. W. N. P. and Rietveld, P. (1995). The potential of information provision in a simulated road transport network with non-recurrent congestion. *Transportation Research C*, 3(5):293–309.

Epstein, J. M. (2008). Why model? *Journal of Artificial Societies and Social Simulation*, 11(4).

Fellendorf, M. and Vortisch, P. (2010). Microscopic traffic flow simulator vissim. *Fundamentals of Traffic Simulation*.

FHWA (2005). Traffic congestion and reliability: Trends and advanced strategies for congestion mitigation. Technical report, U.S. Department of Transportation.

Florian, D., Balakrishna, R., Ben-Akiva, M., and Wen, Y. (2006). Evaluation of on-line dynamic traffic assignment using microsimulation. *Second International Symposium of Transport Simulation (ISTS06)*.

Flyvbjerg, B. (2005). Measuring inaccuracy in travel demand forecasting: Methodological considerations regarding ramp up and sampling. *Transportation Research A: Policy and Practice*, 39(6):522–530.

Flyvbjerg, B., Holm, M. K. S., and Buhl, S. L. (2006). Inaccuracy in traffic forecasts. *Transport Reviews*, 26(1):1–24.

Frejinger, E. (2008). *Route choice analysis : data, models, algorithms and applications.* PhD thesis, École Polytechnique Fédérale de Lausanne.

Fujii, S., Gärling, T., and Kitamura, R. (2001). Changes in driversŠ perceptions and use of public transport during a freeway closure. *Environment and Behaviour*, 33:796–808.

Gao, S. (2002). *Optimal adaptive routing and traffic assignment in stochastic time-dependent networks.* PhD thesis, MIT, Cambridge.

Gao, S., Frejinger, E., and Ben-Akiva, M. (2008). Adaptive route choice models in stochastic time-dependent networks. *Transportation Research Record 2085*, pages 136–143.

Gao, S., Frejinger, E., and Ben-Akiva, M. (2010). Adaptive route choices in risky traffic networks: A prospect theory approach. *Transportation Research Part C: Emerging Technologies*, 18(5):727–740.

Gao, S., Frejinger, E., and Ben-Akiva, M. (2011). Cognitive cost in route choice with real-time information: An exploratory analysis. *Procedia - Social and Behavioral Sciences*, 17:136–149.

Golledge, R. G. and Garling, T. (2001). Spatial behavior in transportation modelling and planning. Technical report, University of California Transportation Center.

Greenshields, B. D. (1935). A study of traffic capacity. In *Proceedings of the Highway Research Board*, volume 14.

Hackney, J. K., Bernard, M., Bindra, S., and Axhausen, K. W. (2007). Predicting road system speeds using spatial structure variables and network characteristics. *Journal of Geographical Systems*, 9:397–417.

Han, S. (2003). Dynamic traffic modelling and dynamic stochastic user equilibrium assignment for general road networks. *Transportation Research Part B*, 37(3):225–249.

Han, Y. and Moutarde, F. (2013). Statistical traffic state analysis in large-scale transportation networks using locality-preserving non-negative matrix factorisation. *IET Intelligent Transportation Systems*, 7(3).

Harwood, D. W., May, A. D., Anderson, I. B., Leiman, L., and Archilla, A. R. (1999). Capacity and quality of service for two-lane highways. Technical report, National Cooperative Highway Research Program, Transportation Research Board.

Haselkorn, M., Spyridakis, J., Conquest, L., and Barfield, W. (1989). Surveying commuter behavior as a basis for designing motorist information systems. In *Proceedings of the First Vehicle Navigation and Information Systems Conference, IEEE, Toronto, Canada.*

He, R., Kornhauser, A. L., and Yelinek, M. (2006). A study on temporal and spatial variability of travel time. In *Joint International Conference on Computing and Decision Making in Civil and Building Engineering.*

He, X. (2010). *Modelling the Traffic Flow Evolution Process after a Network Disruption.* PhD thesis, University of Minnesota.

He, X. and Liu, H. X. (2012). Modelling the day-to-day traffic evolution process after an unexpected network disruption. *Transportation Research Part B: Methodological*, 46(1):50–71.

Herring, R., Hofleitner, A., Abbeel, P., and Bayen, A. (2010). Estimating arterial traffic conditions using sparse probe data. In *Intelligent Transportation Systems (ITSC), 2010 13th International IEEE Conference on*, pages 929–936. IEEE.

Horowitz, J. L. (1984). The stability of stochastic equilibrium in a two-link transportation network. *Transportation Research Part B*, 18(1):13–28.

Hu, T. and Mahmassani, H. (1997). Day-to-day evolution of network flows under real-time information and reactive signal control. *Transportation Research C*, 5:51–69.

Hyder Consulting (2010). Motorway travel time reliability. Technical report, The Highways Agency.

Iida, Y., A. T. and Uchida, T. (1992). Experimental analysis of dynamic route choice behavior. *Transportation Research B*, 26B(1):17–32.

Immers, B., Bleukx, A., Stada, J., Tampère, C., and Yperman, I. (2004). Robustness And Resilience Of Road Network Structures.

Jan, O., Horowitz, A. J., and Peng, Z. R. (2000). Using gps data to understand variations in path choice. In *79th Annual Meeting of Transportation Research Board, Washington DC.*

Jenelius, E., Rahmani, M., and Koutsopoulos, H. N. (2012). Travel time for urban road networks using low frequency vehicle probe data. Technical report, Div. of Traffic and Logistics, KTH Royal Institute of Technology.

Jha, M., Madanat, S., and Peeta, S. (1998). Perception updating and day-to-day travel choice dynamics in traffic networks with information provision. *Transportation Research Part C*, 6(3):189–212.

Joshi, C., Darwent, C., and Giese, K. (2009). Transportation modeling for the 2010 winter olympic games. Technical report, PTV America, City of Vancouver.

Kahneman, D. and Tversky, A. (1979). Prospect theory: An analysis of decision under risk. *Econometrica*, 47:263–291.

Kaplan, S. and Prato, C. G. (2012). Closing the gap between behavior and models in route choice: The role of spatiotemporal constraints and latent traits in choice set formation. *Transportation Research F: Traffic Psychology and Behaviour*, 15:9–24.

Katsikopoulos, K. V., Fisher, D. L., Duse-Anthony, Y., and Duse-Anthony, S. A. (2002). Risk attitude reversals in drivers' route choice when range of travel time is provided. *Human Factors*, 44(3):466–473.

Kearns, S. (2012). Games-time travel planning. Powerpoint presentation.

Khattak, A. J., Shofer, J. L., and Koppelman, F. S. (1995). Effect of traffic information on commuter's propensity to change route and departure time. *Journal of Advanced Transportation*, 29(2).

Knoop, V., Hoogendoorn, S., and Adams, K. (2009). Capacity reductions at incidents sites on motorways. *EJTIR*, 9(4):363–379.

Krichene, W. (2010). Travel time estimation using approximate belief states on a hidden markov model. Talk given at Mines Paristech, France, September 2010.

Kriger, D., Shiu, S., and Naylor, S. (2006). Estimating toll road demand and revenue - a synthesis of highway practice. Technical report, NCHRP Synthesis 364, Transport Research Board.

Kwon, J. and Murphy, K. (2000). Modeling freeway traffic with coupled hmms. *Univ. California, Berkeley, CA, Tech. Rep.*

LeBlanc, L. J., Morlok, E. K., and Pierskalla, W. P. (1975). An efficient approach to solving the road network equilibrium problem. *Transportation Research Part B: Methodological*, 9:309–318.

Li, H., Guensler, R, ., Ogle, J., and Wang, J. (2004). Using global positioning system data to understand day-to-day dynamics of morning commute behavior. *Transportation Research Record: Journal of the Transportation Research Board*, (1895):78–84.

Liu, R., Van Vliet, D., and Watling, D. (2006). Microsimulation models incorporating both demand and supply dynamics. *Transportation Research A*, 40(2):125–150.

Liu, R., Van-Vliet, D., and Watling, D. P. (1995). Dracula: dynamic route assignment combining user learning and microsimulation. *Proceedings of the 23rd PTRC European Transport Forum E*, pages 143–152.

Liu, T. L. and Huang, H. J. (2007). Multi-agent simulation on day-to-day route choice behaviour. In *Third International Conference on Natural Computation*, volume 5, pages 492–498.

Long, J., Gao, Z., Ren, H., and Lian, A. (2008). Urban traffic congestion propagation and bottleneck identification. *Science in China Series F: Information Sciences*, 51:948–964.

Long, J., Gao, Z., Zhao, X., Lian, A., and Orenstein, P. (2011). Urban traffic jam simulation based on the cell transmission model. *Networks and Spatial Economics*, 11(1):43–64.

Lotan, T. (1997). Effects of familiarity on route choice behavior in the presence of information. *Transportation Research Part C: Emerging Technologies*, 5(3):225–243.

Lu, X., Gao, S., and Ben-Elia, E. (2010a). Information impacts on route choice and learning behaviour in a congested network: An experimental approach. *Transportation Research Record*.

Lu, X., Gao, S., and Ben-Elia, E. (2010b). Information impacts on route choice and learning behaviour in a congested network: An experimental approach. *Transportation Research Record*.

Mahmassani, H. and Jou, R. (2000). Transferring insights into commuter behavior dynamics from laboratory experiments to field surveys. *Transportation Research Part A: Policy and Practice*, 34(4):243–260.

Mahmassani, H. S. (1990). Dynamic models of commuter behavior: Experimental investigation and application to the analysis of planned traffic disruptions. *Transportation Research A*, 24A(6):465–484.

Mahmassani, H. S. and Chang, G. (1986). Experiments with departure time choice dynamics of urban commuters. *Transportation Research Part B*, 20(4):297–320.

Mahmassani, H. S. and Chang, G. (1987). On boundedly rational user equilibrium in transportation systems. *Transportation Science*, 21(2):89–99.

Mahmassani, H. S. and Liu, Y. H. (1999). Dynamics of commuting decision behaviour under advanced traveller information systems. *Transportation Research Part C: Emerging Technologies*, 7:91–107.

Mannering, F. L. (1987). Poisson analysis of commuter flexibility in changing route and departure time. *Transportation Research Part B*, 23(1):53–60.

McAdams, R. H. (2008). Beyond the prisoners' dilemma: Coordination, game theory, and law. *South California Law Review*, 82:209.

McNally, M. G. (2000). *Handbook of transport modelling*. Elsevier Ltd.

Meister, K., Balmer, M., Ciari, F., Horni, A., Reiser, M., Waraich, R. A., and Axhausen, K. W. (2010). Large-scale agent based travel demand optimization applied to switzerland, including mode choice. *12th World Conference on Transportation Research*.

Meite, O. (2011). Gaining new insights regarding traffic congestion by explicitly considering the variability in traffic. Master's thesis, Delft University of Technology.

Min, W. and Wynter, L. (2011). Real-time road traffic prediction with spatio-temporal correlations. *Transportation Research C: Emerging Technologies*, 19(4):606–616.

Mitchell, R. B. and Rapkin, C. (1954). *Urban Traffic: A Function of Land Use*. New York: Columbia University Press.

Nagel, K. and Flötteröd, G. (2011). Agent based traffic assignment: going from trips to behavioural travelers. *Resource paper for workshop 'Advances in modeling network dynamics incorporating behavioural considerations*.

Nagel, K. and Marchal, F. (2006a). *Moving through nets: The physical and social dimensions of travel*, chapter Computational methods for multi-agent simulations of travel behavior, pages 131–188. Elsevier, Oxford.

Nagel, K. and Marchal, F. (2006b). *Moving through nets: The physical and social dimensions of travel*, chapter Computational methods for multi-agent simulations of travel behavior, pages 131–188. Elsevier, Oxford.

National Audit Office (2004). Tackling congestion by making better use of england's motorways and trunk roads. Technical report, National Audit Office.

NATS (2010). September 2010 traffic forecasts. In *CP3 Workshop*.

Nunez, A. (2007). *Sources of Errors and Biases in Traffic Forecasts for Toll Road Concessions.* PhD thesis, Université Lumiére Lyon.

Ortúzar and Willumsen (2001). *Modelling Transport.* Wiley, 3rd edition.

Outram, V. E. and Thompson, E. (1978). Driver's perceived cost in route choice. In *PTRC Annual Meeting, London*, pages 226–257.

Papinski, D., Scott, D., and Doherty, S. T. (2009). Exploring the route choice decision-making process: A comparison of planned and observed route obtained using person-based gps. *Transportation Research F: Traffic Psychology and Behaviour*, 12:347–358.

Peirce, S. and Lappin, J. (2004). Why donŠt more people use advanced traveller information? evidence from the seattle area. In *83rd Meeting of the Transportation Research Board.*

Petrella, M. and Lappin, J. (2004). Comparative analysis of customer response to online traffic information in two cities: Los angeles, california and seattle. *Transportation Research Record*, 1886:10–18.

Prato, C. G., Bekhor, S., and Pronello, C. (2005). Methodology for exploratory analysis of latent factors influencing drivers' behavior. *Transport Research Record*, 1926:115–125.

Raghubir, P. and Krishna, A. (1996). As the crow flies: bias in consumers' map-based distance judgements. *Journal of Consumption Research*, 23(1):26–39.

Ramming, M. (2001). *Network Knowledge and Route Choice.* PhD thesis, Massachusetts Institute of Technology.

Raney, B. and Nagel, K. (2003). Truly agent-based strategy selection for transportation simulations. In *Proceedings of the 82nd Annual Meeting of the Transportation Research Board.*

Resnick, M. (1997). *Turtles, Termites and Traffic Jams: Explorations of massively parallel microworlds.* MIT Press, Cambridge.

Ronald, N., Arentze, T., and Timmermans, H. (2010). Validation of complex agent-based models of social activities and travel behaviour. In *Proceedings of the 12th World Congress on Transport Research.*

Rossetti, R. J. F., Bordini, R. H., Bazzan, A. L. C., Bampi, S., Liu, R., and Van-Vliet, D. (2002). Using bdi agents to improve driver modelling in a commuter scenario. *Transportation Research Part C*, 10:373–398.

Rossetti, R. J. F. and Liu, R. (2005). A dynamic network simulation model based on multi-agent platforms. *Applications of agent technology in traffic and transportation*, pages 181–192.

Schlich, R. and Axhausen, K. (2003). Habitual travel behaviour: evidence from a six-week travel diary. *Transportation*, 30:13–36.

Selten, R. J. F., Chmura, T., Pitz, T., and Schreckenberg, M. (2007). Commuters route choice behavior. *Games and Economic Behaviour*, 58(2):394–406.

Sheffi, Y. (1984). *Urban Transportation Networks*. Prentice-Hall, Englewood Cliffs.

Shrank, D. and Lomax, T. (2009). The 2009 urban mobility report. Technical report, College Station: Texas Transportation Institute, Texas A&M University.

Simon, H. A. (1955). A behavioral model of rational choice. *The quarterly journal of economics*, pages 99–118.

Skabardonis, A., Varaiya, P. P., and Petty, K. F. (2002). Measuring recurrent and non-recurrent traffic congestion. Technical Report FHWA/CA/PR-2003/04, State of California Department of Transportation.

Smith, B. L., Qin, L., and Vankatanarayana, R. (2003). Characterization of freeway capacity reduction resulting from traffic accidents. *Journal of Transportation Engineering*, 129(4):362–368.

Smith, M., Hazelton, M. L., Lo, H. L., Cantarella, G. E., and Watling, D. P. (2013). The long term behavior of day-to-day traffic assignment models. *Transportmetrica: A: Transport Science*.

Smith, M. J. (1979). The existence, uniqueness and stability of traffic equilibria. *Transportation Research B*, 17(1):291–301.

Snowdon, J. (2013). Convergence and equilibrium analysis under strategic route choice behaviour. In *UTSG: 45th Annual Conference of the Universities' Transport Study Group Meeting*.

Snowdon, J. and Waterson, B. (2013). When congestion can be useful: modelling driver diversion behaviour in road traffic networks. In *12th European Conference on Artificial Life*.

Snowdon, J., Waterson, B., and Fangohr, H. (2012a). Evolution of adaptive route choice behaviour in drivers. In *UTSG: 44th Annual Conference of the Universities' Transport Study Group Meeting*.

Snowdon, J., Waterson, B., and Fangohr, H. (2012b). The evolution of driver route switching behaviour in stochastically perturbed networks. In *International Symposium on Dynamic Traffic Assignment*.

Snowdon, J., Waterson, B., and Fangohr, H. (2012c). The evolution of driver route switching behaviour in stochastically perturbed networks. In *4th International Symposium on Dynamic Traffic Assignment*.

Su, X. (2007). Bounded rationality in newsvendor models. *Manufacturing and service operations management*.

Sykes, P. (2010). *Fundamentals of Traffic Simulation*, chapter Traffic Simulation with Paramics. Springer.

Tang, W. and Levinson, D. M. (2015 (accessed July 19, 2015)). *Multiday GPS Travel Behavior for Travel Analysis*.

Tiang, L., Huang, H. J., and Liu, T. L. (2010). Day-to-day route choice decision simulation based on dynamic feedback information. *Journal of Transportation Systems Engineering and Information Technology*, 10:78–85.

TomTom (2013). Tomtom european congestion index. Technical report, TomTom.

Transport for London (2012). Travel in london report 5. Technical report, Transport for London.

Ullman, E. (1941). A theory of location for cities. *American Journal of Sociology*, 46(6).

Unnikrishnan, A. and Waller, S. T. (2009). User equilibrium with recourse. *Networks and Spatial Economics*, 9(4):575–593.

Van der Horst, R. S. N. and Ettema, D. (2005). Use of travel information and effects on mode choice for recreational trips. In *84th Meeting of the Transportation Research Board, Washington DC, USA*.

van Lint, J. W. C., van Zuylen, H. J., and Tu, H. (2008). Travel time unreliability on freeways: Why measures based on variance tell only half the story. *Transportation Research Part A: Policy and Practice*, 42(1):258–277.

Wardman, M., Bonsall, P. W., and Shires, J. D. (1997). Stated preference analysis of driver route choice reaction to variable message sign information. *Transportation Research Part C: Emerging Technologies*, 5(6).

Wardrop, J. G. (1952). Some theoretical aspects of road traffic research. *Proceedings, Institute of Civil Engineers*, 1(2):325–378.

Watling, D. (2002). A second order stochastic network equilibrium model, ii: Solution method and numerical experiments. *Transportation Science*, 36(2):167–183.

Watling, D. and Hazelton, M. L. (2003). The dynamics and equilibria of day-to-day assignment models. *Networks and Spatial Economics*, (3):349–370.

Watling, D. P. (1999). Stability of the stochastic assignment problem: a dynamical systems approach. *Transportation Research Part B*, 33(281):281–312.

Weijermars, W. and van Berkum, E. (2005). Analyzing highway flow patterns using cluster analysis. In *8th International IEEE Conference on Intelligent Transportation Systems*.

Whitaker, M. (2012). Tfl surface transport - planning for and delivery of the 2012 olympic and paralympic games. Powerpoint presentation.

Xing, T. and Zhou, X. (2011). Finding the most reliable path with and witwith link travel time correlation: a lagrangian substitution based approach. *Transportation Research Part B*, 45(10):1660–1679.

Xu, H., Zhou, J., and Xu, W. (2011). A decision-making rule for modeling travelers' route choice behavior based on cumulative prospect theory. *Transportation Research Part C: Emerging Technologies*, 19(2):218–228.

Yai, T., Iwakura, S., and Morichi, S. (1997). Multinomial probit with structured covariance for route choice behavior. *Transportation Research B*, 31(3):195–207.

Zhang, B. and Juan, Z. (2013). Modelling user equilibrium and the day-to-day traffic evolution based on cumulative prospect theory. *Information Science Letters*, 2(1):9–12.

Zhong, S. and Ghosh, J. (2001). A new formulation of coupled hidden markov models. Technical report, Tech. Report, Dept. of Electronic and Computer Engineering, U. of Texas at Austin, USA.

Zhu, S. and Levinson, D. (2010). Do people use the shortest path? an empirical test of wardrop's first principle. In *4th International Symposium on Transportation Network Reliability*.

Zhu, S., Levinson, D., Liu, H. X., and Harder, K. (2010). The traffic and behavioural effects of the i-35w mississippi river bridge collapse. *Transportation Research A: Policy and Practice*, 44(10):771–784.