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An agent-based approach to modelling driver route choice behaviour under the influence of real-time information

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Abstract

This paper presents an agent-based approach to modelling individual driver behaviour under the influence of real-time traffic information. The driver behaviour models developed in this study are based on a behavioural survey of drivers which was conducted on a congested commuting corridor in Brisbane, Australia. Commuters' responses to travel information were analysed and a number of discrete choice models were developed to determine the factors influencing drivers' behaviour and their propensity to change route and adjust travel patterns. Based on the results obtained from the behavioural survey, the agent behaviour parameters which define driver characteristics, knowledge and preferences were identified and their values determined. A case study implementing a simple agent-based route choice decision model within a microscopic traffic simulation tool is also presented. Driver-vehicle units (DVUs) were modelled as autonomous software components that can each be assigned a set of goals to achieve and a database of knowledge comprising certain beliefs, intentions and preferences concerning the driving task. Each DVU provided route choice decision-making capabilities, based on perception of its environment, that were similar to the described intentions of the driver it represented. The case study clearly demonstrated the feasibility of the approach and the potential to develop more complex driver behavioural dynamics based on the belief–desire–intention agent architecture.

Keywords: Autonomous agents; Intelligent transportation systems; Traveller information systems; Travel behaviour; Microscopic traffic simulation

1. Introduction

The provision of real-time travel information is increasingly being recognised as a potential strategy for influencing driver behaviour on route choice, trip making, times of travel and mode

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choice. Understanding travellers' response to this information is therefore critical to the design and implementation of effective intelligent transport systems strategies such as mobile or fixed advanced traveller information systems (ATIS). These systems provide drivers with real-time information about traffic conditions, accident delays, roadwork and route guidance from origin to destination. Some of the methods used for providing drivers with this information include traffic information broadcasting, pre-trip electronic route planning, on-board navigation systems, electronic route guidance systems and strategically located variable message signs (VMS). The principal aim of these systems is to influence drivers' behaviour on route choice and departure time decisions in order to improve mobility and reduce traffic congestion. Despite the obvious need for assessing user acceptance and the potential impacts of these systems in terms of improving traffic conditions for individual drivers and the overall transportation system, there has been a lack of models to evaluate their full impacts (Ben-Akiva et al., 1997). Typically, ATIS have been evaluated through operational tests, travel surveys or traffic simulators (Bonsall and Parry, 1991). Although these tests and experiments are very useful, they are very expensive to conduct and do not allow for effective evaluation of different alternatives. Computer simulation models, on the other hand, allow for testing alternative system designs before conducting operational tests, thus resulting in more effective operational tests and implementation. These simulation models typically consist of two main components: a dynamic driver behaviour model and a traffic simulation model.

This study aims to demonstrate the feasibility of using autonomous agents for modelling dynamic driver behaviour and analysing the effects of ATIS on the performance of a congested commuting corridor in Brisbane, Australia. The overall modelling framework will consist of a decision component that determines drivers' responses to the supplied information and a traffic simulation component. The agent-based driver decision component will be used to determine individual drivers' preferences and route switching decisions as a function of the supplied information. Unlike previous studies which modelled driver response to ATIS based on data collected from either travel simulators or travel surveys, this research is based on a behavioural survey of congestion on a real-world traffic commuting corridor. The results from the behavioural survey were used to determine the factors influencing route choice decisions and formed the basis of the agent-based driver behaviour model.

This paper will first present an overview of agent-based applications in transportation engineering. This will be followed by an overview of existing dynamic driver behaviour models and some of their limitations. A behavioural survey of drivers, which was conducted on a congested commuting corridor in Brisbane, will then be discussed and the results from a number of discrete choice models used for determining the factors influencing route choice will be presented. The agent-based framework for modelling driver behaviour and response to information is then discussed in the context of a case study on the same commuting corridor where the travel behaviour survey was conducted. A number of model application areas are then identified and details of ongoing research efforts to further develop these models is presented.

2. Intelligent agents applications in transportation

Intelligent Agents is a relatively recent computing paradigm comprising autonomous software components that can each be assigned a set of goals to achieve and a database of knowledge comprising certain beliefs, intentions and preferences concerning the task under consideration. Intelligent Agents can be thought of as computer surrogates for a person or process that fulfil a stated need or action. They comprise knowledge about the needs, preferences, and patterns of behaviour of that person or process. An Intelligent Agent provides decision-making capabilities, based on perception of the environment that are similar to the described intentions of a human and maybe given enough of the persona of a user or the gist of a process to perform a clearly defined task.

A number of transportation related agent-based applications have already been reported in the literature. Most of these are still under development or at experimental stages, but they clearly demonstrate the potential of implementing these technologies to improve the performance of traffic and transportation systems. Roozemond (1999) describes the development of an agent-based urban traffic control system that reacts to changes in the traffic environment and adapts its parameters in real-time in accordance with travel demand, traffic flow and changes to the traffic environment (e.g. the occurrence of incidents). The architecture of this system is based on intersection agents (local control) and authority agents (controlling several intersections). The authority agents in the network co-ordinate their tasks with the objective of achieving a globally optimum system performance. Kukla et al. (2001) describe the development of a microscopic simulation tool for modelling pedestrian flow using autonomous agents. Once tested and verified, the developers hope to use the model to make predictions about the traffic flow of people in virtual environments and thus provide a means to optimise the design of public areas with regard to their efficiency and attractiveness. Each pedestrian, represented by an autonomous agent, can occupy a space in an orthogonal grid. The agent would react to other agents and features of the environment such as kerbs, edges and obstructions. Hernández et al. (1999) describe the development of a knowledge-based agent architecture for real-time traffic management at a strategic level in urban, interurban or mixed areas. The traffic network is divided into several sections called *problem areas*. Every area represents a part of the city where a determined traffic behaviour is usually present and where a set of signal elements can be managed to influence this behaviour. An agent that understands the traffic conflicts that may appear, the usual behaviour of vehicles in the area and the signal action or real-time information that may improve the traffic state, supervises each of the areas. The control strategies generated by every agent are then received by a higher level agent, called the *co-ordinator*, whose aim is to produce global strategies for the whole city. The authors report that the feasibility of the approach was demonstrated by implementing the model on an extensive network in Barcelona comprising one co-ordinator, 22 local agents, 52 VMS panels, 300 loop detectors and 89 knowledge bases.

A number of studies proposing the implementation of different agent-based architectures for modelling driver route choice decisions are also presented in the literature. Dia and Purchase (1999) and Dia (2000) proposed the use of a cognitive agent architecture composed of beliefs, capabilities, commitments and behavioural rules to model individual drivers based on behavioural surveys. Rossetti et al. (2000) propose the implementation of similar techniques within the DRACULA traffic simulation model. Wahle et al. (1999) proposed a two-layer agent architecture for modelling individual driver behaviour. The first layer (tactical) describes the perception and reaction of the driver-vehicle entity on a short time scale. This layer can be modelled by any microscopic traffic flow model, and there are many appropriate examples already in use. The second strategic layer, however, extends the basic layer and is responsible for information assimilation and the decision-making process. The work reported in this paper extends the modelling frameworks proposed in the previous studies and demonstrates the feasibility of the approach through a case study.

3. Dynamic driver behaviour

Traditional travel behaviour frameworks described in the literature generally take into account the fact that an individual has access to limited information, has a limited capacity to process the information and attempts to find the best alternative within a time constraint. An example of dynamic driver behaviour modelling framework is shown in Fig. 1 (Ben-Akiva et al., 1991). Drivers set out with goals to travel between an origin and destination within a given period of time while incurring the lowest possible cost in terms of travel distance or travel time. They acquire information about the performance of the road system through direct observation or by having access to electronic information systems. They process and interpret the information in light of their current knowledge and in accordance with their ability to combine and process a variety of information concerning road conditions. The interpretation translates into perceptions of travel time and delay. Perceptions, restrictions and individual characteristics form preferences for certain alternatives (modes, routes and departure times). The preferences also depend on the previously acquired knowledge, stored in the memory, and on certain thresholds whereby motorists only switch from their current path if the improvement in travel time exceeds some threshold level associated with each driver. These preferences result in observable choices that have outcomes (e.g. arrival time at work). If the outcome is satisfactory, then the same choice is likely to be repeated on the following trip forming a commute pattern (Ben-Akiva et al., 1991). The repetition of a choice in the commute context also depends on the future or anticipated outcomes. These outcomes also provide feedback to the memory in the form of knowledge updates. In unexpected

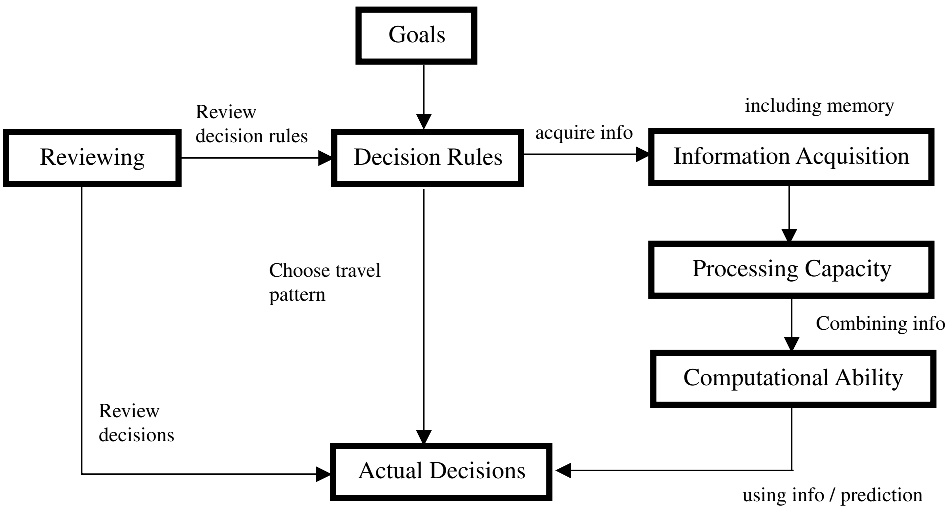

Fig. 1. Driver decision process (Ben-Akiva et al., 1991).

delay situations, the anticipated outcomes are often unsatisfactory triggering review of preferences and changes in normal travel patterns on a real-time and day-to-day basis (Ben-Akiva et al., 1991).

Various aspects of travel information influence drivers' decisions. The processing of information depends on its content or meaning, nature (whether it is static, dynamic or predictive), type (whether it is quantitative or qualitative) and presentation style. In addition, drivers are more likely to rely on relevant and accurate information. For example, under incident congestion, the perception of delay and the quality of real-time information are critically important in changing travel behaviour. Obviously, the success of driver behavioural models will depend to a large extent on capturing the different parameters mentioned above. Most previous research on driver behaviour modelling has focused on modelling ATIS usage and travel response decisions based on data from travel surveys or travel simulators (Koutsopoulos et al., 1995). These behavioural models mostly used drivers' socio-economic characteristics and attributes of usual travel patterns as explanatory variables. In contrast to previous research, the work reported here is based on real data comprising the complete set of drivers' choices as determined from a driver behavioural survey.

4. An agent-based approach to modelling driver behaviour

The data obtained from the driver behavioural survey will be used to model the travel behaviour, personal preferences and goals of all drivers in the survey using simple agent models. As was mentioned earlier, these are software components that can each be assigned a set of goals to achieve (e.g. travel between points A and B in a network) and a database of knowledge comprising certain beliefs, intentions and preferences concerning the task under consideration (e.g. the driving task). The characteristics of autonomous agents suggest that they have the potential for successful implementation in dynamic driver behaviour modelling. Each individual driver, with his/her own knowledge, preferences, perceptions, goals and personal characteristics as determined from the behavioural survey can be modelled using an agent. The main advantage of using agents in travel behaviour modelling is that they are active entities that interact with their environment (e.g. by receiving and reacting to real-time traffic information) and in concert with other agents (drivers) in the system.

Advanced agent architectures also allow for co-ordination of agents tasks and actions such that their individual goals and preferences are balanced against those of the multi-agent system. This modelling of co-ordination between agents can be useful for modelling the interaction between informed and uninformed drivers and co-ordination of their goals which so far has eluded conventional driver behaviour modelling techniques. The agent approach, as a computing paradigm, has the potential to overcome this limitation because of its emphasis on the consequences of interactions between many individuals, each with their own goal. This framework also allows for the updating of drivers' decisions and knowledge (learning) on a real-time basis rather than the day-to-day basis approach adopted in other studies (Mahmassani and Jayakrishnan, 1991). The agent-based architecture therefore represents a departure from the traditional view of route choice as an individual issue and attempts to study the collective behaviour of individual drivers as more than rational decision makers who have a limited view of their environments and react only according to pre-established rules. The driver decision making process is obviously much more complex and is not based only on logical components but also involves some emotional elements which are typically non-logical and may even seem irrational. Using autonomous agents, drivers can be modelled with their different beliefs, motives, impulsive actions and even simply their willingness to alter their behaviour. Agents equipped with such mental states formed the basis of the driver behavioural model described in this paper.

Based on the results obtained from the behavioural survey, the parameters which define each driver (preferences, knowledge and goals) will be identified. Suitable parameters and their potential values will also emerge from the analysis of survey results as will be discussed in later sections of this paper.

4.1. Intelligent agents architecture

The motivation of the agent architectures proposed for use in this study is the earlier research work in developing cognitive (mental model-based) agents (e.g. Shoham, 1993; Thomas, 1993). Their work postulated that cognitive agents possess a mental state which is composed of various mental elements: *beliefs*, *capabilities*, *commitments; and behavioural and commitment rules* as shown in Fig. 2.

Beliefs: *Beliefs* are a fundamental part of the agent's mental model. They represent the current state of the agent's internal and external world and are updated as new information about that world is received. An agent can have beliefs about the world, about another agent's beliefs and about interactions with other agents. For the purpose of driver behavioural models, these beliefs will include information about the driver's travel patterns, preferences for routes, perceptions of the network and of other drivers' route choices.

Capabilities: A *capability* is a construct used by the agent to associate an action with that action's necessary pre-conditions i.e. those pre-conditions that must be satisfied before execution of the action. An agent's list of capabilities defines the actions which the agent can perform provided that the necessary pre-conditions are satisfied. A capability is static and holds for the lifetime of an agent. However, the actions an agent can perform may change over time because changes in the

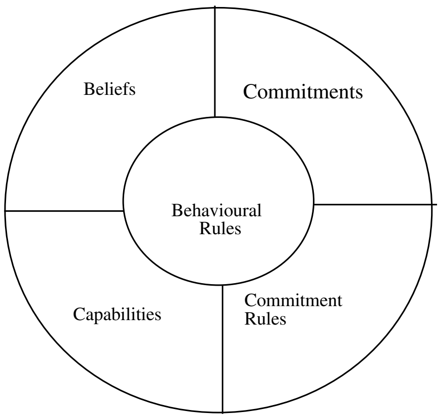

Fig. 2. Intelligent agent mental model.

agent's beliefs may alter the truth value of pre-condition patterns in the capability. Actions are classified in two main categories: private actions and communicative actions. Private actions are those that affect the environment of the agent and do not depend on interaction with other agents. Communicative actions, on the other hand, are those that interact with other agents. For the purpose of driver behavioural models, capabilities represent actions that the driver can perform such as switching routes, altering departure time and changing mode of transport.

Commitments and commitment rules: A *commitment* is an agreement to attempt a particular action at a particular time if the necessary pre-conditions for that action are satisfied at that time. An agent must be able to test the necessary pre-conditions of the committed action to ensure that the action can be executed. To test the pre-conditions, agents must match the pre-condition patterns against their current beliefs. If all patterns evaluate to true, the agent can then initiate execution of the committed action. For the purpose of driver behavioural models, commitments may represent a driver's initial agreement to switch routes if travel delays along a particular route exceed a certain threshold (i.e. delay tolerance thresholds).

Behavioural rules: Behavioural rules determine the course of action an agent takes at every point throughout the agent's execution. Behavioural rules match the set of possible responses against the current environment as described by the agent's current beliefs. If the rule's conditions are satisfied by the environment, then the rule is applicable and the actions it specifies are performed. For the purpose of driver behavioural models, behavioural rules determine which routes drivers are willing to take when presented with certain information or when faced with alternative route choices to their destinations.

4.2. Belief–desire–intention (BDI) framework

The BDI agent framework has its roots in philosophy and cognitive science, and in particular the work of Bratman on rational agents (Bratman, 1987; Rao and Georgeff, 1991). A rational agent has bounded resources, limited understanding and incomplete knowledge of what happens in its environment. Intelligent agents using the BDI model have a set of beliefs, desires/goals, intentions and a set of plans to achieve certain outcomes or respond to events. An intention is a commitment to perform a plan. When an event occurs, the agent looks for relevant plans and then for each relevant plan the agent examines its appropriateness to the current situation. The agent then selects and starts executing the most appropriate plan. In general, a plan is only partially specified at the time of its formulation because the exact steps to be performed may depend on the state of the environment at the time they are executed. Additionally, the agent performs ongoing reasoning functions to determine what goal to pursue or which events to react to; how to pursue its desires and when to abandon the goal (Busetta et al., 1999). The agent may also vary its balance between reactive and deliberative behaviour by changing the amount of time allowed for deciding what to do next. This enables the agent to be *more or less* sensitive to changes in the environment or to be more or less committed to its current plan, as in rational human behaviour. The BDI approach has been shown to be well suited to modelling different types of behaviour and has been successfully adopted in a number of fields such as tactical decision making in military operations and air traffic management (Busetta et al., 1999). The implementation of the BDI approach in modelling driver behaviour provides a number of advantages such as enabling agents to dynamically adjust their behaviour and update their knowledge in real time.

The work reported in this paper is based on a simple agent architecture and is aimed at demonstrating the feasibility of the agent-based approach and its interface to a microscopic traffic simulation tool. Current research is focused on implementing complex BDI architectures and frameworks for modelling *dynamic* driver behaviour using a state-of-the-art intelligent agent simulation environment.

5. Behavioural survey of drivers on a congested commuting corridor in Brisbane

Behavioural surveys of drivers during congested traffic conditions are best suited to developing ATIS behavioural models. Properly designed surveys that capture the interactions in the travel behaviour model would allow for the investigation of the influence of (a) unexpected and expected congestion, (b) the various types and quality of information received about congestion and (c) drivers' experiences with congestion and related information on the whole spectrum of pre-trip and en-route decisions. In particular, these behavioural surveys would allow for the relationship between a driver's response to qualitative, quantitative, predictive delay and both prescriptive and descriptive information to be modelled in combination with actual behaviour. The data collection methodology adopted in this study is discussed below.

5.1. Data collection

User response to ATIS is typically modelled using data collected from a behavioural survey of congestion (Khattak et al., 1996). For this study, mail-back questionnaires were distributed to peak-period automobile commuters travelling along a traffic commuting corridor in Brisbane. The survey comprised questions in the following five categories:

1. *Personal information*: A driver's age, occupation and gender may influence certain travel behaviours.
2. *Normal travel patterns*: These include day-to-day behaviour such as work schedule, route choice and response to recurring congestion.
3. *Pre-trip response to unexpected congestion information*: The knowledge that road conditions are abnormal may influence drivers' decisions regarding departure time and route choice before setting out on their journeys.
4. *En-route response to unexpected congestion information*: When drivers learn of abnormal road conditions while driving, they may change certain travel decisions.
5. *Willingness to change driving patterns*: Given some incentive (e.g. reduction in travel time), drivers may be willing to leave early or take an alternative route. Furthermore, more aggressive drivers are less likely to tolerate delays exceeding certain thresholds. The behavioural survey will provide a useful insight into some of these parameters (delay tolerance thresholds) that could have an influence on driver compliance with the provided information.

Two questionnaire forms were distributed: the first form included questions from categories 1, 2, 3 and 5 (for pre-trip information) whereas the second form included all questions from categories 1, 2, 4 and 5 (for en-route information). User response to ATIS is based on: (a) revealed preference

(RP) data in which the actual behavioural response to expected/unexpected delay is reported and (b) stated preference (SP) data in which a driver's behaviour under a hypothetical ATIS scenario is reported. A total of 490 questionnaires were distributed to drivers on a traffic commuting corridor in Brisbane during the morning and afternoon peak periods. The mail-back questionnaire had a response rate of 34% (167 questionnaires) comprising a total of 82 pre-tip and 85 en-route questionnaires. This response rate compares favourably with the results obtained from overseas research (Khattak et al., 1996) in which substantial financial incentives were offered to respondents. The format and presentation of the questionnaire is believed to be a key factor in achieving this response rate, considering it was anticipated that it would take 20 min to complete each questionnaire.

5.2. Selected survey results

The main objective of the behavioural survey was to determine the factors that influence route change, the frequency of route change and traffic information preferences by respondents. Only selected results relevant to the development of the agent-based behavioural model are presented in this paper. A more detailed discussion of survey results can be found in Dia et al. (2000).

Socio-economic attributes of respondents: Socio-economic and travel attributes of respondents have an important effect on travel behaviour. As part of this survey, a rich source of individual data has been collected which will be important in modelling the factors that affect trip change behaviour, willingness to pay for ATIS services and compliance with travel information. Table 1 presents a summary of selected socio-economic attributes of the respondents.

The average respondent is middle-aged and has resided in the area for 8.3 years, indicating a good level of familiarity with network conditions. The respondents are divided fairly equally between males and females with 56% of respondents being males. The average annual income is $62,000 and 64% of respondents have either undergraduate or postgraduate qualifications.

The respondent in the sample held primarily professional, clerical/service, executive and managerial/administration jobs which suggests that upper-income groups and well-educated individuals were over-represented when compared to census demographic profiles of the Brisbane population. However this problem has also been experienced in other similar studies conducted in San Francisco and Chicago as described in Dia et al. (2000). The three surveys had similar sample characteristics and captured more male respondents than female. The Brisbane survey, however, had a lower travel time than the other surveys but also had a significantly higher average duration of residence in the area reflecting a more network familiar driver population.

Frequency of route change: The frequency of route change was examined by asking the respondents to provide information on the frequency of taking alternative routes in the past month. The results are displayed in Table 2 below.

On average respondents took an alternative route 3.55 times in a month. This is a relatively insignificant result considering there were more than 40 work-related trips during that month. By determining the factors that influence route change this frequency can be increased and can potentially contribute to relieving congestion in this corridor.

Analysis of en-route responses to hypothetical ATIS messages: The effect of providing alternative forms of en-route information was also evaluated. Respondents were asked to state whether they would change travel decisions if they were alerted of delays. Each of five different information types being tested were then presented to the respondents. These are discussed below.

Table 1
Summary of selected socio-economic attributes of respondents

Personal Attributes		Percentage (%)
Gender	Male	56.1
	Female	43.9
Age (average age = 40)	Under 18	0.6
	18–29	23.5
	30–39	22.4
	40–49	28.8
	50–64	22.4
	65 & over	2.4
Education	High School	15.9
	Technical School	20.0
	Undergraduate	33.5
	Postgraduate	30.6
Occupation	Clerical/Service	14.6
	Executive	11.7
	Retired	0.0
	Professional	40.9
	Salesperson/buyer	9.4
	Student	2.3
	Technical	4.1
	Managerial/Administration	11.1
	Tradesperson	3.5
	Labourer	0.0
	Production/transport	1.2
	Other	1.2
Personal income (average income = $62,331)	<$20,000	4.9
	20,000–40,000	25.8
	40,001–60,000	27.0
	60,001–80,000	15.3
	80,001–100,000	11.0
	>100,000	16.0

Table 2
Respondents' frequency of route change in the previous month

No. of times/month	Frequency	Percentage (%)
None	37	25.5
1	14	9.7
2	25	17.2
3	19	13.1
4	17	11.7
5	17	11.7
6+	16	11.0

Qualitative information: In this situation the device only offered a simple message: ‘‘Unexpected Congestion on ‘your usual route’’’ (Fig. 3(a)), where your usual route is the road that respondents indicated they normally used for their travel. While this is only simple information, it represents the type of information that is commonly available to travellers via radio or electronic message signs.

Quantitative Information: For this scenario, respondents were provided with the same message as before, but the device also displayed the expected delays on the usual route and the travel time on the best alternate route (as specified by respondents), as shown in Fig. 3(b) and (c) below.

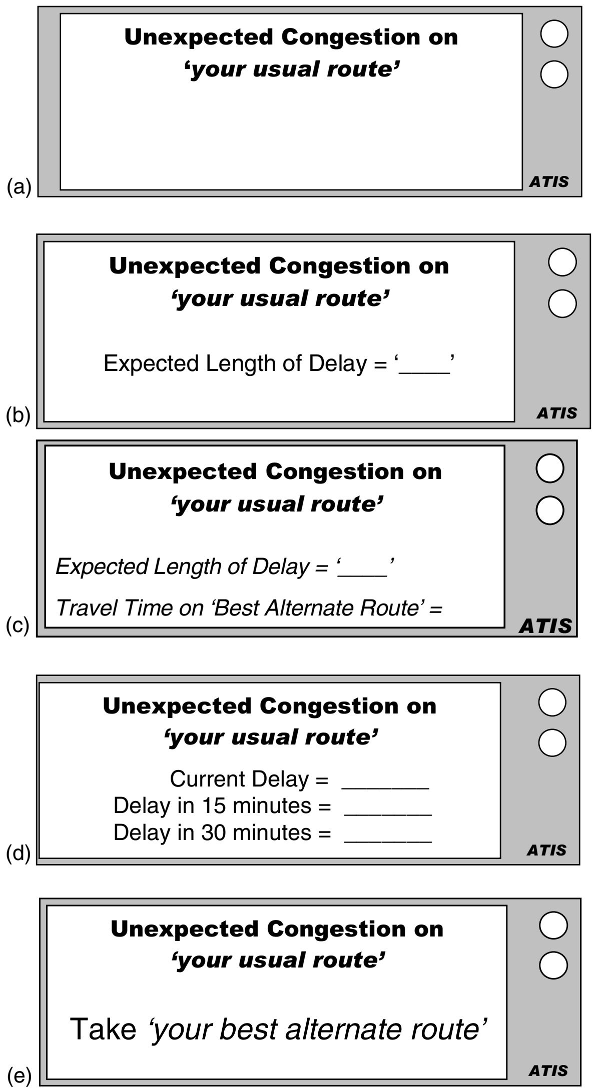

Fig. 3. (a) Qualitative information message, (b) quantitative information message—usual route, (c) quantitative information message—usual and best alternate routes, (d) predictive information message, (e) prescriptive information message.

Predictive Information: For this scenario, respondents were asked how they would modify their travel choices if the device provided them with the delays at the present time, and accurately predicted the expected delays in 15 and 30 min into the future, as shown in Fig. 3(d).

Prescriptive Information: This scenario explored the response to recommendations offered by the ATIS which suggested taking the route which the respondents indicated was their best alternative route to their destination (Fig. 3(e)).

Respondents were asked to indicate their preferences when presented with hypothetical ATIS information by choosing from a set of finite responses which included: "definitely take my usual route"; "probably take an alternative route"; "definitely take best alternative route"; "probably take best alternative route" and "can't say". A summary of respondents' choices is presented in Table 3.

The results reported in Table 3 provide one of the most significant findings from the ATIS experiment. These results clearly indicate that prescriptive, predictive and quantitative real-time delay information provided for both the usual and best alternate routes are most effective in influencing respondents to change their routes. Therefore, detailed discrete choice models were developed and investigated for each of these significant ATIS scenarios as discussed next.

Estimation of en-route response to information: As was mentioned earlier, one of the major objectives of this study was the development of models that can be used to estimate or predict the degree of drivers' compliance with traffic information. This route choice decision model is basically a discrete choice problem. Two approaches are available for developing route choice models: discrete choice and artificial neural network techniques. Both methodologies are being explored in this research but this paper presents only the results based on discrete choice models. Detailed information about discrete choice models and econometric techniques is beyond the scope of this paper. However, a comprehensive treatment of these models and their applications can be found in Greene (2000). For the purposes of this study, discrete choice modelling techniques, and the Multinomial Logit models in particular, were used to model drivers' responses; identify the parameters influencing their route choice decisions and determining the values of these parameters. Discrete choice models assume that the probability of an individual choosing a given option from a finite set of alternatives is a function of the context variables (e.g. the individual's

Table 3
En-route stated preferences for unexpected congestion

Attributes	Qualitative delay information	Quantitative real-time delay information	Quantitative real-time delay on best alternative route	Predictive real-time delay information	Prescriptive best alternative route
Definitely take my usual route	12.0	10.3	8.0	9.3	6.3
Probably take my usual route	28.9	29.5	12.0	16.0	13.9
Definitely take my best alternate route	32.5	29.5	41.3	41.3	53.2
Probably take my best alternate route	25.3	24.4	33.3	29.3	22.8
Cannot say	2.3	7.7	5.3	5.3	3.8

socio-economic characteristics) and the relative attractiveness of the option under consideration. The attractiveness of the alternatives is described and quantified by a utility function which individuals typically seek to maximise. To determine if an alternative will be chosen, the value of its utility is compared with the utility of the alternative options and transformed into a probability value between 0 and 1. For each form of information provided in Table 3 (e.g. quantitative delay, predictive and prescriptive delay), a Multinomial Logit model was developed to determine the socio-economic and context variables that are most significant in influencing driver compliance for that type of information. For economy of presentation, only a sample model for estimating en-route responses to quantitative delay information is presented here as shown in Table 4.

Table 4
Multinomial logit model for en-route quantitative delay information

Variable	Coefficient	*t*-statistics
Option 1: Definitely take usual route		
Constant	−5.6347	−2.1928*
Flexible time	1.0838	1.0713
Income	0.0963	0.2609
Education	−0.0641	−0.1369
Age	0.1881	0.4029
Gender	2.7024	2.0295*
Years at residence	0.0183	0.3604
Option 2: Probably take usual route		
Constant	0.2517	0.2186
Flexible time	−0.8974	−1.4778**
Income	−0.0314	−0.1480
Education	−0.1117	−0.4089
Age	−0.0522	−0.1942
Gender	−0.3171	−0.5608
Years at residence	−0.0257	−0.7382
Option 3: Definitely take alternative route		
Constant	−1.2155	−1.0428
Flexible time	−0.6867	−1.1601
Income	−0.1595	−0.7943
Education	0.0594	0.2263
Age	0.2462	0.9226
Gender	−0.2066	−0.3712
Years at residence	0.0115	0.3721
Option 4: Probably take alternative route		
Constant	1.0427	0.7837
Flexible time	1.2165	1.8192**
Income	0.1825	0.6796
Education	−0.2332	−0.7265
Age	−0.6516	−1.8982**
Gender	−0.5681	−0.8257
Years at residence	−0.0750	−1.2660

*Significant at 5%.
**Significant at 10%.

The results reported in Table 4 indicate that young drivers and those with flexible work schedules have an increased propensity to take an alternative route when provided with quantitative delay information. The effect of gender, however, is positive and significant (at the 5% level) for the 'definitely take the usual route' option indicating that females are very likely to remain on their usual route when provided with the same information. A number of other Multinomial Logit models were developed and the results were used to identify the relevant factors and their suitable values for implementation in the agent-based behavioural models. It should be mentioned here that other models, including ordered logit, ordered prohibit and neural networks are also being investigated to improve the accuracy of the results.

6. Microscopic traffic simulation

Based on the results obtained from the behavioural survey, the parameters which define individual driver characteristics and preferences have been identified and their values determined from discrete choice models. Having defined the behavioural modelling framework, it can now be interfaced to a microscopic traffic simulation model to evaluate the impacts of providing drivers with travel information. The traffic simulation component will be used to represent individual vehicular movements on the traffic commuting corridor. Given the static characteristics of the commuting corridor network, its link capacities, connections and speeds, this component takes a time-dependent loading pattern and handle the movement of individual vehicles on links as well as the transfer between links. The instructions needed to direct individual vehicles under the influence of real-time information will be provided by the agent-based driver behaviour model. This model will specify how a particular driver-vehicle-unit (DVU) with given goals, characteristics, preferences and knowledge of prevailing conditions, selects the next link when approaching a given node.

A commercially available microscopic traffic simulation model (Quadstone, 2000) has been selected to simulate the commuting corridor under consideration. This particular simulation software has a number of unique features which allow the user to customise many features of the underlying simulation model through an application programming interface (API). This feature is critical for this study as it will allow for interfacing the agent behaviour model with the traffic simulation tool. The traffic simulation will follow a deterministic, fixed time-step approach. At each time step (e.g. 0.1 min), vehicles will be moved at the prevailing local speed on the same link or transferred to another link. The latter is determined by the agent-based driver behaviour model according to user preferences, perceptions, path-switching thresholds and other factors identified and discussed previously. These will be provided to the traffic simulation model through the API. Travel times are then calculated from each node based on the current link speeds and the simulation continues until all DVUs reach their destinations.

It should be mentioned here that the computational requirements of agent-based systems are strongly correlated to the total number of agents (DVUs) and to the level of detail used to model each agent, i.e. the complexity of the behavioural rules. Although no comparative evaluations have yet been performed in this study between agent based and traditional modelling approaches, results from other studies suggest that agent-based systems are suitable for implementation in real-time traffic management systems. Hernández et al. (1999) successfully implemented a distributed set of Unix processors to analyse the 1-min real-time data for a Barcelona model which comprised one co-ordinator, 22 local agents, 52 VMS panels, 300 loop detectors and 89 knowledge bases.

7. Case study: Brisbane western corridor

To demonstrate the feasibility of integrating the agent-based driver behavioural model with the microscopic traffic simulation tool, a traffic simulation model was developed for the same commuting corridor where the behavioural survey of drivers was conducted. Details of field data collection, calibration and verification of the traffic simulation model can be found in Cottman and Dia (2000). Fig. 4 shows a screen capture of the simulation model (covering an area of approximately 3 km^2 and more than 40 origin–destination zones) in which two alternatives routes to the Central Business District (CBD) are clearly marked. The first major route commonly travelled by respondents is Coronation Drive (route A–C). The alternative route to the CBD is through Milton Road (route A–B–C). A variable message sign (VMS) is also simulated near Point A where the behavioural survey was conducted. The VMS is strategically located at that point to provide DVUs with traffic information about delays along the major and alternative routes to the CBD. Drivers' response and compliance with the traffic information is provided by the agent-based behavioural model. For the purposes of this demonstration, the following factors affecting drivers' compliance have been considered: driver aggression, driver awareness or familiarity with the

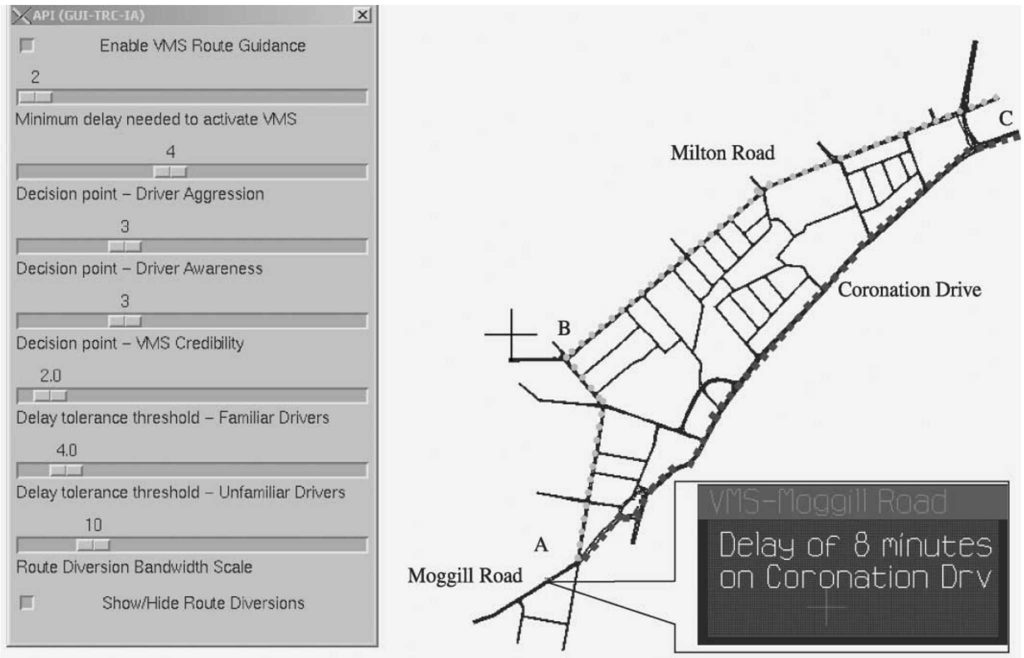

Fig. 4. Screen capture of Brisbane's western commuting corridor simulation model.

network, VMS credibility and delay tolerance thresholds for both familiar and unfamiliar drivers. As discussed previously, these factors have been found to have an influence on drivers' route choice along the commuting corridor. Control points, or locations where DVUs access the VMS information and make their route choice decisions need to be designated. It is assumed that a VMS will only be provided near control point A. DVUs passing, or on approach to the control point will assess their environments (using the agent behaviour model) and decide whether they are going to comply with the information provided on the VMS.

An interface linking the driver compliance models to the microscopic traffic simulation software is also shown in Fig. 4. The interface (created using the simulation software's API facility), comprises an ATIS plug-in which can activate route guidance within the model via variable message signs (VMS). During model execution, the ATIS plug-in allows manipulation of the variables influencing driver compliance via the graphical user interface (GUI) shown in Fig. 4. Under non-congested conditions, the VMS would be blank, indicating that conditions are free flowing. As congestion builds and reaches a threshold (set by the "Minimum delay needed to activate VMS" slider), the VMS is activated and displays delay information to the DVUs. It is here that the agent-based DVU model is implemented. Each driver is assigned aggressiveness, awareness, VMS credibility, acceptable delay threshold, gender, age and familiarity with network values determined from the behavioural survey and other information sources. To determine whether a DVU complies with the provided information, the values assigned to each of its characteristics (as defined by the GUI) are determined and compared to the decision points. A DVU is assumed to have complied with the information if it met each of the criteria provided by the GUI. If the DVU complies with the provided information, it is routed along the prescribed alternative route. Otherwise, the DVU will continue on its original route. Familiar and unfamiliar drivers are treated differently by the ATIS plug-in and by default, familiar drivers have a lower delay tolerance threshold than unfamiliar drivers and are therefore more likely to change routes if faced with congestion. Detailed information about network performance, average travel times, average speeds, pollution levels and percentage of drivers complying with information is collected by the traffic simulation tool. The model developed for the commuting corridor will provide road authorities with a valuable tool for assessing the impacts of different traffic management and traveller information scenarios on network performance. A number of potential applications are discussed next.

8. Model application areas

The models developed in this study will be used to evaluate the impacts of different ATIS scenarios in terms of improved traffic conditions for individual drivers and the overall transportation system. For example, a base scenario, reflecting the network conditions without a proposed ATIS strategy, can be first generated. All other tested scenarios will be referenced to this base scenario for comparison. The measures of effectiveness to be used may include: vehicle-kilometres travelled, vehicle-hours travelled, travel time, speed and number of lane changes. These measures have been chosen to capture both the spatial and temporal impacts of ATIS initiatives. The model developed in this study will also allow for the investigation of a number of scenarios and key policy issues such as those presented below.

8.1. Impacts of ATIS under recurrent and non-recurrent congestion

The models can be used to evaluate the impact of providing drivers with real-time traffic information during peak-hour and incident conditions. Drivers will be provided with real-time traffic information regarding congestion conditions, expected delays and alternative routes. The model will then be used to evaluate (based on drivers' preferences, characteristics, goals and perceptions) the impact of providing this information. Similarly, incidents can be simulated in the system (e.g. by blocking one of the lanes on the facility) and drivers provided with information regarding incident location, severity, expected duration and alternative routes. The models can be used to evaluate the effect of different ATIS scenarios aimed at alleviating the impact of incidents on the traffic corridor.

8.2. Fraction of users provided with information

The fraction of users which should be informed is an important policy variable. The impact of information on traffic conditions is not necessarily a linear function of the number of informed drivers. For example, if every driver has access to the same information as the other drivers, then a great number of drivers may select the best routes and consequently drivers with similar preferences will tend to concentrate on the same routes (Ben-Akiva et al., 1991). On the other hand, information accessible to only a limited fraction of users would likely result in benefits to these individuals, and possibly to other drivers as well by diverting a sufficient number of informed drivers.

8.3. Accuracy of information

The actual benefits that will be realised from driver information systems depend heavily on the quality of the traffic information provided to drivers. Inaccurate or imperfect data may result in poor guidance directives being provided to drivers. The models developed in this study can be used to evaluate the impact of using different ATIS technologies (varying accuracy rates) on the performance of the transportation system.

8.4. Types of information

As was discussed previously, some types of information are less likely to produce concentration of drivers on the same routes (Ben-Akiva et al., 1991). One way to avoid concentration, when advice is provided, is to take into account specific individual preferences to guide different vehicles along different routes. The models developed in this study provide for the investigation of different types of information on the effectiveness of the overall transportation network.

9. Implementation of the BDI architecture

Work is currently underway to implement complex BDI architectures for modelling driver behaviour. At the moment, the proposed BDI architecture can be implemented in stand-alone software tools similar to those used by Busetta et al. (1999). It is proposed that the BDI models be developed within a proven Intelligent Agent software environment and then be exported to Java or C++. The exported models can then be interfaced with microscopic simulation through the API.

10. Conclusions

The work reported in this paper is part of an on-going research project aimed at developing dynamic driver behaviour models using intelligent agents. Unlike other studies which relied on simple hypothetical road networks and generalised driver characteristics, this study was based on a field behavioural survey of drivers conducted on a congested real-world commuting corridor. Based on the results obtained from the behavioural survey, the parameters which define each individual driver's characteristics and preferences were identified and their values determined from discrete choice models. DVUs were modelled as autonomous agents and were assigned a set of goals to achieve and a database of knowledge comprising certain beliefs, intentions and preferences concerning the driving task. The driver behavioural model was then interfaced to a microscopic traffic simulation tool which was calibrated to simulate the movement of individual DVUs between their origins and destinations in the network. A case study demonstrating the feasibility of the approach and the implementation of the agent driver behavioural framework within the traffic simulation model was also presented. Work is currently underway to further develop these models by incorporating more complex BDI agent frameworks to enable agents to *dynamically* adjust their behaviour and update their knowledge base in real time. There is also scope in future research work to validate the performance of these models through detailed route-choice field surveys. A number of potential model application areas have also been identified in this paper to aid in the evaluation and design of effective ATIS strategies aimed at influencing travel behaviour, reducing congestion and enhancing the performance of the road network.

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References

Ben-Akiva, M., Koutsopoulos, H.N., Mishalani, R., Yang, Q., 1997. Simulation laboratory for evaluating dynamic traffic management systems. ASCE Journal of Transportation Engineering 123 (4), 283–289.

Ben-Akiva, M., Palma, A.D., Kaysi, I., 1991. Dynamic network models and driver information systems. Transportation Research Part A 25A (5), 251–266.

Bratman, M.E., 1987. Intentions, Plans and Practical Reasoning. Harvard University Press, Cambridge, MA.

Bonsall, P., Parry, T., 1991. Using an interactive route-choice simulator to investigate drivers' compliance with route guidance advice. Transportation Research Record 1306, Transportation Research Board, pp. 59–68.

Busetta, P., Ronnquist, R., Hodgson, A., Lucas, A., 1999. JACK Intelligent Agents—Components for Intelligent Agents in Java. Available from http://www.agent-software.com (Accessed 28 December 2000).

Cottman, N.J., Dia, H., 2000. A methodology for modelling the environmental impacts of intelligent transport systems. Proceedings of the 22nd Conference of Australian Institutes of Transport Research, CAITR 2000, 6–8 December, the Australian National University, Canberra, ACT, Australia.

Dia, H., 2000. A conceptual framework for modelling dynamic driver behaviour using intelligent agents. Proceedings of the 6th International Conference on Applications of Advanced Technologies in Transportation Engineering, 28–30 June 2000, Singapore.

Dia, H., Harney, D., Boyle, A., 2000. Analysis of commuters' responses to travel information: implications for ATIS deployment in Brisbane. Proceedings of the 22nd Conference of Australian Institutes of Transport Research (CAITR 2000), 6–8 December 2000, The Australian National University, Canberra, ACT, Australia.

Dia, H., Purchase, H., 1999. Modelling the impacts of advanced traveller information systems using intelligent agents. Road and Transport Research 8 (3), ARRB Transport Research Ltd., Vermont South, Victoria, Australia.

Greene, W.H., 2000. Econometric Analysis, fourth ed. Prentice Hall, NJ.

Hernández, J., Cuena, J., Molina, M., 1999. Real-time traffic management through knowledge-based models: the TRYS approach. Tutorial on Intelligent Traffic Management Models, the 11th Mini-Euro Conference on Artificial Intelligence in Transportation Systems and Science, August 1999, Helsinki, Finland.

Khattak, A., Polydoropoulou, A., Ben-Akiva, M., 1996. Modeling revealed and stated pretrip travel responses to advanced traveler information systems. Transportation Research Record 1537, Transportation Research Board, pp. 46–54.

Koutsopoulos, H., Polydoropoulou, A., Ben-Akiva, M., 1995. Travel simulators for data collection on driver behavior in the presence of information. Transportation Research, Part C 3 (3), 143–159.

Kukla, R., Kerridge, J, Willis, A., Hine, J., 2001. PEDFLOW: Development of an autonomous agent model of pedestrian flow. Transportation Research Record No. 1774, Transportation Research Board, pp. 11–17.

Mahmassani, H.S., Jayakrishnan, R., 1991. System performance and user response under real-time information in a congested traffic corridor. Transportation Research 25 (5), 293–307.

Quadstone, 2000. Paramics Software Tools for Microscopic Traffic Simulation. Quadstone Limited, Edinburgh, Scotland. Available from: http://www.paramics-online.com (Accessed 28 December 2000).

Rao, A.S., Georgeff, M.P., 1991. Modelling rational agents within BDI architecture. In: Proceedings of the International Conference on Knowledge Representation and Reasoning. Morgan Kaufmann, San Mateo, CA.

Roozemond, D.A., 1999. Using intelligent agents for urban traffic control systems. Proceedings of the 11th Mini-Euro Conference on Artificial Intelligence in Transportation Systems and Science, 2–6 August 1999, Helsinki University of Technology, Espoo, Finland.

Rossetti, R., Bampi, S., Liu, R., Van Vleit, D., Cybis, H., 2000. An agent-based framework for the assessment of drivers' decision-making. Proceedings of the 2000 IEEE Intelligent Transportation Systems, Dearborn, MI, USA, 1–3 October 2000, pp. 387–392.

Shoham, Y., 1993. Agent-oriented programming. Artificial Intelligence 60 (1), 51–92.

Thomas, S.R., 1993. PLACA, an Agent Oriented Programming Language. Ph.D. Thesis, Stanford University.

Wahle, J., Bazzan, A.L.C., Klügl, F., Schreckenberg, M., 1999. Anticipatory traffic forecast using multi-agent techniques. In: Helbing, D., Hermann, H., Schreckenberg, M., Wolf, D. (Eds.), Traffic and Granular Flow'99. Springer, Heidelberg.