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An Agent-Based Framework for the Assessment of Drivers' Decision-Making

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Abstract

This paper addresses the complexity of modelling drivers' behaviour by the adoption of agent-based techniques. As human factors are central to Intelligent Transportation Systems (ITS), it has become imperative to consider the uncertainty and variability inherent in drivers' behaviour for simulation frameworks aimed at assessing ITS technologies. An agent-based extension to an existing microscopic simulation model, DRACULA, is suggested, which aims at benefiting from characteristics such as reasoning capabilities and autonomy, offered by agent-based approaches. The scope of this work is particularly concerned with the departure time and route choice processes in a commuter scenario.

1. Introduction

The rapid growth of urban areas has necessitated special attention from the scientific and technical community over the last few years; new management policies and planning strategies are required in order to tackle the problems that arise from today's urban scenarios. Not surprisingly, transportation and traffic systems are objects of concern as they play an important and indispensable role in society. However, today's road infrastructures are insufficient to meet the increasing demand and traffic congestion is frequently encountered in most commuters' journeys. This implies considerable economic, social, and environmental losses, which must be minimised. Definitely, physical modification to the road infrastructure is no longer the best alternative to tackle such a problem. Besides the high cost of implementation, it causes disruptions and damages the environment. Alternatively, some efforts have been identified in order to increase road capacity by improving the efficiency of traffic control systems. Although such efforts have contributed to the reduction of problems related to traffic jams, they cannot be considered a lasting solution either.

Therefore, current research still seeks alternative means to cope with traffic and transportation problems. First attempts to improve road capacity relied on dealing with the static part of the system, namely the road infrastructure and control system. However, another approach has been experienced, which, on the other hand, relies on maximising the use of the actual road capacity by directly influencing the users' behaviour patterns. The contribution of Intelligent Transportation Systems (ITS) has been increasingly significant in this scenario. The recent advances in communication and in computer technologies have encouraged the use of such systems as a means to tackle problems in the field of traffic and transportation engineering. The underlying concept of ITS is to ensure productivity and efficiency by making better use of existing transportation systems. It is mainly concerned with the application of distributed solutions; each deals with specific issues of users' needs on an individual basis [6]. A complex communication and on-line computing infrastructure may be the instrument leading to ITS applications, in which traffic improvement results from directly influencing the real-time behaviour of the drivers. Hence, autonomy and intelligence are two concepts that must be present in such IT systems. Integrating all factors, both dynamic and static, which can somehow affect the traffic flow, is central to ITS. In this scenario all components are expected to work together in a co-operative way seeking to maximise the efficiency of the system.

As the driver has become an important facet of contemporaneous traffic systems, models used to represent such a domain need now to consider the uncertainty inherent in human behaviour. Such need leads to lower levels of abstraction that increase the modelling complexity. Hence, practitioners will need systems capable of dealing with the new performance measures brought about by the deployment of these intelligent and adaptable technologies. Owing to the use of simplified approaches, some traditional models have failed to represent such complex scenarios [16]. Therefore, many efforts have been carried out in order either to adapt these models to meet ITS requirements or, more recently, to develop new-generation traffic network models, which explicitly incorporate the driver behaviour [5, 8, 9]. In this way, agent-based techniques seem to be a very appropriate approach to represent such a domain.

Multi-agent system (MAS) is a subfield of Distributed Artificial Intelligence (DAI), which has deserved an increasing interest in the last few years [1]. The rapid evolution in the available computational resources, both in hardware and in software, which support a widely physically distributed computing environment, has contributed for that. Moreover, the increasing demand for suitable tools to represent the complexity inherent in some application domains has motivated much research on MAS. This work aims at exploring the potentials offered by the reasoning and autonomous characteristics of agent-based techniques to represent the uncertainty of human behaviour, envisaging the application of ITS technologies. The model presented is particularly concerned with the departure time and route choice processes in a commuter scenario. It is proposed on the basis of an extension to an existing microscopic simulation model.

2. ITS from a Multi-Agent System Perspective

The concept of a multi-agent system is a modelling approach devised to represent systems whose entities, coined agents, exhibit intelligence, autonomy, and some degree of interaction, both with one another and with the environment. The abstraction approach of MAS consists of representing a system by multiple agents that exist in a common environment and interact in order to achieve specific goals. An agent can, therefore, be any entity capable of perceiving facts through sensors and acting upon the environment through effectors. Some degree of interactions will also imply the presence of communication capabilities.

Basically, two extreme kinds of agent structures can be identified: the reactive and the cognitive agents. The former is based on a simple approach of mapping perceptions to actions whereas the latter could be fully endowed with reasoning capabilities. Nonetheless, depending on the application, an agent's structure can range from pure reactive to pure cognitive, mostly exhibiting both characteristics to some extent. Considering a more cognitive structure, an agent could possess knowledge about its internal state, about the dynamics of the world, i.e., how the world evolves, the likely outcomes of its actions, and some definition of utility. This set of information is the basis for implementing a decision-making mechanism [13]. In this sense, MAS has the ability to represent mental attitudes, such as beliefs, desires, and intentions, which are intrinsic to the human reasoning process. Besides, agent-based models are ideal to deal with entities that are geographically and functionally distributed. The great commitment in representing entity ontology ensures agent-based models' scalability and robustness, which are desirable characteristics for ITS models.

Some examples of applied MAS in the field of traffic and transportation engineering can be found in the literature. However, most of the applications are concerned with the control system, not the driver. The basic assumption in such examples relies on the representation of adaptable control system as a community of controller agents, which co-operate in order to achieve an optimum plan to meet the variable demand [1, 10, 12]. The movement is represented on the basis of simplified car-following and lane-changing models, which in the great majority adopt a simple approach of using a reactive structure. Nonetheless, some attempts of modelling interactions between drivers and service providers are also identified [4, 7] as well as of modelling drivers endowed with mental attitudes, as in [2]. Envisaging the benefits that could arise from the use of such technologies, Bouchefra and colleagues [3] suggested a methodology to represent IVHS (Intelligent Vehicle Highway Systems) using different levels of granularity.

The greatest advantage of applying agent-based approaches is their use of the entity ontology. It is reasonable to see traffic systems as formed by heterogeneous entities, which are geographically and functionally distributed throughout the environment. Thus, entities of such a system could be viewed as agents in a multi-agent system. In this work, the environment and the

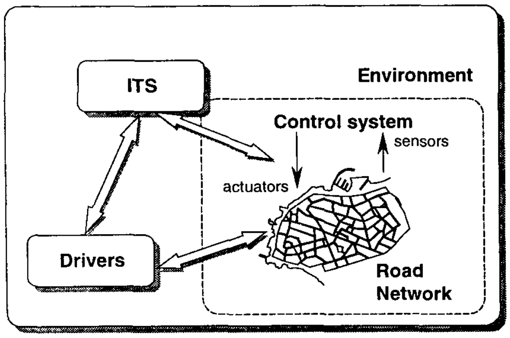

Figure 1: Abstraction of today's traffic scenario from a MAS point of view.

moving particles, which are the drivers travelling through the road network, are considered the basic components in the MAS. The environment can be viewed as the road network itself and the control system, which dictates the movement rules (e.g., traffic signals and traffic signs). The Intelligent Transportation Systems are further components integrated into the environment. Bearing this structure in mind, the moving particles will constitute the demand for travel competing for limited resources, i.e., the limited capacity of the road infrastructure. On the other hand, IT technologies will play a role of mediating conflicts in order to optimise the use of such resources (see Figure 1). Examples of environments where a mediator agent tries to sort out conflicting situations can be found in [14, 15].

When considering a modelling approach to represent decision-making mechanisms in traffic systems, the driver definitely will be the main subject of concern, and modelling such an entity deserves special attention. Nonetheless, the other elements within the system are equally important. Most of the components, e.g., basic traffic control systems, could be modelled as reactive agents, as their tasks are very specific and their reactions to events are well defined. However, this approach may be too simplistic to model some features of drivers' behaviour. When answering to control systems or responding to some stimuli brought about by, for instance, the presence of surrounding vehicles, drivers' behaviour is basically reactive. The car-following and lane-changing models are traditional representations of such a reactive behaviour, as they use defined rules to map actions to specific events, such as the red light of a traffic signal. However, when planning a trip, choosing a route and the time to depart, or even when deciding whether to divert in the presence of a traffic jam, drivers must exert their reasoning capabilities, which account for mental attitudes such as beliefs, desires, and intentions. Therefore, cognitive structures seem to be more suitable in these situations. The utility-based agent, proposed in [13], could be used as a basic structure for a driver agent, as drivers make decisions mostly accounting for a trade-off between cost and utility.

All of the agents in a traffic domain will interact with each other and with the environment in order to improve the system performance. Despite living in the same environment, a driver agent does not depend on others to carry out its own tasks and to seek its goals. In this sense, drivers' social behaviour could be seen as simple co-habitation with others. Nonetheless, other types of social interactions, such as collaboration and co-operation, can be easily identified among drivers and service providers, such as Dynamic Route Guidance. Interaction between agents and between an agent and the environment is a factor of huge importance to share information in MAS, and that is also true in an agent-based traffic model. Therefore, besides the built-in knowledge of drivers, they can acquire information by accessing, for example, Variable Messages Signs, and also by observing the environment in previous journeys. Another important issue is the time-dependent nature of such interactions. This characteristic becomes more evident and significant for IT technologies, which must rely on efficient and reliable means of communication in order to deliver information in a timely basis. As consequence of failure in an Advanced Traveller Information System (ATIS), for instance, drivers could experience increases in travel cost by virtue of an unadvised traffic jam.

3. The DRACULA Framework

The basic structure of some microscopic models, such as DRACULA (Dynamic Route Assignment Combining User Learning and microsimulAtion) developed at the Institute for Transport Studies, University of Leeds, UK [8], takes into account two concepts that are of central importance: the within-day decision-making process and the day-to-day dynamics (see Figure 2). The former focuses on the travel choices made by an individual to perform a journey. Travel goals, travel needs, perceptions, behavioural pattern, and cognitive abilities that influence the choice processes, are reflective of the state of those variables at the instant the choice is being undertaken. The dynamic formulation, on the other hand, is concerned with modelling how the state of the network changes from day to day and evolves over time. In addition, the spatial knowledge of a driver is constantly evolving in response to trips made through the network.

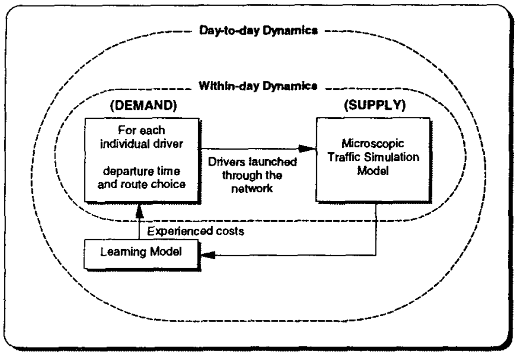

Figure 2: Basic relations in DRACULA model.

Such frameworks give special emphasis to the microscopic simulation and are basically composed of both a demand and a supply model. In the demand model, drivers are individually represented. For each individual, daily departure time and route choices are made on the basis of both past travel cost experiences and the knowledge built from perceptions of the network conditions. Contrary to models based on a fixed matrix approach, the demand stage predicts the level of individual demand for a day 'i' from a full population of potential drivers. In the supply model, on the other hand, vehicles individually move through the network and follow their routes according both to the car-following and to the lane-changing rules. The resulting travel conditions of a certain day 'i' and the costs experienced by drivers are then re-entered into their individual knowledge basis. Such an internal model will affect the demand for the next period, i.e., day 'i+1'. This process continues for a pre-specified number of days. Figure 3 depicts a basic microsimulation framework, such as DRACULA.

When explicitly representing driver behaviour in microscopic simulation models, two aspects of human reasoning deserve special attention, namely the learning mechanism and the decision-making process. Drivers definitely need to make decisions regarding departure time, which route to take, trip purpose, and so forth, to perform a journey. It is also quite intuitive that drivers make use of remembered past experiences to aid their decisions as they become more familiar with the network. However, decision-making processes have been approached in a centralised way, which means that there exists a module that is responsible for assigning the values for each attribute of the drivers' decision.

There are basically two ways used to assign departure time choice in DRACULA, as it has been implemented so far [8]. The first and simplest method is to randomly

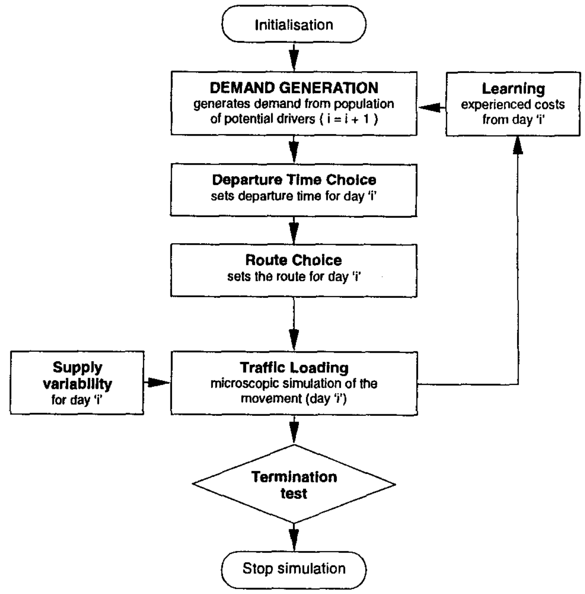

Figure 3: The basic structure of the DRACULA framework.

assign a desired departure time for each potential driver in the modelled population. When drivers choose to travel on a certain day, they will depart at that desired departure time, independently of route choice and any previous experiences. In this case, the departure time profile could be flat or distributed according to some user-specified distribution.

The second method incorporated into DRACULA, and considerably more complex, implements the choice in response to travellers' experience. In such a method, departure time is chosen prior to every journey. This process is based both on travellers' preferred arrival time and on experiences gathered from previous days. The costs experienced are used to build a knowledge basis, which helps drivers 'to forecast' the future state of the network. If the difference between the desired arrival time plus a scheduled delay and the actual arrival time is bigger than nil, the driver should adjust the departure time. Otherwise, the current departure time will be retained.

The process of choosing routes is also based on past experiences. After each journey, individuals use the cost experienced from each link along the chosen route to update their information about the network conditions. This is achieved by providing individuals with memory. Hence, the perceived cost will be an average of the remembered experiences for each link. The model adopted in DRACULA assumes drivers will take their

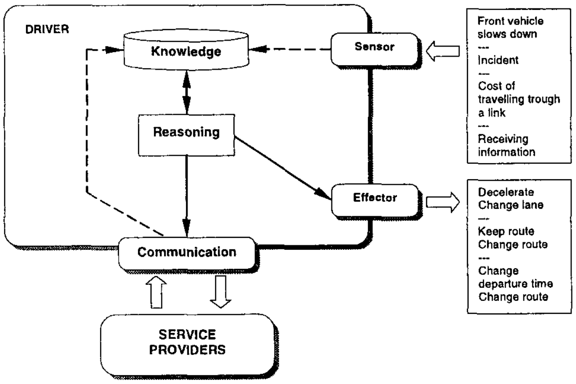

Figure 4: The driver agent.

usual daily route unless the cost of travelling through the minimum cost route is significantly better [8, 9]. Route choices are taken prior to the journey and drivers are not able to make en-route diversions.

Given the implementation approach used, DRACULA may also be seen as a reactive multi-agent system, since most of driver behaviours reflect a mapping from perceived events to corresponding actions. Drivers are launched onto the network at their origins and will follow their routes to their destinations. Once performing their trips, drivers are ruled by car-following and lane-changing models, and can memorise the costs, in terms of travel time for instance, on a link-by-link basis.

4. An Agent-Based Demand Model

The extension proposed in this work benefits from the potentials offered by agent-based techniques. Therefore, drivers are modelled as autonomous and intentional agents fully endowed with reasoning capabilities (see Figure 4).

Drivers are autonomous in the sense they can take decisions on their own in order to achieve their goals. Contrary to some models, the decision-making process is made in a decentralised basis. In this way, it is the driver's own responsibility to identify his needs, to manage his resources, and to take his decisions. Drivers are also intentional entities in the sense that decisions are taken as a result of a reasoning chain performed on driver's mental states, such as beliefs, desires, and intentions, ending at a commitment of achieving a certain goal.

Drivers are then dealt with as cognitive entities through the use of a BDI approach [11], where the internal model

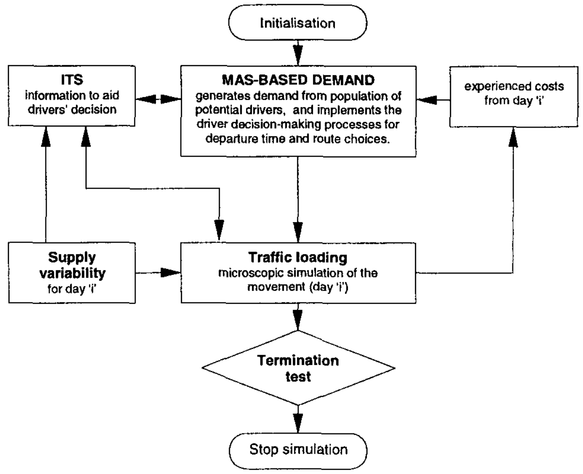

Figure 5: The extended DRACULA framework.

of each agent is represented by sets of beliefs, goals, and intentions. The presence of communication facilities allow drivers to interact with different IT technologies, e.g. ATIS, which act as 'mediators' in order to sort out conflicting situations. In this way, some IT agents have a global model of the world. The DRACULA framework is then extended to deal with the demand side by means of a population of driver agents, which make their decisions on their own. Besides, IT technologies can be featured in the framework in order to aid such decision-making processes (see Figure 5).

Considering the commuter scenario, for instance, a driver agent should have autonomy to decide whether to travel, accounting for his knowledge about the most preferable routes and the dynamics of the traffic system. The capacity to learn from previous experiences affects driver's beliefs, enhances his knowledge, and improves the decision-making process. As commuters know about constraints posed by non-flexible arrival time at destinations, a trade-off between whether to change route or departure time should also be considered. Driver's knowledge may also be enriched with information provided by systems such as ATIS. An important factor that plays a special influence on forming driver's beliefs on the current route conditions is the information from exogenous sources. Therefore, the user should be able to perceive the environment state either by accessing some sort of information system or by 'forecasting' it from his knowledge.

This framework consists of an extension to the DRACULA environment, specifically in the demand model. Through the use of the MAS approach, such an architecture aims at addressing variable demand and, together with an object-oriented implementation in C++, it introduces modularity and scalability to the original DRACULA structure.

5. Conclusions

Clearly, driver behaviour plays a central role in today's traffic scenarios. New measures brought about by Intelligent Transportation Systems are mainly intended to improve the use of existing road capacity. To achieve this purpose, ITS mainly relies on directly influencing behavioural patterns. Therefore, modelling the uncertainty and variability of human behaviour becomes imperative to traffic analysis in order to assess, for example, the level of acceptance for information provided by ATIS. The application of such new technologies demands efficient means to represent the dynamic and adaptable nature of these systems. Hence, agent-based techniques seem to be a very appropriate approach to represent the emerging IT scenarios. They mainly contribute to modelling drivers' decision-making processes, which in turn contribute directly to a more accurate prediction of the actual departure times, arrival times, and routes. The framework herein proposed adopts an object-oriented implementation in C++. Together with the agent-based approach, it gives the original DRACULA structure modularity and scalability, which allows the assessment of drivers' behaviour in the presence of different types of ITS technologies.

Acknowledgements

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