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An Agent-Based Approach to Assess Drivers' Interaction with Pre-Trip Information Systems

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This article reports on the practical use of a multi-agent microsimulation framework to address the issue of assessing drivers' responses to pretrip information systems. The population of drivers is represented as a community of autonomous agents, and travel demand results from the decision-making deliberation performed by each individual of the population as regards route and departure time. A simple simulation scenario was devised, where pretrip information was made available to users on an individual basis so that its effects at the aggregate level could be observed. The simulation results show that the overall performance of the system is very likely affected by exogenous information, and these results are ascribed to demand formation and network topology. The expressiveness offered by cognitive approaches based on predicate logics, such as the one used in this research, appears to be a promising approximation to fostering more complex behavior modelling, allowing us to represent many of the mental aspects involved in the deliberation process.

Keywords Cognitive Agents; Pretrip Information Systems; Driver Behavior Modelling; Microscopic Simulation

INTRODUCTION

Traffic and transportation systems have long attracted great interest among technical and scientific communities. Not only because of the great relevance transport systems have in society, but also because they are likewise seen as the ground for assessing methodologies or developing theories in a variety of scientific fields. Solving the congestion phenomenon in urban traffic networks and managing the limited road capacities to cope with the ever-increasing demand have never been more challenging than recently. The physical modification of infrastructures and the improvement of control systems are two attempts to tackle the problem of traffic congestion that have met with moderate success. When similar measures have been used to try to deal with the demand side issue, the results have been less successful as they are primarily used to deal with the static part of the system, namely the road network and control mechanisms.

An alternative solution relies on dealing directly with the demand side, which is the dynamic and behavioral element in the system. It has been found that route and departure-time changes are two most important effects of demand management policies (SACTRA, 1994). Reducing the number of vehicles travelling throughout the network at peak periods should be the instrument leading to significant decreasing on demand for limited road capacity. This may be reached by adopting strategies such as increasing vehicle occupancy, implementing public transport subsides, re-orienting travel patterns to less congested itineraries, or shifting them to off-peak periods; in other words, influencing travellers' behavior somehow. This is an underlying approach of the Intelligent Transportation Systems (ITS) which seeks to improve the system efficiency through the application of distributed solutions that handle users' needs on an individual basis (Chatterjee and McDonald, 1999). Heterogeneity, uncertainty, and dynamics are key elements in this scenario. So, how could one assess with these complex measures brought Q1

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about at the deployment of these new technologies through modelling?

Representing human behavior has received special attention from technical and scientific communities, not only traffic and transportation counterparts. Owing to a scope rather oriented to the problem to be modelled, existing microscopic approaches suffer from various shortcomings and the need for more robust and expressive modelling tools are frequently recognized (Ettema et al., 2003; Watling, 1994). Nonetheless, much effort has been devoted to adapting traditional models to meet ITS requirements and has significantly contributed to building up the roadmap toward the development of new generation traffic network models, which explicitly incorporate driver behavior (Arnott et al., 1991; Mahmassani and Jayakrishnan, 1991; Cantarella and Cascetta, 1995; Liu et al., 1995; Bazzan et al., 2000).

Recently, agent-based techniques have been increasingly applied in that way. Schleiffer (2000) claims that modelling heterogeneity in a microscopic level is a key step towards the understanding of macroscopic behavior. The author suggests that the use of artificial agents to represent simple fundamental individual mechanisms is the tool to better comprehend highly complex and dynamic collective behavior of traffic. Autonomy, social ability, reactivity, adaptability, and pro-activity are some important features that turn multi-agent systems (MAS) into an interesting and appealing metaphor to represent complex domains, naturally including traffic and transportation engineering (Schleiffer, 2002).

Not surprisingly, most works report on applying the agent-based techniques to control systems and traffic management to make those systems more autonomous and responsive to recurrent traffic demand (e.g. Hernández et al., 2002). Nonetheless, an increasing effort has also been dedicated to representing driver behavior and its underlying decision-making mechanism, as proposed in (e.g., Dia, 2002; Rossetti, Liu, et al., 2002; Rossetti, Bordini, et al., 2002). The analysis of ITS systems through this approximation has been investigated as well (e.g., Wahle et al., 2002), and some other works report on applications to freight transport and optimization of resource use (e.g., Haddadi, 1993; Adler and Blue, 2002).

Contrarily to exploring the emergent behavior of multiple interacting reactive entities, in this work we focus on the practical implementation of a cognitive model to base the decision-making carried out by driver agents. The driver is modelled in terms of a two-layered architecture in which one layer hosts a BDI (Beliefs, Desires, and Intentions) model, whereas the other represents the more instinctive behavior of the car-following and lane-changing models. Thus, the mental states of the driver agent should be the elements conditioning the cognitive behavior. We named this model MADAM (Multi-Agent DemAnd Model). Our approach relies on an extension to an existing microscopic simulation suite, DRACULA (Dynamic Route Assignment Combining User Learning and microsimulAtion) (Liu et al., 1995; Rossetti et al., 2000). The framework we shall present is intended to serve as an aid to assessing the impact that individual driver decision-making may have on traffic conditions at the aggregate level, allowing for the representation of interactions with novel intelligent transportation solutions, such as exogenous information systems.

THE BDI DRIVER AGENT

The main protagonist within MADAM is the driver. It is represented in terms of an autonomous agent, capable of making decisions on its own. We have designed a two-layered architecture to base the driver model. So, it is able to exhibit both reactive and cognitive behaviors to some extent. The reactive layer relies on a simple set of rules that map perceptions to actions. Individual drivers' attitude in movement, in terms of car-following and lane-changing behaviors, is performed in this layer. The more complex decisions, such as whether to travel, which itinerary to follow, and what time to start the journey are addressed in the cognitive layer, which is built on the basis of the BDI logics.

The architecture for the driver agent is depicted in Figure 1. As in the basic structure of an agent (Russell and Norvig, 1995), drivers can perceive facts through sensors and act onto the environment through effectors. The communication ability is also present, which is modelled in terms of message passing. Messages are sent through actions and received as perceptions. The reader is referred to (Rossetti, Bordini, et al., 2002) for a more comprehensive explanation on this feature. When a change in the environment happens, the agents' knowledge base is updated through a belief revision function. This can either be associated to the premise of a perception-action rule in the reactive layer, or it can trigger a more sophisticated reasoning process at the cognitive level. If the perception can be evaluated in both layers, the reactive approach will always be evaluated first. If no conclusion is drawn from the set of base rules, then a complete deliberation process starts to find out a reasonable solution. Nonetheless, frequent exercise of heavy deliberation performed for some decision-makings will be transformed into a natural aptitude in a longer-term, allowing the driver to behave more instinctively as the result of a learning process, through which new rules might be assimilated.

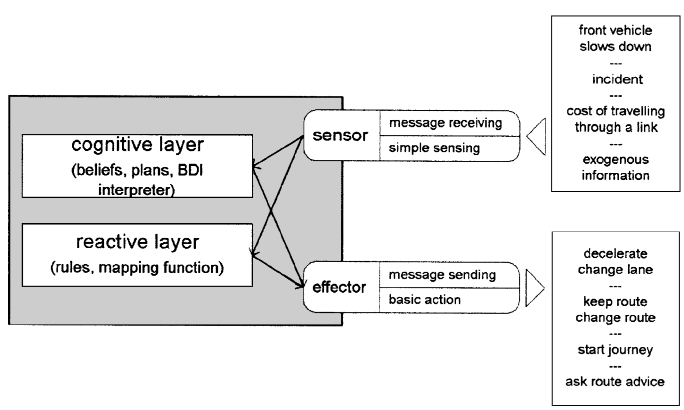

Figure 1 A two-layered architecture for the driver agent.

In this article, we focus on the cognitive ability of drivers. Rao and Georgeff (1991) proposed their BDI theory on the basis of the Bratman's principles (Bratman, 1987), which present rational reasoning as resulting from intentions in addition to beliefs and desires. The logics behind the work by Rao and Georgeff (1991) present both ontological and epistemological commitments, and become a methodology suitable for representing complex application domains where entities are endowed with mental attitudes. In order to turn their BDI theory into practice, Rao (1996) devised the AgentSpeak(L) language, also formalized by d'Inverno and Luck (1998). The language provides a good means for an elegant and clear specification of BDI agents, as claimed by Machado and Bordini (2001). However, owing to the lack of space, we refer to (Rao, 1996; d'Inverno and Luck, 1998) for formal definitions and semantics of the AgentSpeak(L) constructors.

Accordingly to the AgentSpeak(L) language, our driver is represented by the tuple $\langle E, B, P, I, A, S_E, S_O, S_I\rangle$, where E, B, P, I, and A are sets of events, base beliefs, plans, intentions, and basic actions, respectively. The terms S_E, S_O, and S_I are used to designate the selection functions for events, applicable plans, and intentions, in this order (see Definition 6 in Rao, 1996). In Rao's language, the task of defining an agent is basically reduced to identifying the sets of base beliefs and plans. Intentions are generated dynamically from triggering events, which can be either external, when originated from perceptions, or internal, when subplans are necessary for the accomplishment of a certain goal.

To illustrate such an approach, let us consider the habitual driver as presented by Rossetti, Liu, and colleagues (2002). The behavior focused departure time and route choices and was adapted from the decision-making approaches currently implemented in DRACULA (Liu et al., 1995). Departure time is chosen in response to the traveller's previous experiences and preferred arrival time. The absolute delay for a driver m travelling from certain origin i to a destination j on day k is given in Equation 1, where $d_{ijm}^{(k)}$ is the departure time, $t_{ijm}^{(k)}$ is the travel time, and $a_{ijm}^{(k)}$ is the desired arrival time. Drivers are also assumed to be indifferent to a delay of $\varepsilon_m t_{ijm}^{(k)}$ (relative to the travel time experienced). Equation (2) represents the lateness actually perceived by individuals.

$$\delta_{ijm}^{(k)} = d_{ijm}^{(k)} + t_{ijm}^{(k)} - a_{ijm}^{(k)} \tag{1}$$

$$\Delta_{ijm}^{(k)} = \delta_{ijm}^{(k)} - \varepsilon_m t_{ijm}^{(k)} \tag{2}$$

As suggested by Mahmassani and colleagues (1997), drivers are likely to be indifferent to early arrivals. Accounting for that fact, we consider that users only adjust their departure time for a future journey in the case of $\Delta_{ijm}^{(k)} > 0$, otherwise they will keep the same departure time. The adjustment is made as in Eq. (3).

$$d_{ijm}^{(k+1)} = \begin{cases} d_{ijm}^{(k)}, & \text{if } \Delta_{ijm}^{(k)} \le 0 \\ d_{ijm}^{(k)} - \Delta_{ijm}^{(k)}, & \text{if } \Delta_{ijm}^{(k)} > 0 \end{cases} \tag{3}$$

An important simplification of this model is that drivers are virtually indifferent to early arrivals, which may not be so related to the reality of commuters. Other types of behavior were also suggested and modelled according to this approach and can be found in (Rossetti, Bordini, et al., 2002), where all the plans and base beliefs were specified in AgentSpeak(L).

The route choice model is one based on the bounded rational behavior, as suggested by Mahmassanin and Jayakrishnan (1991). Drivers are assumed to use their habit routes as on the last day, unless the cost expected for the minimum cost route is significantly better. Thus, a driver will use the same route unless $C_{p_1} - C_{p_2} > \max(\eta \times C_{p_1}, \tau)$, where C_{p_1} and C_{p_2} are the costs along the habit and the minimum cost routes, respectively. The parameters η and τ, representing the relative and the absolute cost improvement required for a route switch, are associated to the trip belief of each driver agent rather than dealt with as global variables.

THE SIMULATION ENVIRONMENT

A microscopic simulation environment is set up to represent the interaction between the demand, as modelled in MADAM, and network supply conditions. The approach relies on the extension proposed for the original DRACULA structure, as presented by Rossetti and colleagues (2000).

The DRACULA model is a microscopic traffic simulation suite that has been developed in the Institute for Transport Studies, University of Leeds (Liu et al., 1995). A key element of the DRACULA model is variability. Two concepts are of central importance in its structure, namely the day-to-day dynamics and the within-day decision-making process. The former is concerned with modelling how the state of the network changes over time, while in the latter all choices regarding a journey are assigned to individuals. In the day-to-day formulation, the spatial knowledge of a driver is constantly evolving in response to trips made through the network on a daily basis. Also, travel goals, travel needs, perceptions, behavioral patterns, and cognitive abilities that influence the choice process are given in terms of the state of those variables at the instant the choice is being undertaken. This is rather a centralized mechanism performed by a single module over all drivers.

The main choice dimensions available in DRACULA are route and departure time, although its modularity allows for the development of other ones, such as an en-route diversion capability. On each day when a driver is supposed to perform a trip, he is launched onto the network at the departure time and follows his chosen route to the destination. The experienced costs (given in terms of travel time along the route on a link-by-link basis) are taken into account for future journeys. In our approach, MADAM will play the demand side in the DRACULA simulation framework. Rather than representing travel choices through variable values in a simple data structure, demand results from the cognition mechanism of each single BDI driver agent. The

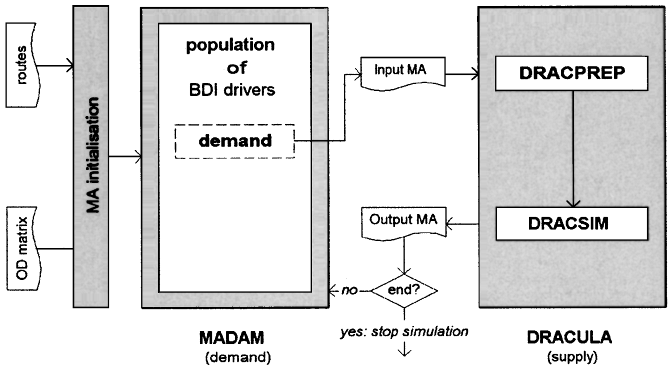

Figure 2 The MADAM+DRACULA simulation framework.

conceptual framework integrating MADAM and DRACULA is presented in Figure 2.

On the *Demand* side, day-to-day variability is represented in terms of individuals that have decided to travel on a certain day. Decision-makings are driven by mental attitudes of each of our BDI agents. JAM (Hubber, 1999) was used to underlie the implementation of the AgentSpeak(L) specifications of the driver behaviors. On the *Supply* side, the movement is represented on a microscopic basis, which implements both car-following and lane-changing models. *Dracprep* sets network conditions on each day (road capacity may vary due to weather, parked cars, and accidents, for instance) whereas *Dracsim* actually executes the microscopic simulation of each individual's trip.

The *MA Initialisation* module synthesises the population for the experiment from an *OD matrix* and route alternatives are assigned to each driver from a list of possible *routes* for each origin and destination pair. The initial set of base beliefs for each driver agent of the population can be either generated after a first run of the *Supply* side, so that the usual desired arrival time is estimated, or set to default values.

The *Input_MA* file gathers drivers' decisions on route and departure time, so that they can be launched onto the network to perform their journeys at selected departure times on each day. On the other hand, the *Output_MA* file returns the travel costs experienced by each driver in terms of the travel time experienced (these are the perceptions of each driver during the course of the journey simulated in DRACULA) and the base beliefs sets are updated. On the following day, the driver uses his updated beliefs to make his decision and this process is repeated all over for a specified number of days, which is defined at the beginning of the simulation.

A SIMPLE SIMULATION EXPERIMENT

Some experiments were carried out in order to demonstrate the methodological approach presented in this work. A small network with 54 links (unidirectional road segments) connected through 14 junctions was selected for this purpose. The network is schematically represented in Figure 3. Most road junctions

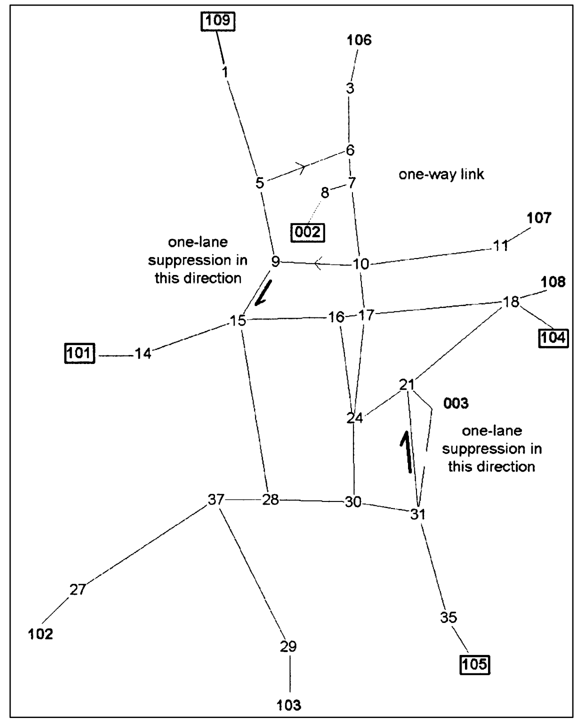

Figure 3 A schematic representation of the network. The zone numbers of the three main OD pairs are displayed in squares, also displayed are the nodes within the possible itineraries between them.

follow a priority regime, whereas two of which are governed by traffic signals (at nodes 15 and 17).

In this simple example, demand is generated from a population of 2,323 habitual drivers who wish to travel in a one-hour morning peak period, and their day-to-day choices on route and departure time are simulated. The agents can perform their trips to/from 11 zones, that is, there are 11 zones generating traffic onto and 11 zones draining traffic from the network. A hypothetical morning peak period starting at hour eight is considered and the simulation is carried out from day zero to day 100.

In a first scenario, no exogenous information was considered and drivers were expected to choose route and departure time according to the habitual behavior presented earlier. The evolution of the departure time for a habitual driver over the simulation period is depicted in Figure 4. This behavior is very tolerant to early arrivals, as only the perceived lateness is considered for departure time adjustment on the next day. Thus, as long as the arrival time on each day is kept below the lateness tolerance, which is relative to the travel time, the departure time on the next day will be repeated. Variability in travel time is ascribed to the stochastic nature of the environment, which is emulated by the supply side of the framework. Thus, even if the driver keeps the same departure time, arrival will be subject to the trip experienced on each day, in terms of the actual travel time perceived.

This behavior has a direct influence onto the system performance, as the average travel time for all the drivers in the population converges very quickly (mean-square-root errors [MSRE]

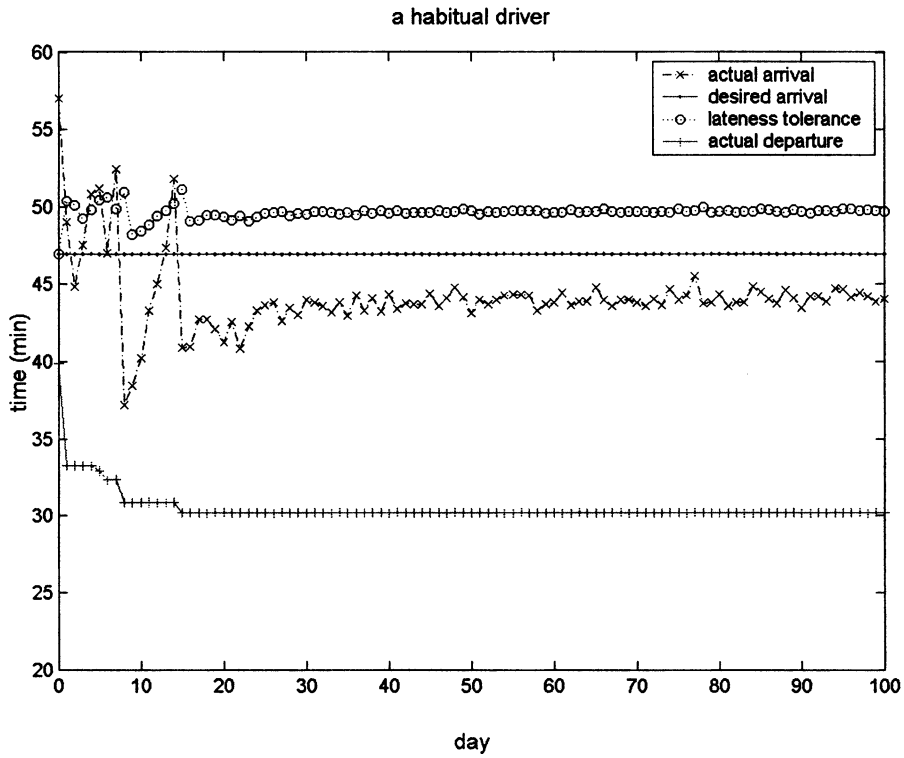

Figure 4 The departure time behavior of a habitual driver.

close to zero), as depicted in Figure 5. Thus, longer journeys are not actually a problem for such habitual drivers. The longer the trip the more tolerant the driver is with regard to lateness. Also, the driver can easily afford long trips provided he is able to arrive earlier than his perceived lateness so as to meet the scheduled delay.

In order to test the ability of our approach to cope with the representation of pretrip information sources and their interactions

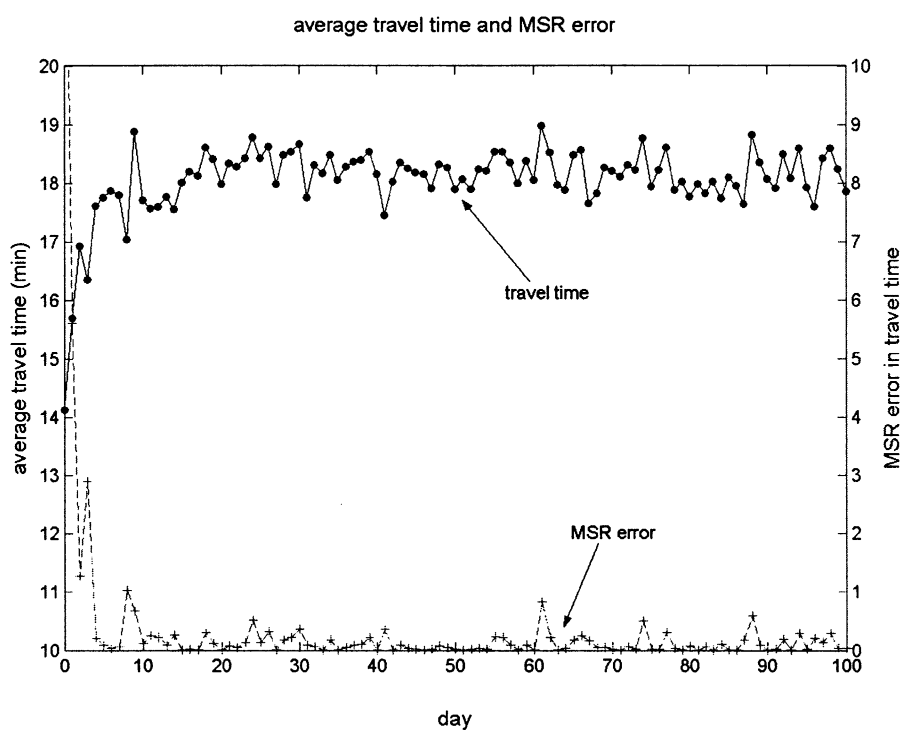

Figure 5 System performance for a population of habitual drivers.

Table 1 Demand compositions for the experiments carried out

Demand composition		
Total number of agents	Agents in each observed OD pair	Fraction of informed users
2323 agents	285 agents, from 109 to 105	0%
		25%
	202 agents, from 105 to 104	50%
		75%
	12 agents, from 101 to002	100%

with drivers, two incidents were introduced (in terms of one-lane suppression) in the links from node nine to node 15, and from node 31 to node 21, as indicated in Figure 3. In this second scenario, the incidents were programmed to start on day 50 and to last for the whole peak period until day 100. At the beginning of each day, users of pretrip information systems are supplied with updated information on the prevailing conditions of the network, so that drivers can revaluate their choices. Three different origin-destination (OD) pairs were observed then. Different fractions of informed drivers were considered in different runs of the experiment (see Table 1 for different compositions of population), which represent the percentage of drivers that effectively use the information provided. After being informed that a link within its itinerary is probably congested, the driver agent tries to select the best alternative path among those that do not include the link affected by the incident. If it is not possible to avoid the constrained link, then the driver keeps on his original route choice.

Possible paths for each OD pair observed in this experiment are listed in Table 2. As we shall see in the simulation results, one OD pair seems to be affected to some extent by the flow incurring in another. This is quite reasonable as routes between different OD pairs may possibly share one or more common links. Moreover, even if the traffic flows in opposite directions between some common nodes, turning manoeuvres of drivers travelling within one OD pair may disturb trips of drivers travelling within the other OD pair.

The simulation results were plotted in the graphs of Figures 6, 7, and 8 to represent the average travel time for each OD pair observed over the total number of days simulated. In Figure 6, the average travel time for trips performed from origin 109 to destination 105 experiences an increase after day 50, for all fractions of informed drivers. This is the most populated OD pair of the network, and three possible routes are considered. The incident on links, 9–15 directly affects two of these routes, whereas the third option will also be conditioned as the traffic jam extrapolates to links, 1–5. Thus, all alternatives are influenced by the lane suppression in links, 9–15 in their very early stages. This way, a considerable increase in travel time is observed for this OD pair. Nonetheless, there is a tendency for the average travel time to settle down after the introduction of the incidents onto the network, although at higher levels. Also, the information provided seems to have a direct impact on such aggregate behavior, as the different compositions of the populations, in terms of exogenous information users, tend to stabilize at different levels. For this specific OD pair, the best level is reached when 50% of the drivers are informed about the incident prior to starting their journeys. The results also show that the worst levels are yielded when none or only few (25%) of the drivers have access to the information about the incident for this OD pair, as already suggested in other works (e.g., Arnott et al., 1991; Bazzan et al., 2000).

Table 2 Possible itineraries for each OD pair observed

Possible Itineraries	
OD pair	Nodes within each route
109–105	{1, 5, 9, 15, 28, 30, 31, 35}
	{1, 5, 6, 7, 10, 17, 24, 30, 31, 35}
	{1, 5, 9, 15, 16, 17, 24, 21, 31, 35}
105–104	{35, 31, 21, 18}
	{35, 31, 30, 24, 21, 18}
101–002	{14, 15, 9, 5, 6, 7, 8}
	{14, 15, 16, 17, 10, 7, 8}

For drivers performing their trips between zones 105 and 104, the results may seem to be counterintuitive at a first glance. Indeed, contrarily to what has been observed for the first OD pair, average travel time tends to settle down in better levels after the incidents are introduced onto the network. One possible reason is that all route options from zone 109 to zone 105 cross most links of routes from zone 105 to zone 104 in the opposite direction. Thus, as the traffic within the 109-105 OD pair becomes very conditioned after day 50, trips within the 105-104 OD pair seem to be lesser affected by traffic interaction at intersections. Nevertheless, travel time also tends to settle down at different levels for each composition of the population, although a decrease has been observed in this case. However, the best situation is verified when the whole population is informed about the network conditions, that means when all the drivers travelling through that OD pair avoid the route with the constrained link. This again may be explained by the traffic interactions with other OD pairs within the network. The worst case still happens when none of the drivers is aware of the incidents, in a similar way as for the case of the previous OD pair.

The third OD pair observed is the one with origin at zone 101 and destination at zone 002, illustrated by the graph of Figure 8. Oppositely to the previous OD pairs selected, in this case trips are not directly influenced by the incidents, as none of the links with one-lane suppression is within the possible itineraries from zone 101 to zone 002. Nonetheless, this OD pair is very illustrative of the effects of traffic interaction on the performance of the whole network. The movement through nodes 9-5-6 is completely conditioned by the gap distribution that arises from the traffic through nodes 1-5-9, which on the other hand is directly affected by the one-lane suppression on link 9-5. Again, travel time settles down in different levels for each demand composition, in terms of informed drivers. A completely noninformed

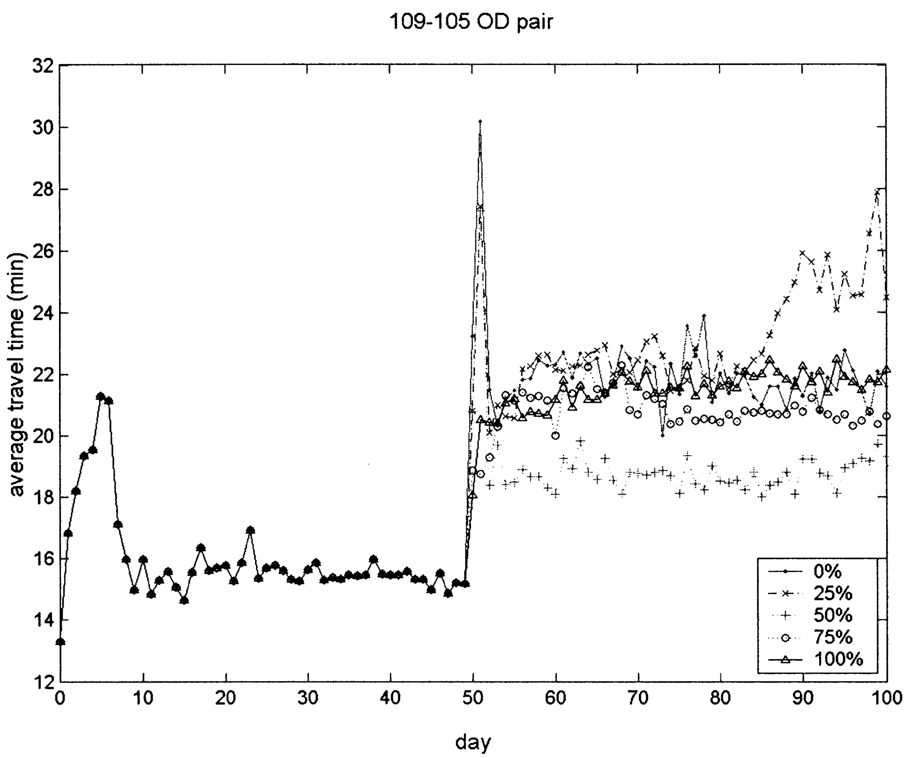

Figure 6 Average travel time for drivers travelling from origin 109 to destination 105.

population seems to present an increasing behavior in travel time, whereas the best situations are achieved when the greater part of the population is aware of the traffic conditions and avoid itineraries through nodes 9-5-6.

From the examples presented above, it is important to notice 405
that informing all drivers will not always produce the best result, as already suggested in other works (Arnott et al., 1991; Bazzan et al., 2000). However, contrarily to what has been observed

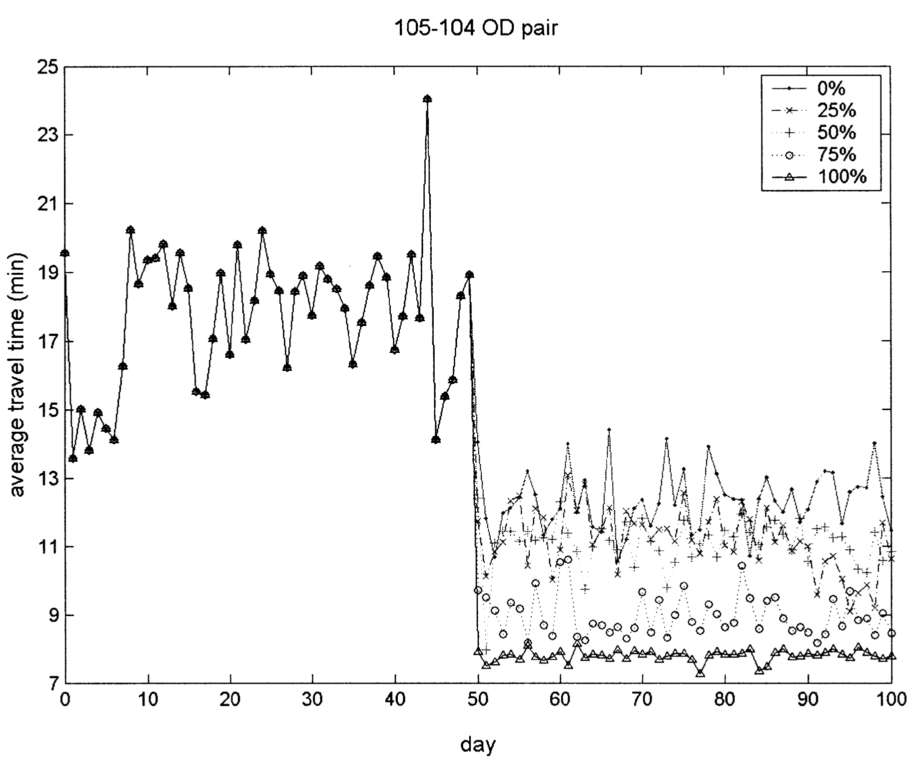

Figure 7 Average travel time for drivers travelling from origin 105 to destination 104.

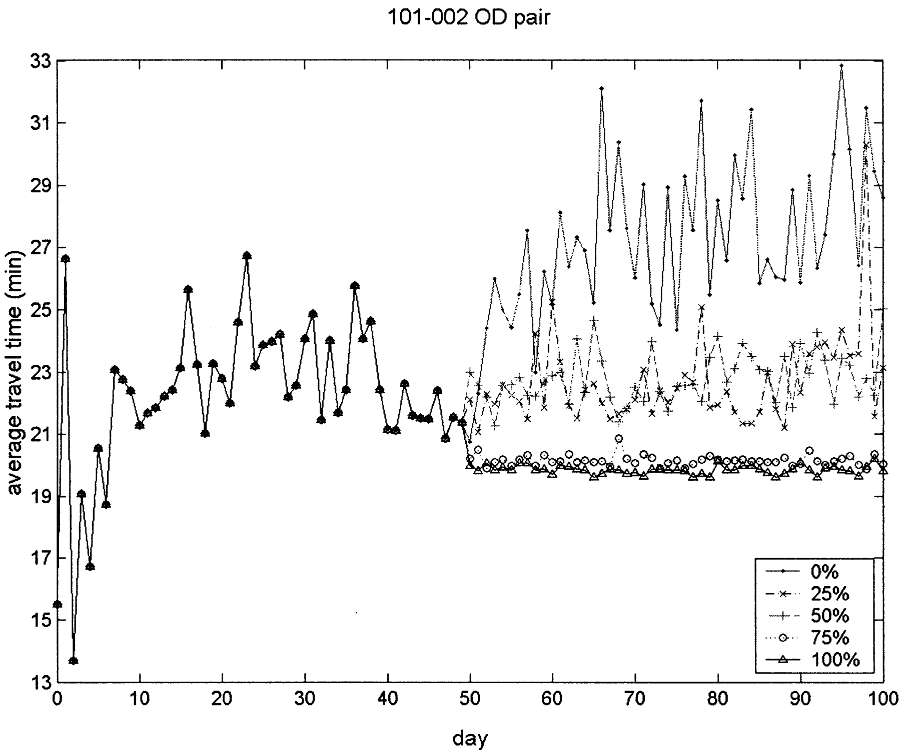

Figure 8 Average travel times for drivers travelling from origin 101 to destination 002.

for route options in a single OD pair scenario (Bazan et al., 2000), traffic interaction seems to have a great influence on the effects of exogenous information provided to drivers. This way, network topology and demand composition become factors of great importance when information systems are to be applied as an attempt at improving the overall system performance. As suggested by Arnott et al. (1991), exogenous information should be used with caution, as some important issues on the efficiency and interaction with such technologies remain to be fully explained and understood.

CONCLUSIONS

In this work we modelled demand as a population of autonomous agents and we used the Rao and Georgeff's (1991) formalism to underlie the cognitive behavior of drivers. Also, we presented a framework to aid the assessment of pretrip information technologies and their effects on drivers' decision-making. The use of mental attitudes, such as beliefs, desires, and intentions allows for an appropriate representation of drivers' cognition on trip parameters, as proposed in previous works (Dia and Purchase, 1999; Rossetti, Liu, et al., 2002; Rossetti, Bordini, et al., 2002).

The simple scenarios simulated within MADAM+DRACULA have shown the ability of our framework to cope with the assessment of pretrip information systems and their interactions with drivers. Nonetheless, we believe this can be extended in such a way that other ITS-based technologies can also be modelled and evaluated in more realistic scenarios. The very first step following this work toward such an enhanced environment is to overcome the weak integration between the multi-agent demand model and the microscopic simulation of supply in terms of agents' en route decision-making behavior. After accomplishing this aim, modelling more complex scenarios including dynamic route guidance will be possible as well. We also plan to devise a methodological approach that allows for the representation of more realistic behaviors, including their calibration and validation against real world observation. Dia and Purchase (1999) have proposed a survey of driver behaviors to provide useful insight into the characteristics of commuters, their preferences and thresholds, as further discussed in (Dia, 2002). Results from such a survey could be easily specified in terms of AgentSpeak(L) constructors. The use of virtual simulated environments, such as the one implemented in Vladimir (Bonsall et al., 1997), could also serve to this purpose.

Unfortunately, a high computation has been noticed while simulating the simple scenarios herein presented, and this is an important issue to overcome for larger networks. In our simulation set-up, a population of 2,323 BDI drivers took approximately ten hours' computer processing unit time, running sequentially in a personal computer featured with an AMD Athlon Q4
processor at 1.1 GHz. In fact, cognitive approaches, such as the one adopted in this work, have been found to be very suitable from a psychological perspective, as all mental attitudes are accounted for when modelling the complex nature of the human reasoning. However, only systems with a reduced number of decision-making entities have been represented in terms of

cognitive models. On the other hand, reactive solutions relying on the overall behavior emerging from the interaction of simpler agent structures have proven to be very effective when applied to larger data sets (Balmer et al., 2003; Gloor et al., 2004). Thus, a coupling of both behaviors within the layered architecture we have proposed could be the basis for profiting from the qualities of the reactive and the cognitive approaches. Indeed, the frequent exercise of heavy deliberation performed for some decision-makings is very likely to be transformed into a natural aptitude in a longer-term, allowing the individual to behave more instinctively as the result of a learning process, through which new rules might be assimilated. So, complex driver behaviors could be modelled and analyzed on a individual basis in a cognitive level, while the simpler reactive behavior could be used to assess the overall system performance in complex and highly dynamic scenarios on aggregate basis.

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