Agents in Traffic and Transportation: Preface

Integrating researchers from artificial intelligence – in particular from the area of autonomous agents and multiagent systems – and transportation has been the purpose of the workshop series “Agents in Traffic and Transportation” (ATT), now in its fourth edition. This series aims to discuss issues such as how to employ agent-based simulation, distributed scheduling techniques, as well as open problems in traffic and transportation which pose challenges for multiagent techniques.

This fourth edition of ATT was held together with the International Conference on Autonomous Agents and Multiagent Systems (AAMAS), in Hakodate on May 9, 2006. Previous editions were: Barcelona, together with Autonomous Agents in 2000; Sydney, together with ITS 2001; New York, together with AAMAS 2004. The Barcelona and New York editions had selected papers published by the Transportation Research C journal in 2002 and 2005 respectively.

The present edition has attracted a broad range of papers tackling the use of tools and techniques from the field of autonomous agents and multiagent systems, such as agent-based simulation, reinforcement learning, collectives, etc.

All papers have been thoroughly reviewed by renowned experts in the field. We are grateful to all the people involved: from authors and reviewers to hosts and chairs of the AAMAS conference.

Hakodate, May 2006
Ana Bazzan, Brahim Chaib Draa, Franziska Klügl, Sascha Ossowski

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Traffic Network Equilibrium using Congestion Tolls: a case study

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ABSTRACT

One of the major research directions in multi-agent systems is learning how to coordinate. When the coordination emerges out of individual self-interest, there is no guarantee that the system optimum will be achieved. In fact, in scenarios where agents do not communicate and only try to act greedly, the performance of the overall system is compromised. This is the case of traffic commuting scenarios: drivers repete their actions day after day trying to adapt to modifications regarding occupation of the available routes. In this domain, there has been several works dealing with how to achieve the traffic network equilibrium. Recently, the focus has shifted to information provision in several forms (advanced traveler information systems, route guidance, etc.) as a way to balance the load. Most of these works make strong assumptions such as the central controller (traffic authority) and/or drivers having perfect information. However, in reality, the information the central control provides contains estimation errors. The goal of this paper is to propose a socially efficient load balance by internalizing social costs caused by agents' actions. Two issues are addressed: the model of information provision accounts for information imperfectness, and the equilibrium which emerges out of drivers' route choices is close to the system optimum due to mechanisms of road pricing. The model can then be used by traffic authorities to simulate the effects of information provision and toll charging.

Keywords

User vs. System Optimum, Emergence of Coordination, Route Choice, Road Pricing for Traffic Management

1. MOTIVATION AND GOALS

In traffic and transportation engineering many control strategies were developed for different purposes, such as single intersection control, synchronization of traffic lights in an arterial, traffic restrictions in roads integrating urban and freeway traffic, etc. Freeways (highways) were conceived to provide almost unlimited mobility to road users since freeway traffic has no interruption caused by traffic lights. However, the increasing demand for mobility in our society has been causing frequent jams due both to high demand in peak hours as well as weather conditions and incidents. As to what regards the former, control measures have been proposed to better control the utilization of the available infra-structure [20]: ramp metering (on-ramp traffic lights), link control (speed limits, lane control, reversable flow, etc.), and *driver information and guidance systems* (DIGS).

In this paper we focus on the latter due to the interesting challenges these systems pose for the area of multiagent systems in terms of mechanism design, since it involves a very complex factor: human-made decisions behind the steering wheel.

Information provision and route guidance strategies may aim either at achieving the *system* optimum (minimization or maximization of some global objective criterion) or the *user* optimum. From the point of view of the user, the latter implies equal costs for all alternative routes connecting two points in the network. This eventually leads to the system's suboptimality. If the focus is on global optimum, then the route guidance system may eventually recommend a route which is costlier (for a single user) than it would be the case if the user optimum were to be recommended. In general, traffic control authorities are interested in the system optimum, while the user seeks its own optimum.

One of the challenges of DIGSs and Advanced Travel Information Systems (ATISs) is to achieve an adequate modeling and control of traffic flow. This is an issue of ever increasing importance for dynamic route guidance systems. To be effective, such systems have to make assumptions about the travel demand, and hence about travel choices and, especially, about the behavior of people. It is clear that the decisions made in reaction to the information an ATIS provides alter the traffic situation and potentially make the predictions of the system obsolete.

Although a road user does not reason about social actions in the narrow sense, traffic systems obviously exhibit social properties, a kind of N-person coordination game. The interdependence of actions leads to a high frequency of implicit coordination decisions. The more reliable the information that a driver gets about the current and future state of the traffic network, the more his actions — e.g. his route choice

— depend on what he believes to be the decisions of the other road users. Especially interesting is the simulation of learning and self-organized coordination of route choice which is further detailed in Section 2.1.2.

The aim of the present paper is to investigate the question of how to include externalities in the utility of drivers in a commuting scenario. Previous work on this and other issues related to traffic management and control measures are briefly presented in the next section. Section 3 introduces the model based on road pricing as well as discusses the relationship between the control system and the user/driver. The mechanism for driver adaptation regarding route choice is also discussed in this section. Section 4 shows the results achieved in different scenarios. A conclusion is given in Section 5.

2. RELATED WORK: TRAFFIC AND INFORMATION

2.1 Traffic

In their paper of 1994, Arnott and Small [4] mention the following figures: about one-third of all vehicular travels in metropolitan areas of the United States take place under congested conditions, causing a total delay in trips of about 6 billion vehicle-hours per year. Despite the fact that the figures are quite old, the situation has shown no significant improvement, if any. With costs of extending traffic networks skyrocketing, policy-makers have to carefully consider the information provision and behavioral aspects of the trips, i.e. the drivers behind the steering wheel. Fortunately, there is also a tendency of reducing that gap: several researchers are conducting simulations and/or proposing more realistic models which incorporate information and behavioral characteristics of the drivers, i.e. how they react to this information ([3, 8, 9, 18] among others).

There are two main approaches to the simulation of traffic: macroscopic and microscopic. Both allow for a description of the traffic elements but the latter considers each road user as detailed as desired (given computational restrictions), thus allowing for a model of drivers' behaviors. Travel and/or route choices may be considered. This is a key issue in simulating traffic, since those choices are becoming increasingly more complex, once more and more information is available. Multi-agent simulation is a promising technique for both approaches.

Modeling traffic scenarios with multi-agent systems techniques is not new. However, as to what regards traffic problems as traffic agents monitoring problem areas (as in [19]), the focus has been mainly on a coarse-grained level. On the other hand, our long term work focuses on a fine-grained level or rather on traffic flow control. Currently, in order to make traffic simulations at the microscopic level, one may have to consider travel alternatives (and consequently an extensive search of information), joint and dynamic decision-making, contingency planning under uncertainty (e.g. due to congestion), and an increasing frequency of co-ordination decisions. This has consequences for the behavioral assumptions on which travel choice models needed to be based. At this level, there is now an increasing number of research studies as for example [7, 10, 12, 21, 22, 23].

Therefore, one easily realizes that the multiagent community is seeking to formalize the necessary combination of methods and techniques in order to tackle the complexity posed by simulating and anticipating traffic states. No matter the motivation behind (training of drivers, forecast, guidance to drivers, etc.), the approaches seem to converge.

Next, we describe some studies focussing on informed drivers' decision making. We start with works from the traffic engineering and traffic economics communities. After, we review the previous results by one of the authors on iterated route choice.

2.1.1 Travelers Information System

In Al-Deek and colleagues [1] the goal is to develop a framework to evaluate the effect of an ATIS. Three types of drivers are considered: those who are unequipped with electronic devices of any kind (i.e. they are able to get information only by observing congestion on site); those who only receive information via radio; and those equipped only with an ATIS. The device in the latter case informs drivers about the shortest travel time route. Some drivers of the first type are completely unaware of the congestion event. In this case, they take their usual routes. Average travel time was measured and it was found that this time improves marginally with increased market penetration of the ATIS. In general, the benefits of ATIS are even more marginal when there is more information available to travelers, especially through radio, but also through observation. These induce people to divert earlier to the alternative route.

2.1.2 Iterated Route Choice

A commuting scenario is normally characterized by a driver facing a repeated situation regarding route selection. Thus, a scenario of iterated route choice provides a good opportunity to test learning and emergence of coordination. Of particular interest is the simulation of learning and self-organized coordination of route choice. This has been the focus of the research of one of the authors. The main problem is to achieve a system's optimum or at least acceptable patterns of traffic distribution out of users' own performance strategies, i.e. users trying to adapt to the traffic patterns they experience every day.

There are different means for achieving a certain alignment of those two objectives (system and user optimum) without relegating important issues such as traffic information, forecast and non-commuter users (who possibly do not have any experience and make random route choices for instance), etc. A scenario was simulated where N drivers had to select one of the available routes, in every round. At the end of the round, every driver gets a reward that is computed based on the number of drivers who selected the same route, in a kind of coordination game.

The case of simple user adaptation in a binary route choice scenario was tackled in [15]. The results achieved were validated against data from real laboratory experiments (with subjects playing the role of drivers). To this basic scenario, traffic forecast was added in [14]. Decisions were made in two phases: anticipation of route choice based on past experience (just as above) and actual selection based on a forecast which was computed by the traffic control system based on the previous decision of drivers. In [16] different forms of traffic information – with different associated costs – were analyzed. In [5], the role of information sharing was studied: information was provided by work colleagues, by acquaintances from other groups (small-world), or by route guidance systems. Besides, the role of agents lying about their choices were studied. Finally, information recommendation and manipulation was tested in [6] with a traffic control center giving manipulated information for drivers in the scenario of the Braess Paradox, as a means of trying to divert drivers to less congested routes. In the Braess Paradox, the overall travel time can actually increase after the construction of a new road due to drivers not facing the social costs of their actions.

The main conclusions of these works were:

- under some circumstances, a route commitment emerges and the overall system evolves towards equilibrium while most of the individual drivers learn to select a given route [15];
- this equilibrium is affected by traffic forecast [14]; however, forecast implies that the control system must have at least good estimatives of route choices in order to compute future traffic state;
- many aspects regarding the type of information as well as its contents or forms influence the behavior of drivers; providing *different kinds of information* may affect the performances (individual as well as global) [16];
- it is interesting to have a system giving recommendations to drivers; however, the performance of the related people (groups of acquaintances) decreases when too many drivers deviate from the recommendation; when there is no social attachment and the behavior is myopic towards maximization of short time utility, the performance is worse; information manipulation may ruin the credibility of the information on the long run;
- in scenarios such as the Braess Paradox, providing some kind of route recommendation to drivers can divert them to a situation in which the effects of the paradox are reduced [6].

In all these works, different means of utility alignment were tested. Some were more successful than others as to what regards performance of the global metrics. However, in the present paper we want to drop the "perfect information" assumption (both the traffic control center and all individuals having knowledge of all alternatives). This assumption is usually made because there is a gap between the engineering and behavioral models. Therefore, the traffic models do not account for the effect of information on the performance of the system, be it at the global level or the individual one.

Kobayahsi and Do [17] formulate network equilibrium models with state-dependent congestion tolls in an uncertain environment, showing that the welfare level of drivers improve. This is also used in the road pricing scenario as discussed in the next section.

2.2 Road Pricing

From the perspective of the economics of traffic, Arnott and Small [4] analyze cases in which the usual measure for alleviating traffic congestion, i.e. expanding the road system, is ineffective, as in the case of the Braess Paradox. The resolution of this and other paradoxes employs the economic concept of externalities (when a person does not face the true social cost of an action) to identify and account for the difference between personal and social costs of using a particular road. For example, drivers do not pay for the time loss they impose on others, so they make socially-inefficient choices. This is a well-studied phenomenon, known more generally as The Tragedy of the Commons [13]. Besides, it has been demonstrated that providing information does not necessarily reduces the level of congestion. One of the reasons is that naïve information provision can cause the traffic to be shifted from one route to other alternative(s). This of course does not improve the global cost balance (system optimum).

Road pricing and specifically congestion tolls are concepts related to balancing marginal social costs and marginal private costs (Pigouvian tax). Negative external effects of road user i over others is in this way accounted for while at the same time attaining Wardrop's user equilibrium [24]. It has been conjectured that road pricing improves the efficiency of network equilibrium [2]. Besides, congestion tolls convey information to drivers since they can assess the state of traffic by means of the amount of toll [11]. In any case, the toll is calculated by the control center which has the information about the current traffic situation.

This way, road pricing has been proposed as a way to realize efficient road utilization i.e. to achieve a distribution of traffic volume as close as possible to the system optimum. Congestion toll is one of the road pricing methods: considering the system optimum, a toll is computed which is the difference between the marginal social cost and the marginal private cost. Notice that this difference can be negative, meaning that drivers actually get a reimbursement. This mechanism is not to be mistaken with toll charging for the sake of covering costs of road maintenance or simply for profit.

Regarding the future traffic situation as well as the *effects* of the toll system (and other measures to control the traffic), most of the work published has assumed that the control center has perfect information, meaning that it will know precisely the states of near future traffic conditions. This is a hard assumption given that acurate weather and accident forecasts are not possible. Even if they were, other unpredictable factors alter the state of traffic. Therefore simple traffic information cannot provide a perfect message to the driver.

A state-dependent toll pricing system is discussed in [17]. Additionally, they investigate which the impacts of two alternatives toll schemas are: toll is charged before (*ex-ante*) or after (*ex-post*) drivers select a route. This distinction is important because congestion tolls, when announced before drivers make their decisions, carry some meaningful information. They allow for the calculation of the system optimum in terms of traffic volume, as well as the drivers expected welfare (average over all drivers).

In the present paper we compare their results with the distribution of traffic volume which is achieved when drivers make their route choices based on the toll they receive, in a bottom-up, agent-based approach.

3. MODEL

We developed a simple model for the adaptive route choice. Since an agent has only qualitative information about routes, and none about other agents, initially, an agent forms an expectation about the costs he will have if he selects a certain route. This is achieved by computing the probability with which a driver selects one route. For instance, if it is 1 for route r then the driver always takes route r.

With a certain periodicity, driver d updates this heuristics according to the rewards he has obtained on the routes he has taken so far. The update of the heuristics is done according to the following formula:

$$heuristics(d, r_i) = \frac{\sum_t utility_{r_i}(d, t)}{\sum_i \sum_t utility_{r_i}(d, t)} \qquad (1)$$

The variable $utility_{r_i}(d, t)$ is the reward agent d has accumulated on route r_i up to time t. There is a feedback loop – the more a driver selects a route, the more information (in the form of a reward) he gets from this route. Therefore an important factor is how often the heuristics is updated. This is particularly relevant since the reward depends on those of other agents. When the agent is learning, he is also implicitly adapting himself to the others.

With this model for the driver, we performed experiments by varying such frequency of heuristics adaptation and focused on the organization of overall route choice. To prevent that all agents update their heuristics during the same round, each agent adapts with a given probability.

In order to model the imperfectness of information, we follow [3] where traffic conditions are represented as L discrete states. We also consider K information types. For each combination of state and information type, there is a cost function which also depends on the traffic volume. This is by no means a top-down information. Rather, this is the signal given to drivers by the environment during the process of reinforcement learning. Thus, the dynamic selection of the routes is simulated according to those abstract cost functions, which nonetheless can reproduce the macroscopic behavior *of the system*, given that it includes a stochastic component regarding the traffic states (q_l). This basically eliminates the need of running actual simulations on a microscopic simulator in order to account for the actual traffic flow (as in [16]).

The functions we use were adapted from [17], from which we also use much of the nomenclature, cost functions, and some scenarios, althought these were slightly modified to include the drivers's adaptation to route choice.

We also assume R alternative routes between two points in the network. Both have a traffic capacity of M vehicles. Traffic can be in one of L states (e.g. if $L = 2$ we can have congested/non-congested states only). In the model, each state occurs randomly with probability q^l (we use a normal distribution). The control center predicts traffic based on imperfect information and provides information to drivers which is also imperfect. There can be K types of information. At a given time, one information k is given randomly with probability p^k. There can be any correspondence between K and L but mostly it is assumed that $L \geq K$, $K \geq 2$, and $L \geq 2$.

The probability of a state l to occur after information k is provided is given by $\pi^{k,l}$. If $\pi^{k,l} = 1/L$, the information conveys basically no meaning i.e. it is tantamount to no information. When $L = K$ (i.e. for each k there is an exclusive l) we can have perfect information provided one of the π's is one and the others are zero. For example, if $K = L = 2$, when $\pi^{k,l_1} = 1$ and $\pi^{k,l_2} = 0$ ($l_1 \neq l_2$), this is a situation of *perfect information provision* because it is known for sure which state is expected to occur after the information is provided.

3.1 Parameters and Settings

In the examples discussed here, $R = K = L = 2$, and the travel cost functions used are linear functions of type $c_i^l = \zeta_i^l + v_i^l \times x_i^k$, where x is the number of drivers in route i receiving information k. In particular we use the following functions [17]:

$c_1^1 = 1.0 + 0.6 \times 0.001 \times x_1^k$
$c_1^2 = 1.5 + 1.6 \times 0.001 \times x_2^k$
$c_1^2 = 1.0 + 0.4 \times 0.001 \times x_1^k$
$c_2^2 = 1.5 + 0.1 \times 0.001 \times x_1^k$

The meaning of these functions is that the marginal costs (v_i^l) of each route r_i differ: for state $l = 1$ this marginal cost is higher for route 2 than for route 1, whereas for $l = 2$ the opposite is true. We therefore expect the number of drivers to be smaller in route 2 when $l = 1$. In [17] the system equilibrium (without any toll etc.) is calculated. When drivers are risk-neutral and the utility is given by $U(y) = -0.1 \times y$ (y being the cost), the system equilibrium is as shown in Table 1.

k	route 1	route 2
1	2391.5	608.5
2	1927.3	1072.7

Table 1: Traffic volumes for system equilibrium

This equilibrium is never achieved when drivers use greedy strategies such as selection of route based on average of past travel time, as we show in the next section. However, when the selection is based on an utility function which includes the toll paid or the amount reimbursed, then traffic volumes are close to the system equilibrium.

3.2 Scenarios

To perform the simulations, we use a commuting scenario. As already mentioned, there are two possible routes, 1 and 2. Depending on the number of drivers that decide to take route 1, route 2 might be faster. As to what regards drivers or agents, these go through an adaptation process in which the probability to select a route is computed based on the reward they have received given that the specific information was provided.

In **scenario I** we are interested in reaching the equilibrium by only allowing users to apply their probabilities to select route r_i, given the information provision k. In our case this is done via adaptation of these probabilities (denoted as $\rho^d_{r,k}$) given the past utilities which are function of the costs (similarly to what is done with Eq. 1). The basic mechanism for each driver d is given by:

$$\rho^d_{r,k} = \frac{\overline{U^d_{r,k}}}{\sum_{i=1}^{R} \overline{U^d_{i,k}}}, 1 \leq i \leq R \quad (2)$$

where $\overline{U^d_{r,k}}$ is the average of the past utility for selecting route r_i when the information provided was k.

In **scenario II** a toll is computed by the traffic control center and communicated to the driver. This computation is performed according to information k so that drivers have to remember their choices made when k was provided. The toll value for each driver on route r_i is calculated as:

$$\tau^k_{r_i} = \frac{x^k_r - x^{k^*}_r}{x^k_r} \quad (3)$$

where:

$x^{k^*}_{r_i}$ is the number of drivers *in the equilibrium situation* for route r_i given information k, and $x^k_{r_i}$ is the expected number of drivers, estimated by the last time k was provided.

Notice that this value can be positive (driver pays) or negative (driver gets a reimbursement).

The reasoning of the driver d is:

- if information k is provided and the last time this happened I was reimbursed because I chose route r_i, then I had better select r_i again with probability $\rho^d_{r_i,k} = 1 - rate_{cur}$
- if information k is provided and the last time this has happened I had to pay, then I select r_i with probability $\rho^d_{r_i,k} = \tau^d_{r_i,k}$

where:

- $rate_{cur}$ is the rate of curiosity, i.e. a probability of d experimenting another route (other than r_i) even though r_i was good the last time. In the next section we show the results for $rate_{cur} = 0$ and for $rate_{cur} = 0.2$
- $\tau^d_{r_i,k}$ is the toll paid by driver d when selecting route r_i under information k

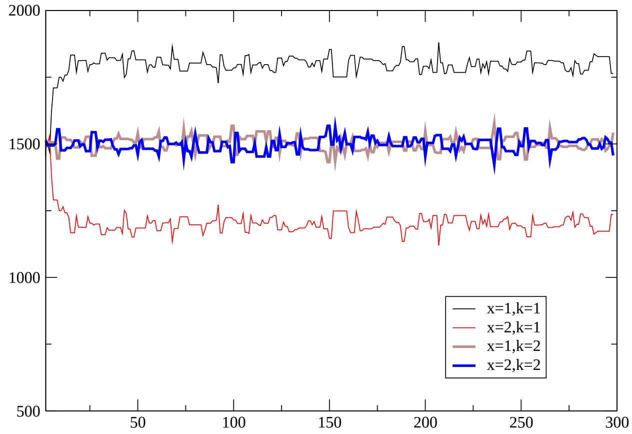

Figure 1: Number of drivers in each route, for each k; learning happens in every time step

4. RESULTS

In this section we present our simulation results. All quantities are analyzed as a function of time (1000 simulation steps which means about 300 trips for each agent on average).

We perform the simulations with M=3000 agents in order to compare the results to those in [17] since these authors have calculate the system equilibrium. In the beginning of the simulation, each agent has equal probabilities of selecting each one of the routes.

Figure 1 depicts the distribution of drivers between the two routes, for each information type k. In this case, the adaptation is made at each time step, *i.e.* the learning probability is one for each agent. We have also run simulations with other learning probabilities without finding significantly different results, so those graphs are not depicted.

For this scenario, if we let drivers select routes only according to the utility they perceive (Eq. 1) causing the update of route choice probability (Eq. 2), then an user's stable state is reached. However this is far from the system optimum. As it is shown in Figure 1, the number of drivers in each route does not correspond to those in Table 1. For $k = 2$ the $M = 3000$ drivers basically select each route with equal probability, so that nearly 1500 end up on each route at any given time. This happens because the utility of drivers is nearly the same when we substitute $x^k_i = 1500$ in the cost functions (cost of each route). For $k = 1$, the user equilibrium is two-thirds on route 1 and one-third on route 2. This equilibrium is never reached: no matter what happens, users are stuck in a suboptimal stable state. Thus, a mechanism is needed which internalizes the externalities caused by the drivers selections.

As already mentioned different mechanisms were applied in the past with different rates of success. Charging a congestion toll is a measure that is both a current trend and also easy to implement since it does not require sophisticated information provision.

Our scenario II simulates exactly what happens when drivers update their route choice probabilities according to a utility

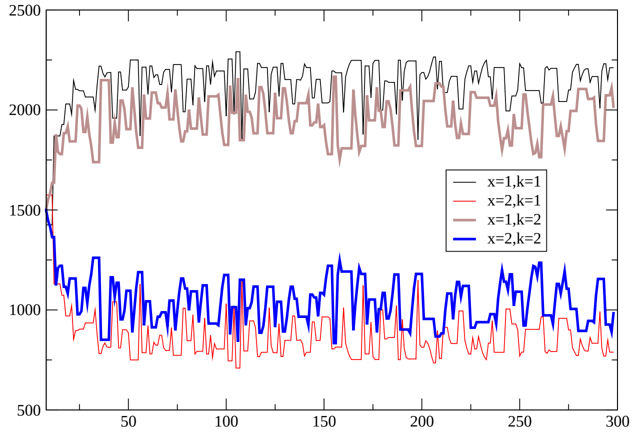

Figure 2: Number of drivers in each route, for each k; with toll and curiosity rate equal 0

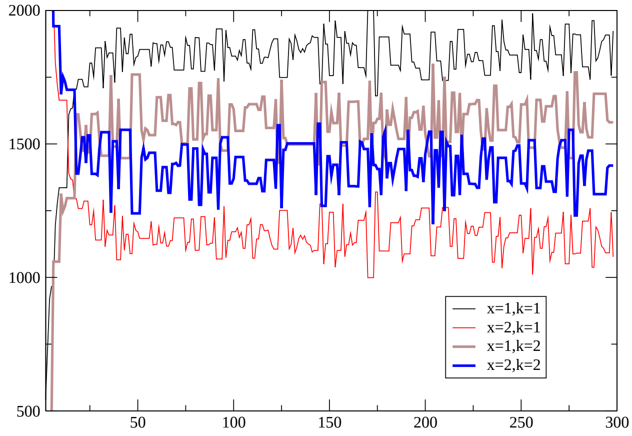

Figure 3: Number of drivers in each route, for each k; with toll and curiosity rate equal 0.2

which is based on the past toll (Eq. 3). Figure 2 depicts the number of drivers in each route, for each k, when a toll is charged and the curiosity rate is zero. This means that drivers act only based on the the reward or punishment represented by the toll the last time information k was provided.

As one can see in that graph, the user equilibrium is now much closer to the system equilibrium. For $k = 1$ the distribution of drivers is around 2300 to 700 (routes 1 and 2 respectively), and for $k = 2$ this distribution is around 2000 to 1000.

Notice that the deviations are higher here than in scenario I. This happens because those drivers who got a reimbursement select one given route with high probability $(1-rate_{cur})$, thus causing many people to select the same route. This in turn increases the toll for it, causing those drivers to divert to the other route, and so on.

As expected, different rates of curiosity change those previous figures and how close the system equilibrium is reached. The higher the rate, the more drivers deviate from the system equilibrium. For $rate_{cur} = 0.2$ (20%), the distribution of drivers is as in Figure 3, meaning that 20% of curious drivers can cause a high perturbation in the system.

5. CONCLUSION AND OUTLOOK

The main issue tackled in this study is the question of how to include externalities in the utility of drivers in a commuting scenario. This is a key issue in traffic control and management systems as the current infrastructure has to be used in order to reach optimal utilization. Traffic engineering normally approaches this problem with top-down solutions, via calculations of network equilibria etc. However, when bottom-up approaches such as emergence of behavior of drivers are considered, other issues such as how these drivers select a strategy to perform route choice have to be considered. Normally, drivers tend to use myopic or greedy strategies which end up causing system suboptimum. This can be seen in the context of previous works on actual route choice, as was shown in Section 2.1.2.

The present paper shows that congestion tolls are useful to internalize the costs drivers impose on others when they act greedly. It is more efficient than information manipulation for instance. This method was also simulated by one of us in a previous paper and despite being effective, it is sometimes criticized for causing drivers to mistrust the information system, at least on the long run. Also provision of traffic forecast was simulated by us with effective results. However, the forecast depends on the system knowing or estimating the intentions of drivers regarding the next route choices.

A congestion toll is a way to somehow punish bad choices and reward good ones. In commuting scenarios, where drivers make choices repeatedly, keeping track of the toll paid or received, given that a certain information was provided, is an effective way to convey information to drivers. Moreover, it is the equivalent of the utility alignment proposed in the COIN framework, but departing from the assumption that agents are cooperative.

As a final remark, for the context of multiagent systems, the present work can contribute to the development of a more general method of mechanism design, specially when agents are self-interested and the system optimum has to be reached without imposing explicit central coordination. In the near future we want to focus on more formal framework for mechanism design such as auctions protocols in order to perform comparisons with the present toll mechanism. However, one concern is that auctions require more communication. Also, it is not clear whether the decision time is compatible with real time scenarios.

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Agent Architecture for Simulating Pedestrians in the Built Environment

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ABSTRACT
The paper discusses an agent architecture for investigating visualized simulated pedestrian activity and behavior affecting pedestrian flows within the built environment. The approach will lead to a system that may serve as a decision support tool in the design process for predicting the likely impact of design parameters on pedestrian flows. UML diagrams are used to communicate about the interpretation of the agent architecture.

1. INTRODUCTION
To date 3D models of the built environment are predominantly used for presentation of the design to non-professionals and for design evaluation amongst professionals [35]. Increasingly, such presentations are done in an interactive and real-time manner, using VR-based techniques. Although images of humans do occur in such presentations, these are hardly ever interactive, nor do they display human behavior. This is all the more striking, as in architectural and urban design human behavior is the starting point. Why not test (intermediate) design performances by simulating human behavior? Therefore, we need virtual persons that show representative behavior and that allow us to analyze the performances of the design.

Scientifically, a lot of research is related to the design process by using virtual humans as substitutes for testing and evaluation purposes, such as hazard situations, crowding and queuing, wayfinding, perception, building efficiency, and training.

By allowing virtual humans to populate a design in a specific situation, behavior of groups as it occurs in 3D space can be studied in real-time. Such simulation can give valuable feedback on design performance.

More seriously, we want to take this one step further by developing a system that relates human behavior to design parameters. For example, consider the design of a shopping center. Critical performance indicators related to human behavior include the distribution of visitors across the center as a function of layout, and the functional characteristics of the center and its shops.

The conceptual underpinnings of the system approach are based on a hybrid approach including cellular automata and agent technology. The system simulates how agents move around in a particular 3D environment, in which space is represented as a lattice of cells with local states, subject to a uniform set of rules, which drives the behavior of the system. Agents represent whether virtual humans or more specifically pedestrians with their own behavior, moving over the network. First, the approach in a 2D environment will be worked out for verifying the underpinnings.

The paper is organized as follows. First, we will give some background of the motive of developing a multiagent system for simulation pedestrian behavior. Next, we discuss some related research. Than, we will discuss the pedestrian model and agent structure. Next, we will discuss the simulation of pedestrian behavior. We will conclude with a brief discussion.

2. BACKGROUND
Since the 1990s, several models of pedestrian movement and pedestrian traffic flows have been developed. Noticeable is the success of cellular automata models in various disciplines, including transportation (e.g. [7,23,29]). Most models are concerned with pedestrian movement in hazardous situations, such as evacuation and escape situations (e.g. [19,21,24]). After the September 11 disaster, great importance has been attached to these models because the prediction of such behavior is of great public interest.

In line with this tradition, several years ago we started a research project that has received the acronym *AMANDA*, which stands for A Multi-Agent model for Network Decision Analyses. The purpose of this research project is to develop a multi-agent system for network decision analyses [12]. The term network decision analysis is used to encompass all design and decision problems that involve predicting how individuals make choices when moving along a network such as streets and corridors in a building.

The popularity of cellular automata models is possibly based on its property that simple principles can be used to successfully simulate complex traffic flows. A cellular automata model therefore seemed suitable to simulate other types of movement in an urban environment. Based on the Nagel-Schreckenberg model the dynamics of cellular automata models have been investigated [25,17,5]. The generalization of cellular automata models from simulated traffic flows to pedestrian movement is considerably more complicated. While car movements are restricted to lanes, pedestrian movement is a complex and chaotic process. Nevertheless, available evidence [6] indicates that cellular automata models are powerful tools to simulate pedestrian movement. Road traffic simulation and generation [11,28] as well as intelligent traveler information systems, traffic management [20,32,22] and driving agent [16,33,18] systems are subjects in the context of traffic analysis and finding efficient ways to model and predict traffic flow.

Previous models of pedestrian behavior have focused primarily on movement rules, lane forming and crowd dynamics. We want to extend these models with destination and route choice, and activity scheduling. To that effect, we started with the basics of other approaches that have focused on destination and route choice [8,9]. In these approaches, it was not so much the actual detailed movement itself, but rather the outcomes of such movements in terms of destination and route choice that were the purpose of the modeling process.

We assume that in turn destination and route choice decisions are influenced by factors such as motivation, activity scheduling, store awareness, signaling intensity of stores, and store characteristics.

3. RELATED WORK

Agent-based modeling of pedestrian movement in urban spaces, especially the implications for the design and modeling of effective pedestrian environments has been discussed in the research of Willis *et al.* [34]. Microscopic movement trajectories of involved pedestrians were investigated in a video-based observational study. The results of this study led to a clear insight into individuals' movement preferences within uncluttered environments, desired walking speed, microscopic position preferences, etc. In other words, insight into movement principles that are of interest in steering mechanism approach.

Research on multilayered multi-agent situated systems provides a framework that explicitly defines the spatial structure of the environment in which a system of situated agents act and interact [3,4]. With respect to agent behavior, both agent state and position can be changed by the agent itself according to a perception-deliberation-action mechanism. In the perception view, an agent state determines receptiveness and sensitivity. Receptiveness modulates field intensity and sensitivity filters not perceivable signals; where field diffusion emits signals that spread throughout the spatial structure of the environment. At this, we perceive some correspondence with the *AMANDA* environment; signaling intensities of objects can spread throughout the cellular grid that contains information about agents and their occupation. Agents can perceive their environment and sense the information the environment contains.

Nagel [26] pointed out that traffic simulations need to include other modes of transportation besides car. In a multi-modal approach a conceptual representation of network layers provisions for multi-modal trips is explained. Balmer *et al*. [2] distinguish two layers of a mobility simulation system: the physical layer and the mental layer. The physical layer simulates the physical world where agents move, avoid each other, go around obstacles, etc. In the mental layer, agents generate strategies, such as routes, mode choice, daily activity plans, etc. In addition, a feedback is used for adapting mobility simulation results to the initial mental condition. Hereby, simulation results are the outcomes of computing strategies by running the mental module. Starting from our ideas about activity behavior and movement, we notice some similarities. An agents' activity agenda will be updated after an action selection that influences the movement pattern.

4. PEDESTRIAN MODEL

We want to extend the virtual human behavior approach to a more generic approach by introducing more behavioral concepts. To populate an environment with agents representing pedestrians, we will consider a shopping mall or shopping environment with shopping pedestrians. Consider a shopping mall or shopping environment with shopping pedestrians. This environment consists of streets, which can be represented by a network consisting of N nodes and L links, and a set of establishments, consisting of J stores, restaurants, etc. A subset E of these N nodes represents the entry/departure points of the system. Let us assume that the pedestrians can be represented by a multiagent system approach with I agents. Each agent i is supposed to carry out a set of activities A_i. That is, agents are supposed to purchase a set of goods, become involved in window-shopping, and possibly conduct other activities such as having lunch, going to a movie, etc. We assume that the activity agenda is time-dependent to allow for changes in the agenda during the trip. The need to actually realize the various planned activities may differ, partly in relation to the nature of the trip. If the reason for the trip is primarily leisure-oriented, the goals and activity agenda may be relatively fuzzy. In contrast, if the trip is initiated because of some urgent goal, the need to realize the activity that serves this goal would be high.

We assume that the completion of an activity is a key decision point, where agents will adjust, if necessary, their activity agenda and anticipated time allocation to the activities not yet completed. Another decision point is every node of the network where agents may decide to take another route, changing the anticipated duration of the overall visit in the shopping center.

Agents can perform the activities in a set of J stores or establishments. Over time, agents form and update beliefs about these stores. We assume that that these beliefs are a function of the degree to which the beliefs of the store, driven by their actual attributes, match the agent's ideals.

In order to implement the activity agenda, the agents need to successfully visit a set of stores and move over the network. We assume that the agents' behavior is driven by a series of decision heuristics. Agents need to decide which stores to choose, in what order, and which route to take, subject to time and institutional constraints. We also assume that agents are in different *motivational states.* They may at every point during the trip have general interests in conducting particular activities, without having decided on the specific store or establishment to visit, but they may also be in a more goal-directed motivational state in which case they have already decided which store to visit.

When moving over the network, we assume that agents have *perceptual* fields. *Perceptual fields* may vary according to the agent's *awareness threshold*, which in turn may depend on his motivational state, age, travel party, eye-sight, and the like, and the *signaling intensity* of the store, which is assumed a function of distance, appealing architecture, and whether or not the view is interrupted by other agents [13].

5. AGENT ARCHITECTURE

5.1 General description

To better communicate our interpretation of agent architecture, we use UML (Unified Modeling Language) diagrams to guide an implementation design

Vidal et al. [31] point out that is not trivial to implement common agent architectures using object-oriented techniques. They make a UML agent description by figuring out agent features that are relevant to implementation: unique identity, proactivity, autonomy, and sociability, inherits its unique identity by being an object but an agent is more than just a single object. The mentioned features proactivity, autonomy and sociability have to do with the common agent notion that an agent perceives its environment, uses what it perceives to choose an action and then perform the action.

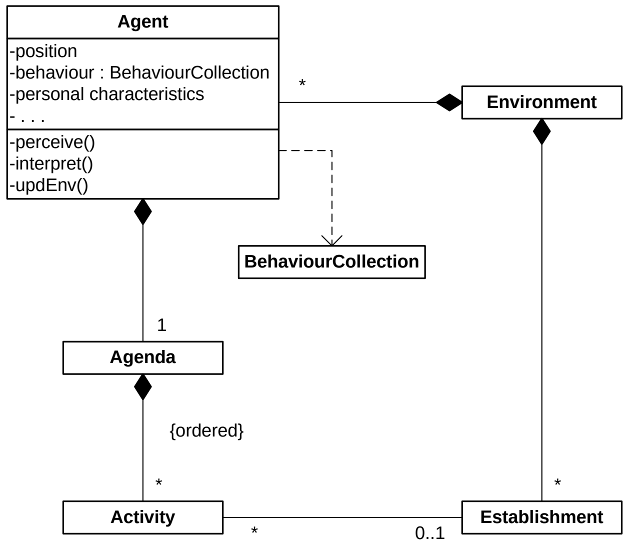

Figure 1. UML diagram of a pedestrian agent

Figure 1 shows the initial concept of a pedestrian agent description as basis a generic agent structure that can be applied. By declaring the methods *perceive, interpret* and *updEnv* private, the agent has its own control of the methods. The declaration of *behaviour* represents the set of possible attitudes. In this diagram it is not worked out.

The environment consists of streets, a set of establishments and pedestrians represented by agents. Streets are presented as a cellular grid, which is used to simulate agent movement. An agent moves with his own behavior and personal characteristics. Every time step, there is an update about agent's positions. In fact, each cell in the cellular grid can be considered as an information-container object. It contains information about the signaling intensity of an establishment and information about agent's positions. We regard a restricted environment E of an agent in the cellular grid. The cellular grid provides percepts to the agent and the agent performs actions in them. Therefore, we distinguish the functions perceive and interpret:

$$Perceive: E \rightarrow P^*$$

The function *perceive* represents the perception process of the agent. It maps the environment E to a set of percepts. The function *interpret* represents the decision making process of the agent and has a more complex form because an agent has an internal state, which includes the built-in knowledge. The function *interpret* is of the following *type*:

$$Interpret: P^* \times I \times G \rightarrow A^*$$

The *interpret* function maps the perception (P) of the environment, the current internal sate (I) and the current activity agenda (G) into a list of one or more actions A, for instance The interpret function updates the internal state based on its percepts and the activity agenda; select actions (*act*) based on the updated activity agenda and the *updated* internal state.

$$UpdStatePandG: P^* \times I \times G \rightarrow I \times G$$
$$act: I \times G \rightarrow A^*$$

The function updEnv represents the reaction of the environment to the agents' actions.

$$UpdEnv: E \times A^* \rightarrow E$$

A new state of the environment is realized.

5.2 Basic Agent

Figure 2 represents a UML diagram of the suggested agent architecture. In particular, the upper part of the diagram provides the agent description. The Agent class is of the type BasicAgent, which consists of a Body and a Sensor. This corresponds with Brooks' notions about thought and reason [10]. In the discussion about behavior-based robots, he characterizes among others the key aspects situatedness and embodiment. In our case, the Body embodies the object in question in the urban environment, and the Sensor is needed to observe the visual area. The Body class has attributes that specify an agent's position, direction, speed and other object specific attributes that define its movement in the regarded environment. The Body class is of the type Vehicle with basic attributes of its movement through the environment. For its part, the Vehicle is of the type Movable with a position and bounding box. In other words, the Body has dimensions and is movable with a certain speed and direction. The Body implies the characteristics *Situatedness* and *Embodiment* [10]. In our case, the Body represents a pedestrian, is situated in the world and experience the world directly.. The suggested description involves other approaches of body, for instance driver.

Furthermore, the Agent will be driven by the Brain. It reflects the relationship between the mind and the brain. What is perception and how is it related to the object perceived. While the mind remains a mysterious and inaccessible phenomenon, many components of the mind, such as perception, behavior generation, knowledge representation, value judgment, reason, intention, emotion, memory, imagination, recognition, learning, attention, and intelligence are becoming well defined and amenable to analysis.[1].

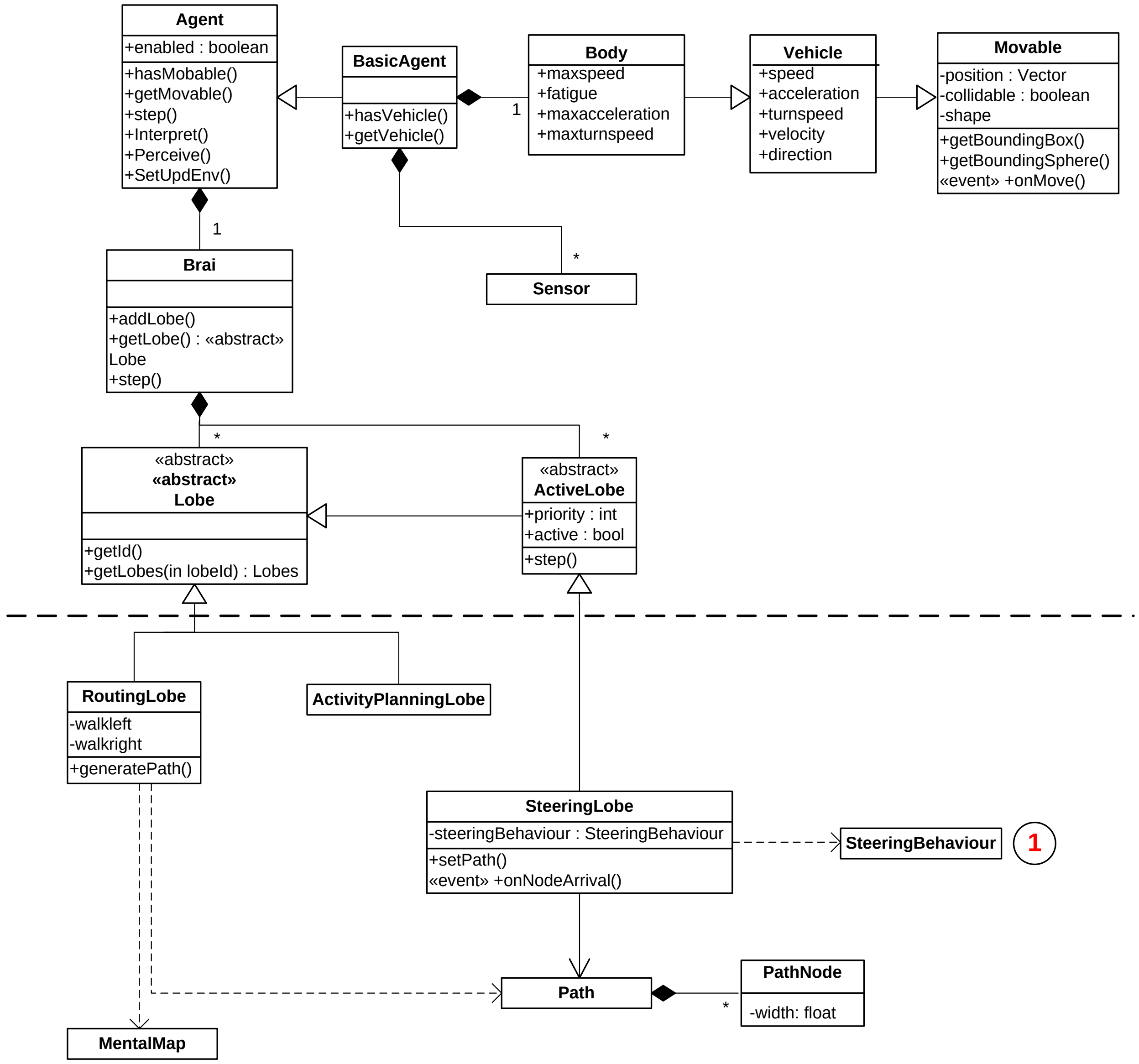

Figure 2. Agent Diagram

In this way, the Brain consists of functional elements. On the one hand, behavior generation such as the planning and control of action designed to achieve behavioral goals, on the other hand sensory perception for the transformation of data into meaningful and useful representations of the world. We assume the Brain class consists of active and passive lobes that can be extended with other lobe such as ShoppingLobe that is not included in the diagram. Active lobes are lobes for which the step function will be called regularly; they are continuously active. On the other hand, Passive lobes must be triggered before its specific functionality getting active. Subtypes of the ActiveLobe class are among others the SteeringLobe class which drives steering behavior; which differs from agent to agent. The SteeringBehaviour class is connected with the SteeringLobe class (quoted as 1. in figure 2.). Herein, the SteeringActuator class executes a behavior and let an assigned vehicle move according to that behavior.

Other subtypes of the ActiveLobe class are the PlanCheckerLobe, the SensingLobe class, and the ConductActivityLobe class. PlanCheckerLobe checks if the activity schedule needs to be updated because the current plan is not accurate or viable anymore. SensingLobe will be a special event generation system. ConductActivityLobe simulates doing an activity. Subtypes of the passive Lobe class are the RoutingLobe class and the ActivityPlanningLobe class. RoutingLobe uses visible data from the neighborhood and data in memory for parts of the environment that are not visible to plan routes. The ActivityPlanningLobe makes up an activity schedule.

5.3 Steering Behavior

Graphs are used for path finding to a specific location in the environment; each node of the graph has a corresponding location in the environment. When using graphs as mental map of virtual humans, the graph can be part of the virtual environment and thus identical for all its inhabitants or it can be constructed by each virtual human individually. In the last case nodes as possible location to go, must be generated by the system, for instance as grid points that are flooded over the environment.

The cellular grid divides the environment in cells. Each cell has one or more attributes to express physical conditions (e.g. wall) or a state (e.g. occupied). Steering is implemented by moving through the grid and meanwhile inspecting the neighborhood cells. Dependent on the physical condition and the state of cell the decision is made whether or not moving on in that direction is possible. Evidently the environment and its occupying objects must neatly be fitted in the grid, which is not always trivial (e.g. curved objects).

Figure 3 shows the steering behavior diagram; the SteeringBehaviour class determines the existence of the vehicle and how behavior is assigned to that vehicle. SteeringActuator executes a behavior and an assigned vehicle moves according to that behavior which includes all checks and the movement itself. The composite design pattern SteeringComposition indicates how the different SteeringBehaviours are coordinated. The steering behavior diagram is the base of the steering algorithm and contains different methods of combining steering behaviors and is extendable. The steering algorithm will make use of the properties to determine its behavior but also the composition of steering behaviors will influence the way the steering will work. Vehicles use steering behavior including (i) path following to follow paths generated by path generation algorithms, (ii) unaligned collision avoidance to avoid collisions with moving objects or agents, (iii) obstacle avoidance or containment to avoid bumping into static obstacles and buildings, and (iv) non penetration constraint to avoid vehicles to overlap with each other or obstacles. The steering module will complete integrate with the environment. Figure 4 shows a simplified steering object diagram.

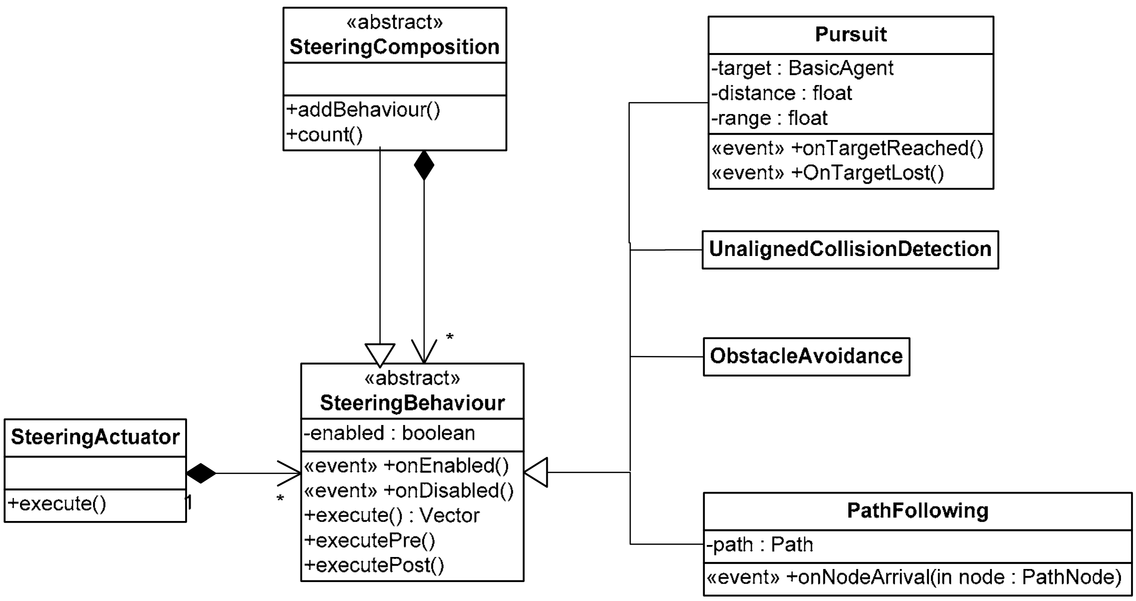

Figure 3. Steering Diagram

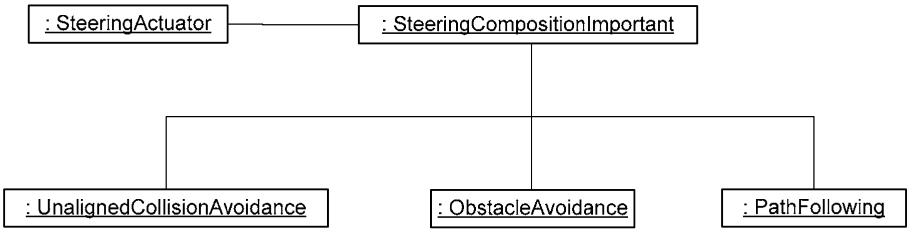

Figure 4. Steering Object Diagram

5.4 Environment model

In the *AMANDA* model system, we populate an environment representing pedestrians. Polygons are used to indicate borders and functional areas like walkways. Discretisation of these polygons generates a grid of cells, which is called a cellular grid. Therefore, a cellular grid together with the polygons represents the environment. Each cell in the cellular grid can be considered as an information container object. It has information about which agents and polygons occupy it. Also, it contains information about other features such as appearance characteristics or establishments that are observable from that cell.

Figure 5 shows the environment diagram. The environment class consists of a cellular grid and a Layer class. Movables can be positioned in cells of the grid. The environment will use layers to classify the meaning of the containing polygons.

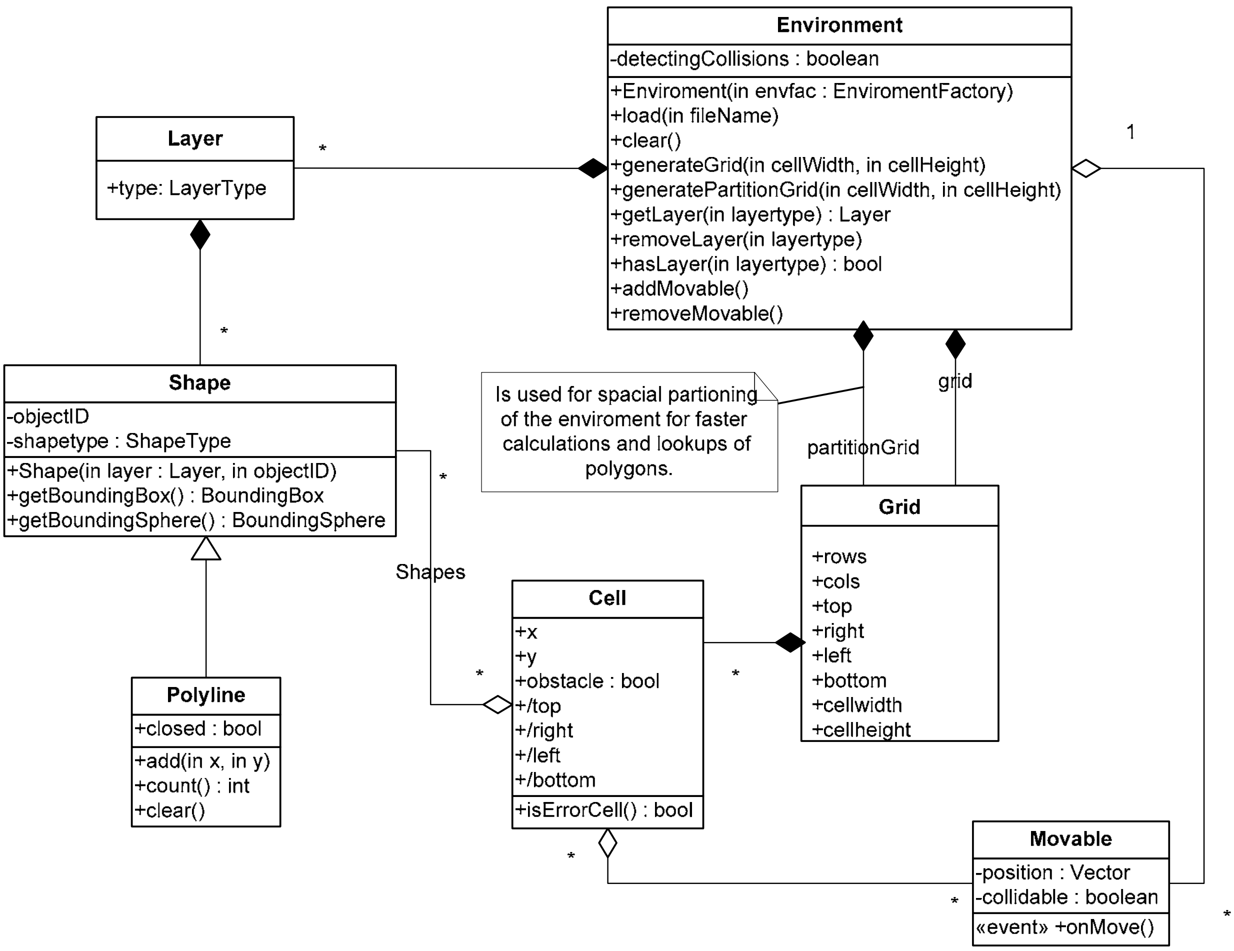

Figure 5. Environment Diagram

We suggest a dual definition of the environment. The environment is defined using polygons with a reference to one information object for each polygon. Otherwise, the environment is described as a lattice of cells. Each cell references to an information object. Often, a lot of cells will reference to the same information object, simply because for example a stroe will be made up of multiple cells. Also a cell could involve information about the attraction of a store, smell, noise, etc. Cells nearby the store have a more noticeable perception than cells farther away.

6. PEDESTRIAN SIMULATION

Two aspects are relevant for understanding the simulation of individual pedestrian behavior: steering including path determination, and action selection including strategy, goal formulation and planning.

Action selection ➔ Steering ➔ Movement

6.1 Action selection

We assume that pedestrian movement is embedded in the larger problem of activity scheduling [30]. It is assumed that individuals made decisions regarding their activity agenda, destination and route choice when moving over the network. We assume that the completion of an activity results in adjustments, if necessary, of a pedestrian's activity agenda.

In other words, action selection can be viewed as scheduling and rescheduling activities. Such scheduling decisions involve decisions about which activities to conduct, where, in what order, when and for how long. Pedestrians can perform the activities within the shopping environment in a set of stores or establishments.

Action selection may depend on personal characteristics, motivation, goals, time pressure/available time budget and familiarity with environment respectively stores and establishments. In addition, store and establishment characteristics, duration, and awareness also influence the scheduling of a pedestrian's activity agenda [13].

The visible action of the agents is movement, which realizes a new agent's position on the cellular grid. A behavior can be distinguished into a hierarchy of three layers: action selection, steering and movement [27].

6.2 Steering

Steering reacts to continuous changes in the environment. With respect to navigation, an agent may decide for a faster or slower lane, window-shopping is done at the outer lanes; there is tendency to keep right (left), etc. Speed may be influenced by socio-economic variables (gender, age, etc.), physical features such as obstacles, passages, crossings, and width of the corridor or street. All these facets influence agent movement and are part of the simulation process.

6.3 Illustration

The simulation of pedestrian behavior will be applied to the city center of Eindhoven as an illustration. Behavioral principles towards perceptual field and activity agenda of agents in particular environments are described elsewhere [13].

As a consequence, data requirements are formulated and empirical data were collected by interviewing pedestrians at several points along the main shopping street. Pedestrians were asked to list the stores they perceived immediately after crossing some point on the network. One group of pedestrians was asked to list the stores they perceived in front of them. In an attempt to obtain as reliable data as possible, respondents were first unobtrusively triggered to change their position such their back was turned to the shopping street in their walking direction. A second group of pedestrians was asked to list the stores they were aware in the section of the shopping street they had just passed. These collected empirical data were used to estimate the parameters of the equations that drive the behavior principles of the simulation [14]. First empirical results of a model predicting the perceptual field of agents moving over a network has been reported in Dijkstra *et al.* [15]. Herein, it was hypothesized that the probability of spotting a store is a function of the signaling intensity of the store and awareness threshold, which in turn is a function of distance and some other factors.

7. DISCUSSION

In this paper, we have set out the agent architecture for simulating pedestrian behavior. In a way, it is hybrid approach; on the one hand the actual movement of pedestrians is based on steering. On the other hand, an extension of the cellular grid is proposed by preserving information about objects like establishments etc. and the state changes in cells besides the agent's position.

As opposed to other existing traffic behavior models, we show an agent diagram for a better understanding of the mechanisms of the model system. Besides the basic agent diagram, also the mechanism of steering behavior is

The *AMANDA* model system where the above discussion proceeds, is currently under development to allow designers, and urban and transportation planners to assess the effects of their policies on pedestrian movement. At this, the main part of the agent diagram and the environment diagram are already implemented.

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Human-Usable and Emergency Vehicle-Aware Control Policies for Autonomous Intersection Management

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ABSTRACT

Traffic congestion and automobile accidents are two of the leading causes of decreased standard of living and lost productivity in urban settings. Recent advances in artificial intelligence and, specifically, intelligent vehicle technology suggest that vehicles driven entirely by autonomous agents will be possible in the near future. In previous work, we presented a novel reservation-based approach for governing interactions of multiple autonomous vehicles, specifically at intersections. This approach alleviated many traditional problems associated with intersections, in terms of both safety and efficiency. However, such a system relies on all vehicles being equipped with the requisite technology — a restriction that would make implementing such a system in the real world extremely difficult. In this paper, we augment the system such that it is able to accomodate traditional human-operated vehicles using existing infrastructure. Furthermore, we show that as the number of autonomous vehicles on the road increases, traffic delays decrease monotonically toward the levels exhibited in the system involving only autonomous vehicles. Additionally, we demonstrate how the system can be extended to allow high-priority vehicles such as ambulances, police cars, or fire trucks through more quickly without placing undue burden on other vehicles. Both augmentations are fully implemented and tested in our custom simulator, and we present detailed experimental results attesting to their effectiveness.

1. INTRODUCTION

Traffic congestion and automobile accidents are two of the leading causes of decreased standard of living and lost productivity in urban settings. According to a recent study of 85 U.S. cities [21], annual time spent waiting in traffic has increased from 16 hours per capita to 46 hours per capita since 1982. In the same period, the annual financial cost of traffic congestion has swollen from $14 billion to more than $63 billion (in 2002 US dollars). Each year, Americans burn approximately 5.6 billion gallons of fuel while idling in heavy traffic. Furthermore, while vehicle safety has historically made gradual improvements each year, collisions cost the United States over $230 billion annually [11]. Globally, automobile accidents account for 2.1% of all deaths, which makes them the 11th overall cause of death [2]. Recent advances in artificial intelligence suggest that autonomous vehicle navigation will be possible in the near future. Individual cars can now be equipped with features of autonomy such as adaptive cruise control, GPS-based route planning [17, 19], and autonomous steering [13, 15]. In fact, in early 2006, DaimlerChrysler began selling the Mercedes-Benz S-Class, which comes with with radar-assisted braking that automatically applies the correct amount of braking force, even if the driver does not. Once individual cars become autonomous, many of the cars on the road will have such capabilities, thus opening up the possibility of autonomous interactions among multiple vehicles.

Multiagent Systems (MAS) is the subfield of AI that aims to provide both principles for construction of complex systems involving multiple agents and mechanisms for coordination of independent agents' behaviors [20]. In earlier work, we proposed a novel MAS-based approach to alleviating traffic congestion and collisions, specifically at intersections [5].

In this paper, we make three main contributions. First, we show how to augment our existing intersection control mechanism to allow use by human drivers with minimal additional infrastructure. Second, we show that this hybrid intersection control mechanism offers performance and safety benefits over traditional traffic light systems. Thus, implementing our system over an extended time frame will not adversely affect overall traffic conditions at any stage. Furthermore, we show that at each stage there exists an incentive for individuals to use autonomous driver agent-equipped vehicles. Historically, many technologies and transit systems aimed at improving safety and decreasing congestion have suffered from a lack of incentive for early adopters. For example, if everyone used mass transit, traffic would be reduced to an extent that the bus or light rail would be cheaper, faster, and safer than driving a personal vehicle is currently. However, given the current state of affairs, it is not in any one person's interest to make the switch. Our third contribution is a separate augmentation that allows the system to give preference to emergency vehicles such as ambulances, police cruisers, and fire trucks. We demonstrate that this is not overly detrimental to the rest of the vehicles. Both augmentations are fully (though separately) implemented and tested in our custom simulator and complete experimental results are presented.

The rest of this paper is organized as follows. In Section 2, we briefly review the reservation system as described in previous work. In Section 3 we explain how our original reservation-based intersection control mechanism can be augmented to allow for human drivers (or cyclists or pedestrians). In Section 4, we describe additions to the system and communication protocol that give further benefits to emergency vehicles without causing excessive delays to civilian traffic. We present the experimental results of these fully-implemented augmentations in Section 5. In Section 6, we discuss the experimental results in the context of related work. Section 7 describes where we plan to take this line of research in the near future, and we conclude in Section 8.

2. RESERVATION SYSTEM

Previously, we proposed a novel reservation-based multi-agent approach to alleviating traffic, specifically at intersections [5]. This system consists of two types of agents: *intersection managers* and *driver agents*. For each intersection, there is a corresponding intersection manager, and for each vehicle, a driver agent. Intersection managers are responsible for directing the vehicles through the intersection, while the driver agents are responsible for controlling the vehicles to which they are assigned.

To improve the throughput and efficiency of the system, the driver agents "call ahead" to the intersection manager and request space-time in the intersection. The intersection manager then determines whether or not these requests can be met based on an *intersection control policy*. Depending on the decision (and subsequent response) the intersection manager makes, the driver agent either records the parameters of the response message (the *reservation*) and attempts to meet them, or it receives a rejection message and makes another request at a later time. If a vehicle has a reservation, it can request that its reservation be changed or can cancel the reservation. It also sends a special message when it finishes crossing the intersection indicating to the intersection manager that it has done so.

The interaction among these agents is governed by a shared protocol which we have published in a technical report [3]. In addition to message types (e.g. REQUEST, CONFIRM, and CANCEL), this protocol includes some rules, the most important of which are (1) that a vehicle may not enter the intersection unless it is within the parameters of a reservation made by that vehicle's driver agent, (2) that if a vehicle follows its reservation parameters, the intersection manager can guarantee a safe crossing for the vehicle, and (3) a driver agent may have only one reservation at a time. While some may argue that insisting a vehicle adhere to the parameters of such a reservation is too strict a requirement, it is useful to note that vehicles today are already governed by a similar (although much less precise) protocol; if a driver goes through a red light at a busy intersection, a collision may be unavoidable. Aside from this protocol, no agent needs to know how the other agents work — each vehicle manufacturer (or third party) can program a separate driver agent, each city or state can create their own intersection control policies (which can even change on the fly), and as long as each agent adheres to the protocol, the vehicles will move safely through the intersection. A diagram of one type of interaction in the mechanism can be seen in Figure 1.

2.1 First Come, First Served (FCFS)

To determine whether or not a request can be met, our intersection manager uses a "first come, first served" (FCFS) intersection control policy which works as follows:

- The intersection is divided into a grid of $n \times n$ *tiles*, where n is called the *granularity*.
- Upon receiving a request message, the policy uses the parameters in the message to simulate the journey of the vehicle across the intersection. At each time step of the simulation, it determines which tiles the vehicle occupies.
- If throughout this simulation, no required tile is reserved by another vehicle, the policy reserves the tiles for the vehicle and confirms the reservation. Otherwise, the request is rejected.

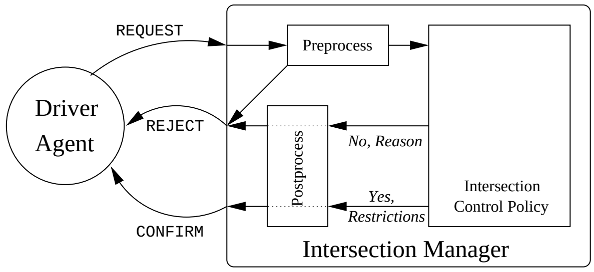
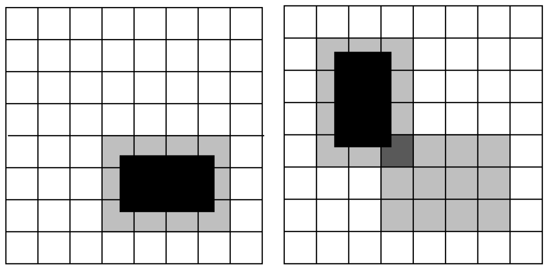


Figure 1: The interaction between the Intersection Manager, Intersection Control Policy, and Driver Agent when a REQUEST message is sent.

The policy derives its name from the fact that the policy responds to vehicles immediately when they make a request, confirming or rejecting the request based on whether or not the space-time required by the vehicle is already claimed. If two vehicles require some tile at the same time, the vehicle which requests the reservation first will be given the reservation (provided there are no conflicts in the rest of the required space-time). Figure 2 shows a successful reservation (confirmed) followed by an unsuccessful reservation (rejected).



(a) Successful reservation (b) Failed reservation

Figure 2: The grid for a granularity-8 FCFS policy. In 2(a), the policy is simulating the trajectory of vehicle A and finds that at some time t, all the tiles it requires are available. A's request is confirmed. In 2(b), vehicle B makes a subsequent reservation request. During the simulation of B's trajectory, at time t, the policy finds that a tile required by B is already reserved by A. B's reservation request is thus rejected.

2.2 Other Intersection Control Policies

While the reservation system was designed with the FCFS policy in mind, it can accomodate any intersection control policy that can make a "yes or no" decision based on the parameters in a request message. This includes policies that represent familiar intersection control mechanisms like traffic lights and stop signs. Because the reservation system can behave exactly like our most common modern-day control mechanisms, we can absolutely guarantee that the performance of the reservation mechanism will be no worse than current systems. The descriptions given below are abbreviated; full descriptions (including the STOP-SIGN policy) may be found in our tech report [3].

2.2.1 TRAFFIC-LIGHT

Traffic lights are the most common mechanism used to control high-traffic intersections. The TRAFFIC-LIGHT policy emulates a real-life traffic light by maintaining a model of how the lights would be changed, were they to exist. Then, upon receiving a request message, the policy determines whether the light corresponding to the requesting vehicle's lane would be green. If so, it sends a confirmation, otherwise, it sends a rejection.

2.2.2 OVERPASS

Although called OVERPASS, this policy does not represent a real overpass (or cloverleaf), which are very expensive and built only at the largest and busiest of intersections. Instead, it represents an optimal intersection control policy — one which never rejects a vehicle. This would not be useful in real life as it makes no guarantees regarding the safety of the vehicles, but it does serve as a good lower bound for delays.

2.3 Measuring Performance

After creating a custom simulator (Figure 3 shows a screenshot of the graphical display), we evaluated the performance of the FCFS policy against the OVERPASS and the TRAFFIC-LIGHT policies. Using the simulator, we showed that with the FCFS policy, vehicles crossing an intersection experience much lower *delay* (increase in travel time from the optimal) versus TRAFFIC-LIGHT [4, 5]. The FCFS policy approached OVERPASS in terms of delay, offering safety guarantees that OVERPASS could not. Furthermore, we showed that the FCFS policy increases the throughput of the intersection far beyond that of TRAFFIC-LIGHT. For any realistic (safe) intersection control policy, there exists an amount of traffic for which vehicles arrive at the intersection more frequently than they can leave the intersection. At this point, the average delay experienced by vehicles travelling through the intersection grows without bound — each subsequent vehicle will have to wait longer than all the previous cars. The point for which this occurs in the FCFS policy is five or six times higher than TRAFFIC-LIGHT.

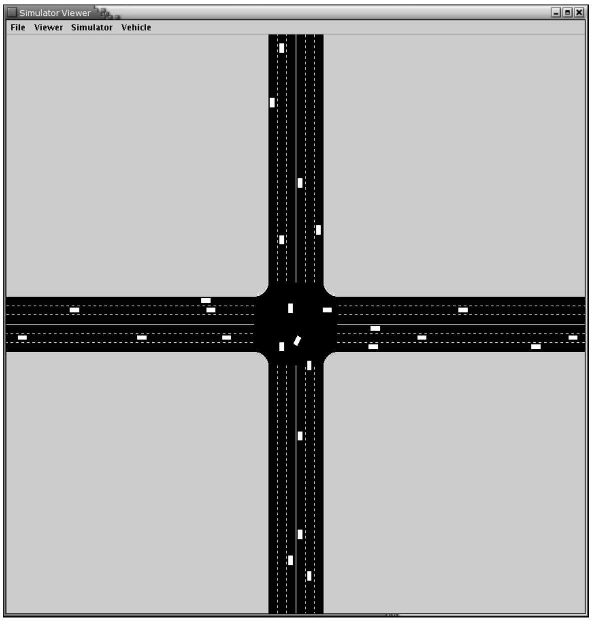


Figure 3: A screenshot of the graphical display of our simulator.

3. INCORPORATING HUMAN USERS

While an intersection control mechanism for autonomous vehicles will someday be very useful, there will always be people who enjoy driving. Additionally, there will be a fairly long transitional period between the current situation (all human drivers) and one in which human drivers are a rarity. Even if switching to a system comprised solely of autonomous vehicles were possible, pedestrians and cyclists must also be able to traverse intersections in a controlled and safe manner. For this reason, it is necessary to create intersection control policies that are aware of and able to accomodate humans, whether they are on a bicycle, walking to the corner store, or driving a "classic" car for entertainment purposes. In this section we explain how we have extended our FCFS policy as well as the reservation framework to incorporate human drivers. Adding pedestrians and cyclists follows naturally and though while we have not actually implemented them in our system, we give brief descriptions of how this would differ from the extensions for human drivers.

3.1 Using Existing Infrastructure

Adding human drivers to the mix means that we need a reliable way to communicate information to the drivers. The best way to do this is to use a system that drivers already know and understand — traffic lights. Traffic light infrastructure is already present at many intersections and the engineering and manufacturing of traffic light systems is well developed. For pedestrians and cyclists, standard "push-button" crossing signals could be used that would give enough time for a person to traverse the intersection. These could also serve to alert the intersection to their presence.

3.2 Light Models

If real traffic lights are going to be used to communicate to human drivers, they will need to be controlled and understood by the intersection manager. Thus, we add a new component to each intersection control policy, called a *light model*. This model controls the actual physical lights as well as providing information to the policy with which it can make decisions. In more complicated scenarios, the light model can be modified by the control policy, for example, in order to adapt to changing traffic conditions. The lights are the same as modern-day lights: red (do not enter), yellow (if possible, do not enter; light will soon be red), and green (enter). Each control policy will need to have a light model so that human users will know what to do. For instance, the light model that would be used with ordinary FCFS would keep all the lights red at all times, informing humans that at no time is it safe to enter. The TRAFFIC-LIGHT policy, on the other hand, would have lights that corresponded exactly to the light system the policy is emulating. Here, we describe a few light models used in our experiments.

3.2.1 ALL-LANES

In this model, which is very similar to some current traffic light systems, each direction is successively given green lights in all lanes. Thus, all northbound traffic (turning and going straight) is given green lights while the eastbound, westbound, and southbound traffic all have red lights. The green lights then cycle through the directions. Figure 4 shows a graphical depiction of this light model.

3.2.2 SINGLE-LANE

In the SINGLE-LANE light model, the green lane rotates through the lanes one at a time instead of all at once. For example, the left turn lane of the northbound traffic would have a green light, while all other lanes would have a red light. Next, the straight lane of the northbound traffic would have a green light, then the right

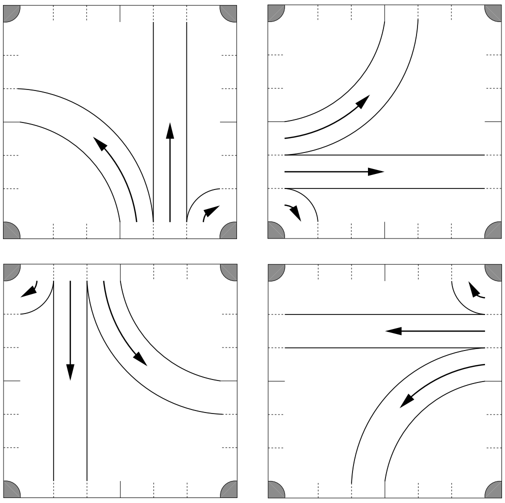


Figure 4: The ALL-LANES light model. Each direction is given all green lights in a cycle: north, east, west, south. During each phase, the only available paths for autonomous vehicles are right turns.

turn. Next, the green light would go through each lane of eastbound traffic, and so forth. The first half of the model's cycle can be seen in Figure 5. This light model does not work very well if most of the vehicles are human-driven, but as we will show, is very useful for intersections which control mostly autonomous vehicles but need to also handle an occasional human driver.

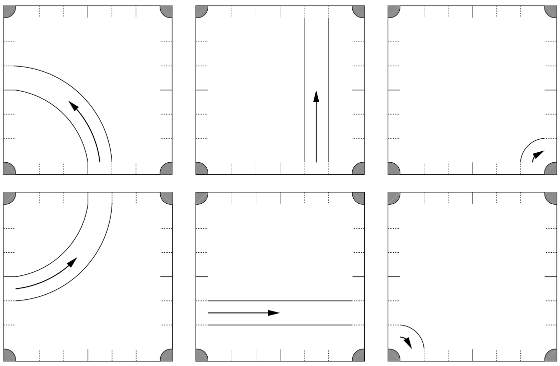


Figure 5: The first half-cycle of the SINGLE-LANE light model. Each individual lane is given a green light (left turn, straight, then right turn), and this process is repeated for each direction. Note how a smaller part of the intersection is used by turning vehicles at any given time. This provides an advantage for autonomous vehicles - there are many available paths through the intersection.

3.3 The FCFS-LIGHT Policy

In order to obtain some of the benefits of the FCFS policy while still accomodating human drivers, a policy needs to do two things:

1. If a light is green, ensure that it is safe for any vehicle (autonomous or human-driven) to drive through the intersection in the lane the light regulates.
2. Grant reservations to driver agents whenever possible. This would allow autonomous vehicles to move through an intersection where a human driver couldn't — similar to a "right on red", but extended much further to other safe situations.

The policy FCFS-LIGHT, which does both of these, is described as follows:

- As with FCFS, the intersection is divided into a grid of $n \times n$ tiles.
- Upon receiving a request message, the policy uses the parameters in the message to establish when the vehicle will arrive at the intersection.
- If the light controlling the lane in which the vehicle will arrive at the intersection would be green at that time, the reservation is confirmed.
- If the light controlling the lane would instead be yellow, the reservation is rejected.
- If the light controlling the lane would instead be red, the journey of the vehicle is simulated as in FCFS (Section 2.1).
- If throughout the simulation, no required tile is reserved by another vehicle or in use by a lane with a green or yellow light, the policy reserves the tiles and confirms the reservation. Otherwise, the request is rejected.

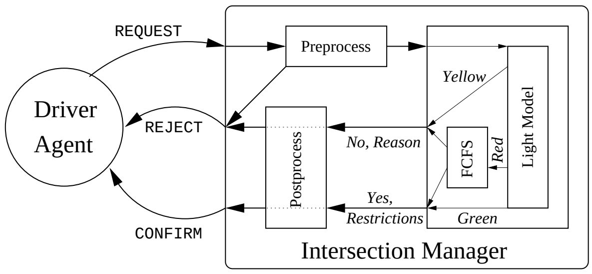


Figure 6: FCFS-LIGHT is the combination of FCFS and a light model. When a request is received, FCFS-LIGHT first checks to see what color the light would be. If it is green, it grants the request. If it is yellow, it rejects. If it is red, it defers to FCFS.

3.3.1 Off-Limits Tiles

Unfortunately, simply deferring to FCFS does not guarantee the safety of the vehicle. If the vehicle were granted a reservation that conflicted with another vehicle following the physical lights, a collision could easily ensue. To determine which tiles are in use by the light system at any given time, we associate a set of *off-limits tiles* with each light. For example, if the light for the northbound left turn lane is green (or yellow), all tiles that could be used by a vehicle turning left from that lane are off-limits. While evaluating a reservation request, FCFS also checks to see if any tiles needed by the requesting vehicle are off limits at the time of the reservation. If so, the reservation is rejected. The length of the yellow light is adjusted so that a vehicle entering the intersection has enough time to clear the intersection before those tiles are no longer off limits.

3.3.2 FCFS-LIGHT *Subsumes* FCFS

Using a traffic light-like light model (for example ALL-LANES), the FCFS-LIGHT can behave exactly like TRAFFIC-LIGHT on all-human driver populations. However, with a light model that kept all lights constantly red, FCFS-LIGHT behaves exactly like FCFS. That is, if any human drivers are present it will fail spectacularly, leaving the humans stuck at the intersection indefinitely. However, in the absence of human drivers, it will perform exceptionally well. FCFS is, in fact, just a special case of FCFS-LIGHT. We can thus alter FCFS-LIGHT's behavior to vary from strictly superior to TRAFFIC-LIGHT to exactly that of FCFS.

4. EMERGENCY VEHICLES

In current traffic laws there are special procedures involving emergency vehicles such as ambulances, fire trucks, and police cars. Vehicles are supposed to pull over to the side of the road and come to a complete stop until the emergency vehicle has passed. This is both because the emergency vehicle may be travelling quickly and because the emergency vehicle must arrive at its destination as quickly as possible — lives may be at stake. Hopefully, once a system such as this is implemented, automobile accidents — a major reason emergency vehicles are dispatched — will be all but eradicated. Nonetheless, emergency vehicles will still be required from time to time as fires, heart attacks, and other emergencies will still be around. While we have proposed other methods for giving priority to emergency vehicles [6], here we present a new, simpler method, which is fully implemented and tested.

4.1 Augmenting The Protocol

In order to accomodate emergency vehicles, the intersection manager must first be aware of their presence. We discovered that the easiest way to accomplish this was simply to add a field to all request messages. In our implementation, this field is simply a flag that indicates to the intersection manager that the requesting vehicle is an emergency vehicle in an emergency situation (i.e. with the siren and the lights on). In practice, however, safeguards would need to be incorporated to prevent normal vehicles from abusing this feature in order to obtain preferential treatment. This could be accomplished using some sort of secret key instead of simply a boolean value, or even some sort of public/private key challenge/response scenario. This level of implementation, however, is beyond the scope of this project and is already a well-studied area of cryptography and computer security.

4.2 The FCFS-EMERG Policy

Now that the intersection control policy has a way to detect emergency vehicles (in emergency situations), it can process reservation requests giving priority to the emergency vehicles. A first-cut solution is to simply deny reservations to any vehicles that were not emergency vehicles. This, however, is not satisfactory, because if all the traffic comes to a stop due to rejected reservation requests, the emergency vehicle(s) may get stuck in the resulting congestion. The FCFS-EMERG policy prevents this by keeping track of which lanes currently have approaching emergency vehicles. As long as at least one emergency vehicle is approaching the intersection, it only grants reservations to vehicles in those lanes. This ensures that vehicles in front of the emergency vehicles will also receive priority. Due to this increase in priority, even when traffic is fairly congested, lanes with emergency vehicles tend to empty very rapidly, allowing the emergency vehicle to continue on its way relatively unhindered.

5. EXPERIMENTAL RESULTS

We tested the efficacy of our new control policies with our custom-built, time-based simulator. The simulator models one intersection and has a time step of .02 seconds. The traffic level is controlled by changing the spawn probability — the probability that on any given time step, the simulator will attempt to spawn a new vehicle. For each experiment, the simulator simulates 3 lanes in each of the 4 cardinal directions. The total area modelled is a square with sides of 250 meters. The speed limit in all lanes is 25 meters per second. For each intersection control policy with reservation tiles, the granularity is set at 24. We also configured the simulator to spawn all vehicles turning left in the left lane, all vehicles turning right in the right lane, and all vehicles travelling straight in the center lane[1]. During each simulated time step, the simulator spawns vehicles (with the given probability), provides each vehicle with sensor data (simulated laser range finder, velocity, position, etc.), moves all the vehicles, and then removes any vehicles that have completed their journey. Unless otherwise specified, each data point represents 180000 time steps, or one hour of simulated time. Videos of each policy in action (as well as other supplementary material) can be found at `http://www.cs.utexas.edu/users/kdresner/aim/`.

As shown in our earlier work, once all vehicles are autonomous, intersection-associated delays can be reduced dramatically by using the two light models presented in Section 3.2. However, our experiments suggest a stronger result: delays can be reduced at each stage of adoption. Furthermore, at each stage there are additional incentives for drivers to switch to autonomous vehicles. Finally, our experiments verify the efficacy of the FCFS-EMERG policy, reducing emergency vehicle delays across the board.

5.1 Transition To Full Implementation

The whole point of having a hybrid light/autonomous intersection control policy is to confer the benefits of autonomy to passengers with driver-agent controlled vehicles while still allowing human users to participate in the system. Figure 7, which encompasses our main result, shows a smooth and monotonically improving transition from modern day traffic lights (represented by the TRAFFIC-LIGHT policy) to a completely or mostly autonomous vehicle mechanism (FCFS-LIGHT with the SINGLE-LANE light model). In early stages (100%-10% human), the ALL-LANES light model is used. Later on (less than 10% human), the SINGLE-LANE light model is introduced. At each change (both in driver populations and light models), delays are decreased. Notice the rather drastic drop in delay from FCFS-LIGHT with the ALL-LANES light model to FCFS-LIGHT with the SINGLE-LANE light model. Although none of the results is quite as close to the minimum as pure FCFS, the SINGLE-LANE light model allows for greater use of the intersection by the FCFS portion of the FCFS-LIGHT policy, which translates to more efficiency and lower delay.

For systems with a significant proportion of human drivers, the ALL-LANES light model works well — human drivers have the same experience they would with the TRAFFIC-LIGHT policy, but driver agents have extra opportunities to make it through the intersection. A small amount of this benefit is passed on to the human drivers, who may find themselves closer to the front of the lane while waiting for a red light to turn green. To explore how much the average vehicle would benefit, we ran our simulator with the FCFS-LIGHT policy, the ALL-LANES light model, and a 100%, 50%, and 10% rate of human drivers. This means that when a vehi-

[1] This is a constraint we will likely relax in the future. It is included in this work to give the SINGLE-LANE light model more flexibility and for a fair comparison to the FCFS policy, which performs even better in its absence.

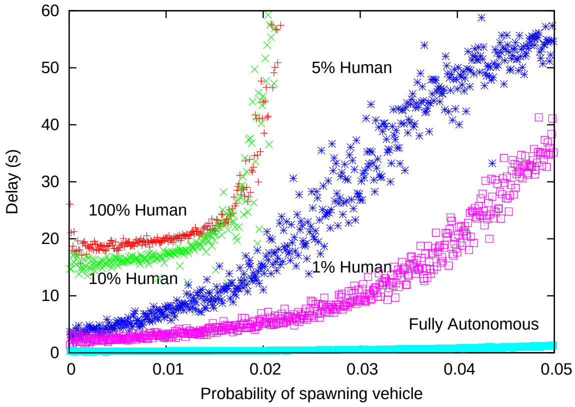


Figure 7: Average delays for all vehicles as a function of traffic level for FCFS-LIGHT with two different light models — the ALL-LANES light model, which is well-suited to high percentages of human-driven vehicles, and the SINGLE-LANE light model, which only works well with relatively few human-driven vehicles. As adoption of autonomous vehicles increases, average delays decrease.

cle is spawned, it receives a human driver (instead of a driver agent) with probability 1, .5, and .1 respectively. As seen in Figure 8, as the proportion of human drivers decreases, the delay experienced by the average driver also decreases. While these decreases are not as large as those brought about by the SINGLE-LANE light model, they are at least possible with significant numbers of human drivers.

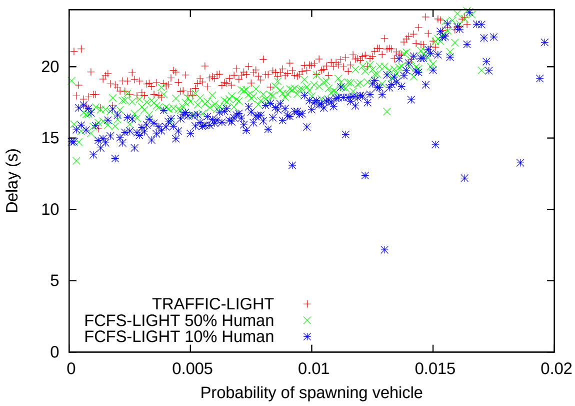


Figure 8: Average delays for all vehicles as a function of traffic level for FCFS-LIGHT with the ALL-LANES light model. Shown are the results for 100%, 50%, and 10% human-driven vehicles. The 100% case is equivalent to the TRAFFIC-LIGHT policy. Note that the average delay decreases as the percentage of human-driven vehicles decreases.

5.2 Incentives For Individuals

Even without any sort of autonomous intersection control mechanism, there are incentives for humans to switch to autonomous vehicles. Not having to do the driving, as well as the myriad safety benefits are strong incentives to promote autonomous vehicles in the marketplace. Our experimental results show additional incentives. Using our reservation system, autonomous vehicles experience lower average delays than human-driven vehicles and this difference increases as autonomous vehicles become more prevalent.

Shown in Figure 9 are the average delays for human drivers as compared to autonomous driver agents for the FCFS-LIGHT policy using the ALL-LANES light model. In this experiment, half of the drivers are human. Humans experience slightly longer delays than autonomous vehicles, but not worse than with the TRAFFIC-LIGHT policy. Thus, by putting some autonomous vehicles on the road, all drivers experience equal or smaller delays as compared to the current situation. This is expected because the autonomous driver can do everything the human driver does and more.

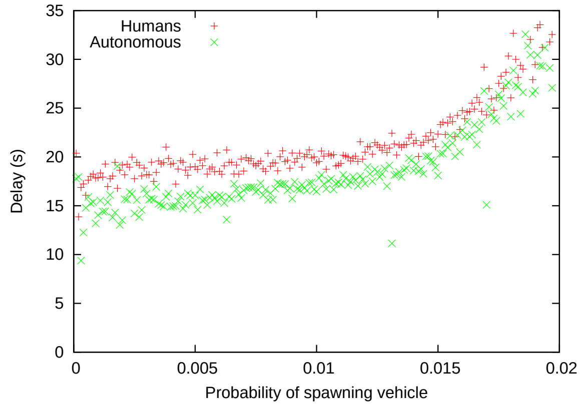


Figure 9: Average delays for human-driven vehicles and all vehicles as a function of traffic level for FCFS-LIGHT with the ALL-LANES light model. In this experiment, 50% of vehicles are human driven. Autonomous vehicles experience slightly lower delays across the board, and human drivers experience delays no worse than the TRAFFIC-LIGHT policy.

Once the reservation system is in widespread use and autonomous vehicles make up a vast majority of those on the road, the door is opened to an even more efficient light model for the FCFS-LIGHT policy. With a very low concentration of human drivers, the SINGLE-LANE light model can drastically reduce delays, even at levels of overall traffic that the TRAFFIC-LIGHT policy can not handle. Using the this light model, autonomous drivers can pass through red lights even more frequently because fewer tiles are off-limits at any given time. In Figure 10 we compare the delays experienced by autonomous drivers to those of human drivers when only 5% of drivers are human and thus the SINGLE-LANE light model can be used. While the improvements using the ALL-LANES light model benefit all drivers to some extent, the SINGLE-LANE light model's sharp decrease in average delays (Figure 7) comes at a high price to human drivers.

As shown in Figure 10, human drivers experience much higher delays than average. For lower traffic levels, the delays are even higher than they would experience with the TRAFFIC-LIGHT policy. Figure 7 shows that despite this, at high levels of traffic, the humans get a performance benefit. Additionally, these intersections will still be able to handle far more traffic than TRAFFIC-LIGHT.

The SINGLE–LANE light model effectively gives the humans a high, but fairly constant delay. Because the green light for any one lane only comes around after each other lane has had a green light, a human-driven vehicle may find itself sitting at a red light for some time before the light changes. However, since this light model would only be put in operation once human drivers are fairly

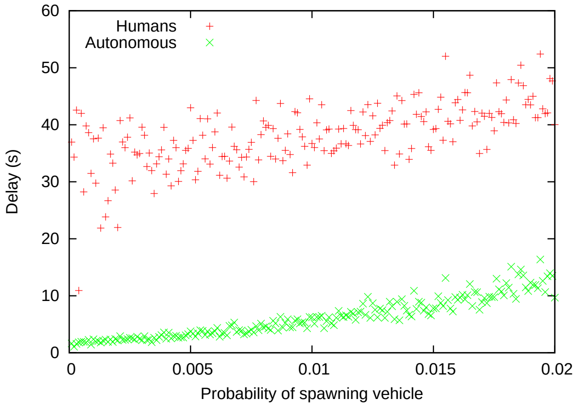


Figure 10: Average delays for human-driven vehicles and all vehicles as a function of traffic level for FCFS-LIGHT with the SINGLE-LANE light model. Humans experience worse delay than with TRAFFIC-LIGHT, but average delay for all vehicles is much lower. In this experiment, 5% of vehicles are human-driven.

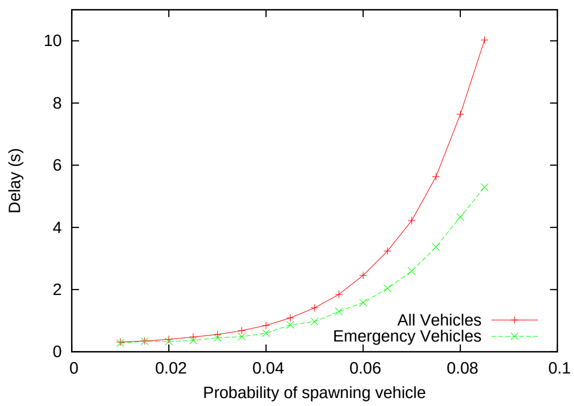


Figure 11: Average delays for all vehicles and emergency vehicles as a function of traffic level for the FCFS-EMERG policy. One out of a thousand vehicles (on average) is an emergency vehicle. Delays for the emergency vehicles are lower for all data points.

scarce, the huge benefit to the other 95% or 99% of vehicles far outweighs this cost. In Section 7, we propose a solution that could ameliorate these long delays for human drivers as well as slightly improving the overall performance of the system.

These data suggest that there will be an incentive to both early adopters (persons purchasing vehicles capable of interacting with the reservation system) and to cities or towns. Those with properly equipped vehicles will get where they are going faster (not to mention more safely). Cities and towns that equip their intersections to utilize the reservation paradigm will also experience fewer traffic jams and more efficient use of the roadways (along with fewer collisions, less wasted gasoline, etc.). Because there is no penalty to the human drivers (which would presumably be a majority at this point), there would be no reason for any party involved to oppose the introduction of such a system. Later, when most drivers have made the transition to autonomous vehicles, and the SINGLE-LANE light model is introduced, the incentive to move to the new technology is increased — both for cities and individuals. By this time, autonomous vehicle owners will far outnumber human drivers, who for high volumes of traffic will still benefit.

5.3 Lower Delays For Emergency Vehicles

While we have already shown that FCFS on its own would significantly reduce average delays for all vehicles, FCFS-EMERG helps reduce delays for such vehicles even further. To demonstrate this improvement, we ran our custom simulator with varying amounts of traffic, while keeping the proportion of emergency vehicles fixed at 0.1% (that is, a spawned vehicle is made into an emergency vehicle with probability 0.001). Because of the very small number of emergency vehicles created with realistically low proportions, we ran each configuration (data point) for 100 hours of simulated time — much longer than the other experiments. As shown in Figure 11, the emergency vehicles on average experienced lower delays than the normal vehicles. The amount by which the emergency vehicles outperformed the normal vehicles increased as the traffic increased, suggesting that as designed, FCFS-EMERG helps most when more traffic is contending for space-time in the intersection.

6. RELATED WORK

Currently, there is a considerable amount of research underway relating to intersection control and efficiency. Rasche and Naumann have worked extensively on decentralized solutions to intersection collision avoidance problems [12, 14]. Many approaches focus on improving current technology (systems of traffic lights). For example, Roozemond allows intersections to act autonomously, sharing the data they gather [18]. The intersections then use this information to make both short- and long-term predictions about the traffic and adjust accordingly. This approach still assumes human-controlled vehicles. Bazzan has used an approach using both MAS and evolutionary game theory which involves multiple intersection managers (agents) that must focus not only on local goals, but also on global goals [1].

Work is also being done with regard to the control of the individual vehicles. Hallé and Chaib-draa have taken a MAS approach to collaborative driving by allowing vehicles to form *platoons*, groups of varying degrees of autonomy, that then coordinate using a hierarchical driving agent architecture [7]. While not focusing on intersections, Moriarty and Langley have shown that reinforcement learning can train efficient driver agents for lane, speed, and route selection during freeway driving [10].

On real autonomous vehicles, Kolodko and Vlacic have created a small-scale system for intersection control which is very similar a reservation system with a granularity-1 FCFS policy [9].

Actual systems in practice (not MAS) for traffic light optimization include TRANSYT [16], which is an off-line system requiring extensive data gathering and analysis, and SCOOT [8], which is an advancement over TRANSYT, responding to changes in traffic loads on-line. However, almost all of the methods in practice or discussed above still rely on traditional signalling systems.

7. FUTURE WORK

Our system as demonstrated can vastly improve the traffic flow and transportation times experienced by all sorts of commuters. In this section, we present some ideas for improving and extending the system further.

7.1 More Intermediate Light Models

In order to smooth the transition further and reap the benefits of autonomous vehicles earlier, we plan to create light models that use less of the intersection than ALL-LANES, but don't restrict human drivers as much as SINGLE-LANE. These would provide the needed flexibility to let autonomous vehicles traverse the intersection using the FCFS portion of FCFS-LIGHT more frequently, decreasing delays relative to ALL-LANES.

7.2 Dynamic Light Models

All the light models presented in this paper have been static — that is they don't change as traffic conditions change. Traffic light systems in use today change throughout the day and week according to pre-programmed patterns created from expensive and time-consuming traffic studies. With the information gathered by the intersection manager and intersection control policy (via messages from the driver agents), the light model could be altered on-line. For example, in a situation with very few human drivers, the light model could keep all lights red until a human vehicle is detected (for example, with a transmitter), at which point the lane or direction from which the human driver is coming could be turned green. Once the human driver is through the intersection, the light(s) could be turned red again. This could offer a two-fold improvement over the SINGLE-LANE light model. First, the human drivers would benefit from not having to wait for the green light to make its way through all the other lanes at the intersection. This would make the system much more equitable to human drivers (who might otherwise have all the fun of driving taken away by extremely long delays at red lights). Secondly, the autonomous vehicles stuck behind the human drivers which would otherwise be stopped at red lights would also benefit. This secondary effect would likely have a much higher influence on the overall average delays, as the scenario assumes human drivers make up only a very small percentage of the total.

7.3 FCFS-LIGHT-EMERG?

This paper begs the question, "What about using both improvements simultaneously?" Unfortunately, making FCFS-LIGHT emergency vehicle-aware requires a dynamic light model as discussed above. However, given a dynamic light model, such an implementation is easy to describe. When the intersection control policy becomes aware of the emergency vehicle, the light model can be changed to one in which the green light rotates through the lanes that contain any approaching emergency vehicles.

7.4 Switching Policies On The Fly

While we have shown that the FCFS-LIGHT policy (with different light models) can span the gamut of scenarios from an all-human to all-autonomous driver population. With dynamic light models, it would seem that any situation could be handled by FCFS-LIGHT. However, should the need arise for a more radical change in intersection control policy (for example, to a stop sign policy in the case of road work or obstacle cleanup in the intersection), the reservation system should have a way to smoothly transition between the policies.

7.5 Learning Light Models/Policy Selection

Once we have a way to change between policies on-line, the next logical step is to get the intersection manager to choose its own policy or light model based on traffic conditions. If vehicles report their delays to the intersection when they finish crossing, the intersection manager will have access to a reinforcement signal that could be used to tune a light model or select a completely different policy altogether.

8. CONCLUSION

A science-fiction future with self-driving cars is becoming more and more believable. As intelligent vehicle research moves forward, it is important that we prepare to take advantage of the high-precision abilities autonomous vehicles have to offer. We have previously proposed an extremely efficient method for controlling autonomous vehicles at intersections. In this work, we have shown that at each phase of implementation, the system offers performance benefits to the average driver. Autonomous drivers benefit above and beyond this average improvement. We have also shown that the reservation system can be adapted to give priority to emergency vehicles, resulting in lower delays. Efficient, fast, and safe automobile transporation is not a fantasy scenario light-years away, but rather a goal toward which we can make worthwhile incremental progress.

Acknowledgements

This research is supported by NSF CAREER award IIS-0237699.

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Cooperative Adaptive Cruise Control: a Reinforcement Learning Approach*

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ABSTRACT

As a part of Intelligent Transport Systems (ITS), Cooperative Adaptive Cruise Control (CACC) systems have been introduced for finding solutions to the modern problems of automotive transportation such as traffic efficiency, passenger comfort and security. To achieve cooperation, actors on the road must use internal sensors and communication. Designing such a controller is not an easy task when the problem is considered in its entirety, since the interactions taking place in the environment (from vehicle physics and dynamics to multi-vehicle interaction) are extremely complex and hard to model formally. That is why many ITS approaches consider many levels of functionnalities. In this article, we will show our work toward the design of a multiple-level architecture using reinforcement learning techniques. We explain our work on the design of a longitudinal ACC controller, which is the first step toward a fully functionnal CACC low-level controller. We describe the design of our high-level controller used for vehicles coordination. Preliminary results show that, in some situations, the vehicle-following controller is stable. We also show that the coordination controller allows to have an efficient lane allocation for vehicles. At last, we present some future improvements that will integrate both approaches in a general architecture centered on the design of a CACC system using reinforcement learning.

1. INTRODUCTION

More and more sensors are used today to gather information related to a number of components inside vehicles. Even though this information is used mainly for monitoring, some applications go even further and use it to gain knowledge on the environment of the vehicle. With information on the state of the environment, it becomes possible to make driving decisions that can help solve today's transportation problems, working toward an increase in the efficiency of traffic but also in the comfort and security of passengers. Intelligent Transport Systems (ITS) [19] are interested in developing technology to settle those issues.

One of ITS's main focus is on Adaptive Cruise Control (ACC), which is a good example of where the technology is headed. ACCs use sensors to detect preceding vehicles and adapt the cruising velocity of a car according to what might lie ahead. If a preceding vehicle is present, the car automatically slows down to avoid collision and keep a safe distance behind. Already, ACCs are available in high-end vehicles [2]. Still, today's ACC systems are limited as they do not provide a mean to share information between surrounding vehicles. As states Tsugawa [18], the use of inter-vehicle communication could help fulfill the goals of ITS by providing a system for vehicles to share with others sensor data representing their environment. With a communication system, ACCs become Cooperative Adaptive Cruise Control systems (CACCs), which have communication and cooperation between vehicles as primary concerns. Clearly, the ultimate goal is to design controllers in order to enhance today's traffic efficiency and passenger comfort and security.

To design ACC and CACC controllers, reinforcement learning is certainly a good solution. Indeed, some reinforcement learning algorithms allow us to learn an optimal policy for acting in an environment without knowing its exact inner workings. However, in the most general case, it is not possible to design a controller taking into account the entire problem of cooperative cruise control because of the complexity of the task. In this case, we consider a two levels approach. The first one is focusing on low-level control where a vehicle follows another vehicle at a secure distance, by acting directly with the throttle and observing the concrete results on the inter-vehicle gap. This level is car-centered and can be modeled by a Markov Decision Process (MDP) that can be solved using algorithms that learn on-line, such as Temporal-Differences (TD) algorithms. On the other hand, the second level is of higher level and focuses on vehicle coordination. In that context, a learned policy could choose the best driving lane for every vehicle located on a highway system. Because of the multiagent point of view of this subproblem, it could benefit from the use of Stochastic Games to be modeled as an extension to MDP.

In this article, we will present some results in the design of controllers working together in solving both the low-level and the high-level previously introduced. In the next section, we present the state of the art of MDP and reinforcement learning for mono and multiagent settings. In section 3, we present the general architecture that links the low and high-level controllers. In section 4, we present the design of the low-level ACC controller. In section 5, the high-level coordination controller is introduced. Then, section 6 presents

*This research is funded by the AUTO21 Network of Centres of Excellence, an automotive research and development program focusing on issues relating to the automobile in the 21st century. AUTO21 is a member of the Networks of Centres of Excellence of Canada program. Web site: www.auto21.ca

experiments for both layers and section 7 presents a discussion on the improvements that can be done on both sub-problems. At last, section 8 contains related work and we finish with a conclusion.

2. REINFORCEMENT LEARNING AND GAME THEORY

Reinforcement learning allows an agent to learn by interacting with its environment. For a mono agent system, the basic formal model for reinforcement learning is the Markov Decision Process (MDP). A MDP is a tuple $< S, A, \mathcal{P}, \mathcal{R} >$ where

- $S = \{s_0, \cdots, s_M\}$ is the finite set of states where $|S| = M$,
- $A = \{a_0, \cdots, a_p\}$ is the finite set of actions,
- $\mathcal{P} : S \times A \times S \rightarrow \Delta(S)$ is the transition function from current state, agent action and new state to probability distribution over the states,
- $\mathcal{R} : S \times A \rightarrow \mathbb{R}$ is the immediate reward function for the agent.

Using this model, the Q-Learning algorithm calculates the optimal values of the expected reward for the agent in a state s if the action a is executed. To do this, the following update function for state-action values is used:

$$Q(s,a) = (1-\alpha)Q(s,a) + \alpha[r + \gamma \max_{a \in A} Q(s', a)]$$

where r is the immediate reward, s' is the next state and α is the learning rate. An *episode* is defined by a sub-sequence of interaction between the agent and its environment.

On the other hand, Game Theory studies formally the interaction of multiple rational agents. In a one-stage game, each agent i has to choose an action to maximize its own utility $U^i(a^i, a^{-i})$ which depends on the others' actions a^{-i}. An action can be *mixed* if the agent chooses it with a given probability and can be *pure* if it is chosen with probability 1. In game theory, the solution concept is the notion of equilibrium. For an agent, the equilibria are mainly based on the best response to other's actions. Formally, an action a^i_{br} is a best response to actions a^{-i} of the others agents if

$$U^i(a^i_{br}, a^{-i}) \geq U^i(a'^i, a^{-i}),\ \forall a'^i.$$

The set of best responses to a^{-i} is noted $BR^i(a^{-i})$.

The Nash equilibrium is the best response for all agents. Formally, a joint action a_N, which regroups the actions for all agents, is a Nash equilibrium if

$$\forall i,\ a^i_N \in BR^i(a^{-i})$$

where a^i_N is the action of the i^{th} agent in the Nash equilibrium and a^{-i}_N is the actions of other agents at Nash equilibrium. A solution is Pareto optimal if it does not exist any other solution in which one agent can improve its reward without decreasing the reward of another.

The model which combines reinforcement learning and game theory, is called *stochastic games* [1]. This model is a tuple $< Ag, S, A^i, \mathcal{P}, \mathcal{R}^i >$ where

- Ag is the set of agents where card(Ag) = N,
- $A^i = \{a^i_0, \cdots, a^i_p\}$ is the finite set of actions for the agent i,
- $\mathcal{P} : S \times A^1 \times \cdots \times A^N \times S \rightarrow \Delta(S)$ is the transition function from current state, agents actions and new state to probability distribution over the states,
- $\mathcal{R}^i : S \times A^1 \times \cdots \times A^N \rightarrow \mathbb{R}$ is the immediate reward function of agent i. In team Markov games, $\mathcal{R}^i = \mathcal{R}$ for all agents i.

Among the algorithms which calculate an equilibrium policy for team Markov games, Friend Q-Learning algorithm, presented by algorithm 1, introduced by Littman [11], allows to build a policy which is a Nash Pareto optimal equilibrium in team games. More specifically, this algorithm, based on Q-Learning, uses the following function for updating the Q-values at each step:

$$Q(s, \vec{a}) = (1-\alpha)Q(s, \vec{a}) + \alpha[r + \gamma \max_{\vec{a} \in \vec{A}} Q(s', \vec{a})]$$

with $\vec{a}$, the joint action for all agents ($\vec{a} = (a^1, \cdots, a^N)$).

Algorithm 1 Friend Q-Learning

Initialize :
Q = arbitrary Q-Value function
for all episode **do**
  Initialize initial state s
  repeat
    Choose $\vec{a}$ which maximize $Q(s, \vec{a})$
    each agent i carries out action a^i
    Observe r, $\overrightarrow{a^{-i}}$ and next state s'
    $Q(s, \overrightarrow{a^i}) = (1-\alpha)Q(s, \vec{a}) + \alpha[r + \gamma \max_{\vec{a} \in \vec{A}} Q(s', \vec{a})]$
    $s = s'$
  until episode termination condition
end for

There are many techniques for choosing the joint action at each step of the learning in this algorithm. We use in this paper the ϵ-greedy policy. That means that, at each time, each agent has a probability $1-\epsilon$ to choose the action which maximise the Q-value for the current state and a probability ϵ to choose a uniform random action. This allows the exploration of the joint action set. The size of this set is exponential in term of the number of agents. This is a real problem for real situations where the number of agents is high.

3. GENERAL ARCHITECTURE

The general architecture for CACC is described by Figure 1. The positioning and communication systems provide information to build a world model used by the action choice module to give commands to the vehicle. However, as we said before, it is not possible to solve the problem of vehicle cooperation with only one controller designed by reinforcement learning. That is why we divided the problem into two sub-problems and, consequently, two controllers. Furthermore, the action choice module is divided in two layers: the Guidance layer and the Management layer based on Hallé's approach [7] and described in Figure 2.

The Guidance layer controller takes as inputs details on the previous state of the vehicle and, by using communication, on the state of other vehicles to take secure driving decisions. Such a control loop taking into account the state of preceding vehicles could help avoid instability of a string of vehicles controlled by CACC. Inter-vehicle communication is necessary to observe the longitudinal stability of cooperating vehicles [17]. Such stability requires knowledge of the acceleration of the leader of the platoon of the preceding vehicle, which could be provided by cooperation through the communication system. Here, we present a preliminary solution, described in section 4. It is based on reinforcement learning and is used to design an ACC acting policy. We will explain the design of a policy for the longitudinal control of a single vehicle, a follower, that can react to acceleration changes of the leader. Those acceleration changes are given, for now, by a sensor providing the inter-vehicle distance.

On the other hand, the Management layer is in charge of vehicle coordination at high-level. In our current approach, this layer has to find the best driving lane for each vehicle on an highway system according to the other vehicles' states and actions as described in section 5. The Management layer takes as input information from sensors and from the communication system according to a certain partial view of the road. Each vehicle is able to know the current state and the actions of other vehicles in a certain range. With this fixed range, a policy is designed to choose the most effective lane for each vehicle according to the accessible information for each agent. This layer sends recommended driving actions to the Guidance layer by choosing one of the many low-level controllers (for example, following a preceding vehicle, changing lane, etc.). In this article, the low-level controller we present is the vehicle-following controller.

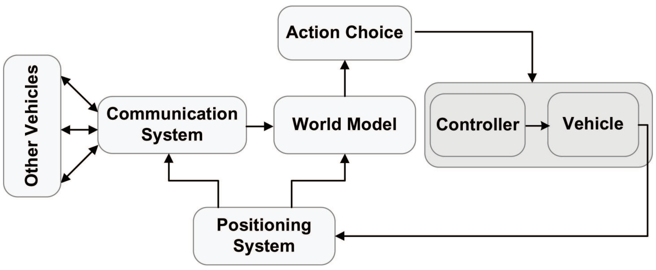

Figure 1: CACC control loop using reinforcement learning

4. REINFORCEMENT FOR GUIDANCE LAYER

Reinforcement Learning (RL) is an interesting technique for the design of a longitudinal controller because it enables us to abstract from the complexity of car physics and dynamics that have an important computing cost. With algorithms such as Q-Learning, one can learn by choosing the actions and observing their results directly in the environment. Put into an ACC context, it is possible to learn an acting policy in a simulated highway system by taking actions on the cars' brakes and throttle, and observing the results. The policy obtained can be used as a longitudinal controller to safely follow a preceding vehicle.

To apply this RL framework, we first had to model the problem by defining the states, actions, goals and rewards. Our first approach was to use variables such as the position of a leading car and of a follower, their velocities and accelerations, etc. Clearly, this state definition put us up against the curse of dimensionality, and it became impossible to have a discrete state space precise enough to learn a valuable policy. We modified our state definition by consolidating numerous state variables. This allowed us to use a smaller discretization and to reach a better precision with only two variables. Since driving can be seen as a sequential decision problem, there is no problem in modelling it using a MDP and discrete state variables. As seen in section 7, part of our future works will be to implement techniques to better approximate the continuous aspects of the problem. For now, our discrete state space was built around a state definition containing variables similar to those used in [14] for a fuzzy logic controller, as we defined our states by the relative distance in time between two vehicles and by the difference between those distances at two consecutive steps.

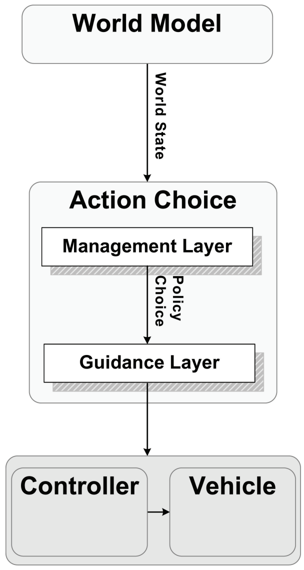

Figure 2: CACC Architecture

$$Dist_{Time} = \frac{(Position_{Leader} - Position_{Follower})}{Velocity_{Follower}} \quad (1)$$

$$\Delta Dist = Dist_t - Dist_{t-1} \quad (2)$$

As seen in Eq. (1) and Eq. (2), the time distance takes into account the relative position between the two vehicles and also the velocity of the follower, while the differences of the time distance between two consecutive time steps gives a signal about the movement of the vehicles relative to each other (whether they are closing up since last step, or getting farther). The time distance is the main variable for identifying the follower's position related to the secure distance, while the difference in time completes the Markovian signal, as it adds to the state definition an evaluation of the relative acceleration or deceleration. This relative movement between vehicles is needed to take an informed decision on the action to take at the next time step. Those actions were taken directly on the brakes or throttle (only one action per time step is chosen), closely simulating human interaction. The actions were discretized, according to a percentage of pressure on the pedal, from 0 to 100 by increments of 20.

The goal was defined as a secure distance to reach behind a preceding vehicle. That distance was specified as a time range and was defined as 2 seconds ($\pm$ 0.1 sec.), as it is a value often used as a secure distance in today's ACC systems [2]. To reach the goal, we set the rewards accordingly, with a positive reward given when the vehicle was located in the specified time range. We also set negative rewards when wandering too far or too close from the time ratio we were looking for. The behaviour the agent was supposed to learn was to reach the secure distance specified as the goal, and to stay in that range for as long as possible.

Those elements were put together in a RL framework, and the policy obtained, learned in a simulated environment, formed the core of our longitudinal controller. The environment, a simulated highway system built in previous work, featured complex car physics and dynamics as described in [9]. Since the simulation environment was using continuous time, we had to define the time interval at which action decisions would be taken. The action chosen at the specified time frame would be taken for the whole frame. To observe an accurate behaviour of the vehicle, we had to set the time step between each action decision to a small value (50 milliseconds). But in such conditions, the observation of real vehicle acceleration needed many consecutive acceleration actions, a behaviour that could not be learned in a decent time with normal state space exploration. To overcome this problem, we had to use a heuristic to speed up learning. The heuristic specified that every time the car was behind the desired time ratio, the best acceleration action known from experience was taken. By ignoring in that case the braking actions, this action selection technique directed rapidly the agent towards more rewarding locations of the state space.

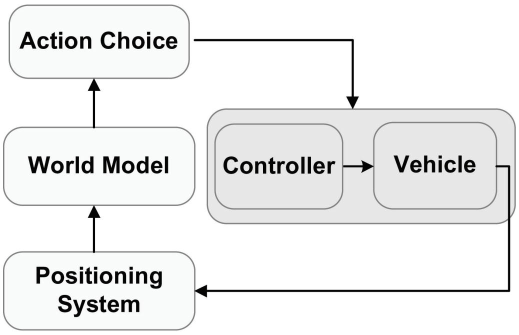

Figure 3: ACC control loop based on reinforcement learning

Put into context, Figure 3 shows that using RL simplifies the design of a longitudinal controller. The closed-loop controller takes as inputs the vehicle's state as described earlier, and selects the appropriate action according to the policy that was learned. Such a technique is obviously simpler than the complex mathematical analysis needed to predict precise car physics and dynamics for acting, as our controller basically hides in a black box vehicle physics and dynamics. It is possible for the agent to learn the optimal behaviour by taking driving actions and observing their results on the time distance and its difference between two time steps. In the next section, we will show results obtained by using this policy for longitudinal vehicle control.

5. COORDINATION BY REINFORCEMENT LEARNING: THE MANAGEMENT LAYER

In this section, we describe the design of the Management layer and, more precisely, the design of the policy to select the most efficient and safest lane for each vehicle according to their current state and action.

5.1 Problem Description

Coordination of vehicles is a real world problem with all the difficulties that can be encountered: the environment is partially observable, multi-criteria, has complex dynamic, and is continuous. Consequently, we establish many assumptions to simplify the problem and apply multiagent reinforcement learning algorithms to solve it.

The vehicle coordination problem presented here is adapted from Moriarty and Langley [12]. More precisely, three vehicles, each

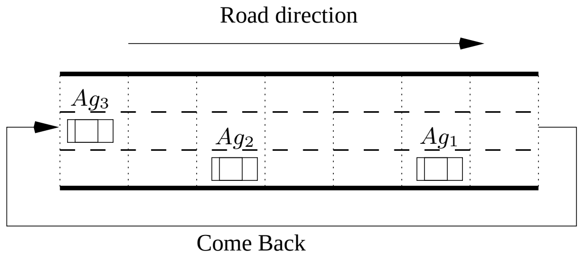

Figure 4: Initial state for 3×7 problem

represented by an agent, have to coordinate themselves to maintain velocity and avoid collisions. Each vehicle is represented by a position and a velocity. The goal of the learning algorithm is to find the best policy for each agent in order to maximize the common reward and also to avoid collision. The common reward is defined as the average velocity at each turn.

Figure 4 represents the problem's initial state. The environment's dynamics, states and actions are sampled in the easiest way: each case represents one meter and we assume that each vehicle can enter in a case. This simple discretization is repaired by the guidance layer, which will effectivelly calculate and apply the real control on the vehicle. This allows to handle uncertainty on position and velocity at this level of decision. The vehicles' dynamics are simplified to the following first order equation with only velocity $y(t) = v \times t + y_0$. For this example, we simulate the road as a ring meaning that a vehicle is returned to the left side when it quits through the right. The state of the environment is described by the position x^i, y^i and the velocity v^i of each agent i. Collisions occur when two agents are located in the same tile. The agents do not know the transitions between states. Those transitions are calculated according to the velocities of the agents and their actions. At every step, each vehicle tries to accelerate until a maximum of 5 m/s is reached. If another vehicle is in front of him, the agent in charge of the vehicle sets its velocity to the front vehicle's velocity. At each step, a vehicle can choose three actions: stay on the same lane, change to the right lane and change to the left lane. Each episode has a maximum of 10 steps. The reward at each step is set to the average velocity among all vehicles. If a collision occurs, the episode stops. The size of the set of states is in $O((X \times Y \times |V|)^N)$ with X the number of lanes, Y the length of the road, V the set of possible velocities and N the number of agents. We assume, in this problem, that each agent controlling one vehicle is able to see only its own local state (position, velocity). To obtain the states of other agents, we assume that communication is needed.

5.2 Partial Observability

In this section, we introduce our approach by describing the Friend Q-learning algorithm with a local view for the agents. Then, we introduce the same algorithm but using a partial local view of distance d. This partial local view allows the reduction of the set of states and/or the set of joint actions. If no reduction is done, the exact algorithm associated is Friend Q-learning. When only the set of states is reduced, we propose Total Joint Actions Q-learning (TJA). From this algorithm, we reduce the set of joint actions and we propose another algorithm: Partial Joint Actions Q-learning (PJA). In this article, we do not consider the reduction of joint actions alone, because this reduction is lower than the reduction of the set of states.

5.2.1 FriendQ with a local view

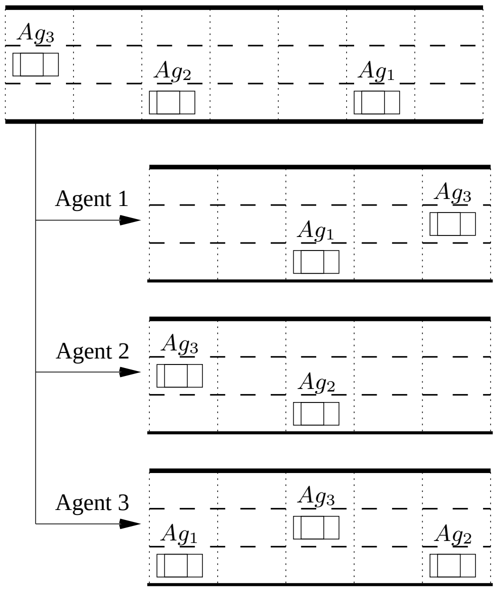

Figure 5: State and Partial States for $d = 2$

To introduce partial observability, we define the notion of local Q-Value and local state. Each agent uses the same algorithm but on different states. A local state is defined from the real state of the multiagent system for a center agent. All other agents positions are defined relatively to this central agent. This means that the same real state belonging to the set S will give different local states. For an agent i, the set of possible local state is S^i. We introduce a function f^i which transforms the real state s to a local state s^i for agent i. Formally, $\forall s \in S, \exists s^i \in S^i$ such that $f^i(s) = s^i$ for all agents i. In this version of the algorithm, each agent uses Friend Q-learning algorithm as described in section 2 but updates its Q-values for the local states and not for the real state.

5.2.2 FriendQ with a partial local view

To measure the effect of partial observability on the performance we define the partial state centered on one agent by introducing a distance of observability d. Consequently, the initial problem becomes a d-partial problem. The distance d can be viewed as an influence area for the agent. Increasing this distance increases the degree of observability. Moreover, from a communication point of view, in real world problems, the communication cost between two agents depends on the distance between them. Communicating with a remote agent is costlier than with a close agent. We define d_{total} as the maximal possible distance of observability for a given problem.

In d-partial problem, the new state is defined as the observation of the center agent for a range d. More precisely, an agent j is in the partial state of a central agent i if its distance is lower or equal than d from the central agent i. Formally, the function f_d^i uses the parameter d to calculate the new local state. Figure 5 provides an example of the application of f_d^i on a state s and gives the resulting partial states for each agent with a distance $d = 2$. Agent 1 sees only Agent 3 but Agent 3 sees both Agent 1 and 2. The new size of the set of states is $O(((2d+1)^2 \times V)^N)$. The number of states is divided by approximately $(Y/(2d+1))^N$, if we neglect the number of lanes which is often small compared to the length of the road.

5.2.2.1 TJA Q-Learning.

In a first step, as in classical Friend Q-learning, we consider an algorithm that takes into account the complete joint actions. This assumption implies that all agents are able to communicate their actions to others at each step without cost. The Q-value update function is now :

$$Q(f_d^i(s), \vec{a}) = (1-\alpha)Q(f_d^i(s), \vec{a}) + \alpha[r + \gamma \max_{\vec{a} \in \vec{A}} Q(f_d^i(s'), \vec{a})]$$

for agent i. When $d = d_{total}$, we have a small reduction factor on the state set of XY, because we do not take into account, in our specific problem, the absolute position of the center agent.

5.2.2.2 PJA Q-learning.

In a second step, the algorithm takes into account only the actions where agents are in the partial local view as specified by d. This reduces dramatically the number of joint actions which has to be tested during the learning. This partial local observability allow us to consider a variable number of agents in the multiagent system.

Formally, we define a function g^i which transforms the joint action $\vec{a}$ into a partial joint action $g_d^i(\vec{a}, s)$. This partial joint action contains all actions of agents in the distance d of agent i. The Q-value update function is now :

$$\begin{aligned} Q(f_d^i(s), g_d^i(\vec{a}, s)) &= (1-\alpha)Q(f_d^i(s), g_d^i(\vec{a}, s)) \\ &\quad + \alpha[r + \gamma \max_{\vec{a_d} \in G_d^i(\vec{A}, S)} Q(f_d^i(s'), \vec{a_d})] \end{aligned}$$

for agent i where $G_d^i(\vec{A}, S)$ returns the set of joint actions with a central agent i and a distance d. We can see that the result of the partial joint action depends on the current state.

6. EXPERIMENTS

6.1 Experiments at Guidance Layer

To learn the control policy, we used the Q-Learning algorithm, as described in section 2, with the reinforcement learning framework described in section 4. The learning task was defined as episodic, with each episode composed of 1000 steps of 50 milliseconds and we considered the task as semi-continuous, since it did not end when the agent reached the goal. The agent's optimal behaviour was to reach the goal, the secure following distance, and stay inside that range for as long as possible. The policy shown here was obtained after running 10 000 episodes.

The learning scenario used two vehicles: an automatically controlled leading car and an agent car trying to learn the control policy to follow the preceding vehicle by using our RL framework. The leading vehicle started 3 meters in front of the learner, and accelerated to reach the velocity of 20 m/s. The agent had to learn the policy by receiving rewards for trying different acceleration or braking actions.

Afterwards, we tested the resulting longitudinal controller based on the policy learned with the same scenario. Notice that the policy was run on-line once, and, as shown in Figure 6 and Figure 7, we obtained good results according to the specified time distance.

Figure 7 shows the time distance between the vehicles during the simulation. Again, we see that the agent was able to learn to stabilize around the goal that the agent was looking after. Those results illustrate that the time distance is much more variable than the distance in meters. This is in part from the fact that slight differences in relative positions or velocities of the vehicles can modify the ratio (see Eq. (1)), although the relative distance in meters between

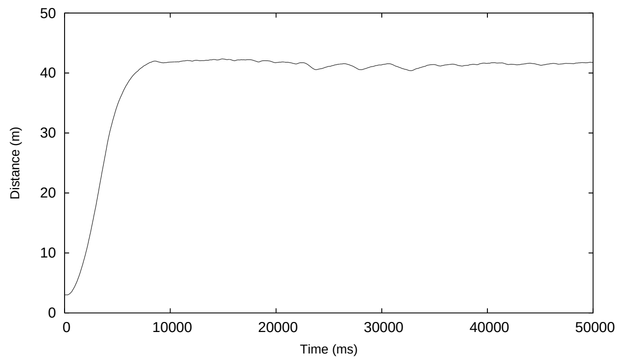

Figure 6: Distance (in m) from the preceding vehicle

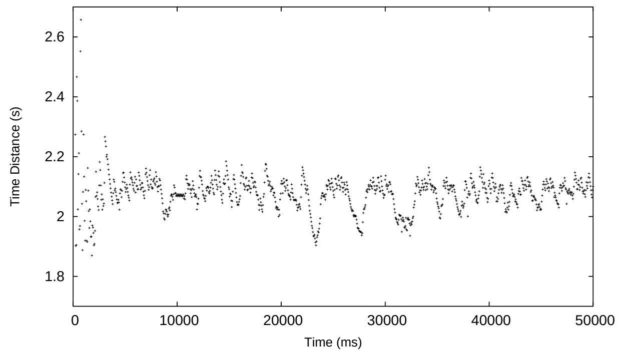

Figure 7: Time distance (in seconds) between vehicles

the vehicles might not change much. Another reason that could explain those results is the fact that our actions were not highly discretised. Hence, choosing at two consecutive steps different actions (for example, a braking action of 60%, followed by an accelerating action of 100%) might in the end affect velocity, causing important modifications on the ratio between two steps. Finally, the ratio used for the calculation of the distance in time (Eq. (1)) again explains the highly unstable values of the first seconds of the simulation (Figure 7), as the time distance is undefined when the velocity of the following vehicle is null.

In the end, we observe good stability around the safe distance which shows that we were able to learn a policy to follow the vehicle safely, without knowledge of the inner workings of the environment. Clearly, small disturbances in time ratio are not amplified but come back to the desired value.

6.2 Experiments at Management Layer

In this section, we compare empirically the performance of the totally observable problem (FriendQ) and the performance of the approximated policy (TJA and PJA). We present three kind of results: first of all, we compare the algorithms on a small problem P_1 defined by size $X = 3$, $Y = 7$, the set of velocities $V = 0, \cdots, 5$ and the number of agents $N = 3$. Consequently, in this problem, the maximal distance that we can use to approximate the total problem is $d_{total} = 3$. The 3-partial state is a local representation of the totally observable state because we are sure that all agents are visible from others in this representation. In the initial state (Figure 4), velocities of the agents are $v^1 = 1$, $v^2 = 2$ and $v^3 = 3$. We present, for all results, the average total sum reward over 25 learnings with each episode lasting 10 steps. More precisely, the reward presented on following figures uses $R = \sum_{t=1}^{10} \overline{v_t}$ where $\overline{v_t}$ is the average velocity over all vehicles at each step t of the episode. The y-axis is consequently the average of R over 25 learnings.

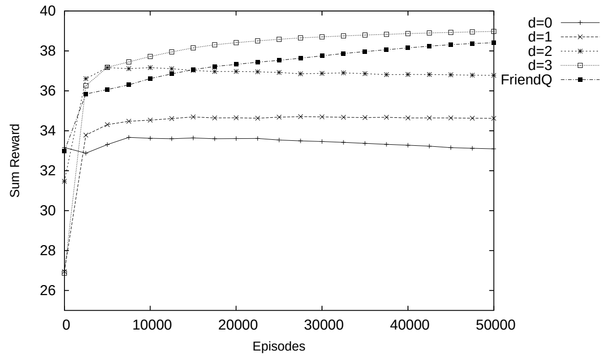

Figure 8: Rewards for Total Joint Action Q-learning for problem P_1

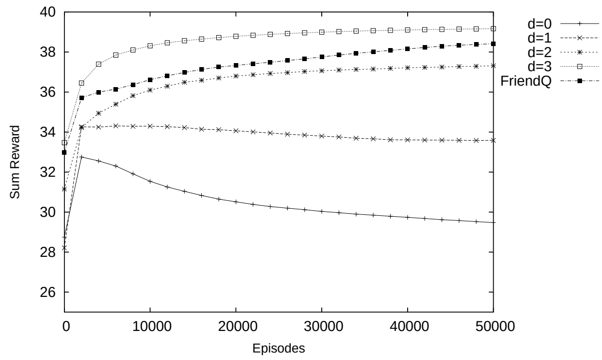

Figure 9: Rewards for Partial Joint Action Q-learning for problem P_1

Figure 8 shows the result of TJA Q-learning with distance from $d = 0$ to $d = 3$. This algorithm is compared to the total observation problem resolved by Friend Q-Learning. For $d = 0$, $d = 1$ and $d = 2$, TJA converges to a local maximum, which increases with d. In these cases, the approximated values are respectively of about 86%, 89% and 94% of the optimal value. When $d = 3$, that is, when the local view is equivalent to the totally observable view, the average sum rewards converges to the total sum rewards of Friend Q-learning. However, since we do not take into account the absolute position of the center agent, TJA converges faster than Friend Q-learning. Figure 9 shows the results of PJA Q-Learning on the same problem. As previously, for $d = 0$, $d = 1$ and $d = 2$, PJA converges to a local maxima respectively of about 76%, 86% and 97%. These values are lower than TJA's value but, for $d = 2$, the value is still close to the optimal.

For the second result, we compare PJA Q-learning for two different problems. We define a correct approximation distance d_{app} for each problem, where the associated policy is close to the optimal value. In the vehicle coordination problem presented here, the optimal value is the best lane choice. The first problem is the same as previously (Figure 9) and we can show that $d_{app} = 3$ for this problem. In the second problem P_2, we enlarge the number of lanes and the length of the road ($X = 5$, $Y = 20$, $V = 0, \cdots, 5$ and $N = 3$). This problem increases the number of states but decreases the possible interactions between vehicles because they have more space. For the second problem P_2, Figure 10 shows the comparison between Friend Q-learning and PJA Q-learning from $d = 0$ to $d = 7$. We can see that from $d = 4$, there are only small differences between PJA and Friend Q-learning. Consequently, for this problem, we can see that $d_{app} = 4$. The difficulty of this approach is the need to calculate the optimal policy, which can be intractable, to get d_{app}.

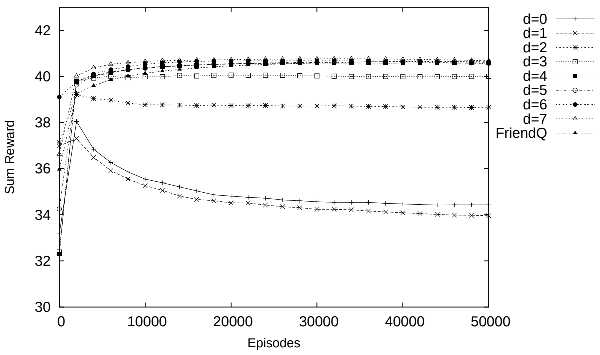

Figure 10: Rewards for Partial Joint Action Q-learning for problem P_2

As we can see, we need to generalize this result to know the d_{app} parameter without calculating the optimal policy. To present the third result, we calculate the ratio $DS = XY/N$ which represents the degree of space for each agent. Obviously, if the space (X or Y) increases, then each agent has more space for itself. As we study a problem where the team of agents has to handle only negative interaction, the higher the ratio, the more space agents have. We compare the performance of our PJA algorithm for different ratios. The ratios for the first two problems are respectively $DS_{P_1} = 7$ and $DS_{P_2} = 33$. We add two new problems P_3 ($X = 5$, $Y = 20$, $V = 0, \cdots, 5$ and $N = 5$) and P_4 ($X = 6, Y = 28, V = 0, \cdots, 5$ and $N = 4$) where the ratios are respectively of 20 and 42. Table 1 presents the results for each problem after 50000 episodes. For each problem, we define the correct approximation distance d_{app} such as $1 - (\frac{R_{d_{app}}}{R_{friendQ}}) < \epsilon$. When $\epsilon = 0.01$, $d_{app}^{P_1} = 3$, $d_{app}^{P_2} = 4$, $d_{app}^{P_3} = 2$ and $d_{app}^{P_4} = 2$.

To discover a relation between the ratio DS and the value of d_{app}, we compare in Figure 11, the link between DS and the degree of observability, defined as $\frac{d_{app}}{d_{total}}$ where d_{total} is the maximal distance for a given problem. For example, d_{total} for the problem P_1 is 3. We can see that the degree of observability decreases with the degree of space for each agent. We calculate an interpolated curve assuming that the degree of observability cannot be higher than 1 when $DS < 7$. We can see that the needed observability decreases and tends to 0 when DS increases. With this relation between both the observability and the degree of space, we can evaluate, for other problems how would be the d_{app} value.

Thus, introducing the locality of the view allows us to limit the observability of the state. More precisely, this approach allows us to use the partial version of Friend Q-learning in real world problems where the state is always partially observable. We obtain an approximation of the optimal policy without knowing the transition function. This approximation can be very close to the optimal policy.

Algorithms	P_1	ϵ_{P_1}	P_2	ϵ_{P_2}
FriendQ	38.4 ± 1.1	-	40.6 ± 0.3	-
PJA $d = 7$	-	-	40.6 ± 0.2	$\sim 0\%$
PJA $d = 6$	-	-	40.5 ± 0.2	$\sim 0\%$
PJA $d = 5$	-	-	40.6 ± 0.2	$\sim 0\%$
PJA $d = 4$	-	-	40.5 ± 0.2	$\sim 0\%$
PJA $d = 3$	39.1 ± 0.2	$\sim 0\%$	40.0 ± 0.2	$\sim 2\%$
PJA $d = 2$	37.3 ± 0.2	$\sim 3\%$	38.6 ± 0.2	$\sim 5\%$
PJA $d = 1$	33.5 ± 0.2	$\sim 14\%$	33.9 ± 0.3	$\sim 15\%$
PJA $d = 0$	29.4 ± 0.3	$\sim 24\%$	34.4 ± 0.4	$\sim 15\%$
Algorithms	P_3	ϵ_{P_3}	P_4	ϵ_{P_4}
FriendQ	37.0 ± 1.2	-	37.6 ± 0.3	-
PJA $d = 7$	37.2 ± 0.7	$\sim 0\%$	38.4 ± 0.2	$\sim 0\%$
PJA $d = 6$	37.9 ± 0.7	$\sim 0\%$	38.8 ± 0.4	$\sim 0\%$
PJA $d = 5$	37.8 ± 0.9	$\sim 0\%$	38.7 ± 0.4	$\sim 0\%$
PJA $d = 4$	38.3 ± 0.8	$\sim 0\%$	38.7 ± 0.2	$\sim 0\%$
PJA $d = 3$	38.7 ± 0.6	$\sim 0\%$	38.9 ± 0.2	$\sim 0\%$
PJA $d = 2$	37.7 ± 0.5	$\sim 0\%$	38.5 ± 0.1	$\sim 0\%$
PJA $d = 1$	35.2 ± 0.3	$\sim 5\%$	35.1 ± 0.4	$\sim 8\%$
PJA $d = 0$	33.5 ± 0.4	$\sim 10\%$	34.3 ± 0.3	$\sim 11\%$

Table 1: Average Rewards and standard deviation after 50000 episodes

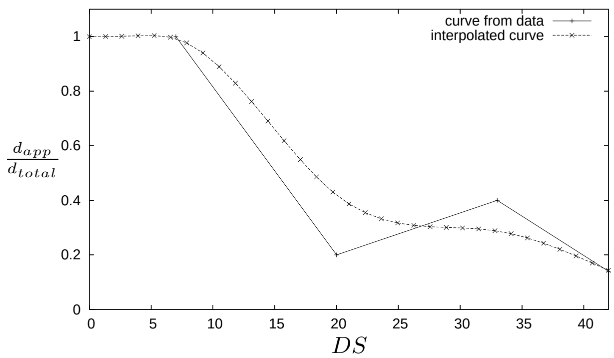

Figure 11: Link between observability and degree of space

In our approach, we do not explicitly take into account communication for many reasons. First of all, in real world problems, choosing the right communication cost is not an easy task. Furthermore, as we said previously, the communication cost depends not only on the messages sent but also on the distance between senders and receivers. This problem complicates the design of communication cost. Knowing the value of the approximated policy and of the associated communication policy (and consequently, the cost of this policy) to obtain the n-partial state, the multiagent system designer can get a good approximation for the real world problem.

7. FUTURE IMPROVEMENTS

The Guidance layer could benefit from a few ameliorations in order to raise its effectiveness and precision. First, as noted in section 4, it is clear that with our current discretization technique, it is necessary to use a heuristic to direct the state space exploration and to observe learning in decent time. However, since the use of the heuristic cannot give us the certainty that every state will be visited, that technique leaves a lot of states unexplored, yet some of those unexplored states could eventually be visited while acting on-line. As a solution, we will be looking to discretize while learning (instead of at the initialization phase) the state variables describing the policy. We could use techniques such as those proposed by Munos [13] where the policy could be discretized according to the areas of the state space where extra precision is needed. We could also discretize actions using such a technique, where refined actions could possibly be used according to the level of discretization of the current state. The use of such a technique could help us approximate continuous actions and state variables and have a more precise control policy.

We would also like to use and take advantage of inter-vehicle communication in the learning process for low-level longitudinal controllers. Vehicle communication could provide environment information for the RL process, and the agent could learn secure longitudinal control policies to be used in environments where multiple vehicles would be involved. We hope to design a CACC longitudinal controller using reinforcement learning, where information on the state of other vehicles would be transmitted and taken into account in the decisions of a driving agent (resulting in a control loop similar to the one in Figure 1). More specifically, we would like to observe how those controllers are doing according to the string stability of a platoon of vehicles using such policies.

We would like to use our learning algorithm on different scenarios (for example, hard-braking of the leader, stop and go situations, etc.) as to obtain a controller that could react to most driving situations.

As for the Management layer, we plan to evaluate more theoretically the relationship between the degree of observability and the performance of the learned policy. To define some formal bounds, we will certainly need to use complex communication cost. Finally, introducing the physical distance for a measure of observability is basic. We plan to discover others kind of distance between agents to measure observability to generalize our approach to positive and negative interaction management problems in teams. Finally, it will be very interesting to study the effect of partial local view to non-cooperative cases.

Finally, since both of our two RL approaches seem to give good results separately, we will look to integrate them into a fully functional CACC system. Consequently, the next step of our work will be to integrate both approaches: the high-level Management Layer will be taking decisions to select the best low-level controller according to its assessment of the multiagent environment.

8. RELATED WORK

A lot of related work has been done in recent years in the design of CACC systems. Regarding the vehicle-following controller, Hallouzi *et al.* [8] did some research as part of the CarTalk 2000 project. These authors worked on the design of a longitudinal CACC controller based on vehicle-to-vehicle communication. They showed that inter-vehicle communication can help reduce instability of a platoon of vehicles. In the same vein, Naranjo and his colleague [14] worked on designing a longitudinal controller based on fuzzy logic. Their approach is similar to what we did with reinforcement learning for our low-level controller. Forbes has presented a longitudinal reinforcement learning controller [5] and compared it to a hand-coded following controller. He showed that the hand-coded controller is more precise than its RL controller but less adaptable in some situations. However, Forbes did not test explicitly communication between vehicles to improve its longitudinal controller to a multi-vehicle environment (which will be the focus of our future work). Our approach will also integrate our low-level controllers with a high-level multiagent decision making algorithm, which was not part of Forbes' work.

Regarding the reinforcement learning in a vehicle coordination problem, Ünsal, Kachroo and Bay [21] have used multiple stochastic learning automata to control the longitudinal and lateral path of a vehicle. However, the authors did not extend their approach to the multiagent problem. In his work, Pendrith [15] presented a distributed variant of Q-Learning (DQL) applied to lane change advisory system, that is close to the problem described in this paper. His approach uses a local perspective representation state which represents the relative velocities of the vehicles around. Consequently, this representation state is closely related to our 1-partial state representation. Contrary to our algorithms, DQL does not take into account the actions of the vehicles around and updates Q-Values by an average backup value over all agents at each time step. The problem of this algorithm is the lack of learning stability.

On the other hand, our high level controller model is similar to Partially Observable Stochastic Games (POSG). This model formalizes theoretically the observations for each agent. The resolution of this kind of games has been studied by Emery-Montermerlo [4]. This resolution is an approximation using Bayesian games. However, this solution is still based on the model of the environment, unlike our approach which does not take into account this information explicitly since we assume that the environment is unknown. Concerning the space search reduction, Sparse Cooperative Q-Learning [10] allows agents to coordinate their actions only on predefined set of states. In the other states, agents learn without knowing the existence of the other agents. However, unlike in our approach, the states where the agents have to coordinate themselves are selected statically before the learning process. The joint actions set reduction has been studied by Fulda and Ventura who proposed the Dynamic Joint Action Perception (DJAP) algorithm [6]. DJAP allows a multiagent Q-learning algorithm to select dynamically the useful joint actions for each agent during the learning. However, they concentrated only on joint actions and they tested only their approach on problems with few states.

Introducing communication into decision has been studied by Xuan, Lesser, and Zilberstein [20] who proposed a formal extension to Markov Decision Process with communication where each agent observes a part of the environment but all agents observe the entire state. Their approach proposes to alternate communication and action in the decentralized decision process. As the optimal policy computation is intractable, the authors proposed some heuristics to compute approximation solutions. The main differences with our approach is the implicit communication and the model-free learning. More generally, Pynadath and Tambe [16] have proposed an extension to distributed POMDP with communication called COM-MTDP, which take into account the cost of communication during the decision process. They presented complexity results for some classes of team problems. As Xuan, Lesser, and Zilberstein [20], this approach is mainly theoretical and does not present model-free learning. The locality of interactions in a MDP has been theoretically developed by Dolgov and Durfee [3]. They presented a graphical approach to represent the compact representation of a MDP. However, their approach has been developed to solve a MDP and not to solve directly a multiagent reinforcement learning problem where the transition function is unknown.

9. CONCLUSION

In this article, we presented a preliminary CACC approach which combines a low-level controller to carry out low-level actions such as following vehicles and a high-level controller which coordinates vehicles and chooses the right low-level controller according to the state of other vehicles. These controllers have been designed using reinforcement learning techniques and game theory for multiagent coordination. We showed that reinforcement learning can provide very interesting results for the efficiency of the low-level ACC controller as well as for coordination control. This article showed promising results for complete CACC design using reinforcement learning.

However, much work has to be done to implement every CACC functionalities with reinforcement learning techniques. Even though we described vehicle-following control and lane-changing coordination, many other control policies could be added. We plan to improve efficiency of our approaches and integrate them into our general architecture to test it in a realistic vehicle simulator.

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Multi-Agent Systems as a Platform for VANETs

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ABSTRACT

Vehicular Ad-hoc Networks *(VANETs)* are MANETs *(Mobile Ad-hoc Networks)* in which the network nodes are primarily located in vehicles. VANETs are a compelling application of ad-hoc networks, because of the potential to access specific context information (e.g. traffic conditions, service updates, route planning) and deliver multimedia services (VoIP, in-car entertainment, instant messaging, etc.). They also offer a potential replacement for fixed-line networks and finesse the problem of limited power in MANETs based on, e.g. PDAs, mobile phones, laptops, etc. However, other MANET problems persist, most importantly the timely self-organization required to respond to a highly dynamic network topology. In this paper, we propose a vehicular information ad-hoc network that consists of three-tier network architecture using Multi-Agent System *(MAS)* technology. The proposed scheme provides flexibility, adaptability and maintainability for traffic information dissemination in VANETs as well as supporting robust and agile network management.

Keywords: Multi-Agent Systems, Ad-hoc networks, MANET, VANET.

1. INTRODUCTION

Despite the evident drawbacks, such as accidents, congestion and negative environmental impact, ground transportation over a publically-owned infrastructure of individuals or cargo (in, respectively, cars or lorries) will remain the dominant form of mass transportation throughout the world. In this case, it is worthwhile considering how information and communication technologies can be leveraged to improve road safety, reduce delays, enhance traveller experience, and so on. One possibility is to create a mobile ad hoc network (MANET) using the vehicles themselves as network nodes.

A Mobile Ad-hoc Network (MANET) is comprised of a group of mobile nodes which have the capability of self-organization in a decentralized fashion and without fixed infrastructure [1]. Moving vehicles equipped with communication devices are exactly coincident with the idea of MANETs. Thus a Vehicular Ad-hoc Network (VANET) is an example of a MANET where the mobile nodes are the vehicles themselves. Communication is possible between vehicles within each other's radio range as well as with fixed road side infrastructure components. The VANET concept is an integral part of the *intelligent transportation system* (ITS) architecture [3], which aims to improve road safety, optimise traffic flow, reduce congestion, and so on.

VANETs could be considered in three ways. Firstly, as a spontaneous, short-lived, self-serving network, designed to communicate local information between the network nodes, with no connection to any existing fixed infrastructure. The nodes themselves are responsible for carrying traffic and run applications which consume content carried in this way. Secondly, as a *replacement* for a fixed network, and the moving nodes are used to carry traffic from end points connected to the highway without the nodes themselves knowing anything about the content they are carrying (i.e. the nodes are routers and no applications run on the nodes). Thirdly, a hybrid (or mixed) situation may be considered, where the VANET is composed of clusters that are connected to each other by gateways, some of which are connected to fixed points, the clusters are in continual free-form, routing is handled by the network nodes themselves, and content-aware applications run on the network nodes.

Some of the most promising end-user applications of such hybrid VANETs include:

- *Traffic control and safety information*: this includes collision warning systems, road conditions, cooperative driving, vehicle speed monitoring, lane traffic, route plan, etc.
- *Location-dependent services*: vehicles equipped with GPS providing accurate geographical position be integrated into services, such as the location of the nearest facilities like fuel stations, parking zones, entertainment places and restaurants, etc. One can imagine this being further integrated into either telemetry (e.g. distance to empty) or higher-level recommender systems providing feedback on facilities from other VANET nodes (e.g. quality, convenience, etc.).

- *Ubiquitous computing*: VANETs provide the potential for the vehical to become a location in ubiquitous computing, and given a policy the vehicle can deliver personalised services according to the user profile of the occupant(s) of the car. This includes session mobility (e.g. as a user moves from one location, their residence say, into the new location (the car); and affective computing (services tailored to emotive mood as well as expressed preferences of the driver).

- *Access to fixed infrastructure*: typically established Internet applications like web browsing, e-mail, chat, mobile commerce, and entertainment can be provided by using road side infrastructure along with VANETs that are connected to fixed infrastructure like Internet and other required networks. Such applications presume an appropriate HCI for the driver which minimises distraction.

- *Other advanced services*: It is possible to imagine other interactions between VANET nodes and the road infrastructure, for example traffic calming measures (including automatic speed limiters), intelligent road signs, tolling (congestion charges for entering urban areas at peak times, cargo monitoring, and so on.

Creating high speed, highly scalable and secure VANETs presents an exceptional technological challenge due to a combination of highly dynamic mobility patterns which result in highly dynamic network topologies, combined with the high speed of vehicles. The fundamental requirement is to provide a stable platform in VANETs that various safety- and information-related applications can stand on to perform their tasks. Basically, the platform should ensure that all necessary information about the network nodes, roads and the services in a VANET get to the nodes that require them. Furthermore, the information available must be current and reliable. It is therefore necessary to enhance the flexibility, adaptability and reliability of VANET services.

In this position paper we present an idea to enhance flexibility and adaptability of VANET services by using a three-tier network architecture with multi-agent systems *(MAS)*, which involves a combination of static and mobile agents. MAS provides a useful and natural way of modeling real world autonomous components which is essentially needed for the VANET. Distributed artificial intelligent agents and mobile agents are the two important types of MAS, which will coordinate and communicate with each other [6].

In a VANET, the logical 'unit of computation' is the network node, sited in the vehicle itself. This computational process is embedded in a rapidly changing environment and must respond to changes in a timely fashion; it is responsible for the state of the node and the vehicle (for example, it might receive instructions to slow down, which it would relay to the driver; but it is very unlikely (at this time) that the vehicle will respond directly to instructions from the fixed infrastructure); and as part of a network it must communicate with other nodes. These three properties – reactivity, autonomy and interactivity – are often cited as the three key properties of *agent*. Addītiionally, the software needs to show aspects of mobility (moving code around the network), rationality (decision-making with respect to local goals), proactivity (anticipating changes as well as responding to changes), continuity (the process has a 'memory'), and so on. All these requirements are also given as properties of agent based systems [20][21].

The remainder of this position paper is organized as follows. Section 2 presents some related works in VANETs, and Section 3 gives an explanation of our proposed work. Section 4 describes some application scenarios, Section 5 briefly revisits the benefits of our approach with respect to various criteria, while some conclusions are drawn in Section 6.

2. RELATED WORKS

There are several works reported that deals with ad hoc networks and their applicability in VANETs. Some of the works are as follows. The work given in [2] describes a system called as Ad Hoc City, which is a multitier wireless ad hoc network routing architecture for general-purpose wide-area communication. The backbone network in this architecture is itself also a mobile multihop network, composed of wireless devices mounted on mobile fleets such as city buses or delivery vehicles.

[4] addresses the issues pertaining to medium access control schemes in highly dynamic automotive networks that reduce latency and perform reliable communication. It also describes a distributed positioning algorithm, called the kernel algorithm, suited for asynchronous ad hoc wireless networks under complexity constraints. Traffic congestion avoidance by disseminating traffic information through peer to peer networks based on WiFi technology is studied in [5].

A mixed mode wireless LAN comprising of infrastructure and ad hoc mode operations is presented in [7] where MANETs are connected through several base stations. Mixed mode WLAN has following benefits: 1) the traffic load at the access point is reduced, hence relieves contention, 2) ad hoc connections are single-hop, hence improving the channel efficiency, 3) ad hoc connections could use different channels, hence multiplying the system bandwidth. A node can dynamically switch between the infrastructure mode and the ad hoc mode according to the instruction of the access point, and hence the switching is transparent to the users. The work given in [8] presents an autonomous, self-organizing and decentralized configuration and management system for a group of base stations in wireless networks. The individual base stations aggregate and share network information. A distributed algorithm computes a local configuration at each base station based on the shared information.

A dynamic clustering solution which is distributed in nature, handles the cluster management by taking into account practicalities like packet losses etc., and integrates with a routing module is presented in [9]. The clustering is handled by two algorithms, initial clustering algorithm and cluster management algorithm. The initial clustering algorithm creates the clusters during the formation of the network and the cluster management algorithm maintains the clusters mainly using periodic transmission of HELLO packets. A security concept based on a distributed certification facility is described in [10]. A network is divided into clusters with one special head node each. These cluster head nodes execute administrative functions and hold shares of a network key used for certification. The work given in [11] introduces a scalable service discovery protocol for MANETs, which is based on the homogeneous and dynamic deployment of cooperating directories within the network. A congestion control method with dynamic clustering for variable topology and link qualities is discussed in [12].

Stealth attacks in the context of three common types of wireless networks, namely ad hoc networks, hybrid networks, and sensor networks are discussed in [13]. Stealth attacks are attacks that can be performed with low effort and cost to and very low risk of detection of the identity (or whereabouts) of the perpetrator. AODV-SEC, a new secure routing protocol has been presented and thoroughly evaluated in [14]. This protocol, takes into account the special security and performance requirements of MANETS, is based on a single PKI. A realistic city mobility model was used to examine the performance of routing protocols AODV, DSR, FSR and TORA by considering urban traffic scenarios in VANETs [15].

Sensor nodes are used to provide variety of services in VANETs [16]. A protocol architecture for VANETs is presented in [17] that describes layer-wise functioning of protocols used for vehicle communication. The work given in [18] presents a multi-agent system for monitoring and assessing air-quality attributes, which uses data coming from a meteorological station. A community of software agents is assigned to monitor and validate measurements coming from several sensors, to assess air-quality, and, finally, to fire alarms to appropriate recipients, when needed. Mobile agent based organization is discussed in [19]. The idea is to model the Internet as a multiplicity of local and active organizational contexts, intended as the places where coordination activities of application agents occur and are ruled.

3. PROPOSED WORK

In this position paper we propose a MAS based vehicular information ad hoc network. Here, all vehicles are considered to be part of a VANET. Each vehicle as well as the road side sensors monitor the traffic situation, such as density, average speed, etc. Based on these assumptions, in this section, we discuss the motivation for our agent-based approach, and then consider in more detail the architecture and functionality required to realise it.

3.1 Agent Technology

The problem we address is that network management, service provisioning and information distribution to (multimedia) applications in VANETs is intrinsically difficult. Our (proposed) solution is a two-layer architecture which integrates *mobile agents* and *norm-aware agents*, the idea being to provide both a rapid response to changes in a 'high speed' environment with rational deliberation about social behaviour, contracts and sub-ideality [22][23].

As stated above, a VANET is a temporary association of mobile nodes which manage themselves independently of any fixed support infrastructure (there may be connections to fixed infrastructure nodes but these do not affect *network management* decisions). They are self-created and self-organized, are inter-connected by mutli-hop wireless paths and operate in strictly peer-to-peer fashion. The benefits include bandwidth re-use, low-cost (or even zero-cost) rapid deployment, and intrinsic fault-tolerance. The disadvantages are, as indicated, that problems of network management, service provisioning and information distribution are exacerbated, because the dynamic network topology renders centralised solutions based on complete information impossible.

MANETs, as originally conceived, were intended to be transient networks, supporting short-lived, opportunistic and spontaneous networks rather than long term inter-operation. VANETs, on the other hand, are expected to have a much longer life-span, and have a unique property in that, in one sense the 'network' is always the same every time a vehicle joins it (e.g. on a commuting route), but each of the nodes which constitute the network are all different. The issue then is that if long-term operation is required, the usual networking solution is to create a backbone (for efficient packet routing); the issue then is how to select the 'vertebrae' when the network nodes are constantly changing (even if the network stays the same). The field of mechanism design in multi-agent systems (the process of designing a choice mechanism that translates expressed preferences into a decision) suggest several solutions (e.g. auctions, voting, etc.), but in any solution agents require accurate, timely information in order to make bids, cast votes, and so on.

To address these issues, there are two requirements. The first requirement is for 'snap decisions' taken at the local point of need taken from an individual perspective. To support this, we suggest using *mobile agents*. The basic idea behind mobile agents is to move code across a network from one node to another. The is technically feasible if basic requirements for secure communication and code execution can be met, and a common execution language which supports process persistence. Note these processes are 'agents if they preserve 'autonomy' of state and decision-making, unlimited outbound communications, and asynchrony of computation. The general motivation for using mobile includes: the code footprint is small compared to data; the process is operating in a dynamic decentralised environments; for efficiency, code can be transported on packets that will be sent anyway (autonomic communications), and the environment demands both location transparency (logical distribution of responsibility and control) *and* location contingency (who's actually doing the work is important). These are all features of the VANET environment.

The second requirement is for 'considered deliberation' from a 'global' perspective, including each other, based on informal social relations (e.g. quid pro quo) or formal commercial relations (e.g. contract). Therefore cooperation in VANETs needs notions of 'trust', 'selfishness', 'fairness', 'judgement', 'punishment' and 'forgiveness', plus a balance between 'local' plus 'global' decision-making which needs notions of delegation, mandate, and authorisation, and so on.

All of the above are socio-legal concepts and are amenable to *normative specification*, and these specifications can be used by *norm-aware agents*. Any set of interacting agents whose behaviour is regulated by norms can be considered a norm-governed system, where a norm is a rule which prescribes organizational concepts like (institutional) power permission, obligation, sanction, and other more complex relations. This approach to multi-agent systems has its roots in the study of legal, social and organizational systems, while formal analyses often use some version of deontic logic which provides route to automation. Such automation offers formal definitions of responsibility and control, interoperability (as defined in terms of external, executable specifications), and reasoning about sub-ideal states of the system (i.e. detecting and recovering from faults in the system, which are to be expected in probabilistic systems like VANETs.)

Therefore, our solution is to propose a two-layer agent architecture comprising: 1)'lightweight', network-facing, mobile agents; 2) 'heavyweight', application-facing, norm-aware agents; and 3) a common language between the two types of agent. The mobile agent layer supports in implementation decisions made by norm-aware agents. Thus we propose to converge 'heavyweight' agents, which operate in the domain of norms and 'codes of conduct' *about* the network, with lightweight mobile agents which operate *in* the domain of network-centric events and parameters in provisioning the network itself. In the following sub-section, we elaborate further on this novel network architecture.

3.2 Network Architecture

Considering all the properties of the agent systems, we propose to implement the two-layer agent architecture over a three-tier network architecture as shown in figure 1. The first tier contains the vehicles which are communicating themselves on the road which are within a given cluster (a VANET). A cluster is formed based on radio range coverage of vehicles and the road-side base station. In the second tier, a set of clusters are there in which each cluster comprises of base stations (C_1 to C_N clusters). The clusters may communicate by using base stations. The third tier is the transport agency (TA), owned by a private body or government agency to monitor the entire transportation infrastructure and offer the relevant services to the vehicles on the road.

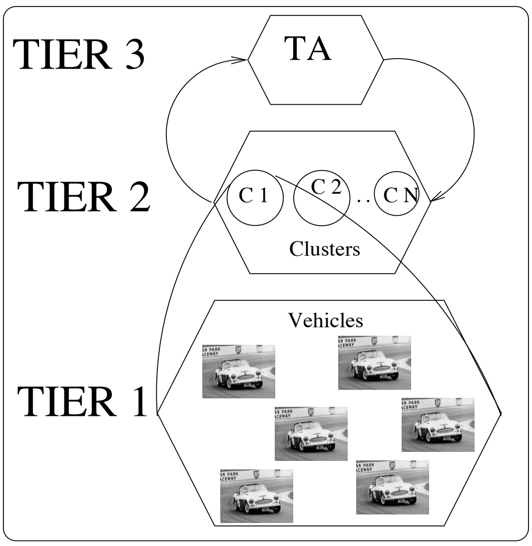

Figure 1: Three tier VANET

From the proposed network architecture, we can categorize the information dissemination and network management model into four parts: vehicle to vehicle, vehicle to base station, cluster to cluster and cluster to transport agency. These are described as follows.

- *Vehicle to Vehicle communication*: (Inter vehicle communication) It resembles peer to peer network architecture. Here, the communication is established between the vehicles within a cluster which will be very useful for cooperative driving. Here, each of the participating vehicles would be equipped with a set of agents such as *Vehicle Manager Agent (VMA), Alarm Agent (AA), and Service Discovery Agent (SDA).* These agents are responsible for collecting and disseminating traffic information. The vehicle agency also consists of a traffic knowledge base (TKB) that works on the principle of blackboard architecture which is used for communication among agents.
  - *VMA*: It is deployed at each vehicle. This is a static agent which creates all the set of agents within the vehicle agency and synchronizes the interactions of all the agents within the vehicle. This directly communicates with the cluster base station to get/disseminate the relevant information/services especially in critical situations. It is a norm-governed heavy weight agent that addresses the following.
    - Decides the critical situations based on certain rules and code of conduct. The situations may be monitored through either sensors or neighboring AAs or the vehicle user. Rules may be based on degree of worsened road conditions, nature of accident, level of fuel, tyre pressure, reliability of neighboring nodes, etc.
    - Provides access to internal services such as audio files, road information, data, etc., to other vehicles based on certain permissions.
    - Manages hand-off based on certain network parameters such as congestion, reduced power, etc.
  - *AA*: It is a mobile agent that travels around the network by creating its clones (a clone is a similar copy of the agent with different destination addresses) to disseminate the critical information during the critical situations. Examples of critical situations are accident, traffic jam, bad weather conditions, fuel status, road maintenance, etc. It also informs the VMA and updates the TKB.
  - *SDA*: It is a mobile agent which travels in the network to search for the required services as desired by the vehicle user. The services may be road maps, traffic density maps, Internet services, and location aware services (commerce, entertainment, parking, fuel stations, etc.). The agent also updates the TKB with services discovered.
  - *TKB*: It comprises of information of critical events such as accidents, traffic density and the services available in the vehicle, services accessed, recently accessed road maps, etc.

- *Vehicle to Base Station*: A fixed infrastructure comprised of (at least) a number of base stations strategically positioned in close proximity to the highways is necessary to facilitate the upload/download of data from/to the vehicles. Each base station covers a cluster. We assume that several sensors information are input to the base station. Information could be traffic density, vehicle types, adverse road conditions, etc. The agency in the base station comprises of following components: *Base Station Manager Agent (BSMA), Service Agent (SA), Advertisement Agent (ADA) and Cluster Knowledge Base (CKB).*

  – *BSMA*: It is a static norm-governed agent deployed at each base station which maintains and synchronizes all the agents that are associated with base station. It regularly updates the CKB with the visited vehicles and its services information by interacting with VMA of each vehicle. Also computes the traffic density maps, adverse road conditions and updates the CKB. Critical information received from VMAs in its cluster is sent to other BSMAs. This agent is responsible for communicating information with VMAs, BSMAs and TA.

  – *SA*: It is a static agent responsible for collecting the services information from the service providers of the cluster and regularly updates the CKB. It also broadcasts any critical information available with it to the vehicles within its cluster upon notification from other BSMAs.

  – *ADA*: It is a mobile agent which roams in the network and informs the visited VMAs about the auctions, special exchange offers, ticket reservations, etc. It may interact with the user and get the information about his participation in auctions or booking tickets or any such tasks as the user wishes.

  – *CKB*: It comprises of information such as critical events within cluster, services available in cluster, visited vehicle information, traffic density maps, road conditions, location aware services, advertisements, etc.

- *Cluster to Cluster*: Clustering provides a method to disseminate the traffic information as well as provide varieties of services. Whole network is divided into self-managed groups of vehicles called clusters. These clusters continually adapt themselves to the changing network topology and new cluster configurations. Communication between the clusters will take place with the help of BSMAs located in base stations that are fixed on the road side, although, as discussed below it is possible to manage clusterign without BMSAs.

- *Cluster to TA*: TA consists of complete information of the transportation infrastructure which is accumulated from various cluster BSMAs. BSMAs of the clusters communicate with the TA manager. TA manager periodically constructs a overall picture of the road ways in terms of traffic, critical events, road conditions, etc., and constructs a road map and distributes to the BSMAs. It also prepares list of services available in its entire area and stores in its knowledge base which may be used by SDA to discover the services.

Practical implementation of the proposed scheme needs the following: 1) the vehicle must be equipped with a computational device comprising a real time operating system, wireless transceiver unit with dynamic ranges, GPS unit, speed sensing unit, inter-vehicle distance monitoring unit, cameras (optional), fuel sensing unit, human interface, embedded tyre air sensing unit, database manager, an agent platform with set of static and mobile agents; 2) the base station must have a computational unit, wireless transceiver unit, real time operating system, agent platform, cameras and database manager; 3) environment and road condition sensors are connected to base station; and 4) Transport agency comprises of computational unit, wireless transceiver unit with dynamic ranges, real time operating system, database manager, agent platform, human interface and Internet connection.

A further refinement of the network architecture, facilitated by the use of agent technology, is this. Instead of fixed base stations situated at strategic points along the highway, each defining a cluster, and vehicles belong to a cluster according to proximity to a base station; we *remove* the base stations altogether (with a few exceptions), and the *logical* clusters now *physically* move the length of the highway, and moving vehicles join or leave clusters according to their ground speed and proximity to identified cluster-heads or gateway nodes. The additional research questions that need to be addressed now include:

- Permanent transience (or transient permanence): how the network stays 'the same', even though every network node is different (by analogy, someone is the 'same person', from one year to the next, even though every cell is different);

- Role-based and policy based network management: who (vehicle node VMAs) gets which role, (e.g. as cluster-head, or gateway, etc.) and why, on what basis, and so on. In other words, some VMAs have to assume the responsibility and functionality of BSMAs. For this we need elections etc. (cf. [23]);

- Anticipation: knowing when a network change is imminent due to role hand-off (vehicle leaving the highway), and to take pre-emptive behavior to ensure the continuous smooth-running of he network. This behaviour could be based on a cognitive characterization (BDI (Belief Desire Intention)-like) of the mental state of the agent (VMA) [24].

4. APPLICATION SCENARIOS

In this section we illustrate the operation of the system to realise three of the application scenarios mentioned earlier. We assume that an agent platform exists in vehicles, base stations and TA. However agents communicate with each other by using traditional exchange mechanisms if an agent platform is not available in any of the components of VANET. The agent platform provides following services: agent creation, mobility, communication, security and fault tolerance.

4.1 Access to Fixed Infrastructure

Access to fixed infrastructure is essentially using the VANET to connect to any computer terminal in the car to the Internet; however, we seek to optimise performance by caching regularly-accessed information in the cluster. Required information is first searched within the cluster, i.e., by polling the BSMA and the VMAs. If the information is not available within the cluster, it searches in the neighboring cluster. The expected information cached would be road maps, traffic density maps, articles, etc.; of course other Internet services e.g. VoIP would also be available.

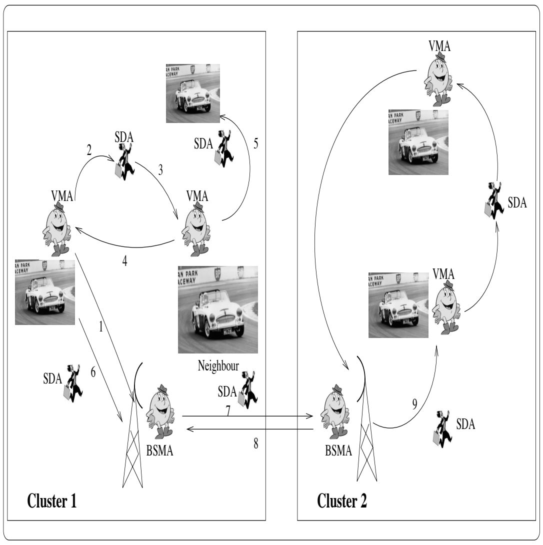

Figure 2: Information access in VANETs

The proposed information access model is shown in figure 4.1. The method to access the information is as follows given in sequence. It is assumed that information required is available in the vehicle of neighboring cluster.

1. The vehicle needing information contacts the BSMA through VMA. BSMA searches information in its CKB and also contacts TA. In this case, BSMA as well as TA does not have the information, hence it informs the VMA.
2. VMA creates the SDA to it's neighboring vehicles.
3. SDA migrates to neighboring vehicle and communicates to VMA through TKB.
4. If the required information is available in TKB of the neighboring vehicles SDA sends the information to the VMA.
5. If the information is not available with the neighboring vehicle, SDA clones from its place and moves to second degree neighbors and so on within the cluster. If it identifies the required information with a particular vehicle then the information will be sent to VMA. SDA and its clone destroy themselves once they reach the end of the cluster.
6. In case if information is not available within the cluster, VMA again generates SDA which migrates to its base station.
7. SDA clones itself to neighboring clusters by communicating with its cluster BSMA under certain norms.
8. In case SDA gets information at neighboring BSMA, it returns to its created VMA.
9. If SDA fails in getting the information from neighboring BSMAs, it searches within the neighboring cluster vehicles as given in steps 3 to 5.

4.2 Critical Information Dissemination

Search for information, in the above application, is concerned with information pull. In this application, we are concerned with information push, whereby vehicles spread messages about safety related events such as *accidents, road conditions (roadworks), inter-vehicle distance, weather conditions ahead*, etc., through AA. Critical information related events may be of two kinds. Firstly, there are events (such as fuel status, vehicle speed, neighbor vehicle distance, etc.) that can be detected by an AA for a particular vehicle. These events will assist the driver in safer driving and it does not need to be spread to other vehicles. Secondly, there are events such as traffic jams, accidents, road conditions, etc., which have to be disseminated to other vehicles in an aggregated way. Aggregation requires aggregating the events sensed by a single vehicle as well as aggregating the events of all the vehicles.

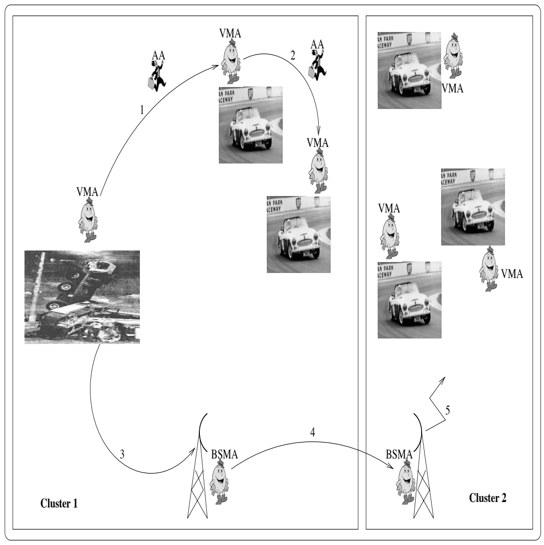

Figure 3: Critical information dissemination model

The critical information dissemination using proposed model is shown in figure 3. The method to disseminate the critical information follows the given sequence:

1. Whenever critical events occur, VMA in a vehicle creates AA to its neighbors. AA communicates with neighboring VMA and informs about the critical event as well as collects any critical information available in the visited vehicle.
2. The neighboring VMA which received the message of critical event, creates clones of AA based on certain norms and spreads the message to its neighboring vehicle and so on. In this way the message is reached

to all the vehicles within the cluster as well as AAs aggregate the critical event information and pass on the information to its VMA. All the cloned agents destroy themselves once they move out of the range of its cluster BSMA.

3. VMA communicates critical information to its BSMA. BSMA updates CKB based on certain permitted actions depending on the norms.

4. BSMA communicates about the received critical information to the neighboring BSMAs as well as to TA.

5. Neighboring BSMAs broadcasts critical information in its cluster.

4.3 Location-Dependent Services

Location-dependent services can be built over the information push-pull model of the two previous scenarios. Certain information such as the location of the nearest facilities like fuel stations, parking zones, entertainment places and restaurants, markets, etc., can be accessed through TA. Figure 4 depicts the information 'advertisement' by using the proposed model. The method to access local information about roadside (or nearby accessible) services is then given by the following sequence.

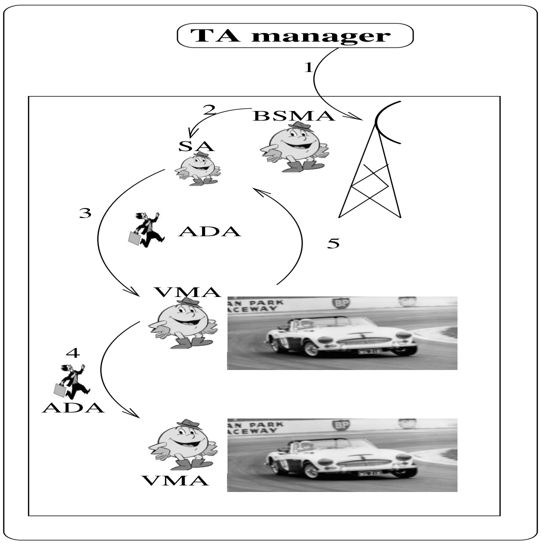

Figure 4: Advertising information from TA

1. TA manager sends the information to all BSMAs.
2. BSMA updates its CKB and informs SA to advertise the message through ADAs.
3. SA creates several ADAs which move to the nearest vehicles and pass on the information to users as well as interact to get some or nil response for the advertisement.
4. ADAs clones themselves and visits all the vehicles that are not visited by any other ADA and repeats the operation as given in step 3.
5. Parent ADA accumulates all the responses and sends the information to SA which in turn passes on the information to TA manager.

5. BENEFITS OF USING AGENTS

The following are some of the benefits of using agents in the proposed vehicular information ad hoc networks:

- *Flexibility*: Agents are flexible to accommodate varieties of services to facilitate information dissemination in VANETs. For example, SDA may be encoded to discover multiple services rather than single service based on user degree of satisfaction.

- *Adaptability*: As we observe in the applications mentioned above, we can see that agents such as AA, SDA and ADA adapt to varied network conditions such as vehicle mobility, occurence of critical events, changes in road and weather conditions, etc.

- *Maintainability*: The agent-based approach we have advocated is predicated entirely on the idea of open systems, that is, the interaction of heterogeneous and unpredictable components. However, the use of norm-aware agents considers situations where design-time specifications may need to be modified at run-time; or where the system specifications may only be partially given at design-time, and the components themselves complete the specifications at run-time. This is an entirely new approach to network management.

- *Survivability*: Wireless networks are specifically designed to operate in the expectation of contention and error. Similarly, in VANETs, it may be that a node fails to comply with the system specifications, either by design, by accident or from necessity. Dealing with such non-compliant behavior, can also be addressed by the norm-governed approach, where appropriate behavior can be stipulated using concepts stemming from the study of legal and social systems: e.g. permissions, obligations and other normative relations such as power, right and entitlement.

6. CONCLUSIONS

Vehicular ad hoc networks provide an exciting area of research at the intersection of a number of disciplines and technologies. There is a good future for applications of VANET, ranging from *diagnostic, safety tools, information services, and traffic monitoring and management to in-car digital entertainment and business services.* However, for these applications to become everyday reality an array of technological challenges need to be addressed.

In this position paper, we have outlined an agent architecture for VANETs inspired by previous work in QoS (Quality of Service) provisioning in MANETS [23], in which we developed a 3-layer system architecture integrating mobile agents and norm-aware agents to deliver a rapid response with rational deliberation about social behaviour, contracts and sub-ideal situations. This solution was based on integrating 'lightweight', network-facing, mobile agents with 'heavyweight', application-facing, norm-aware agents, via a common language so that the mobile agent layer supports in the network those decisions made by the norm-aware agents.

The paper addressed the use of emerging agent technology in VANETs. It can be assumed that multi-gent systems have a great potential to influence the design of future VANET and their services. Multi-agent systems should be regarded as an "add on" to existing service platforms, providing more flexibility, adaptability, and personalization for the realization of services within next generation VANET environments. We are planning to implement the proposed work by using IBM aglets workbench as well as simulate using NS2 to evaluate the performance of the system.

Acknowledgements

Jeremy Pitt was supported by Royal Society Science Network No. 16751 and UK EPSRC Grants GR/S69252 and GR/T20328. We appreciate the reviewers' useful comments.

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An Agent-Based Simulation Model of Traffic Congestion

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ABSTRACT

We present an agent-based exploratory study of a simple congestion model. This model is based on the pioneering work of Vickrey [7], who examined the effect of Departure Time Choice on congestion for a single bottleneck. The agents dynamics, followed in order to reduce the total cost of the journey, including congestion costs and the cost of not arriving at the desired time, are scalable to city sized models.

Homogeneous agent systems, in which all agents wish to arrive at the same time, are unstable. The proportion of agents who review their departure times in the same iteration effects the stability of the system. When the agents were given a normal distribution of preferred arrival times the system was stabilised while the level of congestion remained significant. The variance of this distribution and the reviewing rate are two important parameters that determine the qualitative behaviour of the model. A graph of the stability of the system against these two parameters highlights the parameter space of stable behaviour.

Categories and Subject Descriptors

J.4 [**Social and Behavioural Sciences**]: Economics; I.6.3 [**Simulation and Modelling**]: Applications

General Terms

Agent-based simulation

Keywords

Congestion, stability analysis, Vickrey's model, Nash equilibrium, traffic, transportation

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1. INTRODUCTION

This model uses agents to study the effect of departure time choice on the formation of traffic jams, taking into account the cost of the journey and the cost of not arriving at the desired time, known as the schedule delay cost. The Nash equilibrium is known for this analytic model, though the behavioural processes that could lead to this equilibrium have not, to the authors' knowledge, been studied before using a disaggregate model. The agent-based modelling approach allows these processes to be investigated in a more satisfactory manner than in previous analytical and numerical studies [1, 3, 2].

There are two main motivating factors for investigating the dynamics that could lead to such an equilibrium: Firstly, to discover if the equilibrium is a stable state, and hence a plausible real world description and secondly, can the same dynamics be used to simulate more complex situations for which we do not have an analytical solution.

It is shown that the system evolves towards the Vickrey equilibrium under certain conditions. The overall behaviour of the system can change qualitatively when the agents are heterogeneous instead of homogeneous. Two forms of heterogeneity were introduced in the model.

This paper begins with a brief recall of the Vickrey model, which has been treated in greater detail elsewhere [7, 1, 5].

The third section discusses the agent-based model, results obtained with homogeneous agents and the cause of the oscillations.

In section four, we study the effects of two forms of heterogeneity in the agent population. In particular we examine the interplay between two important parameters of the model, the reviewing rate and the level of heterogeneity. A graph of stability in the space of these two parameters shows the regions of qualitatively interesting behaviour.

2. VICKREY'S MODEL

In this model a fixed number of individuals, N, wish to travel by car on a road with limited capacity to arrive at the same destination at the same time, denoted t^*. The

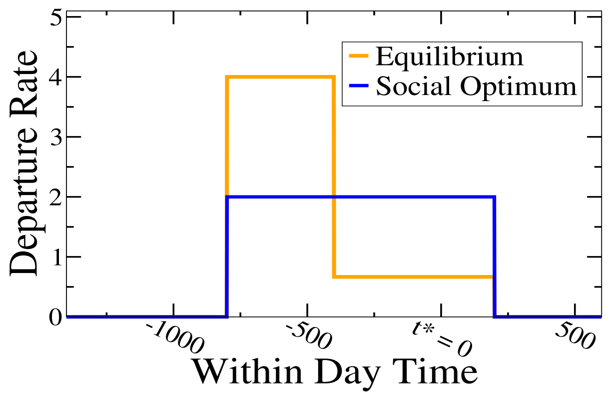

Figure 1: The departure rates for the equilibrium and the social optimum. The capacity of the road is 2 cars per unit time, when this is exceeded a traffic jam forms

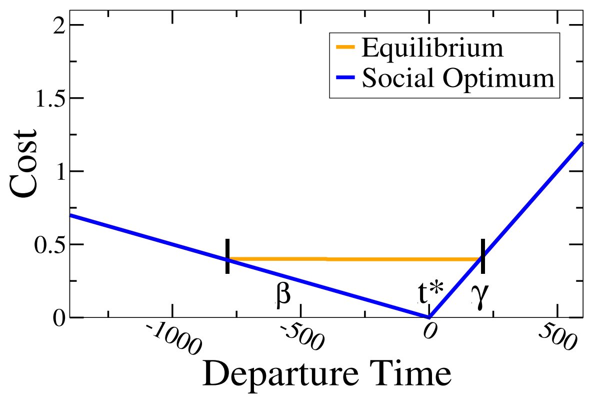

Figure 2: The cost functions for the equilibrium and the social optimum for which there is no congestion. The vertical lines show when the first and last drivers leave.

model examines the departure time choice in this situation.

The capacity of the bottleneck is denoted, S (in cars per unit time), the shortest time in which everybody can pass the bottleneck is N/S. If the departure rate is greater than the capacity a traffic jam is created. This translates into an increased travel time with an associated increase in cost. There are also schedule delay costs, a cost for arriving early and a higher cost for arriving late, both of which increase linearly with time, see figure (2).

Since the fixed travel costs don't change the dynamics of the model, they are normalised to zero. That is, if there is no congestion the arrival time is the same as the departure time.

2.1 Equilibrium of Analytic Model

The Nash equilibrium is the situation in which no individual can reduce the cost he/she pays by changing his/her departure time. In order to better understand the departure rate function of the equilibrium we need first to examine how the level of congestion at any time is calculated and also how the total cost of a journey is calculated.

2.1.1 *Congestion*

Knowing the level of congestion at a certain time enables us to calculate what time someone who departs at that time will arrive. The traffic jam introduces memory into the system because at any time time the size of the jam depends on the number of people who have already left and at what time they departed. The amount of congestion encountered by someone who leaves at time t, is given by

$$Q\left(t\right) = \sum_{t'=\tilde{t}}^{t} r(t') - S(t - \tilde{t}). \tag{1}$$

The first term is the number of people who have joined the traffic jam since it began, the second term is the number of people who have left the traffic jam. $\tilde{t}$ is the moment the traffic jam began and $r(t)$ is the departure rate at time, t. The travel time for someone who leaves at t_d is given by

$$tt\left(t_d\right) = \frac{Q\left(t_d\right)}{S}. \tag{2}$$

The arrival time, t_a, is given by $t_a = t_d + tt(t_d)$.

2.1.2 *Cost*

The cost for an individual who departs at a certain time is given by, the addition of the travel time multiplied by a constant α, and either the time by which the individual arrives early multiplied by a constant β, or the time by which the individual arrives late multiplied by a constant γ. In order to ensure the coherence of the model, we have

$$\gamma > \alpha > \beta \tag{3}$$

see figure (2). The cost of arriving late, γ increases more quickly then the cost of arriving early, β. α is the physical cost of travel, petrol etc..

The cost function is,

$$\begin{aligned} C\left(t_d\right) &= \alpha tt\left(t_d\right) + \beta\left\{t^* - \left(t_d + tt\left(t_d\right)\right)\right\}^+ \\ &\quad + \gamma\left\{\left(t_d + tt\left(t_d\right)\right) - t^*\right\}^+ \end{aligned} \tag{4}$$

where $\{a\}^+ = \max(0, a)$.

2.1.3 *Equilibrium*

The equilibrium departure rate is shown in figure (1) along with that of the social optimum, for which there is no congestion and the route is used at its full capacity. The flat equilibrium cost function is drawn in figure (2).

3. AGENT-BASED MODEL

Each simulated agent represents an individual and is given a simple behavioural rule which is followed in order to reduce

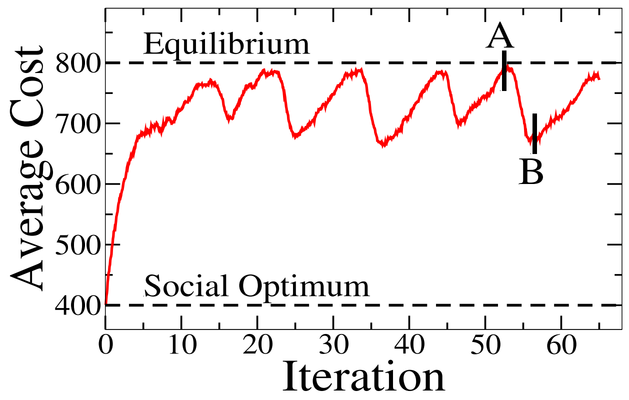

Figure 3: Average cost for 2000 homogeneous agents with a 5% reviewing rate at each iteration.

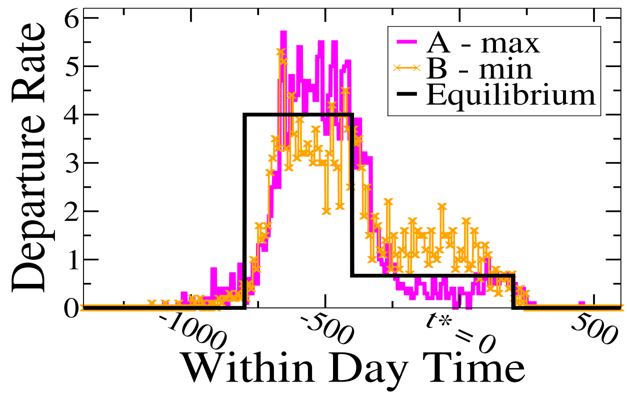

Figure 4: The departure rate functions at points A and B of figure (3)

the cost of the journeys undertaken. An agent who reviews his departure time calculates the cost of a randomly chosen departure time, and changes if this cost is sufficiently cheaper than his current cost. Simulations were performed with agents who had various sensitivities to cost.

Agents have a certain probability, or reviewing rate, of changing their departure time at each iteration. This rate (the percentage of agents who review their departure time at each iteration) is an important parameter of the model that must be carefully calibrated for operational models. The qualitative effects of changing this parameter are discussed below.

At each iteration the agents who review their departure time are chosen randomly, and the new departure time tested is chosen randomly from a flat distribution around the current departure time. This distribution is the same size as the domain of the simulation. All the agents who review their departure time calculate the cost of the new departure time assuming that no other agent changes his/her departure time.

In all the graphs that follow that show the value of a quantity that evolves from day to day the number of iterations is normalised. After one iteration the total number of times that individual agents have reviewed their departure times is equal to the number of agents. In a simulation with 2000 agents after one normalised iteration there have been 2000 reviews of departure time. This was done in order to facilitate comparisons between different reviewing rates.

3.1 Homogeneous Agents

Homogeneous agents all wish to arrive at the same time, t^*, and follow the same rules. For every agent the travel cost per unit time was, $\alpha = 2$, the cost of arriving early was $\beta = 1$ and the cost of arriving late was $\gamma = 4$.

The first simulation was performed with 2000 agents who began with their departure times distributed so that overall the departure rate function was that of the social optimum. 5% of agents reviewed their departure times each iteration. The within day time was broken into 2000 discrete units of time. The agents who reviewed their departure times chose a new departure time, at random, from a flat distribution between 1000 time units before and 1000 units after their current departure time. The average cost for such a simulation can be seen in figure (3). The agents in this simulation and in all other simulations presented here were assumed to be infinitely sensitive to reductions in cost. When the reduction in cost required for agents to change their departure time increased to 20 percent the only effect was to slow the overall evolution of the system, instability was uneffected.

The average cost does not converge but oscillates below 800 which is the value of the equilibrium. Figure (4) shows two departure rates, one for which the average cost is close to the equilibrium value A, and one for which the average cost is significantly below the equilibrium value, B. The departure rate at A has a form closer to that of the equilibrium.

3.1.1 *Explanation of the Oscillations*

The fundamental reason for the oscillations is that an agent who changes to reduce his own cost regularly has a much greater effect on the collective cost, often causing it to increase. When an agent changes from a departure time where he suffers no congestion to one where he encounters a traffic jam, he increases the travel time for all who join the traffic jam after him. An agent who changes to avoid the traffic jam reduces the cost for all who joined the traffic jam after him.

The trajectory of the global cost depends on the average evolution of the departure times:

- The effect of an agent who leaves earlier during rush hour is to increase the congestion experienced by those who leave between his new and old departure times.
- The effect of an agent who leaves later during rush hour is to decrease the congestion experienced by those who leave between his old and new departure times.

3.2 Heterogeneous Agents

Homogeneous agents is a very strong assumption to make and as we have seen leads to instability in the system. In order to add more realism and hopefully find a more stable global system we introduced heterogeneous agents to

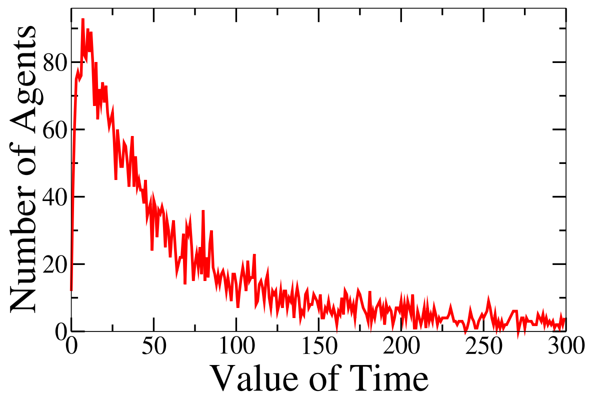

Figure 5: Graph of the number of agents for each value of time for 6000 agents. The values of time are distributed following a log-normal distribution with $\sigma = 1,775$ and $m = 2,423$.

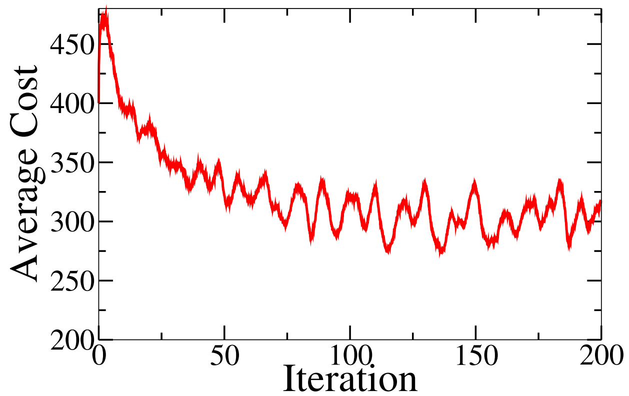

Figure 6: The evolution of the average cost for 6000 agents with the distribution of the values of time in figure (5)

the simulation. The first heterogeneity introduced was in the schedule delay costs, that is the costs of arriving either early or late. Later the agents were given a distribution of preferred arrival times.

3.2.1 *Distribution of Schedule Delay Costs*

We assumed that the agents would not all have the same aversion to arriving early or late. Studies [4, 6] have shown that there is a log-normal like distribution to the value of time among commuters. A study undertaken in Lyon [6] calculated this distribution to be given by the parameters $m = 2,423$ (mean) and $\sigma = 1,775$ (variance). The value of time of the 6000 agents were assigned randomly from such a distribution, figure (5). The schedule delay costs β and γ, see equation (4), for each agent were multiplied by the agent's value of time. It should be noted that α the cost of congestion, see equation (4), was the same for all agents.

The schedule delay costs were calibrated so that on average the cost when the agents were distributed at the social optimum was close to that for homogeneous agents i.e. 400. We can see from figure (6) that the average cost payed by the agents, who began with their departure times distributed

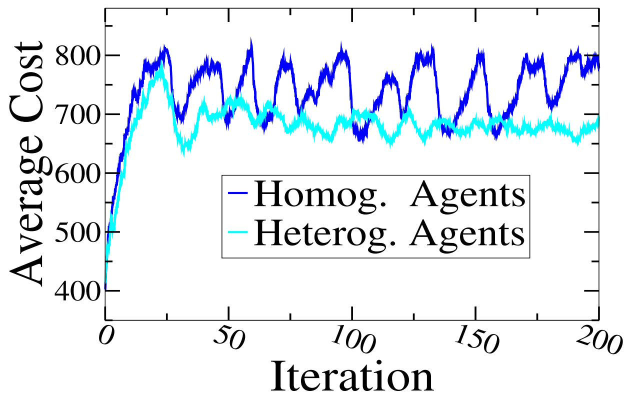

Figure 7: Comparison of average costs for homogeneous agents and agents with a Gaussian distribution of preferred arrival times of variance 100

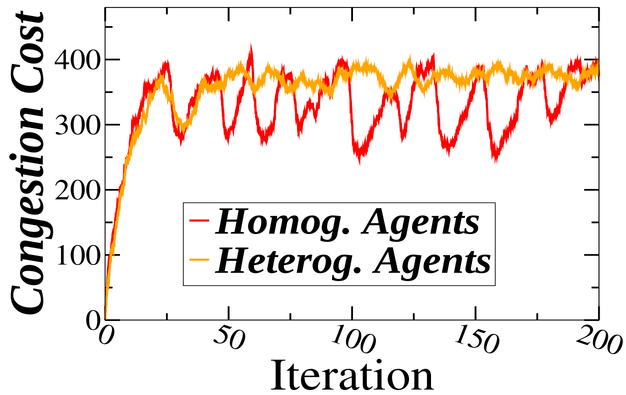

Figure 8: Comparison of congestion costs for homogeneous agents and agents with a distribution of preferred arrival times of variance 100

so that the overall rate of departure was that of the social optimum, reduces. This is because the agents with high schedule delay costs arrive near the desired time while the other agents avoid the high levels of congestion around the preferred arrival time. There are still significant oscillations that would render it very difficult to calibrate the model with observations.

3.2.2 *Distribution of Preferred Arrival Times*

It is clearly unrealistic that everybody wishes to arrive at exactly the same time. In order to correct this, each agent was given a preferred arrival time chosen randomly from a normal distribution around t^*,Many different variances of the normal distribution were tested, see below.

The amplitude of oscillations for a normal distribution of variance 100 were significantly less than those found for homogeneous agents, see figure (7). The average costs are of roughly the same magnitude, though slightly reduced for heterogeneous agents. More importantly, the cost for heterogeneous agents is much more stable. The stability of the average cost for heterogeneous agents comes from the stabilisation of the congestion cost, figure (8).

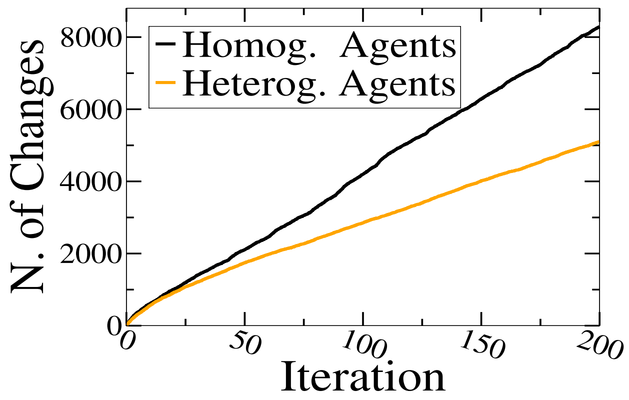

Figure 9: The total number of changes of departure time for heterogeneous and homogeneous agents.

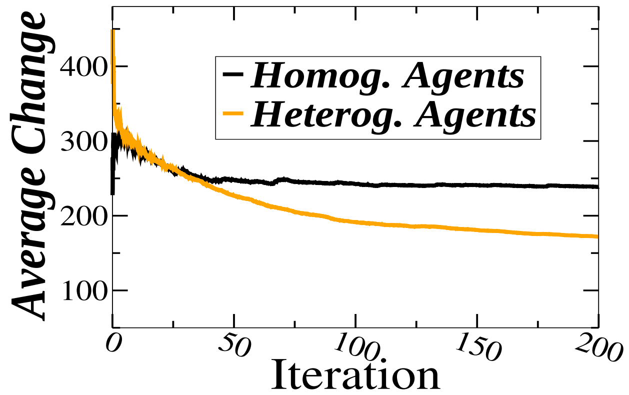

Figure 10: The cumulative average magnitude of changes for both types of agents.

The stability of the average cost is a result of the greater reluctance of the heterogeneous agents to change their departure times and the fact that the changes they do make are smaller in magnitude, see figures (9 & 10). The agents tend to find a niche, a small range of departure times, that give consistently the lowest cost.

3.2.3 Heterogeneity and Reviewing Rate

In order to calibrate any model it is necessary to understand the qualitative effects of important parameters. In which regions of parameter space do we find macro level behaviour that resembles observations. Two parameters of this simple model that have important effects are the reviewing rate, the proportion of agents that try a new departure time at each iteration, and the level of heterogeneity, the variance of the distribution of preferred arrival times.

The stability was taken as the standard deviation between 100 normalised iterations and 800 normalised iterations, during this time the agents have, on average, tried a new departure time 700 times.

From figure (13) we can see that the reviewing rate has a straightforward effect on the stability. When the reviewing rate is increased the system becomes more unstable. The dependence on the variance of the distribution of preferred

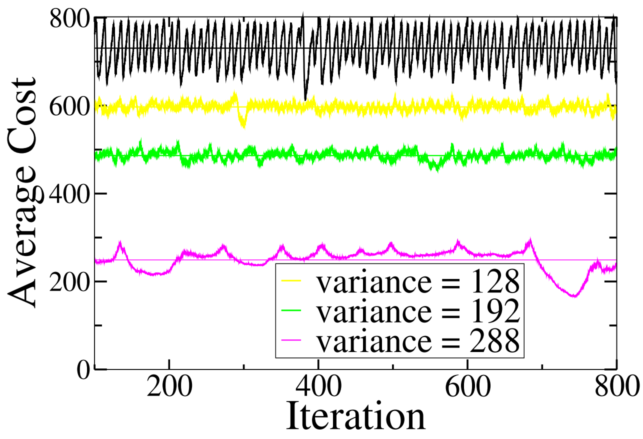

Figure 11: The average cost, with a reviewing rate of 4%, for a range of variances of the distribution of preferred arrival times, the straight lines of the same colour as the average cost curves are the averages between 100 and 800 iterations. The first curve is for homogeneous agents.

arrival times is more complex.

Figures (11 & 12) show the average costs and standard deviations for a range of variances of the distribution of preferred arrival times for a reviewing rate of 4%. Figure (12) is simply a slice taken from figure (13). We see that for a range of variances that the average cost is relatively stable, with a standard deviation of less than ten for average cost values of the order of 500 to 600.

Figure (13) shows some structure in the variation of the stability with increased heterogeneity of the agents. Figures (11 & 12) show that in the region where the instability increases as the heterogeneity increases the average cost oscillates in a different manner, that is with much longer periods. The increase in the standard deviation for variances of the distribution of preferred arrival times greater than 250 occurs in a region where the distribution of PAT becomes unrealistically large. The region in which the instability begins to decrease and then increases for rising heterogeneity at large reviewing rates, is too unstable to be a viable part of parameter space.

The parameter space of stable behaviour is roughly for reviewing rates less than 10% and variances of the distribution of preferred arrival times between 75 and 250.

4. CONCLUSIONS

The aim of this research was to find a robust and convergent model of traffic congestion that could subsequently be extended to a much more complex and realistic road network. It is clear that some level of heterogeneity is required in order to achieve stability. Basing the model on a network instead of a single road would add in itself an element of heterogeneity that could have a stabilising effect. We have found a congestion model that converges with sufficiently heterogeneous agents.

The model of a traffic bottleneck has significant instabilities

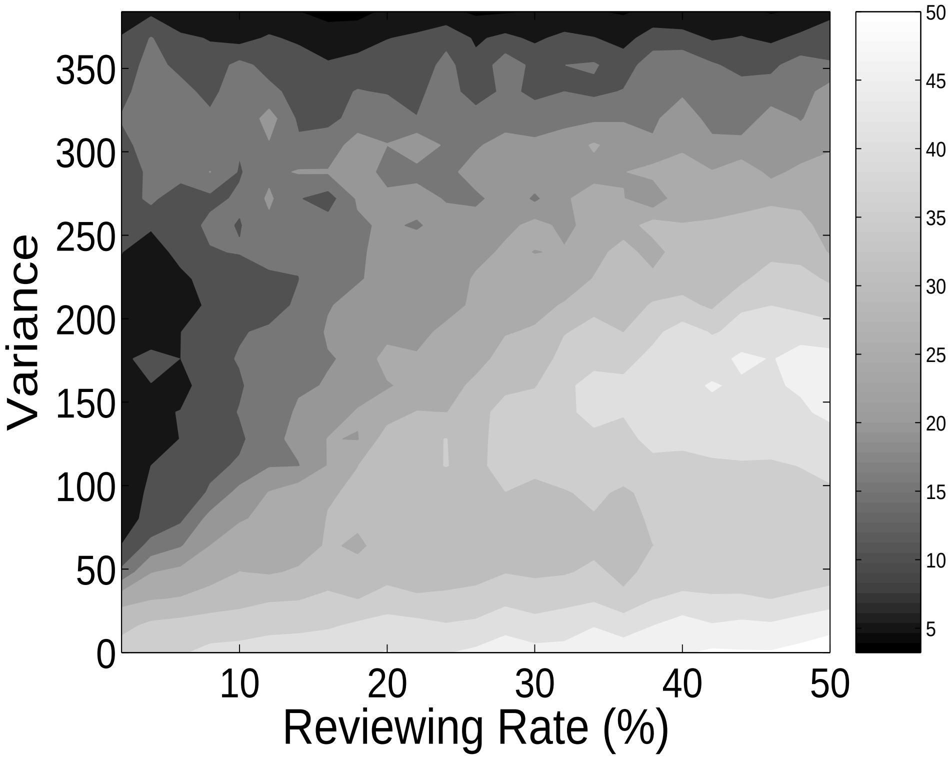

Figure 13: The stability for a range of variances of the distribution of Preferred Arrival Times and reviewing rates. Here the stability is the standard deviation over 700 normalised iterations, averaged over three simulations.

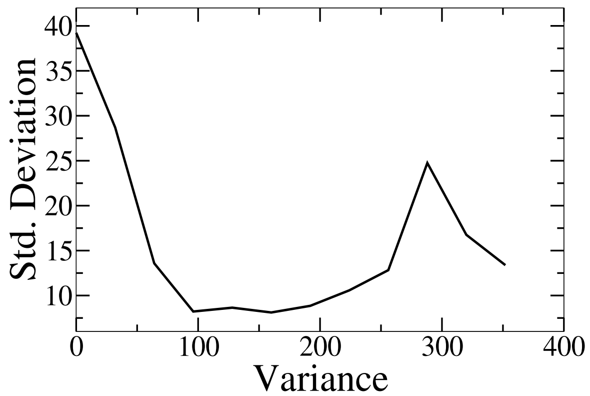

Figure 12: The stability (standard deviation between 100 and 800) against the variance of the distribution of preferred arrival times, as in figure (11) the reviewing rate was 4%.

when implemented with homogeneous agents. We believe these instabilities come from the difference between the benefit an agent accrues from changing its departure time and the effect of this change on the overall system.

Understanding the dynamics of the agent model on a simple example is a pre-requisite to incorporation in a more complex system where the same thorough analysis becomes impossible. We believe that we have found suitable dynamics that are sufficiently well "controlled" and understood, to be incorporated in a realistic transport network.

5. ACKNOWLEDGMENTS

Thanks to ADEME (Agence de l'Environment et de la Maîtrise de l'Energie) for partially financing this research and to Margaret Edwards for generous computing assistance.

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APPENDIX

A. DETAILS OF SIMULATION

The purpose of this appendix is to give sufficient information to reproduce all the results presented in this paper.

Homogeneous agents

All simulations for homogeneous agents were performed with 2000 agents. The temporal size of the simulation was equal to the number of agents in all cases, i.e. there were 2000 discrete time units. The capacity of the bottleneck, S, was 2 cars per unit time, this is equal to the departure rate at the social optimum, see figure (1).

For every simulation the agents were assigned their initial departure times such that the overall departure function was that of the social optimum, see figure (1). The agents depart at the capacity of the bottleneck and the first and last to arrive pay the same schedule delay costs.

In every simulation the percentage of agents randomly chosen to try a new departure time was kept constant. The agents chosen each picked a "test" departure time chosen randomly from a flat distribution, the same size as the temporal domain of the simulation, centred on the current departure time. In order to calculate the cost of the new departure time the entire cost function was recalculated assuming that only this agent changed. It should be noted that in the limit of large numbers of agents this is unnecessary. If the cost of the new departure time was less then that paid in the previous iteration by the agent, the agent adopted this new departure time.

At each iteration the congestion experienced by those who departed at each discrete time were calculated, using equations (1 & 2). The resulting congestion function was used to calculate the arrival time of every agent. The travel time on uncongested roads was normalised to zero as the constant portion of the travel cost does not affect the dynamics we wished to investigate. The total cost payed by each agent was then calculated by combining the congestion cost and the schedule delay cost as in equation(4). The values of α, β and γ in equation (4) were $\alpha = 2$, $\beta = 1$ and $\gamma = 4$.

Heterogeneous agents

In this section we specify how the simulations with heterogeneous agents differed from those with homogeneous agents.

Distribution of Schedule Delay Costs

In the simulations performed with agents who had a distribution of schedule delay cost parameters, presented in section (3.2.1), 6000 agents were used and there were 6000 discrete time units in the simulation.

When the agents were initialised, each was assigned a "value of time" chosen randomly from a log-normal distribution of mean, $m = 2,423$ and variance, $\sigma = 1,775$. In order to calculate the schedule delay cost for each agent the values of β and γ were multiplied by the "value of time" of each agent, the value of α remained 2 for all agents and the capacity S was unchanged. In order that the initial average cost should be comparable to that for homogeneous agents the schedule delay costs of each agent were divided by 32. This was also required to maintain the relevance of the congestion costs versus exploding schedule delay costs.

Distribution of Preferred Arrival Times

All simulations with agents who had a distribution of preferred arrival times were performed with 2000 agents in simulations with 2000 discrete time units.

When the agents were initialised they were each assigned a preferred arrival time,t^*, from a Gaussian distribution whose variance varied from simulation to simulation. This value of t^* was then used in equation (4) for the calculation of the schedule delay costs.

The values of α, β, γ and the capacity, S were the same as for homogeneous agents.

MultiAgent Approach for Simulation and Evaluation of Urban Bus Networks

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ABSTRACT

Evolution of public road transportation system requires analysis and planning tools to improve the service quality. A wide range of road transportation simulation tools exist with a variety of applications in planning, training and demonstration. However, few simulations take into account the specificities of public transportation. We present in this paper a bus network simulation which models these specificities and allows to analyze and evaluate a bus network at diverse space and time scales. We adopt a multiagent approach to describe the global system operation from behaviors of numerous autonomous entities such as buses and travellers. The developed simulation has been integrated into a decision support system for the design and the evaluation of bus networks. Some experimental results on a real case, showing the efficiency of the proposed model, are presented and discussed.

Categories and Subject Descriptors

I.6 [**Computing Methodologies**]: Simulation and Modeling; I.2.11 [**Artificial Intelligence**]: Distributed Artificial Intelligence—*Multiagent systems*

Keywords

Agent-oriented Modeling, Multiagent System, Public Transportation Simulation

1. INTRODUCTION

Users attitude towards transportation is in perpetual evolution for convenience, security and economical or environmental reasons. Public transportation systems, such as bus-networks, are a key design for people mobility. These systems, which are considered in this article, have to adapt to the demand in order to improve the service quality and the benefits. To develop new public transportation solutions it is very difficult or even impossible to use direct experimentation considering legal, financial, material or time constraints. Moreover, we cannot establish a global theoretical model for such systems due to their size and complexity.

A wide range of transportation simulation tools exist with a variety of applications from scientific research to planning, training and demonstration [20]. In the dynamic simulation domain, research usually focus on personal means of transportation and do not take into account the specificities of public road transportation. For example, in bus-network the vehicles are constraint by a timetable. In this paper we propose to integrate these constraints and parameters in the modeling and simulation process.

In a bus-network system we can identify three main components: people behaviors, road traffic dynamics and specific bus-network operations. This last encapsulates the interactions between the buses, passengers and road traffic. Complexity of a bus-network system results from these interactions. In this paper we show that the multiagent approach is an interesting way to model such systems and their interactions. This choice, derives basically from two observations. First, an urban public transport network is a naturally complex system which involves a set of distributed and interacting entities [2, 9, 13]. Secondly, the global system behavior is made of several emergent phenomena that result from the behavior of individual entities and their interactions [10, 12, 19]. For example, the real schedule of a bus is subject to passagers, road traffic and other buses. MultiAgent approach allow to model complex systems where numerous autonomous entities interact to produce global solutions or processes.

In this paper, we propose an original bus-network simulation handling three major constraints. First, the simulation must model the public transportation specificities. Second, it must allow to visualize the evolution of the different system components in simulated time (faster or slower than the real time). Finally, results of simulations must be analyzed at different time and space scales. As emphasized in [22], few works propose to tackle these three objectives in a same simulation tool. These different constraints, which are considered in our approach, were determined from a project related to the design and evaluation of the bus network of Belfort town (France).

This paper is organized as follows : After a presentation of our simulation objectives in Section 2, the architecture of the simulation model is presented in Section 3. Section

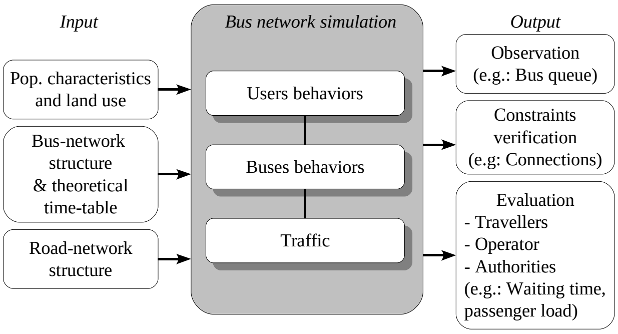

Figure 1: Simulation components.

4 presents its application to real cases and analyze some experimental results. Then, a conclusion and some study's perspectives are drawn in Section 5.

2. OBJECTIVES AND DEFINITIONS

2.1 Objectives of bus network simulation

Simulation of a bus network has three main interests: observation, constraint verification and network evaluation (see Output level in Figure 1). The first one concerns the global observation of the network, from a visual point of view. It allows the designers, operators and public authorities to have a global vision of the network and its dynamics. In other words, the simulation allows to observe the network functioning and to discuss its global design. The second interest of simulating such a network relies on the possibility to check local and global design constraints (e.g. passenger connections, timetable synchronization). Moreover, it allows to evaluate/control dynamic processes that are difficult to analyze from a static point of view. Finally, the third main advantage of the simulation is the evaluation of the network efficiency, considering different static and dynamic criteria through different scenarios.

As the input of the simulation we dispose of some available data. They are the characteristics of the population and the description of transport structures presented in the next section. From these initial data, the simulation must model the evolution of the bus network.

The global running of a bus network results from the behaviors and the interactions of the entities. Three main entities are identified as essential elements involved in a bus network: Buses, Passengers and the Road traffic. Figure 1 represents the main components of the proposed simulation. The model is based on these three elements.

2.2 Bus network structure

Basically, the static structure of a bus network is composed of four elements: itinerary, line, bus stop and bus station (Figure 2(a)). An itinerary is one of the main elements of a bus network. It can be represented by an oriented path on the road network which serves several bus stops. The route between two stops is called an inter-stop. Itineraries are grouped into lines when their functionalities are similar or complementary. For example, in Figure 2(a), the line L_1 is composed of the two itineraries L_1-Iti_1 and L_1-Iti_2 which form a round trip. It is important to differentiate: bus stop and bus station. A bus stop belongs to a single itinerary whereas a bus station gathers a set of close bus stops. The role of a bus station is to allow passenger connections. A temporal aspect is added to this static structure via timetables.

A timetable describes the whole expected arrival or departure bus times on bus stops. It can be represented by several diagrams similar to the one in Figure 2(b). A timetable contains all buses missions for a day. A mission is composed of several journeys performed by a unique bus. Each journey corresponds to an itinerary covered by a bus at a given time. A mission often consists to alternatively cover the itineraries composing a round trip.

The presented structures describe the theoretical evolution of buses into the bus network. However, to plainly describe a bus network and give a relevant evaluation, it is necessary to take into account travellers and the road traffic. Indeed, the global system evolution come from behaviors and interactions between buses, travellers and road traffic. To model such distributed and interacting entities we adopt a agent oriented approach as described in the next section.

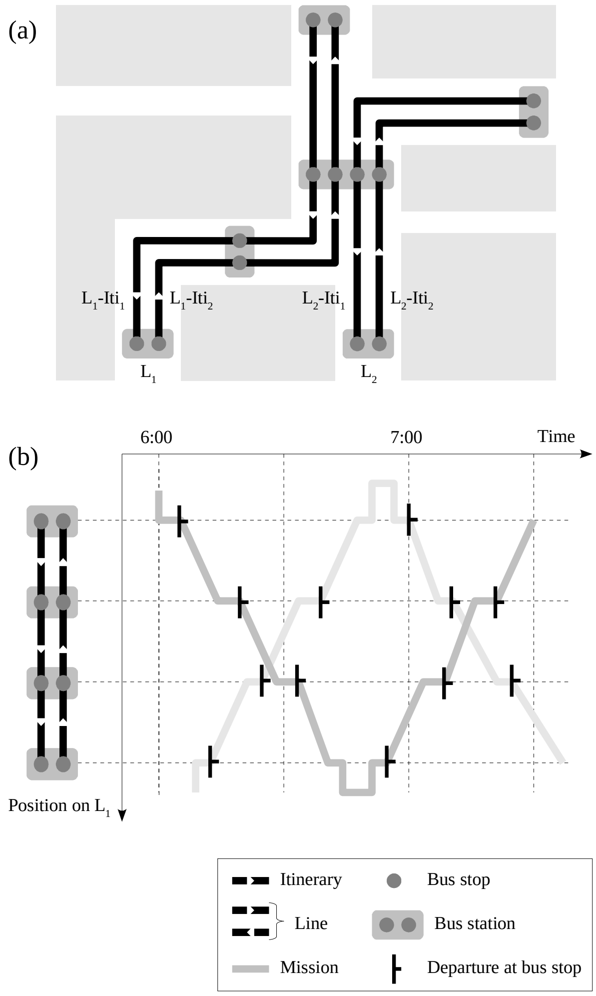

Figure 2: Structure of a bus network: (a) Static structure (b) Timetables view.

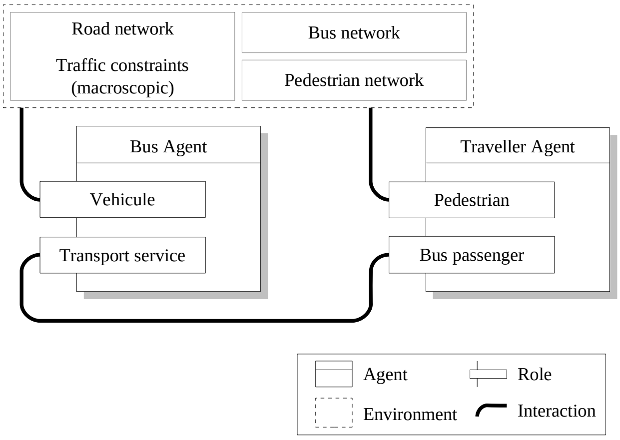

Figure 3: Roles and interactions of agents.

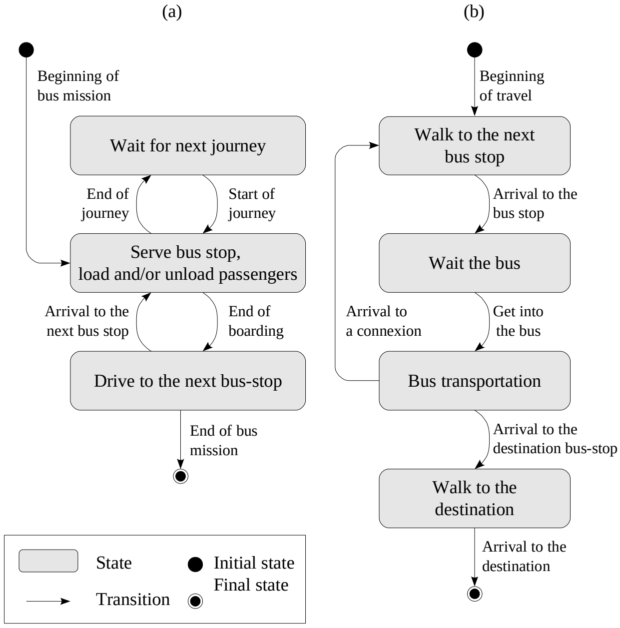

Figure 4: Agents behaviors presented as finite state automata: (a) Bus agent (b) Traveller agent.

3. AGENT ORIENTED MODELING AND SIMULATION

3.1 Interest of a MultiAgent approach

The proposed simulation model of bus network relies on combining an aggregate model of road traffic and Individual Based Models (IBM) of some mobile entities. Buses and travellers are considered as autonomous entities evolving in a wide and complex system. Then, we adopt a situated multiagent approach to model these entities.

Applying the multiagent approach to transport simulation presents several interests. First, there exists some techniques and platforms, as Madkit or Swarm [8, 14], to deal with the simulation of numerous entities. Second, agent modeling is a flexible approach to define autonomous behaviors. There is no constraint on the modelling level, i.e. an agent can describe one simple entity as a set of linked entities. For instance, a *Bus* agent can represent a bus, its driver and a set of passengers. Finally, reactive MAS are good tools to observe and to study emergent phenomenon, because they focus on the modelling of interactions between the entities [23]. The emergence of traffic jams in urban networks can be easily modeled by this way [18]. In our transportation model, where the dynamic is defined at the micro level by agents and their interactions, some global or macroscopic evaluations can be obtained.

3.2 MultiAgent modeling of a bus network

MultiAgent modeling requires to identify the relevant entities of the system and their interactions. In the considered urban environment, the basic components of our system are persons and vehicles. However, the potential number of these entities is too important to "agentify" all of them. Thus, we choose to only model buses and travellers as situated agents, and model other entities in a macroscopic way as shown in Figure 3. This choice allows to focus on buses and travellers activities in order to analyze travel time and network operations.

The environment, where *Bus* agents and *Traveller* agents move, is the composition of *Road network*, *Bus network* and *Pedestrian network*. These three elements are strongly linked by several interfaces. For instance, bus-stops are shared by both *Bus network* and *Pedestrian network*. Environment has a prominent role in situated MAS [25, 26]. In our case, environment is not only a shared common space where agents are located, it exhibits dynamical properties as traffic constraints. The main role of environment is to constraint perceptions and interactions of agents. Indeed, a *Bus* agent and a *Traveller* agent can interact only when they are located at the same bus stop. This constraint is provided by the environment. The two types of agents that move in this environment are now presented.

The *Bus* agent play two roles at the same time: *Vehicle* and *Transport service*. The *Vehicle* role describes the moving of the bus within the road network. This role is constrained by the road traffic and other *Bus* agents. The second role, the *Transport service* one, represents the ability of a bus to transport persons, considering its capacity and the demands. The behavior of a *Bus* agent is detailed in Figure 4.(a). In practice, an instance of *Bus* agent corresponds to a mission (as defined in section 2.2). The planning of the mission is pre-defined by the timetables, however, the progression of a *Bus* in the network is constrained by the road traffic and travellers (see section 3.3).

The *Traveller* agent plays the roles of *Pedestrian* and *Bus passenger* alternatively. The *Pedestrian* role is played when *(i)* the traveller goes to the first station, *(ii)* join a new station for a connection and *(iii)* goes to the travel destination from the last station. The *Bus passenger* role of a *Traveller* takes place when the agent waits at a station with the intention to take a bus. This role persists until the traveller reaches the desired station. The behavior of a *Traveller* agent is detailed in Figure 4.(b). Each bus travel corresponds to an instance of a *Traveller* agent. The route of a *Traveller* agent is pre-determined by a choice model (see section 3.4) but the transport duration results from the buses' behaviors.

3.3 Traffic simulation

We have seen in the previous section that a *Bus* agent interacts with car traffic when it covers an inter-stop. It is, then, necessary to model this traffic because it has a significant impact on the simulated system. Road traffic simulation has attracted much research [20]. Simulation models can be classified in three categories [15, 16]: microscopic, macroscopic and mesoscopic models.

- Microscopic model considers each moving vehicle within the road network. A vehicle has its own characteristics as its instantaneous speed, its size, its driving style, etc. The movement of a vehicle results from these "vehicle scale" properties. In [15], the authors discern submicroscopic models and microscopic models. Submicroscopic simulation models bring an additional level of details by describing the functioning of vehicles' subunits and the interaction with their surroundings.
- Macroscopic models represent traffic by introducing aggregated variables like vehicles density or their mean speed. These variables characterize the traffic at the scale of road segment or network.
- Mesoscopic models derive from both microscopic and macroscopic models. The vehicles are discerned but their movements result from macroscopic variables.

Microscopic simulation models require more detailled input, and greater computational resources than macroscopic and mesoscopic ones [5]. As we need to take into account the road traffic of a whole city and visualize the evolution of the bus network, we chose to develop an hybrid traffic simulation model. Vehicles, except the buses, are simulated with a macroscopic model whereas buses are simulated with a microscopic approach.

For the macroscopic model of traffic, the flow of each road segment for a determined period derives from a travel-demand model which is presented in section 3.4. Then, the *Bus* agents are constrained by these flows when they move. The influence of traffic flow on agents are unilateral. We neglect the direct effect of buses on traffic since they have only a local action on road traffic and it is not our objective to analyze impact of buses operations on road traffic. Moreover, when it is necessary, the *Bus* agents can interact directly to relate local moving constraints.

In addition to this traffic model, the time spent by a *Bus* agent at bus-stops is computed with a model derived from observations of Rajbhandari et al. and Dueker et al. [11, 21]. The model assumes that the main determinants of the dwell time are the number of person boarding and number of person alighting at the bus stop.

3.4 Modeling of travellers objectives

To identify the bus passengers and establish their transport behavior we use a demand model. The objective of a demand model is to determine needs of transportation from population characteristics. Typically, the inputs of the model are land uses, household demographics and other socio-economic factors. The outputs correspond to all trips of the considered population during a fixed period of time. In our model, we estimate the transportation demands from statistic survey, then, we determine the route and transportation mode of each demand.

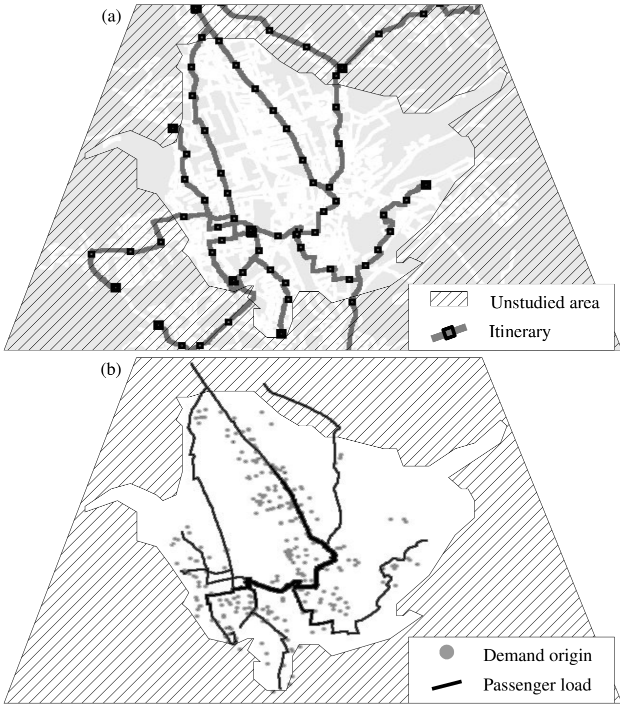

Figure 5: Views from Simulation: (a) Bus network structure (b) Repartition of the demand and passenger load at 8am.

A transportation demand related to a person is defined as an origin, a destination and a departure or arrival date. The demands properties are generated from statistic data (The Figure 5(b) shows such demands at 8am). Within a day, a person can make several transportation demands. For each demand, the user is faced to several alternatives of route, transportation mode or other choices. He makes his transportation choices considering his characteristics and the attributes of each potential alternative. To determine the demands related to the bus network, we focus on the mode choice. We model this choice with a Multinomial-Logit Model (MNL) [1, 3, 17]. This choice model assumes that each alternative is expressed by a value called utility, and include a probabilistic dimension to the decision process.

The multinomial choice model defines the probability for a given individual n to choose transportation mode i within the choice set C_n by

$$P\left(i|C_n\right) = \frac{e^{V_{i,n}}}{\sum_{j \in C_n} e^{V_{j,n}}} \tag{1}$$

Where C_n are the transportation mode alternatives which include personal vehicle like *car*, *walk* or other non-motorized mode, and *bus*. $V_{i,n}$ is the utility function of the transportation mode i. We consider an expression of utility derived from [1] and [6].

$$V_{i,n} = \mu_{cost}\left(c_{i,n}\right) + \mu_{time}\left(d_{i,n}\right) \tag{2}$$

$$d_{i,n} = \beta_{wait} t_{wait_{i,n}} + \beta_{walk} t_{walk_{i,n}} + \beta_{vehicle} t_{vehicle_{i,n}}$$

The utility function $V_{i,n}$ expresses that the perceived cost of a travel is composed of the financial or "out-of-pocket" cost of trip $c_{i,n}$ and the perceived duration of trip $d_{i,n}$ [24]. The parameters μ_{cost} and μ_{time} allow to balance these two costs. Thus, the ratio μ_{time}/μ_{cost} represents the cost of time. The perceived duration of a trip considers the effective duration of waiting, walking and in-vehicle situation of the traveler (t_{wait}, t_{walk} and $t_{vehicle}$). These values are weighted to add a comfort dimension and denote that the three situations, namely walking, waiting and in-vehicle are increasingly comfortable.

This model allows to instantiate the *Traveller* agents of our simulation and determine their route within both pedestrian and bus networks. Then, the results of demand model for personal transportation mode are used by the macroscopic traffic model presented in section 3.3.

4. EXPERIMENTATION

Considering the previous specification of agents and environment, we have implemented a multiagent simulation. In this section, a case study referring to the bus network of Belfort town (France) is presented. This study illustrates the proposed model and different evaluations of a bus network.

The simulation has been entirely implemented in a decision support software for the conception and the evaluation of bus networks. This application uses Java language and is linked to a relational database which involves Geographical Information System (GIS) data and transport structures data. The main objectives of the application are:

- Visualization and edition of a bus network that take into account the road network constraints.
- Static evaluation of a bus network through several measures: bus line length, inter-stop length, covering population by bus-stop, etc.
- Simulation of buses activity for observation and evaluation of operations occurring during a day.

Calibration and validation of the simulation have been performed from the analysis of passenger counter data of the current Belfort bus network. These data correspond to the counting of passenger boardings and alightings for each bus along a day. Then, the simulation has been applied for the design and evaluation of a new bus-network solution of Belfort city. The target area represents approximately 50 square kilometer and about $50,000$ citizen are covered by the bus-network. The last includes 8 bus-lines which represent 35 kilometer of covered roads as shown in Figure 5(a). For this study, input data come from a domestic travel enquiry [7]. This survey provides information about population characteristics and activity patterns. In this case study, a significant number of measures has been produced by the simulation tool. In the next two sections, we focus on two representative results: measure of passenger load and measure of bus passenger waiting time.

4.1 Passenger load of the bus-network

The load of the bus-network corresponds to the number of passengers in buses at a given date. The simulation allows to observe the geographical and temporal distribution

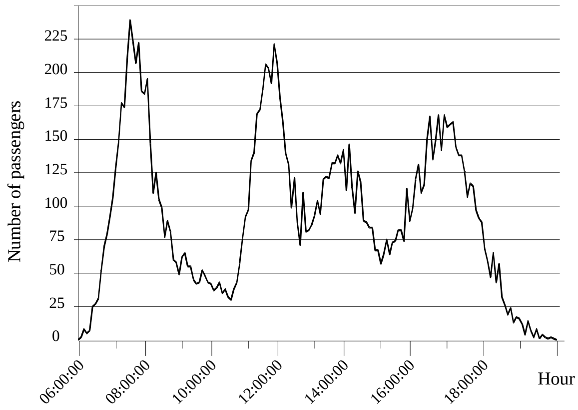

Figure 6: Simulation results for Belfort bus network, measure of the load of passenger.

of this measure in order to adjust, for example, the number of buses. This measure is obtained by counting, at each simulation step, the *Traveller* agents which are in *Bus transportation* state. The *Traveller* agents that walk or wait a bus are not taken into account. Figure 6 plots the simulated distribution of the bus-network load of passenger for a day. This measure results in about $15,000$ bus trips. We can discern the peak periods at 7, 12 and 17 o'clock which are commonly obtained in urban traffic analysis. Figure 5(b) represents the geographical distribution of passenger load at 8am and the associated demands origin. The stroke thickness denote the usage of the bus-network.

These measures allow to locate overload of bus and unused buses. Then, for a specific itinerary and hour the number of buses can be adapted to avoid load problems.

4.2 Passenger waiting time

The previous measure of load of passenger allows to give a first evaluation of the bus network considering the operator point of view. The passenger waiting time, discussed in this section, is a relevant measure to analyze bus network from a passenger's satisfaction point of view. The total waiting time for a bus trip corresponds to the sum of *(i)* the waiting time at the origin station and *(ii)* the waiting time at connections. In our simulation each agent keeps the simulating date of each state change. Thus, after a trip, a *Traveller* agent can calculate its waiting time. Figure 7 shows the average waiting time for different number of active buses on the network. Below a certain number of buses, a correct transportation service cannot be guaranteed. In the case of the studied bus network, if the objective is to obtain a average waiting time of 10 minutes, then the minimum number of buses must be 36.

Simulated planning of a traveller, and consequently its waiting time, result in emergent phenomenons as bus queues. This configuration occurs when two close buses serve the same itinerary. The bus that follows the head one has less passengers than the other, because this last one serves the bus-stops just before it. Then, the following bus spends less time at bus stops and catches the first one up. This phenomenon is commonly observed in reality and the simulation tool can prevent it.

The simulation allows several other measures on bus net-

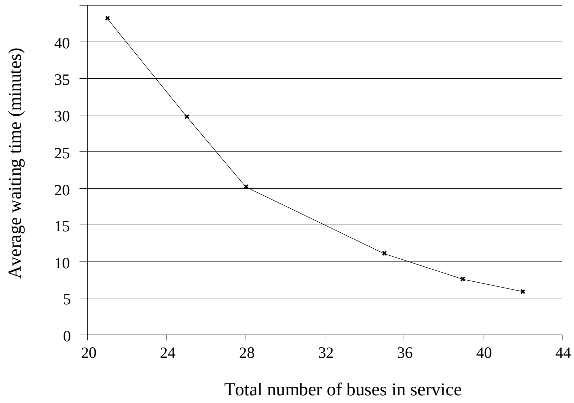

Figure 7: Simulation results for Belfort bus network, measure of passenger waiting time.

work efficiency like the bus saturation and the lack of passenger on bus-stops. Modeling buses and travellers as agents makes easy these kind of measures. Thus, most of evaluations to improve bus networks efficiency can be implemented through the proposed multiagent simulation tool.

5. CONCLUSION

In this paper, a multiagent simulation of bus networks has been presented. The model combines buses operation, traveller behaviors and a road traffic model. The agent-based approach allows to model such autonomous, dynamic and interacting entities. Moreover, this approach gives a solution to integrate an individual-centered view of buses and passengers within a macroscopic model of traffic. This model has been applied and validated on a real case study. Authorities, which manage the bus network of Belfort town (France), use the different functionalities and measures of the simulation tool to design new transportation solutions.

The main perspective of this work is to evaluate Intelligent Transportation Systems (ITS) [4]. They are usefull to regulate bus networks when some particular events happen during missions (e.g. accidents, traffic jam, etc.). Modeling and measuring the efficiency of these strategies is an interesting challenge.

Forthcoming works will consider other modes of public transport, and then the extension of the traffic model to a multi-scale one. It concerns the integration of a mesoscopic model of vehicles in traffic. This objective must provide more realistic bus movements and integrate traffic scenarios (e.g. accidents, roadworks).

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An Agent Framework for Online Simulation

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ABSTRACT
In this paper, we describe an agent framework for online simulation. An agent society is introduced for gathering online traffic measurements, controlling modules for origin-destination estimation and prediction, simulation, route choice and driving behavior. Additional communication agents allow splitting large scale networks into smaller units for a parallel simulation of the network. After the description of the agent framework, we briefly introduce the simulation modules and show results for travel time prediction using the proposed model.

Keywords
Agent Framework, Online, Simulation

1. INTRODUCTION
The main drawback of microscopic simulation models is the huge amount of computation time, which depends on the amount of vehicles in the network. To overcome this disadvantage the simulation can be performed parallel in a computer network. The basic approach is to separate the network in small sub-networks, which overlap each other and to synchronize the models after each or certain time steps. Once the network is divided, the simulation speed is determined by the slowest computer in the network or the busiest network part, where most of the vehicles have to be handled.

Since the amount of vehicles is the problem it seems to be more logical to distribute the computation tasks independent from the network, but according to the amount of vehicles to be handled in a network. The microscopic online simulator MiOS, developed at the Delft University of Technology, uses this approach to be able to handle large networks by parallel simulation. The network is not divided, but the update of the vehicles is done in parallel in a scaleable computer network.

In this paper it is shown that this approach can effectively be used for large scale networks and allows easily distributing microscopic simulations in a scaleable computer network without prior knowledge of the hardware or changes in the network model.

2. AGENT FRAMEWORK
2.1 Online Data Collection
Measurement data is usually stored in databases and can be accessed over the Internet or a local network. Gathering this kind of data, available in a network, is usually done by bots. Bots are software components that are aware of the network and check for new available data according to an internal schedule. Due to the fact that traffic measurements equipment is not always reliable and it requires more than just a pure collecting task collector agents are introduced. They handle the data collection for the MiOS system. They can physically be located at the source of the measurement data, or can request the data via the network. Their main task is to fuse various data types into a given format for further processing in MiOS. Further they are the first stage of data cleaning. If the collected data is outside predefined boundaries, the “wrong” datum will be exchanged by one extrapolated from the previous measurements. If the data is manipulated in this way the dataset, held at the collector agent, gets a manipulation flag that indicates that the datum has been manipulated.

2.2 Simulation Control
The online simulation of a traffic network consists of different tasks. The measurement data is used to estimate and predict OD relations in the network as input for the simulation. This traffic demand gets assigned to the network with a route choice model and the simulated vehicles react according to a driving behavior model. As stated before, for reasons of flexibility these tasks should be autonomous and exchangeable.

That raises the need to coordinate these tasks. Therefore, a control agent is introduced as the core of the system. It receives the input data from the collector agents and distributes the data to the modules performing the tasks for the simulation. Based on the user settings the control agent selects during runtime which modules are used for simulation, OD-estimation and driving behavior. That allows a high degree of flexibility of the framework, where modules can be plugged in and out even during runtime (hot-pluggable).

2.3 System-wide Communication
To deal with large scale networks and to ensure a sufficient simulation speed for microscopic simulation, the traffic network

has to be simulated partially, in a unit. To enable a unit to communicate with neighboring units communication agents are introduced. They provide information they get from control agents to other simulation units. This information not only contains traffic measurement but also the strategy of the subsystem, which is needed to predict the changes in the next time period. Beside that, the most important task is to coordinate the common time in the distributed system. Otherwise the decisions may be based on old data, which is not accurate anymore.

2.4 System Structure

Based on the 3 introduced agents, the structure of a single simulation unit consists of one *control agent*, several *collector agents* and a certain amount of *communication agents*, dependent on the number of neighboring units. The figure below illustrates the coverage of a partial network with a so called agent society.

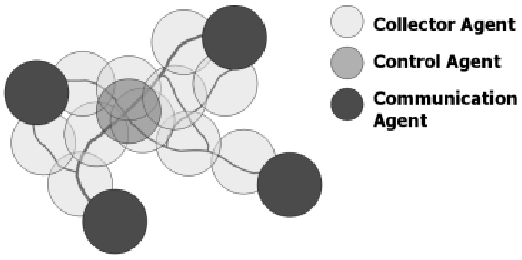

Figure 1: Structure of a road network covered by an agent society

Connecting the agent society with the modules of the MiOS simulator creates a so called simulation unit, in which the *collector agents* collect the measurement information for there area and send the information to the *control agent*. The *control agent* collects the data and triggers the simulation, which includes the modules for simulation, OD estimation, route choice and driving behavior. Simulation results get sent to a post processing unit, which handles the displaying of results and the interaction with the user.

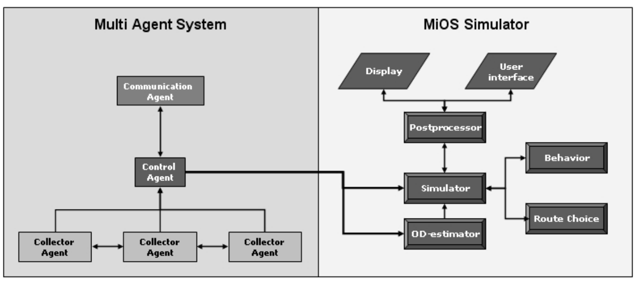

Figure 2: Structure of a simulation unit

3. SYSTEM ARCHITECTURE AND PROGRAMMING LANGUAGE

3.1 Decision of System Architecture

The goals of the software design determine the need for a distributed multi-agent system. Agents should be distributed in the network and remote method calls should enable the information flow as well as the start of processes in the simulation model. The scalability factor in the design leads to a peer to a peer (P2P) system which would offer most advantages. In contrary to the well known client-server (C/S) models, where the role between servers (resource providers) and clients (resource requester) is clearly distinguished, a peer to peer model mixes the roles. Each node can initiate the communication, be subject or object for a request, be proactive and provide capabilities. In such a system the agents and simulation modules have the ability to discover each other during runtime. Computers, running agents or simulation modules can enter, join or leave the network anywhere and any time.

The drawback of the system being fully distributed across the network is that the complexity and bandwidth tends to grow exponentially with the number of connected computers. The absence of any reference in a pure P2P system makes it difficult to maintain the coherence of the network and to discover the offered functions in the network. Also security is quite demanding as each node is entitled to join the network without any control system.

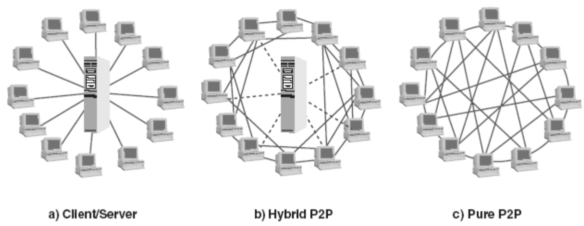

Figure 3: Comparison of different model structures

By choosing a hybrid P2P architecture (see figure 3) this drawback can be overcome. In this architecture one computer is added with special services, which provide a simplified look-up for specific computers or functions in the network, like the white pages for phone users, as well as the capabilities to find a computer in the network to perform a certain task, which would be the equivalent of the yellow pages. This creates less traffic and by adding a registration and authentication of joining computer it also increases the security of the whole system.

3.2 Programming language and Runtime environment

After the design of the system and the architecture is chosen it is time to decide about the runtime environment and the programming language of the system. To follow the principal of independency JAVA was chosen as the main programming language of the system. JAVA allows a platform independent development and also assures the easy use of cross-platform programming if that is needed.

The main requirement of the proposed system is the distribution in the network and so a middleware is needed. Middleware is a general term for any programming that serves to "glue together" or mediate between two separate programs. A common application of middleware is to allow programs written for access to a particular database to access other databases (well know from Internet services). Middleware programs provide messaging services so that different applications can communicate. The systematic tying together of disparate applications through the use of middleware, is known as enterprise application integration. Next to a variety of commercial middleware, the amount of independent and GNU licensed middleware is increasing. So to avoid a dependency to a commercial product the used middleware should be non-commercial.

The middleware Java Agent Development Framework (JADE)[1], developed by the Telecom Italia Lab and published under the Lesser GNU Public License (LGPL)[2], suits all the requirements stated above and has so been chosen for the development. JADE allows a fast development of distributed agent system by providing standard services for communication and life cycle management of the agents according to the standards of the Foundation for Intelligent Physical Agents (FIPA)[3]. An overview of that standard is shown in the figure below.

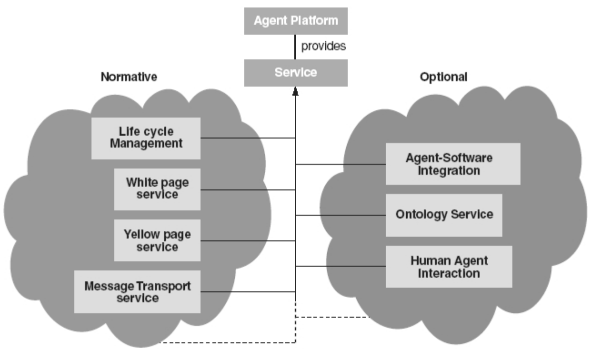

Figure 4: FIPA standard for services provided by a platform

The communication between the agents offered in JADE is done by the Agent Communication Language (ACL), also a standard from FIPA. It is based on the speech act theory [4] and on the assumptions and requirements of the agent paradigm. This paradigm is based on the agent abstraction, a software component that is autonomous, proactive and social:

- *autonomous*: agents have a degree of control of their own actions, they own their own thread of control and, under some circumstances, they are also able to take decisions
- *proactive*: agents do not only react in response to external event, for instance a remote method call, but they also exhibit a goal directed behavior and, where appropriate, are able to take initiative
- *social*: agents are able to, and need to, interact with other agents in order to accomplish their task and achieve the complete goal of the system.

Common patterns of conversations define the so-called interaction protocols that provide agents with a library of patterns to achieve common tasks, such as delegating an action, calling for a proposal and so on. The standardization of this protocol is shown in Figure 5.

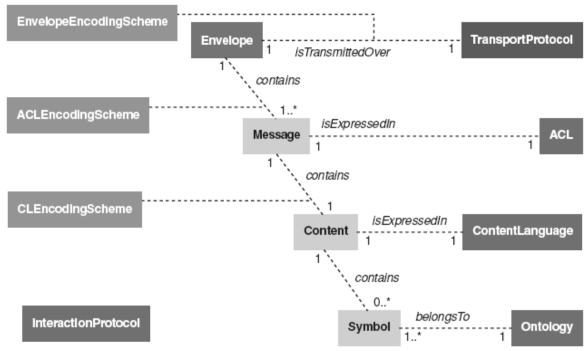

Figure 5: Communication model standard from FIPA

So with the chosen programming language and middleware for the development the further section describes the implementation of the multi-agent system by using the JADE environment.

4. IMPLEMENTATION

JADE organizes the distribution of software modules and agents with containers and platforms. A container runs on a single computer and includes the agents and software modules. The amount of containers in a local network is combined to a platform. According to the hybrid structure, each platform must have a main container, at which all other containers are registered. In this main container, JADE automatically starts two special agents offering the following services:

- The AMS (Agent Management System) that provides the naming service (i.e. ensures that each agent in the platform has a unique name) and represents the authority in the platform (for instance it is possible to create/kill agents on remote containers by requesting that to the AMS).
- The DF (Directory Facilitator) that provides a Yellow Pages service by means of which an agent can find other agents providing the services he requires in order to achieve his goals.

Figure 6 visualizes the JADE concept described above and shows an example for its setup.

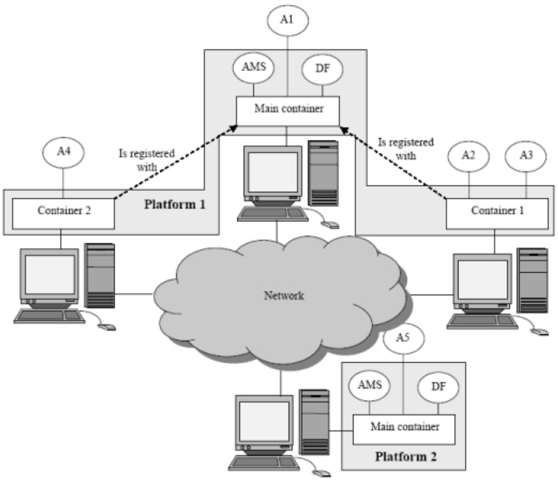

Figure 6: Containers and platforms in JADE

Due to the central role of the main container for the runtime environment and the control agent for a simulation unit, the control agent is started in it as a fixed service. The communication agent instead can be started in any other container of the platform among the modules for the online simulation. Due to the physical independency of the source of traffic measurement data from the control center, collector agents can be installed and started on any other platform in the network.

4.1 Collector agent

For each data source, like traffic measurements, weather data or incident data, the multi agent systems creates a new Collector agent. The attributes for this agent are set via the user interface and include the location of the data source, the frequency of data updates, reasonable boundaries for the data and the protocol to receive the required information. When the agent got started, an internal timer triggers the data request to the data source, which is mostly in form of a database query.

If the data arrives in a predefined time limit the data get pre checked by the collector agent. If the data is outside the defined reasonable boundaries it gets marked as unreliable. This method filters out outliers in the measurements which can occur and would severely change the simulation process. If the data lies close to the boundaries the data gets an incident flag which indicates that either the measurement is unreliable or that the change in traffic conditions signalizes an incident in the network. If no data arrives in the time limit, an empty dataset with an unreliable flag is stored. In any other case the data is stored as it is. The data of the last 5 requests is stored in the collector agent.

After the data is pre processed the collector agent looks up the control agent of its unit and transmits the data.

4.2 Control agent

The control agent as the central point of each unit collects the data from all collector agents and feeds the OD estimator of MiOS with it. Further the control agent triggers the simulation itself. Even though the simulation process is independent from the multi agent framework, the control agent determines which tools are used.

So if no specific algorithm is defined in the framework, the control agent can lookup all simulation tools which are available and chose one. This allows the easy exchange of all components of the system. The same mechanism is used for the robustness of the system. If a simulator or the OD estimation module is not responding anymore it will be replaced by an alternative tool in the network. To enable even more robustness and a smooth exchange, the control agent buffers the simulation states of every key frame. A key frame is the actual traffic situation which is taken as a snapshot in defined frequency. This allows a setup of a new simulation task with the smallest possible delay and assures an ongoing support for a traffic control center.

When different scenarios are calculated with the MiOS system, the control agent distributes the simulation tasks over all reachable simulation modules. The scalability of the system is therefore no problem. Additional simulation modules which are started in the computer network can be looked up easily. Nevertheless, when for any reason the computation time exceeds a critical value, the control agent will limit the simulation tasks and inform the user.

4.3 Communication agent

If more than one control agent is involved in the simulation, a communication agent ensures that the traffic situation in the overlapping areas of the partial networks is transferred. That means that a communication agent does the same as a collector agent, except that the data source is another simulation unit. It collects the actual status of the link and informs the attached unit. Like a collector agent, the communication agent has to ensure the consistency of time. So the slowest unit of the simulation determines the speed of all units. Due to slight oscillation in the computation time the communication agents can buffer up to 50 time steps. If the buffers are full, the communication agent sends a message to its control agent and the faster simulation is halted. If units are on hold longer than a pre defined threshold the user will be informed, so that the area of the units can be changed to balance the computation load.

5. APPLICATION

5.1 The Microscopic Online Simulator MiOS

5.1.1 Cellular automata simulation

In cellular automata systems **space** is represented by a uniform grid. Unlike default cellular automata systems, MiOS uses a cell length of 0.5 m (in stead of 7.5 m). So, a vehicle can occupy a number of cells. This enables MiOS to model different vehicle classes like cars (4.5 m), delivery vans (7.0 m), busses (12.0m) and trucks (17.0 m)[5]. Each cell contains a few bits of data.

In cellular automata systems **time** advances in discrete steps. Unlike the default step of 1 s MiOS uses steps of 0.1 to update the system. This makes the representation of speeds (expressed in 0 to

8 cells per 0.1 s) and the distribution of gap sizes (cells) between cars more accurate.

The **rules** of the system are expressed in a small look-up table, through which at each step each cell computes its new state from that of its close neighbors. Thus, the system's rules are local and uniform. The advantage of the cellular structure is that it allows simple physics.

Every time step, the new **car** positions and speeds are calculated for each individual vehicle based on the same situation; first the most suitable lane (vehicles can follow the chosen route), second the appropriate speed (adjusted desired speed taking into account gaps). This update procedure is done quasi parallel, which means that the new car positions and speeds are calculated for each individual vehicle based on the same situation.

5.1.2 Route Choice

Each OD pair has a set of possible paths Pij. The impedance of the path depends on the link based weights Zij, which are determined by the length of the link Lij from vertex i to vertex j, the actual average speed Uij of V cars on that link, the maximum speed Umax,ij and the recommendation parameter Θ. The parameter Θ distinguishes the different road types and takes in-car route guidance systems and en-route traffic information into account. With T for the road type α as an indicator for in-car systems and β as a factor for en-route information, Θ can be described as:

$$\Theta = (\alpha \cdot \beta) * \mathrm{T} \tag{1}$$

with:

$$\alpha := percentage\ \ of\ equipped\ \ cars,$$

$$\beta := percentage\ of\ \ drivers\ \ following\ the\ advice,$$

$$T := \begin{cases} 1.0 & for\ highways \\ 2.5 & for\ urban\ roads \\ 5.0 & for\ inner-city\ roads \end{cases}$$

That means, that a driver, independent of the type of the road, if his or her navigation system advises a route or a mandatory redirection is given en route. For non-equipped vehicles, the parameter β represents the willingness of the driver to follow en route information. When a vehicle is generated, it is assigned to the shortest route between its origin o and its destination d in an empty network. The driver is trying to find another route if he does not feel comfortable anymore, which means that the comfort factor $C_D < 0$. Let be:

$u_{a,v}$	the actual speed of driver D [km/h]
$u_{d,v}$	the desired speed of driver D [km/h]
$v_{r,v}$	the number of cars on link r, where D is driving and [vehicles]
$c_{r,}$	the maximum amount of vehicles that can be placed in congestion on link r.

Then the comfort factor C_D of driver D is determined as:

$$C_D = \frac{u_{a,v}}{u_{d,v}} - \frac{v_{r,v}}{c_r} \tag{2}$$

Due to the fact that the weights include the recommendation parameter, it is not necessarily the case that a driver can find a route, which gave him more comfort. He or she will maybe stay on a congested link. If a driver does not feel comfortable anymore he triggers the model to calculate a new route. That means, if P^0_{od} is the shortest path between origin o and destination d in the empty network and P_{od} the actual shortest path in the network that:

$$\begin{array}{ll} if\ C_D > 0 & P_{od} = P^0_{od} \\ else & P_{od} = \min P_{od}\ \ in\ G \end{array} \tag{3}$$

A detailed description of the route choice model of MiOS can be found in [6].

5.2 Intersections and Traffic Control

In the current version of MiOS a vehicle actuated traffic control has been implemented without priority rules for public transport and other tactics like parallel green. For each intersection the green times for each stream and the values for the extended green time are given. Furthermore, the clearance time matrix is given.

The intersections have additional components, according to the normal link representation. The centre of the intersection is not covered with cells and is used as a kind of black box. Vehicles, entering this part experience a time delay for crossing the intersection. The last cells of the approaching links control the capacity of the area and show the information of the traffic lights or on non-signalized intersections priority rules. Nevertheless, the intersection component includes the cells for the approaching and off going links and a blocking of an intersection can be simulated as well.

5.3 Region Laboratory Delft (Regiolab)

To measure the current situation, online data is needed. This requires an extended detection and communication system. This online data is available in the real life laboratory in the region of Delft (Regiolab Delft) in the Netherlands. Regiolab Delft is a combined research effort of the Delft University of Technology, the research school TRAIL, the Dutch Ministry of Transport, the province of South Holland, the municipality of Delft and the traffic industry.

A variety of existing and newly developed traffic detection systems enable Regiolab Delft to monitor traffic (flow rates, speed, density, travel time) and to estimate the actual origins and destinations of flows. In addition, in the near future Regiolab

Delft will also receive information about the actual status of the freeway control systems (ramp metering, speed control, lane use), weather conditions, and so on. For research goals, a data storage and analysis system is developed supplying different users with dedicated information.

As the Delft University of Technology has access to all these on-line traffic measurements in this region, the city of Delft was chosen as a test bed for the development of the MiOS system and a traffic management support system based on it. It provides the on-line input and enables to calibrate the model and to evaluate the simulation predictions.

6. RESULTS

As research area the City of Delft was chosen. Two motorways surround the city and an urban road connects these freeways in the South of Delft. The motorways are equipped with inductive double loop detectors and the urban road has video detection with license plate recognition for vehicles going from the A4 in the West to the A13 in the East. Additionally, traffic counts from the major intersections of the urban road are available. The whole Delft area has been simulated on a two-computer network and afterwards the simulation results have been compared to the measurements. Figure 7 shows the results for the motorway A13.

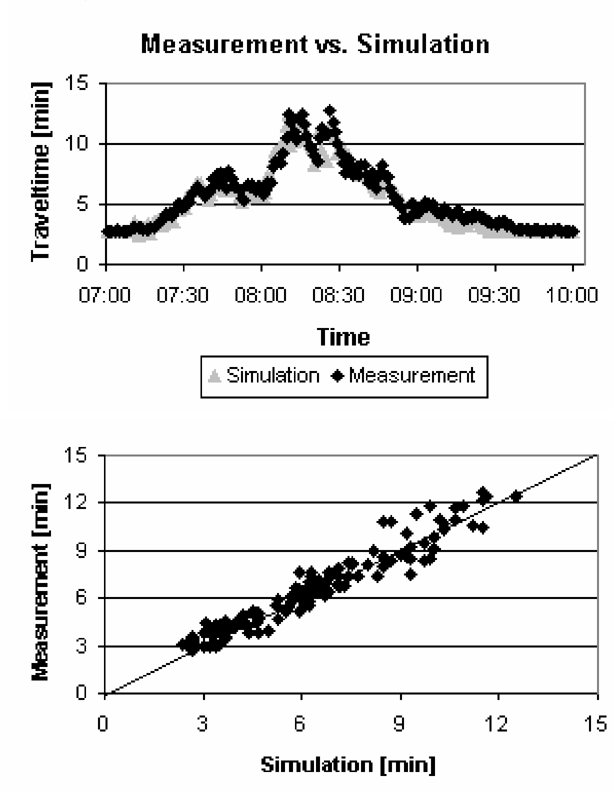

Figure 7: Prediction of travel times compared with measurements on a motorway

Figure 8 shows the results on the arterial road. It can be recognized that the variance in travel times in the prediction is less wide, but the mean travel time is well represented.

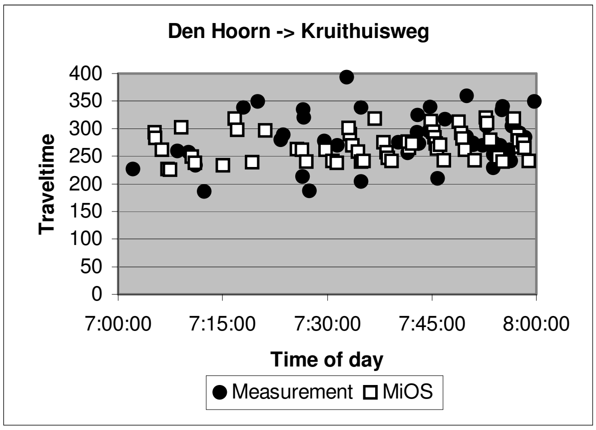

Figure 8: Prediction of travel time compared with measurements on a motorway

7. CONCLUSIONS

It could be shown that the microscopic online simulator MiOS is able to predict travel times as well on motorways a s for arterial roads. The design of the model and the opportunity for parallel simulation in a computer network, organized by agents makes the model highly scaleable to larger networks and gives the opportunity to forecast traffic situation with a rolling horizon, so that road authorities can take measures accordingly.

Further research activities will lead to a decision support system to support traffic control centers, based on the online prediction of the simulator MiOS.

8. ACKNOWLEDGEMENT

The research project is funded by the AVV Transport Research Center of the Dutch Ministry of Transport, Public Works and Water management and is part of the "Region Laboratory Delft", which is a combined research institute of the Delft University of Technology, the Dutch Ministry of Transport, road authorities and the industry.

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A Reactive Agent Based Approach to Facility Location: Application to Transport

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ABSTRACT

Facility location problem concerns the positioning of facilities such as train stations, bus-stops, fire stations and schools, so as to optimize one or several objectives. The review of different facets of this problem shows a real interest for transportation systems. Since the location model decisions are an influencing factor for the relevance and the attractiveness of transportation services. This paper contributes to research on location problem by proposing a reactive multiagent model to deal with a classical variation: the p-median problem, where the objective is to minimize the weighted distance between the demand points and the facilities. The proposed approach has a physical inspiration. It is based on potential fields technique, especially using attractive and repulsive forces between agents and their environment. The optimization of the system is then obtained from a global self-organization of the agents (the facilities). The efficiency of the proposed approach is confirmed by computational results based on a set of comparisons with the K-means clustering technique. Particularly, the approach is evaluated on the problem of bus-stops positioning in a real bus-network.

Categories and Subject Descriptors

I.2.11 [**Distributed Artificial Intelligence**]: Multiagent systems; G.1.6 [**Optimization**]: Global optimization

General Terms

Theory, Experimentation

Keywords

Facility location, P-median Problem, Multiagent systems, Reactive agents, Potential Fields, Optimization, Transport

AAMAS'06 May 8–12 2006, Hakodate, Hokkaido, Japan.

1. INTRODUCTION

The facility location problems have witnessed an explosive growth in the last four decades. As Krarup and Pruzan [15] point out, this is not at all surprising since location policy is one of the most profitable areas of applied systems analysis where ample theoretical and applied challenges are offered. The term facility is used in its broadest sense. It refers to entities such as bus-stops, train stations, schools, hospitals, fire stations, etc. A wide range of facility location models exists [26]: set covering, p-center, p-median, etc. The general problem is, then, the location[1] of new facilities to optimize some objectives such as distance, travel time or cost and demand satisfaction.

The operations research community devoted a strong interest to location problem analysis and modeling. This is due to the importance of location decisions which are often made at all levels of human organization. Then, such decisions are frequently strategic since they have consequential economic effects.

However, location problems are often extremely difficult to solve, at least optimally [9] (classified as NP-Hard). Furthermore, there does not exist a generic solution that is appropriate for all potential or existing applications.
There exists some works based on genetic algorithms, branch and bound, greedy heuristics, etc. These approaches are not easily adapted for dynamic systems where the system constraints or data change. This is a real limitation since most of real problems are subject to change and dynamics. To deal with this lack of flexibility and robustness, we adopt a multiagent approach which is known to be well suited for dynamical problems [8].

This paper proposes a multiagent approach for the facility location problem based on reactive agents. To our knowledge, no reactive agent-based approaches have been already used to deal with this problem. The choice of a multiagent approach provides several advantages. First, multiagent systems are well suited to model distributed problems. In such systems, several entities evolving/moving in a common environment have to cooperate to perform collective and local goals. Second, even if the multiagent approach does not guarantee to find optimal solution, it is able to find satisfying ones without too much computational cost [27]. Through this paper we show that the reactive multiagent

[1]Deployment, positioning and siting are used as synonyms

approach can be an interesting new way for optimization in positioning problems. Then, it provides satisfying solutions in addition to other assets as flexibility, modularity and adaptability to open systems. In our approach, agent behavior is based on the combination of attractive and repulsive forces. The key idea is that agents are attracted to the demands and repulsed by other agents.

This paper is structured as follows: section 2 presents the facility location problems. Then, section 3 details the proposed multiagent approach. Section 4 presents experimental evaluation on two cases: (1) positioning stations on the France map, and (2) positioning bus-stops for the real case of the city of Belfort (France). Section 5 is devoted to the model discussion. Then, the last section gives some conclusions and perspectives.

2. THE FACILITY LOCATION PROBLEM

In the parlance of literature, the general facility location problem consists in locating new facilities to optimize some objectives such as distance, travel time or cost, demand satisfaction. In the following section, we present several variants of facility location problems that can be tackled by our approach.

2.1 Variants of the problem: an overview

There are four components that characterize location problems [21]: (1) a space in which demands and facilities are located, (2) a metric that indicates distance (or other measure as time) between demands and facilities, (3) demands, which must be assigned to facilities, and (4) facilities that have to be located. There exists two types of location problems: continuous and discrete ones.
The problem is continuous when the facilities to be sited can generally be placed anywhere on the plane or on the network. In discrete location problems the facilities can be placed only at a limited number of eligible points.
A non-exhaustive list of facilities problems includes: p-center, p-median, set covering, maximal covering.

- Set Covering Location Problem (SCLP) [26]: the objective is to locate the minimum number of facilities required to cover all the demand nodes.
- Maximal Covering Location Problem (MCLP) [4]: the objective of the MLCP is to locate a predetermined number of facilities such that the covered demand is maximized with the assumption that there may not be enough facilities to cover all the demand.
- p-median problem [10, 11, 3]: this problem locates p facilities that will serve n demand points in some space. The space can be an euclidean plane or a road network. The objective is to minimize the weighted distance between the demand points and the facilities. In this paper we will particularly focus on the p-median problem.
- p-center [10, 11]: the p-center problem addresses the problem of minimizing the maximum distance between a demand and its closet facility, given that we are siting a predetermined number of facilities.

There exists several other classes of location problems [6]: dynamic location problems, where the time dimension is introduced, these problems recognize that the parameters (e.g. demand) may vary over time; stochastic location problems where the problem parameters are not known with certainty; multiobjective location problems that consider multiple, often conflicting, objectives, etc.

2.2 Solving approaches

We have seen in the previous section that there is a wide range of facility location problem variants. Their mathematical formulations are well known [6]. However, formulating is only one step of analyzing a location problem. The other step and the most challenging one is to find optimal solutions.

Typically, the possible approaches to such a problem and especially to the p-median problem, consist in exact methods which allow to find optimal solutions. A well-known example of methods is branch and bound [24]. However, these solutions are quickly inefficient for very complex problems, i.e. with hundreds of constraints and variables. Then obtaining optimal solutions for these problems requires colossal computational resources. This justify the NP-hardness of the p-median problem [9].
Another category of methods are proposed for the p-median problem. These methods, known as heuristics, allow to find good solutions, but do not guarantee finding the optimal one(s): Greedy heuristics [5]; Genetic algorithms [2, 13]; Improvement heuristics [19, 25]; Lagrangean relaxation [7], etc.
However, these approaches have several drawbacks such as the computational cost (huge population size and long convergence time, for example in genetic algorithms); their rigidity and their lack of robustness and flexibility. Particularly, for dynamic problems characterized by the change of the problem constraints, optimization criteria, etc.

This paper explores another possible heuristic which is based on multiagent systems. For the following of the paper we will focus on this approach. After presenting the p-median problem and the reactive multiagent systems, we detail our approach.

3. A REACTIVE APPROACH FOR THE CONTINUOUS P-MEDIAN PROBLEM

In this section we present a reactive agents based solution to the p-median problem. Our model relies on the Artificial Potential Fields (APF) technique. This technique is generally used for decentralized coordination of situated agents [1, 18].

3.1 Problem statement

We consider the problem of continuous stations positioning to illustrate our approach. It consists to locate a fixed number of stations (train stations or bus-stops) such that the whole environment space may be used for locating stations. The objective is to minimize the distance between users demand and the stations.
The problem is expressed as follow [20]:
A = the set of demand points in the plane $\Re^2$ (or more generally $\Re^n$) indexed by a
W_a = a positive weight assigned to each demand
P = the maximum number of facility lo locate
The problem is to find a subset X of P within a feasible

region $S \subset \Re^2$, such that:

$$\min_{X \subset S} F_A(X) \tag{1}$$

$F_A(X) = \sum_{a \in A} W_a \ . \ \min_{x \in X} d(x, a)$

Subject to:

$$\sum_{x \in X} x \leq p \tag{2}$$

The objective function (1) minimizes the demand-weighted distance. Constraint (2) stipulates that at most p facilities are to be located.

3.2 Reactive agent model

An agent can be viewed as an entity that is able to perceive its environment and to act according to its own decisions [8]. The decision making process can be complex, as in cognitive architectures [12], or more simple as in reactive ones.

3.2.1 Potential Fields Based Approach

Reactive agents have simple behaviors based on reaction to stimuli coming from the environment. Intended to handle basic behaviors, their architectures are based on simple routines without abstract reasoning [27]. Such a scheme is more appropriate to deal with numerous agents having collective processes. Agents have numerous interactions between them and their environment in a stimulus-response way to collectively organize the whole system [8].
Reactive agents have been deployed in several fields, such as collective robotics [1], complex systems simulation, distributed problem solving [23], web agents construction [8].
In many works, the behavior of reactive agents is based on the Artificial Potential Field technique. This method has several inspirations (physical, biological, etc.). The concept was introduced in Lewin's topological psychology [16]. The key idea is that the human behavior is controlled by a force field generated by objects or situations with positive or negative values or valences.

During the past decade, potential field theory has gained popularity among researchers in the field of autonomous robots [14] and especially in robot motion planning thanks to their capability to act in continuous domains in real-time. By assigning repulsive force fields to obstacles and an attractive force field to the desired destination [22], a robot can follow a collision-free path via the computation of a motion vector from the superposed force fields [14, 28]. However, the APF technique is limited by a well known drawback: local minima [1]. Indeed, adding attractive and repulsive fields can produce areas where forces are equilibrated. Then, an agent that uses potential fields to move can be trapped in such places. The originality of our approach relies on the fact that we do not try to avoid such local minima. At the opposite, we exploit them as interesting places where facilities are located at the balance of different influences.

3.2.2 Agent characteristics and behaviors

As facilities are elements to be placed in the environment, we consider them as reactive agents. The environment is defined by a finite and continuous space. Demands, which are static data of the problem, are defined as an environment characteristic.

Typically, in a transportation network the objective is to increase accessibility for the customers by satisfying their transportation demands. A customer is covered if the next station is within a specified distance, called the covering radius. This objective is traduced in our model by an attraction behavior, i.e. station agents are attracted by demands. This attraction behavior must be balanced with repulsive forces between agents to avoid agents gathering. The solution we adopt ensures the repartition of agents in the environment. Indeed, stations should not be too far nor too close to each other (it is the inter-agent distance constraint). Agent behavior is then based on the reaction of two types of influences: attractive and repulsive. These influences are generated through agents perceptions following distances separating agents and obstacles, demands, etc.
Each agent has a local perception of the environment and of other agents. As attraction and repulsion influences are considered separately, we define two perception radius: attractive and repulsive radius (see Fig.1).

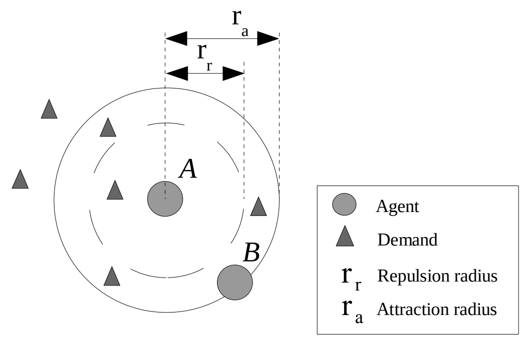

Figure 1: Perception radius of an agent

In order to satisfy the local coverage, we set attraction forces as induced by demands. The attraction is an interaction between agents and their environment. Each agent perceives the demand within its attraction radius (see Fig.2). Considering one demand point, an attractive force is defined from the agent towards the demand. It is expressed as a vector which intensity is proportional to the demand weight and to the distance between the agent and the demand.
Formally, for an agent A perceiving a demand D with weight W_D:

$$\vec{F}_{D/A} = W_D \ . \ \overrightarrow{AD} \tag{3}$$

The influence of the attraction decreases when the agent moves towards the demand. Thus, if the agent attains the demand the attraction behavior is inhibited. Furthermore, if an agent is subject to two attractive forces (from two different demands), it will be more attracted towards the biggest demand. Then, it will move towards a balance point. This point is defined as the place where the two attraction forces are equilibrated.

The global attraction force is the sum of all forces (between the agent and each perceived demand). Formally, the global attraction force undergone by an agent A is computed as follows:

$$\vec{F}_{demands/A} = \frac{\sum_{i=1}^{n} \vec{F}_{i/A}}{n} \tag{4}$$

n is the number of demands perceived by the agent A through its attraction radius ($n = 5$ in Fig.2). The demand is indexed by i.

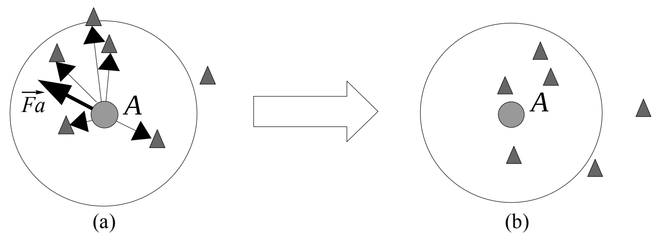

Figure 2: (a) Attraction to demands (b) The agent moves to the balance point

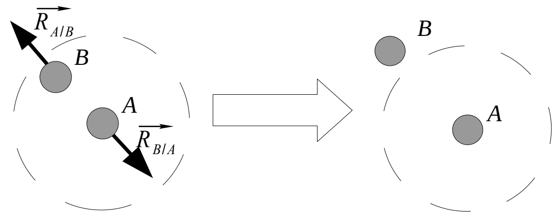

Figure 3: Repulsion between two agents A and B

If we consider only attractions, agents should move towards common locations. Such a process is sub-optimal and does not respect constraints on distances separating facilities in location problems. Then, to ensure an efficient agents repartition, we define repulsive forces between agents. Each agent generates a repulsion force which is inversely proportional to the inter-agent distance (see Fig.3). Consequently, agents will be subject to this force until the inter-agent distance is ensured. Formally the repulsive force induced by an agent B on an agent A is expressed as follow:

$$\vec{R}_{B/A} = \frac{\overrightarrow{BA}}{\left\|\overrightarrow{AB}\right\|^2} \tag{5}$$

Then, the global repulsive force undergone by an agent A is computed as follows:

$$\vec{R}_{agents/A} = \frac{\sum_{j=1}^{m} \vec{R}_{j/A}}{m} \tag{6}$$

m is the number of agents perceived by the agent A. These agents are indexed by j.
Contrary to the attraction influence, the repulsion is an interaction between agents.
The agent behavior is defined as the weighted sum of both global attraction and repulsion forces. Formally, for an agent A, it is expressed as follows:

$$\overrightarrow{Move} = \alpha\ \vec{F}_{demands/A} + (1-\alpha)\ \vec{R}_{agents/A} \tag{7}$$

The coefficient α allows to favour either the attraction or the repulsion. The global solving process is presented in Algorithm 1. The initialization (step 1) and the fitness computation (step 9) will be explained in the next section.

Algorithm 1 The system behavior

1: Initialization of Agent positions
2: **while** Fitness in progress **do**
3:    **for** all Agents **do**
4:       Attraction computation
5:       Repulsion computation
6:       Move computation
7:       Move execution
8:    **end for**
9:    Fitness computation
10: **end while**

4. EXPERIMENTATIONS

After exposing the principle of our approach, we evaluate the model on two case studies. The first one consists in positioning stations (for instance train stations) on a continuous map without environment constraints. The second one consists in locating bus-stops on an existing bus-network (i.e. a constrained environment).

4.1 Application to stations location

In the first case we consider a continuous environment corresponding to the France map presented in Fig.4 (400x400 size). It contains the demand weights which are values between 0 and 255 (randomly generated). These weights are represented as a gradation from black color (255) to white color (0). The initialization step is performed with a random positioning. Parameters values are: $\alpha = 0.5$, $r_a = 25$, $r_r = 20$.

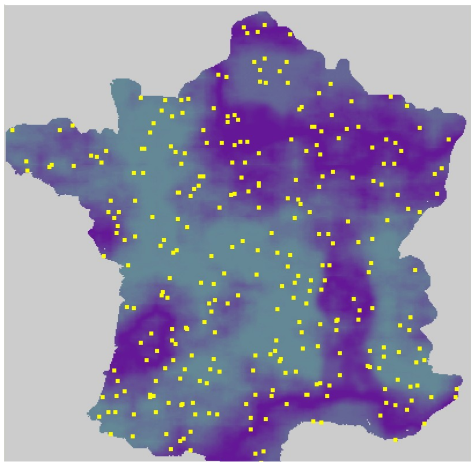

Figure 4: Demand representation (dark areas) and random initialization of station locations

When the algorithm starts, facility agents (the points in Fig.4) move towards demands while avoiding other agents. The repartition is ensured thanks to the combination of attractive and repulsive influences. The system iterates until it attains a global equilibrium state (converge to a stable state). In practice, the system converges to a finite number of close states (see Fig.6). In Fig.5 we notice the final state to which the system converges. We observe the stations repartition which is characterized by an intensification of the agents in areas where demands is high. This result

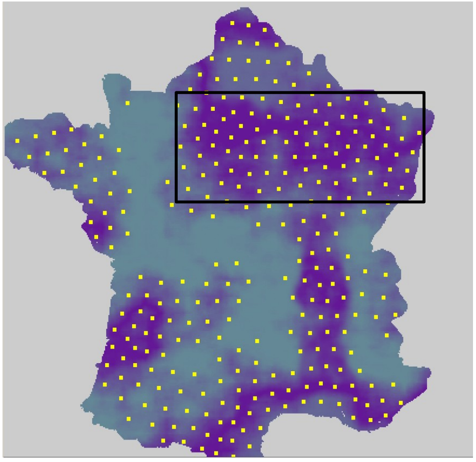

Figure 5: Final result (since the iteration 41)

is clearly visible inside the rectangular area (see Fig.5). It is also visible that all facilities respect the minimal distance between them.

We have compared the performance of our multiagent model with the K-means clustering technique. K-means algorithm is a well known technique that computes very good solutions [17]. It allows to classify or to group objects based on attributes/features into K number of groups. The grouping is done by minimizing the sum of distances between data and the corresponding cluster centroid (see Algorithm 2).

Algorithm 2 The K-means clustering

1: **repeat**
2: Place K points into the space represented by the objects that are being clustered.
3: Assign each object to the group that has the closest centroid. When all objects have been assigned, recalculate the positions of the K centroids as weighted barycenters.
4: **until** The centroids no longer move.

Comparisons are made according to a global fitness index expressed by the formula (8) and corresponding to the mean distance between each demand and the nearest station:

$$Fitness = \frac{\sum_{ij} V_{ij} \, . \, d(C_{ij}, x_{ij})}{\sum_{ij} V_{ij}} \tag{8}$$

Where:
V_{ij} = the demand at point x_{ij}
$d(C_{ij}, x_{ij})$ = the distance between the point x_{ij} and the nearest station C_{ij}

Comparisons are carried out on different number of stations, as shown in Table 1. For each stations number, about 40 tests have been executed.

The fitness values obtained by applying the multiagent approach are very close to the k-means ones. The deviation between the two approaches is small and it is inversely proportional to the number of stations.
Fig.6 plots the evolution of the fitness values for 400 stations. We can see that the fitness decreases until the convergence to a constant value. Here, the convergence is attained rapidly: since the 41 th iteration.

Table 1: Comparison with k-means clustering

Fitness: minimal values					
Stations	**50**	**80**	**100**	**150**	**200**
MultiAgent	16,592	12,501	11,187	9,164	7,945
K-means	15,556	12,253	10,965	9,010	7,820
Deviation	6.65%	2.02%	2.02%	1.7%	1.5%

All the experimentations have shown that the agents systematically converge to a stable location. It corresponds to a global balance between attraction to demands and inter-agents repulsive forces. These results show that the reactive approach is an interesting heuristic technique to deal with such optimization problems. We now present its application to a real transport problem.

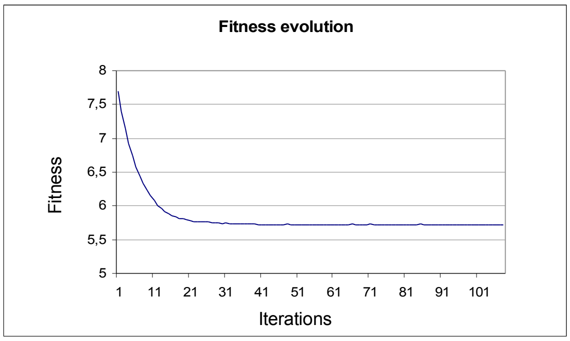

Figure 6: The fitness evolution for the case study with 400 station agents

4.2 Application to bus-stops location

In this section we apply our model to the bus-stops positioning on the bus-network of the city of Belfort (east of France, 60,000 inhabitants). We dispose of the real bus-network, see lines structure in Fig.7, and the real values of demands which correspond to inhabitants density per quarter. In Fig.7, dark areas characterize important demands.
This example introduces an important constraint for facilities. While moving, bus-stop agents must remain on the lines. The integration of this new constraint does not need change in the model. Its adaptation concerns only the projection of the move vector on the bus-lines (i.e. the move vector is transformed so as the agents move along lines).

The initial bus-stop positions are computed randomly (see Fig.7). Agents can be anywhere on the lines network. Each line has a predetermined number of bus-stops. White points in Fig.7 correspond to bus-stop agents. Terminus agents are fixed and are not subject to attractive and repulsive influences. The organization of bus-stop agents is ensured thanks to the previous influences.

Fig.8 shows the final state to which the system converges. We observe the bus-stops repartition which is characterized by an intensification of the agent number in areas where demand is high. The fitness index has been computed for the case of Belfort by using the formula 8. Fig.9 plots the fitness values which decrease until the convergence to a static state. Convergence is attained rapidly: since the 24 th iteration.

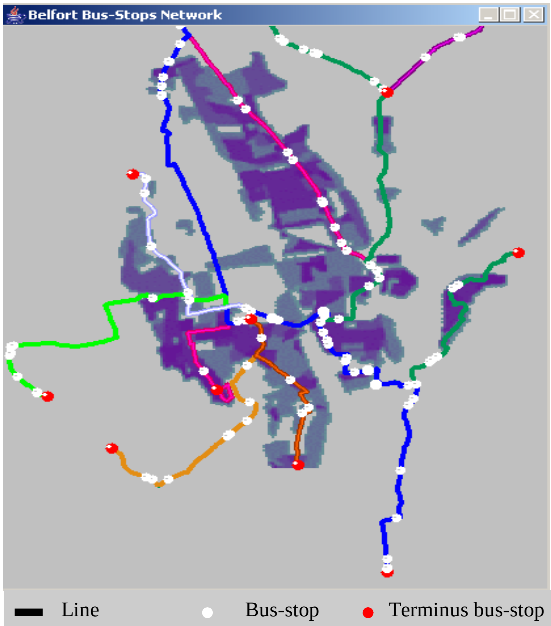

Figure 7: Belfort bus-network; random initialization of the bus-stop agents

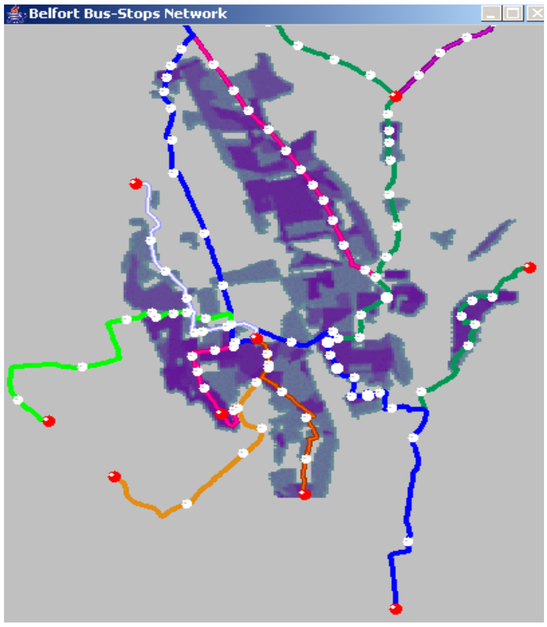

Figure 8: Execution final result

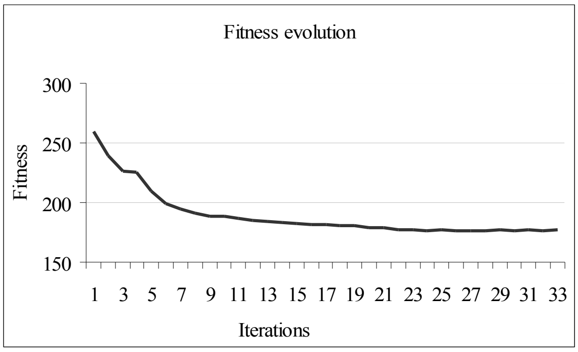

Figure 9: The fitness evolution

The optimal number of this fitness is 175 meters. In other words, for a person demand, the nearest bus-stop is situated at an average distance of 175 meters.

5. DISCUSSION

The previous experimentations allow to point up some observations on the proposed model. The obtained solutions are globally satisfying considering the fitness values. This last are quickly obtained, i.e. few iterations are necessary to reach a stable state.

It is worth noting that the agent initialization has an influence (even if it is slight) on the solution quality.

For each specific application, the parameters setting can be an important step. The results quality can depend on parameter values. However, the model is based only on three parameters: attraction and repulsion radius, and the weight combination of influences (α in formula 7). Attraction and repulsion radius depend on the considered application. Generally, the attraction radius is defined by the coverage distance and the repulsion one is defined by the maximal distance between two facilities. Concerning the parameter α, it allows to express a preference for the satisfaction of the demand constraint or the inter-agent distance constraint.

The existing solutions for facility location are not easily adaptable when the problem changes, particularly, for dynamic systems characterized by a variation of the problem constraints or data. The proposed multiagent approach allows to tackle this lack of flexibility. We have shown that specific constraints can be taken into account without changing the agent behaviors. For instance, when considering the bus-lines network we have just forced the agents to remain on the lines (cf. section 4.2). Other dynamic changes may concern the environment structure (e.g. demands, bus-lines network), the facilities number, etc.

The proposed model is not limited to a specific facility location variant. It can be adapted through changes of the agent behaviors.

Concerning the design of bus-lines network, we extend our model to deal with more complex transport constraints. Particularly, we are currently working on tools computing connections in the network. The approach consists to agentify the lines and to consider the connections as the result of line interactions. These interactions lead to the merging of close bus-stop agents into connections.

6. CONCLUSIONS

This paper has presented a reactive multiagent approach for the facility location problem. Facilities, which are modeled as agents, move in artificial potential fields induced by the demand and close agents. The agent behavior is a combination of reactions to attractive and repulsive influences. Local minima, which must be avoided in the artificial potential fields approach are exploited in our model as balance points between demands.

The relevance of the approach was proved by its application to transport: the location of stations and bus-stops. Then, it was compared with the k-mean clustering technique. The evaluation criteria concerns the deviation from the K-mean clustering and the convergence time. They show that the reactive multiagent approach is a very interesting perspective for such optimization problems.

Future works deal, first, with a more complete evaluation of the global system convergence. Then, we seek to apply our approach to another problematic in location problems: the dimensioning problem. It consists to optimize the number of facilities to locate, since each new facility increases the location cost. We obtain a multicriteria problem. We then propose to add two behaviors based on the creation and the removal of agents to tackle the facility location and number optimization problem.

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A Fuzzy Neural Approach to Modelling Behavioural Rules in Agent-Based Route Choice Models

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ABSTRACT
This paper presents a fuzzy neural approach to modelling behavioural rules in agent-based dynamic driver behaviour models. The data for model development was obtained from a field survey of driver behaviour which was conducted on a congested commuting corridor in Brisbane, Australia. Fuzzy Artificial neural networks were used to describe driving behavioural rules and analyse the impacts of socio-economic, context and information variables on individual behaviour and propensity to change route and adjust travel patterns. A number of neural network architectures were examined. The results showed that Learning Vector Quantization (LVQ) models outperformed the other architectures tested for this application. A number of methods to calibrate the membership functions, fuzzification, and defuzzification are reported in this study. The fuzzy-neural models are also compared to binary probit, logit and ANN models. The results showed that the fuzzy-neural models outperformed the other models tested.

Keywords
Route Choice Model, Intelligent Agents, Fuzzy Set and System, Artificial Neural Networks, Microscopic Traffic Simulation.

1. INTRODUCTION
Most route choice models found in literature are based on random utility theory. One of the limitations of this method is its inability to model the vagueness (fuzziness) in driver behaviour [1] and handle uncertainty; situations commonly encountered in the real world [2]. Fuzzy sets can overcome this situation [3]. Fuzzy logic has been then recognized as a effective method to modelling complex process of route choice behaviour [4-6]. The continuous or fuzzy logic differs from Boolean (binary logic) in the way that the degree of membership varies from 0 to 1. The membership function in binary logic suddenly jumps from 0 to 1 at a crisp point whereas the membership function in fuzzy logic varies smoothly from 0 to 1 and from 1 to 0 [2], and can be overlapping. Key advantages of fuzzy logic are its ability to deal with complex systems and to capture the non-linear relationships between inputs and outputs in uncertainty situation.

A number of studies proposed the fuzzy logic method to overcome the limitations of other techniques. Kuri and Pursula [4] compared logit-type random utility models and fuzzy logic. Henn [5] developed a fuzzy route choice model to accommodate the uncertainties of the drivers' behaviour. The model was compared with a stochastic discrete choice logit model. The effect of the ATIS information is modelled as a modification of the probability (uncertainty) that the traveller perceives regarding the predicted route cost. Teodorovic et al. [6] reported a fuzzy logic model for route choice in which a knowledge base was developed using simple reasoning arguments. The data sets were obtained from a computer simulation.

Artificial neural networks (ANNs) provide a method for modelling driver behaviour. The main advantages of ANNs include the ability to deal with complex non-linear relationship [7]; fast data processing [8]; handling a large number of variables [9] and fault tolerance in producing acceptable results under imperfect inputs [10]. ANNs are also suitable for the reactive behaviour which is often described using rules, linking a perceived situation with appropriate action [11, 12]. Given only a set of input and output during the training process, the neural network is able to determine all the rules relating input and output patterns based on the given data [2].

Combined fuzzy logic and neural networks is an approach for incorporating human expert' decision to deal with complex problems. Fuzzy logic is considered as knowledge representation (both precise and imprecise) while neural networks is a key of data processing and learning capability. This approach has been being recognised as a potential solution to capture uncertainty in driver's behaviour [1, 13].

This study models route choice decision under the influence of real time traffic information. Drivers are modelled as agents where the agent's knowledge relevant to route choice decision is constructed using the fuzzy-neural approach based on socio-economic data. This paper first describes the intelligent agent structure and modelling approaches. Selected results from data collection relevant to model development are described in Section

AAMAS'06, May 8-12, 2006, Hakodate, Hokkaido, Japan.

3. The development of agent-based fuzzy-neural route choice model is explored in Section 4. Fuzzification, defuzzification, and calibration of the fuzzy membership functions are also presented in this section. Summary and future research directions are presented in the final section.

2. MODELLING AGENT-BASED DRIVER BEHAVIOUR

2.1 Intelligent Agent 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. 14, 15] and its application for route choice behaviour [e.g. 16]. 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 Figure 1.

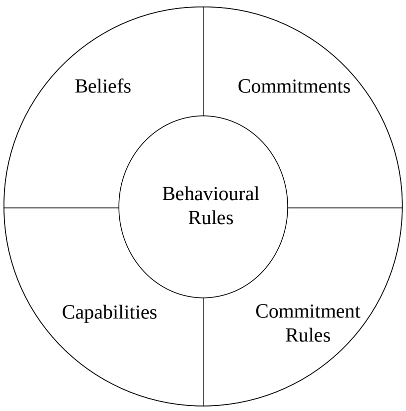


Figure 1. Intelligent Agent Mental Model

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 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 agent'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.

2.2 Agent-based Route Choice Behaviour under Real-time Traffic Information

In this study, drivers are modelled as agents (known as driver-vehicle-agent: DVA). Capabilities of DVAs in the sense of route choice behaviour in this paper can be summarised as follows [17]:

Autonomy: DVA could identify what her objectives were and which actions she needed to carry out to yield the expected results.

Social ability: driver-vehicle-agent could ask for some help in order to ease the execution of his actions, for instance, by contacting a service provider such as a traveller information centre. Another aspect of social behaviour is the necessity of cohabiting with other drivers and of respecting traffic rules to avoid accidents.

Reactivity: responding to traffic signals and braking in order to avoid colliding with others are some well known examples of reactive behaviour.

Adaptability: DVA is adaptable in the sense that she may reconsider her options and adopt another strategy in order to accomplish her goals, in the case that the original plan becomes inadequate.

Pro-activity: DVA must be able to prioritise the execution of an action to the detriment of her original plans, for instance, arriving later at work after adopting another route that is more convenient owing to some other reasons.

DVA has goals (desires) to travel between an origin-destination pair at selected departure time. She is also aware of traffic condition during the morning peak-hour, then she checks the traffic report before making her journey. Having the information, she can estimate the time she will need to make the journey, and then she can plan her trip. She selects a route with departure time to arrive workplace by her desired arrival time. Once the plans have been made, she can execute it. While she has not found any obstacle within the journey, she can keep executing her original plan. The crucial situation occurs when she has just found that certain road on her route is interrupted (i.e. accident, road work) knowing via traffic information reports i.e. VMS, in-vehicle device, radio. As she cannot drive through that road anymore, she has to reconsider her plans and find another alternative route to get to her destination. Therefore, she abandons her original plan and starts executing a new one.

For the purpose of agent-based route choice models in this study, the models are constructed using a combined fuzzy-neural framework to build behavioural rules under the influence of real time information. Fuzzy sets are used to generate sets of rules (i.e. belief of ATIS, socio-economic, familiarity) for decision-making process. The rules can be customised by adjusting membership functions according to survey data. Artificial neural networks involve with data processing process and learning capability. ANNs reduce human's efforts to construct fuzzy knowledge (rule-base) and learning. Compliance/delay threshold during information provided for DVAs is dynamical computed and assigned by the behavioural rules.

In making a decision, DVAs always take the best route described by utility maximisation based on individual characteristic. Nevertheless, the best route for a DVA may not be the best for the others. This also depends on current knowledge and preferences. This issue will be described next.

2.3 Route Utility and Route Choice Preference

The model structure in this study is based on utility distribution combined with fuzzy sets. This technique can be found in various studies [e.g. 18, 19]. The preliminary route utility model can be described as Equations (1) and (2) [18]:

$$U_{in} = V_{in} + \varepsilon_{in} \tag{1}$$

$$U_{in} = \sum_{l} B^{l} X^{l}_{in} + \sum_{m} \gamma^{m} \Omega_{m}\left(Y^{m}_{in}\right) + \varepsilon_{in} \tag{2}$$

where U_{in} is the utility of route i for driver n; V_{in} is the systematic utility of route i for driver n; B^l and γ^m are coefficients of the variables; X^l_{in} is the value of quantitative or adjusted quantitative variable on route i for driver n; Y^m_{in} is the value of qualitative variable m on route i for driver n; $\Omega_m(.)$ is the transformation function to determine the fuzzy value of qualitative variable m; and ε_{in} is the disturbance term for route i for driver n. The first set of variables in Equation (2) represents the quantitative variables and the second set denotes the transformed fuzzy values for the qualitative variables. The disturbance term can be interpreted as incorporating the traditional sources of randomness for the quantitative variables, and additionally potential errors introduced by the fuzzy modelling component. However, it should be noted that the fuzzy component may mitigate error contributions by more robustly representing qualitative variables.

Unlike the previous studies, route utility in this study is pre-defined (based on the survey) and a driver has only two choices (either taking an alternative route or staying on an usual route). The utility of taking alternative route is then assumed as 1.0 (then utility of taking usual route is 0.0) if she prefer alternative. Similarly, the utility of using usual route is assumed as 1.0 (0.0 for the alternative) if she prefers usual route. Potential parameters influencing driver behaviour are transformed into fuzzy sets. Afterward, these sets and route utility can be mapped by training and testing, and then generated *if-then* rules. This method and construction of *if-then* rules will be calibrated and validated later.

3. DATA COLLECTION AND ANALYSIS

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. Some selected results relevant to the dynamics of commuter route choice behaviour are summarised below. A more detailed discussion of survey results can be found in Dia *et al.* [20].

3.1 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 and route directives. Table 1 presents a summary of selected socio-economic attributes of respondents.

Table 1. Characteristics of Travel Behaviour Surveys for Brisbane, San Francisco and Chicago

Description	Brisbane, Australia	San Francisco, U.S.A.	Chicago, U.S.A.
Sample Size	171	3238	700
Gender (%)			
Male	56.1	64.9	54.3
Female	43.9	35.1	45.7
Age (%)			
Less than 19	0.6	0.2	0
20 to 29	23.5	11.4	23.6
30 to 39	22.4	31.1	33
40 to 49	28.8	33.7	29.7
50 to 64	22.4	21.4	12.5
Above 65	2.4	2.2	1.2
Education (%)			
High School or less	15.9	4.3	4.6
Vocational/Technical school	20.0	1.3	19.4
Undergraduate Degree	33.5	61.3	36.1
Post Graduate Degree	30.6	33.1	39.9
Annual Personal Income (%)			
Under $20,000	4.9	3.1	4.3
$20,000-40,000	25.8	18.3	33.1
$40,000-60,000	27.0	23	26.3
$60,000-80,000	15.3	14.2	14
$80,000-100,000	11.0	14.2	6.6
Above $100,000	16.0	27.2	15.7
Travel Time (Minutes)			
On usual route	31	40.6	43
On best alternative route	33	44.8	53.4
Average Duration of Residence in the Area (years)	8.3	6.7	5.3

The average respondent is middle-aged and has resided in the area for 8.3 years. The respondents are divided fairly equally between males and females with 56 per cent of respondents being males. The average annual income is $62,000 and 64 per cent of respondents have either undergraduate or postgraduate qualifications. The primary occupations of this sample are professional, clerical/service, executive and managerial/ administration.

As suggested by these results, upper-income groups and well-educated individuals were over-represented in this survey when compared to census demographic profiles of the Brisbane population. However this problem has also been experienced in other similar studies conducted in the United States as presented by Polydoropoulou and Khattak [21] and shown in Table 1.

3.2 Respondents' Preferences for Traffic Information Sources

Travellers on this corridor received information from a variety of sources. Table 2 lists the current sources of traffic information as indicated by the respondents. Most respondents indicated that their primary source of traffic information was radio traffic reports (74 per cent) and their own observation (64 per cent). About 23 per cent indicated that they relied on variable message signs (VMS) as a source of traffic information on their usual route.

This clearly indicates that the implementation of strategically located and credible VMS has the potential to influence drivers' route choice decisions. Other traffic information sources such as the Internet and in-vehicle navigation systems were rarely used by respondents. This maybe attributed to the limited market penetration rates of in-vehicle navigation systems and the lack of Internet-based traffic information systems in Brisbane at the time the survey was conducted.

Table 2. Current Traffic Information Sources

Information Source	Frequency* (Per Cent)
Radio Traffic Reports	74
Own Observation	64
Electronic Message Signs	23
Conversations with other people	10
Mobile phone	4
Printed matter	2
Television	2
Home / Office telephone	1
In-vehicle Navigation System	1
Internet	1
Other	0

*multiple responses allowed

3.3 Frequency of Route Change and Causes of Unexpected Congestion

The frequency of route change was examined by asking the respondents to provide information on the number of times they changed routes in the past month, in response to the presence of congestion on their usual routes. The results are displayed in Table 3 below.

Table 3. Respondents' Frequency of Route Change in the Previous Month

No. of Times Respondents Changed Route in Previous Month	No. Of Respondents	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

On average respondents took an alternative route 3.6 times in a month (about 20 working days). However, it is believed that the proportion of drivers complying with travel information can be increased by designing effective and credible traveller information systems. This is discussed in more detail in the next sections dealing with the content of the messages and the type of information provided. The causes of unexpected congestion experienced by respondents is presented in Table 4.

Construction and roadworks were reported as the major causes of unexpected congestion on both the pre-trip and en-route questionnaires. Accidents were also a significant source of unexpected congestion. During the time of the distribution of this survey, major maintenance and construction works were being conducted on Coronation Drive and adjoining networks possibly accounting for the severity of unexpected congestion caused by roadworks. This result confirms the need for advanced freeway and arterial incident detection systems capable of detecting incidents in the shortest possible time and making this information available to the travelling public through advanced traveller information systems.

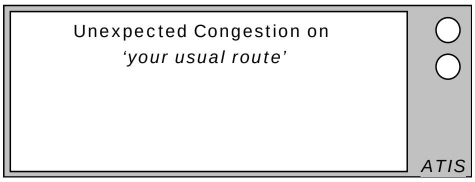
Table 4. Causes of Unexpected Congestion

Cause of Congestion	Pre-trip (%)	En-route (%)
Construction/Roadworks	58.6	42.2
Accident	44.8	40.6
Disabled vehicle	6.9	10.9
Don't know	6.9	21.9
Bad weather	3.4	7.8
Other	0.0	0.0

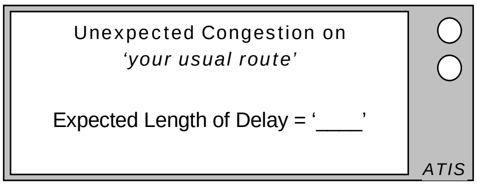
3.4 En-Route Responses to Hypothetical ATIS Messages

This paper aims at analysing en-route responses to traffic information, which is a crucial situation in decision-making process. Drivers' compliance/delay threshold was then captured in the behavioural field survey. The compliance/delay threshold is modelled according to the respondents' answers to the different ATIS scenarios. Respondents were asked to state whether they would change travel decisions if they were alerted of delays.

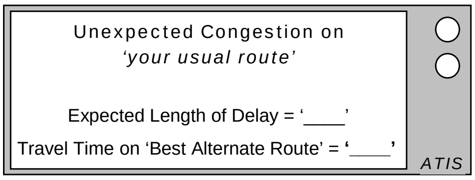
Each of five different information types being tested were then presented to the respondents as depicted in Figure 2(a-e). Details of travel information and data collection can be found in [16, 22]. Brief descriptions of these scenarios are as follows:



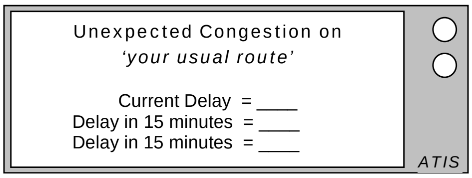
2(a). Qualitative Information Message



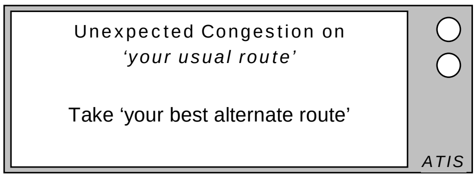
2(b). Quantitative Information Message- Usual Route



2(c). Quantitative Information Message- Usual and Best Alternate Routes



2(d). Predictive Information Message



2(e). Prescriptive Information Message

Figure 2. Hypothetical ATIS Messages for En-route Analysis

Qualitative Delay Information - In this situation the VMS only offered a simple message: "Unexpected Congestion on 'your usual route' " where 'your usual route' as depicted in Figure 2(a) 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 Real Time Delay Information - For this scenario, respondents were provided with the same message as Qualitative Delay Information. In addition, VMS also displayed the expected delays on the usual route in minute as shown in Figure 2(b). The respondents were able to perceive how much delay on their usual route is. And this delay will impact on individual delay threshold. If traffic delay exceeds personal delay threshold, the respondents will take alternative route according to an expectation of improvement in travel time as described in previous research [16].

Quantitative Real Time Delay on Best Alternative Route - For this form of supplied information, respondents were provided with the same message as Quantitative Real Time Delay Information, VMS in addition displayed the travel time on the best alternate route (as specified by respondents), as shown in Figure 2(c).

Predictive Delay 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, this is similar to Quantitative Real Time Delay Information, and accurately predicted the expected delays in 15 and 30 minutes into the future as indicated in Figure 2(d).

Prescriptive Best Alternative Route - This scenario explored the response to recommendations offered by VMS which suggested taking the route which the respondents indicated was their best alternative route to their destination , as presented in Figure 2(e).

Table 5. En-route Stated Preferences for Unexpected Congestion

Attributes	Qualitative Delay Info.	Quantitative Real-Time Delay Info.	Quantitative R-T Delay on Best Alt. Route	Predictive Real-Time Delay Info.	Prescriptive Best Alternate 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
Can't say	2.3	7.7	5.3	5.3	3.8

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 5. These results provide one of the most significant findings from the ATIS experiment. They 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 route choice decision models were developed and investigated for each of these ATIS scenarios as discussed next.

3.5 Identification of Model Parameter

A number of studies [23] have identified some of the factors influencing drivers' route choice behaviour under real time traffic information. The findings show an agreement for road type which has impacts on route choice decision under the influence of traffic information. There was some discrepancy for socio-economic and trip characteristics factors. Only en-route data set is considered in this study as the model emphasises en-route choice decision. The parameters influencing driver's behaviour obtained from the survey data are summarised in Table 6. The average respondent is also middle-aged and has resided in the area for 8.3 years. The respondents are divided fairly equally between males and females. 56 per cent of respondents are male. Majority of respondents has annual income over $40,000 (around 70 per cent) and 64 per cent of respondents have either undergraduate or postgraduate qualifications. Fixed-work respondent (52.4 per cent) dominates the other groups. 52.3 per cent of respondents live in the residential area less than five years. Details can be found in [20, 24].

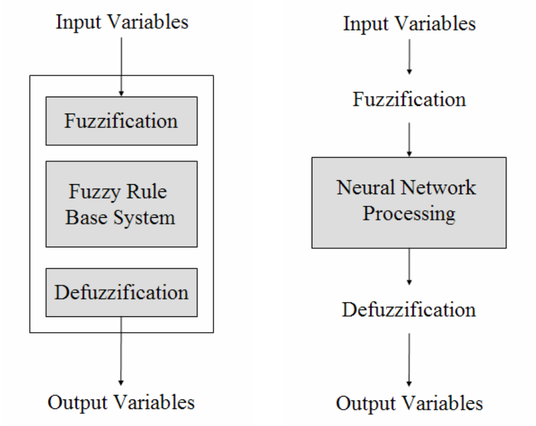
Table 6. Summary of Explanatory Parameters for Model Development

Variables	Number of survey respondents (%)
Gender	
=0, if male	56.1
=1, if female	43.9
Age	
=1, if < 18	0.6
=2, if 18-29	23.5
=3, if 30-39	22.4
=4, if 40-49	28.8
=5, if 50-64	22.4
=6, if >65	2.4
Income	
=1, if <20,000	4.9
=2, if 20,000-40,000	25.8
=3, if 40,000-60,000	27.0
=4, if 60,000-80,000	15.3
=5, if 80,000-100,000	11.0
=6, if >100,000	16.0
Education	
=1, if high school or less	15.9
=2, if Vocational or Technical School	20.0
=3, if Undergraduate Degree	33.5
=4, if Post Graduate Degree	30.6
Flexibility of Working Schedule	
=1, if fixed	53.4
=2, if variable	6.8
=3, if flexible	39.8
Years in Residence	
=1, if <5	52.3
=2, if 5-10	20.5
=3, if 10-15	4.5
=4, if 15-20	10.2
=5, if 20-25	12.5
=6, if >25	0.0

4. FUZZY-NEURAL AGENT-BASED APPROACH

4.1 Combined Fuzzy-Neural Approach

Figure 3 [2] illustrates the difference between fuzzy expert systems and fuzzy-neural networks.



3(a) Fuzzy Expert System 3(b) Fuzzy-Neural Network

Figure 3. Structure of Fuzzy Expert and Fuzzy-Neural Approach

Figure 3(a) depicts the fuzzy expert system which has three distinguished conceptual units. The fuzzification level aims to transform the input information into an appropriate form to be handled by the fuzzy rule based system at its processing level. In the fuzzy rule based system, logical relationships between the fuzzy input sets and fuzzy output sets are revealed and quantified. The results obtained from the fuzzy rule based system are retransformed from the internal fuzzy quantities into numerical quantities and returned to the environment. Most of the existing approaches for combining fuzzy logic and neural network techniques apply fuzzy sets at the interface levels and neural networks at the processing level [2, 25] as described in Figure 3(b). In general, the architectures of the neural networks are standard involving generic basic processing units (neurons) built out of a weighted sum of inputs and followed by a nonlinear static transformation. This concept is to eliminate the fuzzy rule based system and replace it with a neural network. This approach results in significant savings in time and effort, as obtaining human expert's knowledge in terms of fuzzy *if-then* rules is very difficult [2]. Given a set of training data, the neural network find out all the fuzzy rules relating input and output patterns. The fuzzy logic techniques at the interface levels may be viewed as a form of data compression. This improves the neural network training process and also helps interpreting the neural network outputs [2].

As suggested, this paper combines fuzzy logic into the representation of artificial neural networks to modelling driver behavioural rules (*if-then* rules) under the influence of real time traffic information. The study in addition proposes a leaning mechanism relevant to intelligent agent to deal with some situations when the *if-then* rules are inadequate.

4.2 Design of Fuzzy-Neural Agent-Based Drivers' Compliance Model

This section describes the conversion of survey data (crisp values) into the fuzzified inputs for a fuzzy-neural interface. Three steps are involved in using fuzzy-neural networks as follows [2]:

4.2.1 Fuzzification

The membership function for fuzzy system transforms input variable into the set [0, 1]. The possibility is a function that takes values between 0 and 1 indicating the degree of belief that a certain element belongs to a set. This is a mathematical representation of linguistic information. It focuses on the imprecision intrinsic in language and quantifies the meaning of events [26]. Triangular or trapezoidal shapes of membership function are often selected by analytical convenience. This study also employs these shapes and they are also consistent with the survey data.

The socio-economic parameters resulted from survey (in Table 6) describing input variables have already been categorized. Fuzzy membership function then considers the vagueness of input data (e.g. age, income). In this study, membership function is formulated for all parameters in Table 7, except gender which is set up as dummy variable. Only two types of membership functions (in terms of "high" and "low") are applied.

For example, the membership function for driver' age over 65 years is defined as "driver is old" with possibility 1 while driver's age lesser than 29 years is identified as "driver is old" with possibility 0. Similarly, the membership function for driver' age is greater than 50 years is defined as "driver is young" has a possibility 0 whereas the membership function for driver's age is lesser than 18 years is defined as "driver is young" has a possibility 1. The similar concept is applied for the other variables. Income level is transformed to "driver's income is high" and "driver's income is low". Education is considered as "driver is well-educated" and "driver is less-educated". About working time, it can be identified as "high flexibility in working time" and "low flexibility in working time". Years at residence are surrogated for familiarity with road network conditions. In this study, there are two membership functions: "familiarity is high" and "familiarity is low".

In this study, there are two the membership functions for driver's compliance: "compliance is high" and "compliance is low". The membership function for driver's answer of category 1 is defined as "compliance is low" with possibility 1 whereas driver's answer of category 4 is defined as "compliance is low" with possibility 0. While the membership function for driver' s answer of category 1 is defined as "compliance is high" with possibility 0 and driver's answer of category 4 is defined as "compliance is high" with possibility 1.

In addition to triangular shape of membership function, any given value is a member of each of the different ranges to some degree or possibility (at least zero extent). If the given value (x) is in some ranges x_{min} and x_{max}, then membership value of x for all values below x_{min} is 0, for all values above x_{max} is 1, and in this range the membership value of x is $(x-x_{min})/(x_{max}-x_{min})$. Therefore, after fuzzification, the real values of x becomes a fuzzy vector $[y_1y_2y_3...y_n]$ where y_i is the fuzzy membership value of x in i th range and its lower and upper limits are x^i_{min} and x^i_{max}. The described concept is also applied for the membership function for the other input and out variables in this study.

4.2.2 Artificial Neural Network Processing

The simple feed-forward neural network with three layers is used to learn relationships between the fuzzified input and output patterns as presented in Figure 4. As mentioned earlier, six input variables are fed into the network, fuzzification sub-network transforms these real inputs into fuzzified inputs in term of "high" and "low" ranges. Therefore, the input layer consists of 11 neurons (10 for representing the membership function plus a dummy variable of age). The output layer has only two neurons for representing membership function of compliance/delay threshold rate.

A number of neurons in the hidden layer are specified by ANN architecture. Every neuron in the input layer is connected to every neuron in the hidden layer with a weighted arc. Similarly, every neuron in the hidden layer is connected to every neuron in the output layer with a weighted arc. The weights of these connections will be updated as the training of the neural network continues. Several architectures of ANNs are explored in this study.

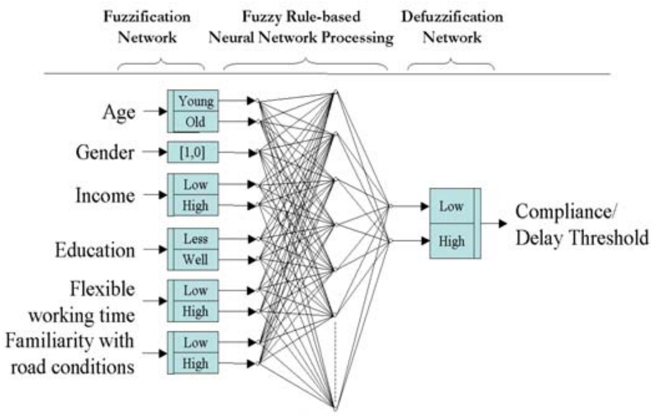


Figure 4. Fuzzy-Neural Interface – Compliance/Delay Threshold Model

4.2.3 Defuzzification Network

This step is the most important stage in the construction of the fuzzy-neural network. It aims to compute the compliance/delay threshold value from fuzzified outputs. The main consideration is the method to represent membership functions of a fuzzified output, and to perform defuzzification. The defuzzification consists of two layers as presented in Figure 4. The first layer the membership functions of fuzzified output. The second layer is defuzzification layer (actual value).

Figure 5 presents *if-then* rules and defuzzification method regarding some income levels. These rules (for example) are also presented below:

Rule 1: *If driver is high-income, then the compliance is high.*

Rule 2: *If driver is low-income, then the compliance is low.*

Both rules are generated fuzzy sets: B^*_1 and B^*_2. Defuzzification is the mechanism to transform these fuzzified outputs to a crisp value. This is implemented by using a defuzzification method to process the aggregated output B*. The centre of sums (COS) method is used to defuzzify the fuzzified output B*. This can be expressed as in Equation (3) below:

$$y^* = \frac{\int_Y y \sum_{i=1}^{n} \mu_{Bi}(y)dy}{\int_Y \sum_{i=1}^{n} \mu_{Bi}(y)dy} \qquad (3)$$

where Y is the rang of compliance level (1-4), n is the number of rules in the category, $\mu_{Bi}(y)$ is the possibility value of y in fuzzy set B_i, and y^* is the crisp value from defuzzification.

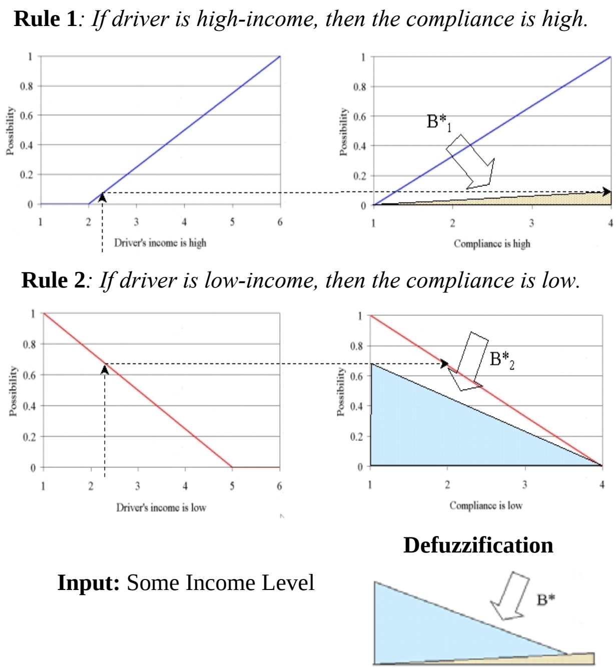


Figure 5. Defuzzification Method of crisp input using if-then rules

4.3 Selection of ANN Architectures

Agent-based fuzzy-neural route choice models can be considered as a classification problem. Some of ANN architectures typically used for classification problems include [27]:

Back-Propagation: this is a general-purpose network paradigm. Back-prop calculates an error between desired and actual output and propagates the error back to each node in the network. The back-propagated error drives the learning at each node.

Fuzzy ARTMAP: this is a general purpose classification network, and is a system of layers which are connected by a subsystem called a "match tracking system." The version used in this study consisted of a single Fuzzy network and a mapping layer which controls the match tracking. If an incorrect association is made during learning, the match tracking system increases vigilance in the layers until a correct match is made. If necessary, a new category is established to accommodate a correct match.

Radial Basis Function Networks: these are networks which make use of radially symmetric and radially bounded transfer functions in their hidden ("pattern") layer. These are general-purpose networks which can be used for a variety of problems including system modelling, prediction, classification.

Learning Vector Quantization (LVQ): this architecture is a classification network, originally suggested by [28], which assigns vectors to one of several classes. An LVQ network contains a Kohonen layer (known as hidden layer) which learns and performs the classification. LVQ provides equal numbers of PEs for each class in the Kohonen.

The development of a neural network model also involves the selection of a suitable objective function and modification of learning rules and transfer functions. Classification rate was selected as the objective function. It represents the percentage of correctly classified observations. A large number of learning rules and transfer functions were also explored. During training and testing phases, it was found that LVQ provided the best CR performance over the other architectures. The CR was favourable around 71-78 per cent as shown in Table 7.

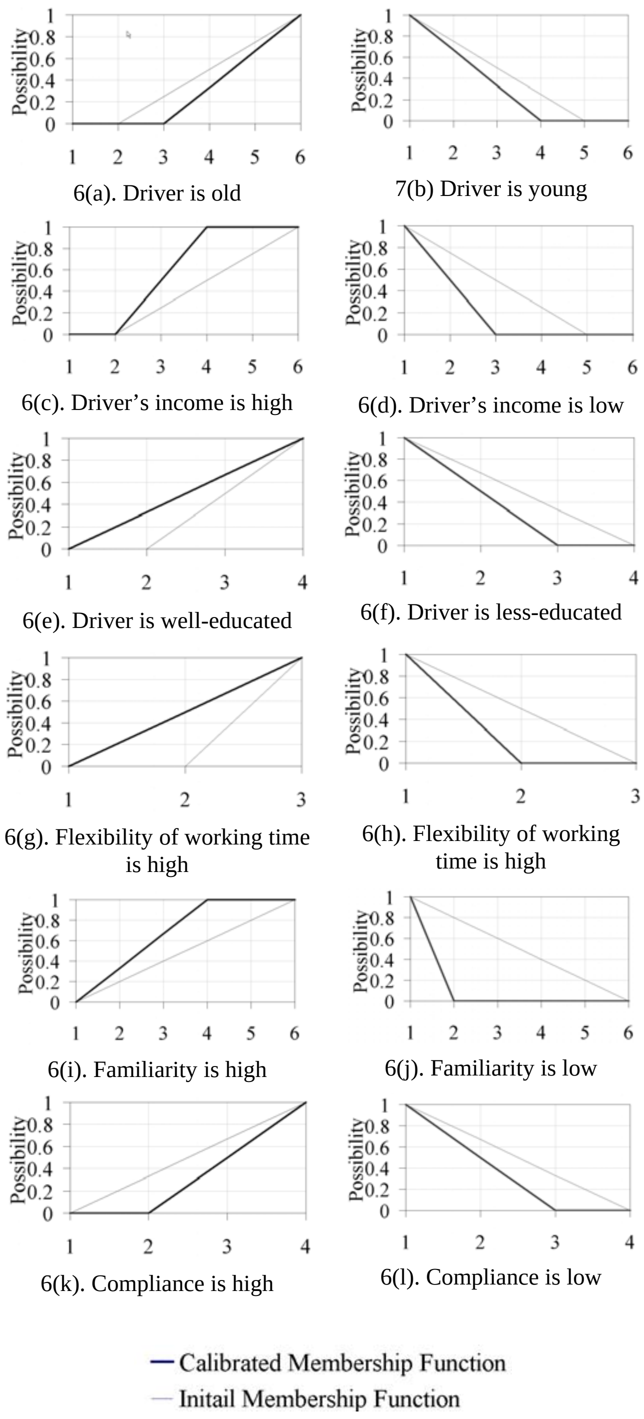
Table 7. LVQ Best Model Performance before Calibrating Membership Function

AITS Scenarios	% Classification Rate
Qualitative Delay Information	77.97
Quantitative Real-time Delay Information	75.79
Quantitative Real-time Delay on Best Alternative Route	77.36
Predictive Delay Information	71.09
Prescriptive Best Alternative Route	74.09

4.4 Calibration of Membership Function

Figures 6(a) to 6(l) present the initial membership functions compared with the calibrated membership function. Initially, the functions have huge degree of overlapping. For example, Figures 6(a) and 6(b) depict membership function of driver's age. The membership function for drivers under 18 years old is defined as "Driver is young" with possibility 1 and for drivers' age 64 years old is defined as "Driver is young" with possibility 0. On the other hand, the membership function for drivers' age 18 years is defined as "Driver is old" with possibility 0 and drivers' age over 65 years is defined as "Driver is old" with possibility 1.

After calibration, by reducing the degree of overlapping, the new membership functions for driver's age can be obtained as shown in Figures 6(a) and 6(b). The drivers' age of under 18 years old is defined as "Driver is young" with possibility 1 and for over 49 years old is defined as "Driver is young" with possibility 0. The membership function for drivers' age of 30 years old is defined as "Driver is old" with possibility 0 whereas drivers' age of over 65 years is defined as "Driver is old" with possibility 1. The other membership functions were also modified in the same technique. Their results are presented in Figures 6(c)-6(l). Having these functions, all fuzzified inputs and outputs can then be trained and tested. The huge improvements have been found for all models as presented in Table 8 below.



6(a). Driver is old
7(b) Driver is young
6(c). Driver's income is high
6(d). Driver's income is low
6(e). Driver is well-educated
6(f). Driver is less-educated
6(g). Flexibility of working time is high
6(h). Flexibility of working time is high
6(i). Familiarity is high
6(j). Familiarity is low
6(k). Compliance is high
6(l). Compliance is low

Figure 6. Modified membership function for which if-then rules (neural-based training) are constructed

Table 8. LVQ Best Model Performance after Calibrating Membership Function

AITS Scenarios	% Classification Rate
Qualitative Delay Information	96.36
Quantitative Real-time Delay Information	90.79
Quantitative Real-time Delay on Best Alternative Route	95.45
Predictive Delay Information	94.43
Prescriptive Best Alternative Route	92.44

4.5 Comparative Evaluation of Fuzzy-Neural Approach, Probit, Logit, and ANN Models

The study also compared the fuzzy-neural models to the binary probit, logit and ANN models using the same data set. The findings showed that binary probit and logit models provided a prediction accuracy of about 61 per cent. The ANN models gave a better degree of accuracy (about 96 per cent) while the developed fuzzy-neural models had an accuracy of 90– 96 per cent. A more detailed description of capabilities for all modelling approaches investigated can be found in [24]. It should be mentioned that while the ANN models may have been more accurate than the binary models, their disadvantage is that the rules are not easily interpreted. In this study, fuzzy sets were used to address this limitation by incorporating them into the representation of ANNs. The model results from this approach can then be interpreted in terms of *if-then* rules.

5. SUMMARY AND FUTURE RESEARCH DIRECTIONS

The work reported in this study is part of an ongoing research topic thesis which aims to model driver behaviour using cognitive agents. The behavioural surveys which provide a useful insight into commuters' needs and preferences for traffic information in the Brisbane metropolitan area have been utilised for model development. A comparative evaluation between fuzzy-neural approach, binary logit, probit and ANN models was also reported in this paper. The fuzzy-neural method was shown to be a suitable approach to modelling route choice behaviour and deriving the rules for implementing agent-based driver behaviour models. The development of the agent-based route choice models will help improve the reliability and credibility of simulation models and their use under ATIS environment. However, there is a need to have extended data collection for further development, calibration, and validation.

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Adaptive Traffic Control with Reinforcement Learning

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ABSTRACT

Most approaches to reduce urban traffic congestion make use of pre-defined and fixed solutions and/or rely on a central controller. These methods are quite inflexible since they cannot cope with dynamic changes in traffic volume. More flexible approaches have been proposed, mainly for coordinated systems, but they usually require the execution of time-consuming and complex processes. This paper presents an approach for optimizing traffic based on reinforcement learning, in which isolated junctions adapt themselves to the traffic flow without requiring explicit communication with neighbors and with no need for traffic expert intervention. The approach is specifically designed to work in non-stationary and dynamic tasks. This is an essential property since traffic control scenarios are intrinsically noisy and dynamic. Experimental results show that the performance of the proposed control mechanism is better than the greedy strategy and other reinforcement learning approaches.

Keywords

Traffic Control, Reinforcement Learning

1. INTRODUCTION

It is a well-known fact that big cities suffer from traffic congestion and all consequences that come with it. Since the expansion of the traffic network is no longer a socially attainable solution to this problem, control systems are used in order to increase the traffic throughput as well as to decrease total travel times. In doing so, control systems must deal with complex scenarios in which safety and pollution levels are just a few among a great number of variables to be taken into account. The most common way to control traffic is to use traffic lights at street junctions[1]. This definitely helps to solve safety problems, but at the cost of decreasing flow and increasing travel times.

Two opposite approaches to traffic lights control exist, namely the *isolated* and *coordinated* approaches. Both types of control systems are implemented either with *pre-designed* and fixed times or with *traffic-responsive* behaviors. Predesigned coordinated approaches normally use historical data to calculate splits and cycle times so as to maximize the flow in a specific junction. The problem with fixed coordination is that the values calculated are optimal only for a given past situation. This requirement is very restrictive since traffic patterns change constantly, not only due to usual flow variations, but also because of reasons as diverse as accidents, natural events (rain, snow, etc), etc. Isolated traffic responsive systems, on the other hand, use inductive loop detectors to determine if there is a long queue of stopped cars, but this decision is only locally optimal.

In this sense, traffic responsive coordinated control may have a better performance. This type of solution requires a centralized controller which calculates the optimal flow in each intersection. This comes at the cost of demanding the installation and operation of communication mechanisms. Moreover, centralized methods require the processing of huge amounts of data and represent a single point of failure, since the control of all traffic lights depends on the central system. Moreover, this approach works well only in traffic networks with well defined traffic volume patterns. In cities where these patterns are not clearly separable (eg. cities where business centers are no longer located exclusively downtown), coordination may not be effective.

Alternative approaches to reduce traffic jams have been proposed in several disciplines, such as traffic engineering, physics and artificial intelligence. Traffic engineering researchers tend to rely predominately on linear programming techniques or local adjustment of parameters for traffic signal plans. This preference is justifiable since totally decentralized approaches impose communication bottlenecks for the negotiation and might require a traffic expert to mediate conflicts which can arise.

For the reasons exposed above, it is widely agreed that more flexible and robust approaches are not only attractive, but necessary. The goal of this paper is to present a new method, based on reinforcement learning, which is capable of optimizing isolated junctions, reducing communication requirements and the need for traffic expert intervention. In this way, the resulting controller not only is decentralized but also is capable of learning with past situations and reusing interesting solutions. Moreover, the system is highly

[1]We use the terms intersection, crossing, junction, and traffic light interchangeably, since in each intersection only one signal-timing plan runs at a time.

AAMAS'06 May 8–12 2006, Hakodate, Hokkaido, Japan.

adaptable and does not rely on offline processing of huge amounts of historical data.

2. TRAFFIC LIGHT CONTROL

Traffic light controllers typically make use of a number of different parameters in order to implement a desired behavior. A *phase* corresponds to the specification of which movements (eg. to leave street 1 and to arrive at street 2) cars are allowed to make. A *signal-timing plan*, or signal plan for short, is a unique set of timing parameters, namely cycle length and split. Cycle lenght corresponds to the total time required for the completion of a whole sequence of the phase changes, and split corresponds to the specification of how much of the cycle length is going to be given for each phase.

Signal timing at a single intersection is chosen so as to minimize the overall delay at that intersection. Several signal plans are normally used in each intersection to cope with changes in traffic volume. This way, each signal plan becomes "responsible" for dealing with a specific traffic pattern. Well-designed signal plans can achieve acceptable results if they are synchronized. In general, the more neighbors are synchronized, the shorter the queues. In general cases, however, it is not possible to synchronize all flow directions at the same time, and therefore specific signal plans must be selected to give priority to particular traffic directions.

In case historical data are not available for the use in fixed strategies, traffic responsive approaches may be applied. Traffic responsive approaches for arterial appeared in the 1980s and, although they have been operating successfully in Europe, they have had limited use in the U.S. One reason is that these systems are complex to operate and pose high costs, both in terms of hardware and communication. In any case, traffic responsive systems are designed to consider only a main path (arterial or similar) and require *a priori* determination of appropriate signal plans for the different times of a day.

Several research groups study alternative paradigms for traffic control. In [1], a MAS based approach is described in which each traffic light is modeled as an agent with a set of pre-defined signal plans which coordinate with neighbors. Different signal plans can be selected in order to coordinate in a given traffic direction or during a pre-defined period of the day. This approach uses techniques of evolutionary game theory, meaning that self-interested agents receive a reward or a penalty given by the environment. Moreover, each agent possesses only information about their local traffic states. The downside of this approach is that payoff matrices (or at least the utilities and preferences of the agents) are required, i.e these figures have to be explicitly formalized by the designer of the system.

In [8] an approach based on cooperative mediation is proposed, which implements a compromise between totally autonomous coordination (with implicit communication) and classical centralized solutions. An algorithm to deal with distributed constraint optimization problems (OptAPO) is applied and results show that the mediation process is able to reduce the frequency of miscoordination between neighbor crossings.

Nunes and Oliveira [7] explore a traffic scenario as a testbed for techniques that enable agents to use information from several sources during learning. The learning occurs among members of a team. Each team is in charge of two connected crossings and each crossing is controlled by a different agent. Members of a team may communicate with their partner (in the same area) or with members of other teams that are solving similar problems in different areas. The main goal of their approach is the study the benefits of communication among heterogeneous groups of agents.

Camponogara and Kraus [2] have formalized a simple traffic scenario, composed by two intersections with traffic lights, as a distributed, stochastic game using reinforcement learning. Each control agent controls an intersection and learns via this distributed RL method. Their solution has outperformed two other control policies.

Finally, approaches based on self-organization of traffic lights via thresholds[2] or reservation-based systems have been proposed [5] but still present low-level abstraction issues which prevents them from being adopted by traffic engineers.

3. REINFORCEMENT LEARNING

In this section we present a brief overview of Reinforcement Learning (RL), which is the central learning paradigm for our mechanism. Reinforcement Learning is a traditional machine learning discipline used to determine best actions in sequential decision problems.

Usually, RL problems are modeled as Markov Decision Processes (MDPs). MDPs are described by a set of states, $\mathcal{S}$, a set of actions, $\mathcal{A}$, a reward function $R(s,a) \rightarrow \Re$ and a probabilistic state transition function $T(s,a,s') \rightarrow [0,1]$. An experience tuple $\langle s,a,s',r \rangle$ denotes the fact that the agent was in state s, performed action a and ended up in s' with reward r. Given a MDP, the goal is to calculate the optimal policy π^*, which is a mapping from states to actions such that the discounted future reward is maximized. In subsections 3.1 and 3.2 we present a two widely adopted RL methods, namely Q-Learning and Prioritized Sweeping. For more information, please refer to [6].

3.1 Q-Learning

Reinforcement learning methods can be divided into two categories: model-free and model-based. Model-based methods assume that the transition function T and the reward function R are available. Model-free systems, on the other hand, do not require that the agent have access to informations about how the environment works. Q-Learning is possible the simplest model-free in use. It works by estimating good state–action values, or Q-values, which are a numerical estimative of quality for a given pair of state and action. More precisely, a Q-value $Q(s,a)$ represents the maximum discounted sum of future rewards an agent can expect to receive if it starts in s, chooses action a and then continues to follow an optimal policy.

Q-Learning algorithm approximates the Q-values $Q(s,a)$ as the agent acts in a given environment. The update rule for each experience tuple $\langle s,a,s',r \rangle$ is:

$$Q(s,a) = Q(s,a) + \alpha \left(r + \gamma max_{a'} Q(s',a') - Q(s,a) \right)$$

where α is the learning rate and γ is the discount for future rewards. As can be seen in the update rule, the estimation

[2]pub. on line at `http://www.nature.com/news/2004/041129/full/041129-12.html`

of the Q-values does not rely on T or R, and this is the reason why the method is said to be model free. When the Q-values are nearly converged to their optimal values, it is appropriate for the agent to act greedily, that is, to always choose the action with the highest Q-value for the current state. However, during learning, there is a difficult exploitation versus exploration problem [6].

3.2 Prioritized Sweeping

Prioritized Sweeping (PS) is somewhat similar to Q-Learning, except for the fact that it continuously estimates a single model of the environment. Also, it updates more than one state value per iteration and makes direct use of state values, instead of Q-values. The states whose values should be updated after each iteration are determined by a priority queue, which stores the states *priorities*, initially set to zero. Also, each state remembers its predecessors, defined as all states with a non-zero transition probability to it under some action. At each iteration, new estimates $\hat{T}$ and $\hat{R}$ of the dynamics are made. The usual manner to update $\hat{T}$ is to calculate the maximum likelihood probability. Instead of storing the transitions probabilities in the form $T(s,a,s')$, PS stores the number of times the transition (s,a,s') occurred and the total number of times the situation (s,a) has been reached. This way, it is easy to update these parameters and to compute $\hat{T}$ as $\frac{|(s,a,s')|}{|(s,a)|}$.

Given an experience tuple $\langle s,a,s',r\rangle$, PS behaves as follows:

Algorithm 1 The Prioritized Sweeping algorithm

1: $V_{old}(s) = V(s)$
2: Update the state's value

$$V(s) = max_a \left(\hat{R}(s,a) + \gamma \sum_{s'} \hat{T}(s,a,s')V(s') \right)$$

3: $priority(s) = 0$
4: Compute the value change: $\delta = |V_{old} - V(s)|$
5: Use δ to modify the priorities of each predecessors s_p of s:

$$priority(s_p) = \delta \hat{T}(s_p, a_p, s)$$

where a_p is any action such that $\hat{T}(s_p, a_p, s) \geq 0$

3.3 RL in non-stationary environments

When dealing with non-stationary environments, both the model-free and the model-based RL approaches need to continuously relearn everything from scratch, since the policy which was calculated for a given environment is no longer valid after a change in dynamics. This causes a performance drop during the readjustment phase, and also forces the algorithm to relearn policies even for environment dynamics which have been previously experienced.

Since this paper deals primarily with traffic control problems, which involve intrinsically non-stationary environments, it is important to state beforehand our assumptions regarding the type of dynamics we expect to happen. Specifically, the class of non-stationary environments that we deal with is similar to the one studied by Hidden-Mode MDPs researchers [3]. We assume that the following properties hold: **1)** environmental changes are confined to a small number of *contexts*, which are stationary environments with distinct dynamics; **2)** the current context cannot be directly observed, but can be estimated according to the types of transitions and rewards observed; **3)** environmental context changes are independent of the agent's actions; and **4)** context changes are relatively infrequent.

In a traffic scenario, these assumptions mean that flow patterns are non-stationary but they can be nearly divided in stationary dynamics (eg. morning rush, afternoon traffic, etc). We do not assume, however, that this division must be known *a priori*. In fact, one of the interesting aspects of our method is exactly its capability of automatically partitioning the environment dynamics into relevant partial models. Moreover, we assume that the current flow pattern is not given or directly perceivable, but can be estimated by observing attributes such as the queue of cars, street densities, etc.

In order to cope with non-stationary environments, alternative RL methods have been proposed. Similar to our approach, we highlight the mechanisms proposed by Choi and colleagues [3] and Doya and colleagues [4]. Unfortunatly, their approaches require a fixed number of models, and thus implicitly assume that the approximate number of different environment dynamics is known *a priori*. Since this assumption is not always realistic, our method tries to overcome it by incrementally building new models.

Besides these approaches, other have been proposed such as mechanisms which vary the learning and adjustment rates in order to balance the importance of long adquired knowledge and just-observed dynamics. These methods work by continuously relearning everything from scratch, since their models only reflect the recently made observations. This means that the algorithm will have to relearn policies even for environment dynamics which have been previously experienced.

4. RL FOR TRAFFIC LIGHTS CONTROL

Traffic optimization is a hard control problem because it deals with highly dynamic and non-stationary flow patterns. Our approach relies on RL methods because they provide online learning capabilities and do not rely on offline analysis. In the next sections we present a RL method suitable for usage in traffic control scenarios.

The RL mechanism we propose assumes that the use of multiple partial models of the environment is a good approach for dealing with non-stationary scenarios such as traffic control. The use of multiple models makes the learning system capable of partitioning the knowledge in a way that each model automatically assumes for itself the responsibility for "understanding" one kind of flow pattern. To each model, we assign an optimal policy, which is a mapping from traffic conditions to signal plans, and a trace of prediction error of transitions and rewards, responsible for estimating the quality of a given partial model.

Moreover, we propose that the creation of new models should be controlled by a continuous evaluation of the prediction errors generated by each partial model. In the following subsections we first describe how to learn contexts (i.e, estimate models for traffic patterns), and then we show how to detect and switch to the most adequate model given a sequence of observations. Our method is called **RL-CD**, or Reinforcement Learning with Context Detection. Initial tests with a mechanism for context detection are described in [9].

4.1 Learning traffic patterns

In the following text, we use the terms *traffic pattern* and *context* interchangeably. In this paper, a context consists of a nearly stable set of traffic flow characteristics. In terms of RL, a context consists of a given environment dynamics, which is experienced by the agent as a class of transitions and rewards. Our mechanism for detecting context changes relies on a set of partial models for predicting the environment dynamics. A partial model m contains a function $\hat{T}_m$, which estimates transition probabilities, and also a function $\hat{R}_m$, which estimates the rewards to be received.

For each partial model, classic model-based reinforcement learning methods such as Prioritized Sweeping and Dyna [10] may be used to compute a locally optimal policy. The policy of a partial model is described by the function $\pi_m(s)$ and it is said to be locally optimal because it describes the optimal actions for each state in a specific context. For example, if the dynamics of a non-stationary environment Θ can be described by m_1, then π_{m_1} will be the associated optimal policy. If the non-stationarity of Θ makes itself noticeable by making π_{m_1} suboptimal, then the system creates a new model, m_2, which would predict with a higher degree of confidence the transitions of the newly arrived context. Associated with m_2, a locally optimal policy π_{m_2} would be used to estimate the best actions in m_2. Whenever possible, the system reuses existing models instead of creating new ones.

Given an experience tuple $\varphi \equiv \langle s, a, s', r\rangle$, we update the current partial model m by adjusting its model of transition and rewards by $\Delta^{\hat{T}}_{m,\varphi}$ and $\Delta^{\hat{R}}_{m,\varphi}$, respectively. These adjustments are computed as follows:

$$\Delta^{\hat{T}}_{m,\varphi}(\kappa) = \tfrac{1}{\mathcal{N}_m(s,a)+1}\Bigg(\tau^{s'}_{\kappa} - \hat{T}_m(s,a,\kappa)\Bigg) \quad \forall \kappa \in \mathcal{S}$$

$$\Delta^{\hat{R}}_{m,\varphi} = \tfrac{1}{\mathcal{N}_m(s,a)+1}\Bigg(r - \hat{R}_m(s,a)\Bigg)$$

such that τ is the Kronecker Delta:

$$\tau^{s'}_{\kappa} = \begin{cases} 1, & \kappa = s' \\ 0, & \kappa \neq s' \end{cases}$$

The effect of τ is to update the transition probability $T(s,a,s')$ towards 1 and all other transitions $T(s,a,\kappa)$, for all $\kappa \in \mathcal{S}$, towards zero. The quantity $\mathcal{N}_m(s,a)$ reflects the number of times, in model m, action a was executed in state s. We compute $\mathcal{N}_m$ considering only a truncated (finite) memory of past M experiences:

$$\mathcal{N}_m(s,a) = min\Bigg(\mathcal{N}_m(s,a)+1,\ M\Bigg) \tag{1}$$

A truncated value of $\mathcal{N}$ acts like a learning coefficient for $\hat{T}_m$ and $\hat{R}_m$, causing transitions to be updated faster in the initial observations and slower as the agent experiments more. Having the values for $\Delta^{\hat{T}}_{m,\varphi}$ and $\Delta^{\hat{R}}_{m,\varphi}$, we update the transition probabilities:

$$\hat{T}_m(s,a,\kappa) = \hat{T}_m(s,a,\kappa) + \Delta^{\hat{T}}_{m,\varphi}(\kappa), \quad \forall \kappa \in \mathcal{S} \tag{2}$$

and also the model of expected rewards:

$$\hat{R}_m(s,a) = \hat{R}_m(s,a) + \Delta^{\hat{R}}_{m,\varphi} \tag{3}$$

4.2 Detecting changes in traffic patterns

In order to detect changes in the traffic patterns (contexts), the system must be able to evaluate how well the current partial model can predict the environment. Thus, an error signal is computed for each partial model. The *instantaneous error* is proportional to a *confidence value*, which reflects the number of times the agent tried an action in a state. Given a model m and an experience tuple $\varphi = \langle s, a, s', r\rangle$, we calculate the instantaneous error $e_{m,\varphi}$ and the confidence $c_m(s,a)$ as follows:

$$c_m(s,a) = \left(\frac{\mathcal{N}_m(s,a)}{M}\right)^2 \tag{4}$$

$$e_{m,\varphi} = c_m(s,a)\Bigg(\Omega(\Delta^{\hat{R}}_{m,\varphi})^2 + (1-\Omega)\sum_{\kappa\in\mathcal{S}} \Delta^{\hat{T}}_{m,\varphi}(\kappa)^2\Bigg) \tag{5}$$

where Ω specifies the relative importance of the reward and transition prediction errors for the assessment of the model's quality. Once the instantaneous error has been computed, the trace of prediction error E_m for each partial model is updated:

$$E_m = E_m + \rho\Bigg(e_{m,\varphi} - E_m\Bigg) \tag{6}$$

where ρ is the adjustment coefficient for the error.

The error E_m is updated after each iteration for every partial model m, but only the active model is corrected according to equations 2 and 3. A plasticity threshold λ is used to specify until when a partial model should be adjusted. When E_m becomes higher than λ, the predictions made by the model are considered sufficiently different from the real observations. In this case, a context change is detected and the model with lowest error is activated. A new partial model is created when there are no models with trace error smaller than the plasticity. The mechanism starts with only one model and then incrementally creates new partial models as they become necessary. Pseudo-code for RL-CD is presented in algorithm 2.

The *newmodel*() routine is used to create a new partial model and initializes all estimates and variables to zero, except T_m, initialized with equally probable transitions. The values of parameters M, ρ, Ω and λ must be tuned according to the problem. Small values of ρ are appropriate for noisy environments; higher values of M define systems which require more experiences in order to gain confidence regarding its predictions; in general applications, Ω might be set to 0.5; the plasticity λ should be set to higher values according to the need for learning relevant (non-noisy) but rare transitions. Formal analytic support for these statements is not shown here and will be addressed in a paper in preparation.

5. SCENARIO AND EXPERIMENTS

5.1 Scenario

Our validation scenario consists of a traffic network which is a 3x3 Manhattan-like grid, with a traffic light in each

Algorithm 2 RL-CD algorithm

Let m_{cur} be the currently active partial model.
Let $\mathcal{M}$ be the set of all available models.

```
m_cur ← newmodel()
M ← {m_cur}
s ← s_0, where s_0 is any starting state
loop
  Let a be the action chosen by PS for the model m_cur
  Observe next state s' and reward r
  Update E_m, for all m, according to equation 6
  m_cur ← arg min_m (E_m)
  if E_{m_cur} > λ then
    m_cur ← newmodel()
    M ← M ∪ {m_cur}
  end if
  Update T̂_{m_cur} and R̂_{m_cur} (equations 2 and 3)
  N_m(s, a) ← min(N_m(s, a) + 1, M)
  s ← s'
end loop
```

junction. Figure 1 depicts a graph representing the traffic network, where the 9 nodes correspond to traffic lights and the 24 edges are directed (one-way) links.

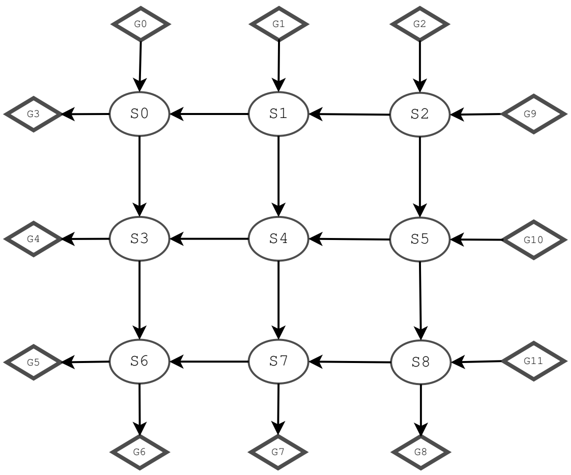

Figure 1: A Network of 9 Intersections.

Each link has capacity for 50 vehicles. Vehicles are inserted by *sources* and removed by *sinks*, depicted as diamonds in figure 1. The exact number of vehicles inserted by the sources is given by a Gaussian distribution with mean μ and a fixed standard deviation σ. If a vehicle has to be inserted but there is no space available in the link, it waits in an external queue until the insertion is possible. External queues are used in order to provide a fair comparison between all approaches. The vehicles do not change directions during the simulation and upon arriving at the sinks they are immediately removed. For instance, a vehicle inserted in the network by the source "G0" with South direction will be removed by sink "G6".

We modeled the problem in a way that each traffic light is controlled by one agent, each agent making only local decisions. Even though decisions are local, we assess how well the mechanism is performing by measuring global performance values. By using reinforcement learning to optimize isolated junctions, we implement decentralized controllers and avoid expensive offline processing.

As a measure of effectiveness for the control systems, usually one seeks to optimize a weighted combination of stopped cars and travel time. In our experiments we evaluate the performance by measuring the total number of stopped vehicles, since this is an attribute which can be easily measured by real inductive loop detectors.

After discretizing the length of queues, the occupation of each link can be either *empty*, *regular* or *full*. The state of an agent is given by the occupation of the links arriving in its corresponding traffic light. Since there are two one-way links arriving at each traffic light (one from north and one from east), there are 9 possible states *for each agent*. The reward for each agent is given locally by the summed square of incoming link's queues. Performance, however, is evaluated for the whole traffic network by summing the queue size of all links, including external queues.

Traffic lights normally have a set of signal plans used for different traffic conditions and/or time of the day. We consider here only three plans, each with two phases: one allowing green time to direction north-south (NS) and other to direction east-west (EW). Each one of the three signal plans uses different green times for phases: signal plan **1** gives equal green times for both phases; signal plan **2** gives priority to the vertical direction; and signal plan **3** gives priority to the horizontal direction. All signal plans have cycle time of 60 seconds and phases of either 42, 30 or 18 seconds (70% of cycle time for preferential direction, 50% of cycle time and 25% of cycle time for non-preferential direction) . The signal plan with equal phase times gives 30 seconds for each direction (50% of the cycle time); the signal plan which prioritizes the vertical direction gives 42 seconds to the phase NS and 18 seconds to the phase EW; and the signal plan which prioritizes the horizontal direction gives 42 seconds to the phase EW and 18 seconds to the phase NS.

In our simulation, one timestep consists of an entire cycle of signal plan. Speed and topology constraints are so that 33 vehicles can pass the junction during one cycle time. The agent's action consists of selecting one of the three signal plans at each simulation step.

In order to model the non-stationarity of the traffic behavior, our scenario assumes 3 different traffic patterns (contexts). Each traffic pattern consists of a different car insertion distribution. In other words, the non-stationarity occurs because we explicitly change the mean μ of the Gaussian distribution in sources. The 3 contexts are:

- *Low*: low insertion rate in the both North and East sources, allowing the traffic network to perform relatively well even if the policies are not optimal (i.e., the network is undersaturated);
- *Vertical*: high insertion rate in the North sources (G0, G1, and G2), and average insertion rate in the East (G9, G10, and G11);
- *Horizontal*: high insertion rate in the East sources (G9, G10, and G11), and average insertion rate in the East (G0, G1, and G2).

The Gaussian distributions in the contexts *Vertical* and *Horizontal* are such that the traffic network gets saturated if the policies are not optimal. Simultaneous high insertion rates in both directions is not used since then no optimal action is possible, and the network would inevitably saturate in few steps, thus making the scenario a stationary environment with all links at maximum occupation.

5.2 Experiments

In our experiments we compare our method against a greedy solution and against classic model-free and a model-based reinforcement learning algorithms. We show that reinforcement learning with context detection performs better than both for the traffic light control problem. In the next experiments, all figures use gray-colored stripes to indicate the current context (traffic pattern) occuring during the corresponding timesteps. The darker gray corresponds to the *Low* context, the medium to *Vertical* context and the lighter to *Horizontal* context. We change the context (traffic pattern) every 200 timesteps, which corresponds to nearly 3 hours of real traffic flow. Moreover, all following figures which compare the performance of control methods make use of the metric described in section 5.1, that is, the total number of stopped cars in all links (including external queues). This means that the lowest the value in the graph, the better the performance.

We first implemented the greedy solution as a base of comparison of our method. The greedy solution is a standard decentralized solution for traffic-responsive networks in which there is no coordination. Each agent takes decisions based solely on the status of the North and East queues, selecting the signal plan which gives priority to the direction with more stopped cars. If the status of both queues is the same, the greedy agent selects the signal plan with equal time distribution. Figure 2 shows the comparison between our method and the greedy solution. Notice that the greedy solution performs better in the beginning, since our method is still learning to deal with changes in the traffic behavior. After a while, however, our method performs better because it explicitly discovers the traffic patterns which occur.

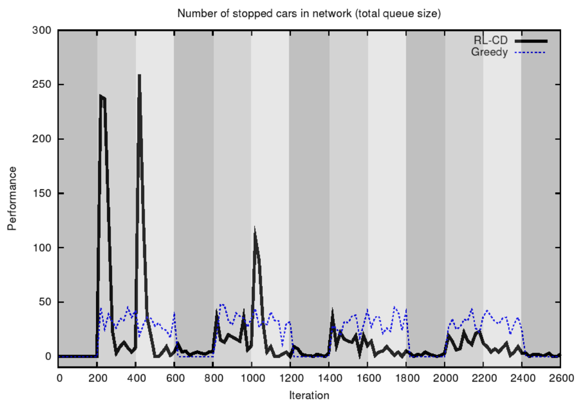

Figure 2: A comparison of performance for RL-CD and a greedy solution.

In figure 3 we present the quality of prediction for each model created by our method. The quality, or eligibility, is simply the complement of the prediction error calculated according to equation 6. The eligibility basically informs how well each model predicts a given traffic pattern: the higher the eligibility, the better the model. The line near zero corresponds to the plasticity threshold. Whenever a model's eligibility gets lower than the threshold, our mechanism either selects a more appropriate model (one which predicts better the dynamics of traffic) or creates a new one, in case no good alternative model is available.

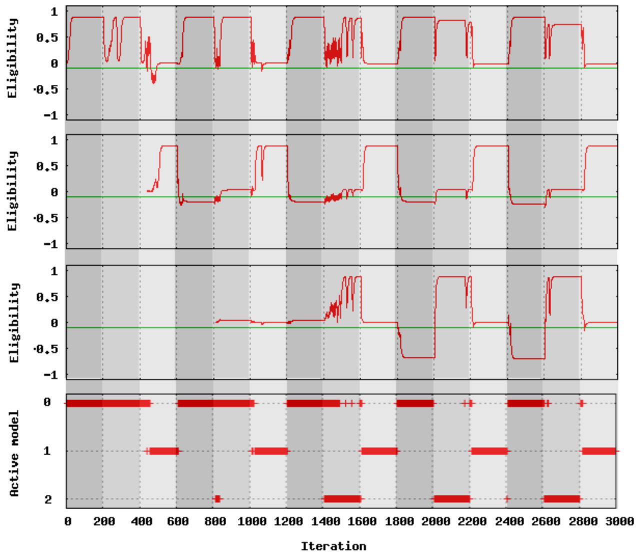

Figure 3: RL-CD eligibility (above) and active model (below).

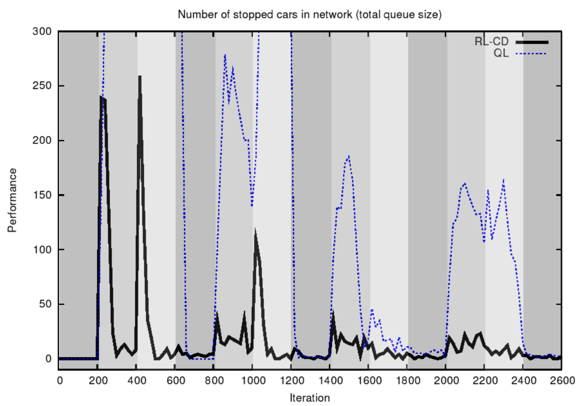

Figure 4: A comparison of performance for RL-CD and Q-Learning.

In our experiment, RL-CD created 3 models to explain the environment dynamics, and the eligibility for each one of these is presented in the 3 graphs in the superior part of figure 3. The last graph in figure 3 represents the active model during each context. As can be seen, the active model alternates between the three available models, according to the one which better predicted the traffic patterns. In the beginning of the simulation, RL-CD created two models. However, somewhere near timestep 1600 it created a third model and then started to correctly associate one partial model to each one of the discovered traffic patterns. This fact indicates that RL-CD was able to correctly create a partial model for each context and also that the models were created on-demand, that is, as the algorithm discovered that its prediction models where no longer satisfying.

In figures 4 and 5 we compare RL-CD performance with two standard RL methods, namely Q-Learning and Prioritized Sweeping, respectively. Since Q-Learning is model-free, it is less prone to wrong bias caused by non-stationarity. However, for the same reason it is not able to build interesting models of the relevant attributes of the dynamics. Prioritized Sweeping, on the other hand, tries to build a single model for the environment and ends up with a model which mixes properties of different traffic patterns. For this reason, it can at most calculate a policy which is a compromise for several different (and sometimes opposite) traffic patterns.

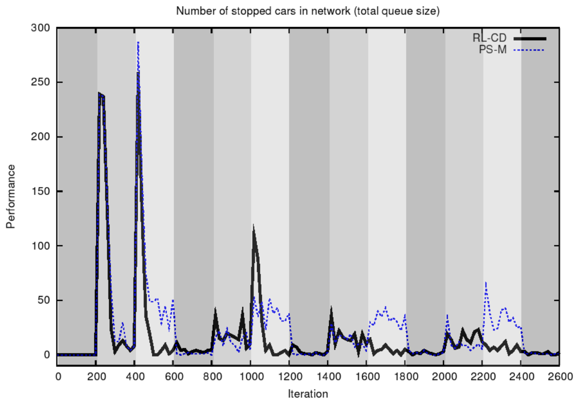

Figure 5: A comparison of performance for RL-CD and Prioritized Sweeping with finite memory

6. CONCLUSIONS

Centralized approaches to traffic signal control cannot cope with the increasing complexity of urban traffic networks. A trend towards decentralized control was already pointed out by traffic experts in the 1980's and traffic responsive systems for control of traffic lights have been implemented.

In this paper we have introduced and formalized a reinforcement learning method capable of dealing with non-stationary traffic patterns. Moreover, we have shown empirical results which show that our mechanism is more efficient than a greedy strategy and other reinforcement learning approaches.

We intend to further analyze the complexity of using our approach and other RL methods for traffic control, since it is a known fact that standard reinforcement learning suffers from the curse of dimensionality. We also plan to study the trade-off between memory requirements and model quality in highly non-stationary traffic scenarios.

Even though this research is still in its initial stages, the present work contributes with one more step forward in the long term effort of testing decentralized and efficient approaches for traffic lights control.

Acknowledgments

Authors are partially supported by CNPq and CAPES.

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Agent Reward Shaping for Alleviating Traffic Congestion

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ABSTRACT

Traffic congestion problems provide a unique environment to study how multi-agent systems promote desired system level behavior. What is particularly interesting in this class of problems is that no individual action is intrinsically "bad" for the system but that combinations of actions among agents lead to undesirable outcomes. As a consequence, agents need to learn how to coordinate their actions with those of other agents, rather than learn a particular set of "good" actions. This problem is ubiquitous in various traffic problems, including selecting departure times for commuters, routes for airlines, and paths for data routers.

In this paper we present a multi-agent approach to two traffic problems, where for each driver, an agent selects the most suitable action using reinforcement learning. The agent rewards are based on concepts from collectives and aim to provide the agents with rewards that are both easy to learn and that if learned, lead to good system level behavior. In the first problem, we study how agents learn the best departure times of drivers in a daily commuting environment and how following those departure times alleviates congestion. In the second problem, we study how agents learn to select desirable routes to improve traffic flow and minimize delays for all drivers. In both sets of experiments, agents using collective-based rewards produced near optimal performance (93-96% of optimal) whereas agents using system rewards (63-68%) barely outperformed random action selection (62-64%) and agents using local rewards (48-72%) performed worse than random in some instances.

1. INTRODUCTION

Multi-agent learning algorithms provide a natural approach to addressing congestion problems in traffic and transportation domains. Congestion problems are characterized by having the system performance depend on the number of agents that select a particular action, rather on the intrinsic value of those actions. Examples of such problems include lane/route selection in traffic flow [7, 10], path selection in data routing [8], and side selection in the minority game [3, 6]. In those problems, the desirability of lanes, paths or sides depends solely on the number of agents having selected them. Hence, multi-agent approaches that focus on agent coordination are ideally suited for these domains where agent coordination is critical for achieving desirable system behavior.

In this paper we apply multi-agent learning algorithms to two separate traffic problems. First we investigate how to coordinate the departure times of a set of drivers so that they do not end up producing traffic "spikes" at certain times, both providing delays at those times and causing congestion for future departures. In this problem, different time slots have different desirabilities that reflect user preferences for particular time slots. The system objective is to maximize the overall system's satisfaction as a weighted average of those desirabilities. In the second problem we investigate route selection where a set of drivers need to select different routes to a destination. In this problem, different routes have different capacities and the problem is for the agents to minimize the total congestion. Both problems share the same underlying property that agents greedily pursuing the best interests of their own drivers cause traffic to worsen for everyone in the system, including themselves.

The approach we present to alleviating congestion in traffic is based on assigning each driver an agent which determines the departure time/route to follow. Those agents determine their actions based on a reinforcement learning algorithm [9, 14, 18]. The key issue in this approach is to ensure that the agents receive rewards that promote good system level behavior. To that end, it is imperative that the agent rewards: (i) are aligned with the system reward[1], ensuring that when agents aim to maximize their own reward they also aim to maximize system reward; and (ii) are sensitive to the actions of the agents, so that the agents can determine the proper actions to select (i.e., they need to limit the impact of other agents in the reward functions of a particular agent).

The difficulty in agent reward selection stems from the fact that typically these two properties provide conflicting requirements. A reward that is aligned with the system reward usually accounts for the actions of other agents, and thus is likely to not be sensitive to the actions of one agent; on the other hand, a reward that is sensitive to the actions of one agent is likely not to be aligned with system reward.

AAMAS'06 May 8–12 2006, Hakodate, Hokkaido, Japan.

[1] We call the function rating the performance of the full system, "system reward" throughout this paper in order to emphasize its relationship to agent rewards.

This issue is central to achieving coordination in a traffic congestion problem and has been investigated in various fields such as computational economics, mechanism design, computational ecologies and game theory [2, 12, 5, 11, 13]. We address this reward design problem using the difference reward derived from collectives [19, 16], which provides a good balance of alignedness and sensitivity. The difference reward has been applied to many domains, including rover coordination [1], faulty device selection problem [15], packet routing over a data network [17, 20], and modeling nongenomic models of early life [4].

In this paper we show how these collective based reinforcement learning methods can be used to alleviate traffic congestion. In Section 2 we discuss the properties agent rewards need to have and present a particular example of agent reward. In Sections 3.1 and 3.2 we present the departure coordination problem. The results in this domain show that total traffic delays can be improved significantly when agents use collective based rewards. In Section 3.3 we present the route selection problem. The results in this domain show that traffic congestion can be reduced by over 30% when agents use collective based rewards. Finally Section 4 we discuss the implication of these results and discuss methods by which they can be applied in the traffic domain.

2. BACKGROUND

In this work, we focus on multi-agent systems where each agent, i, tries to maximize its reward function $g_i(z)$, where z depends on the joint move of all agents. Furthermore, there is a system reward function, $G(z)$ which rates the performance of the full system. To distinguish states that are impacted by actions of agent i, we decompose[2] z into $z = z_i + z_{-i}$, where z_i refers to the parts of z that are dependent on the actions of i, and z_{-i} refers to the components of z that do not depend on the actions of agent i.

2.1 Properties of Reward Functions

Now, let us formalize the two requirements discussed above that an agent's reward should satisfy in order for the system to display coordinated behavior . First, the agent rewards have to be aligned with respect to G, quantifying the concept that an action taken by an agent that improves its own reward also improves the system reward. Formally, for systems with discrete states, the degree of **factoredness** for a given reward function g_i is defined as:

$$\mathcal{F}_{g_i} = \frac{\sum_z \sum_{z'} u[(g_i(z) - g_i(z'))\ (G(z) - G(z'))]}{\sum_z \sum_{z'} 1} \qquad (1)$$

for all z' such that $z_{-i} = z'_{-i}$ and where $u[x]$ is the unit step function, equal to 1 if $x > 0$, and zero otherwise. Intuitively, the higher the degree of factoredness between two rewards, the more likely it is that a change of state will have the same impact on the two rewards. A system is fully factored when $\mathcal{F}_{g_i} = 1$.

Second, an agent's reward has to be sensitive to its own actions and insensitive to actions of others. Formally we can quantify the **learnability** of reward g_i, for agent i at z:

$$\lambda_{i,g_i}(z) = \frac{E_{z'_i}[|g_i(z) - g_i(z_{-i} + z'_i)|]}{E_{z'_{-i}}[|g_i(z) - g_i(z'_{-i} + z_i)|]} \qquad (2)$$

where $E[\cdot]$ is the expectation operator, z'_i's are alternative actions of agent i at z, and z'_{-i}'s are alternative joint actions of all agents other than i. Intuitively, learnability provides the ratio of the expected value of g_i over variations in agent i's actions to the expected value of g_i over variations in the actions of agents other than i. So at a given state z, the higher the learnability, the more $g_i(z)$ depends on the move of agent i, i.e., the better the associated signal-to-noise ratio for i. Higher learnability means it is easier for i to achieve large values of its reward.

2.2 Difference Reward Functions

Let us now focus on providing agent rewards that are both high factoredness and high learnability. Consider the **difference** reward [19], which is of the form:

$$D_i \equiv G(z) - G(z_{-i} + c_i) \qquad (3)$$

where z_{-i} contains all the states on which agent i has no effect, and c_i is a fixed vector. In other words, all the components of z that are affected by agent i are replaced with the fixed vector c_i. Such difference reward functions are fully factored no matter what the choice of c_i, because the second term does not depend on i's states [19]. Furthermore, they usually have far better learnability than does a system reward function, because the second term of D removes some of the effect of other agents (i.e., noise) from i's reward function. In many situations it is possible to use a c_i that is equivalent to taking agent i out of the system. Intuitively this causes the second term of the difference reward function to evaluate the value of the system without i and therefore D evaluates the agent's contribution to the system reward.

The difference reward can be applied to any linear or nonlinear system reward function. However, its effectiveness is dependent on the domain and the interaction among the agent reward functions. At best, it fully cancels the effect of all other agents. At worst, it reduces to the system reward function, unable to remove any terms (e.g., when z_{-i} is empty, meaning that agent i effects all states). In most real world applications, it falls somewhere in between, and has been successfully used in many domains including agent coordination, satellite control, data routing, job scheduling and congestion games [1, 17, 19]. Also note that computationally the difference reward is often easier to compute than the system reward function [17]. Indeed in the problem presented in this paper, for agent i, D_i is easier to compute than G is (see details in Section 3.1.1).

2.3 Reward Maximization

In this paper we assume that each agent maximize its own reward using its own reinforcement learner (though alternatives such as evolving neuro-controllers are also effective [1]. For complex delayed-reward problems, relatively sophisticated reinforcement learning systems such as temporal difference may have to be used. However, the traffic domain modeled in this paper only needs to utilize immediate rewards, therefore a simple table-based immediate reward reinforcement learning is used. Our reinforcement learner is equivalent to an ϵ-greedy Q-learner with a discount rate of

[2]Instead of concatenating partial states to obtain the full state vector, we use zero-padding for the missing elements in the partial state vector. This allows us to use addition and subtraction operators when merging components of different states (e.g., $z = z_i + z_{-i}$).

0. At every episode an agent takes an action and then receives a reward evaluating that action. After taking action a and receiving reward R a driver updates its table as follows: $Q'(a) = (1-\alpha)Q(a)+\alpha(R)$, where α is the learning rate. At every time step the driver chooses the action with the highest table value with probability $1-\epsilon$ and chooses a random action with probability ϵ. In the experiments described in the following section, α is equal to 0.5 and ϵ is equal to 0.05. The parameters were chosen experimentally, though system performance was not overly sensitive to these parameters.

3. EXPERIMENTS

To test the effectiveness of our rewards in the traffic congestion domain, we performed experiments using two abstract traffic models. In the first model each agent has to select a time slot to start its drive. In this model we explore both simple and cascading traffic flow. With non-cascading flow, drivers enter and exit the same time slot, while with cascading flow, drivers stuck in a time slot with too many other drivers stay on the road for future time slots. In the second model, instead of choosing time slots, drivers choose routes. In this model the system reward has different properties and we have the additional complexity of different routes having different capacities.

3.1 Single-Route Congestion Model

In the traffic congestion model used here, there is a fixed set of drivers, driving on a single route. The agents choose the time slot in which their drivers start their commutes. The system reward is given by:

$$G = \sum_t w_t S(k_t) \ . \tag{4}$$

where weights w_t model rush-hour scenarios where different time slots have different desirabilities, and $S(k)$ is a "time slot reward", depending on the number of agents that chose to depart in the time slot:

$$S(k) = \begin{cases} ke^{-1} & \text{if } k \leq c \\ ke^{-k/c} & \text{otherwise} \end{cases} \ , \tag{5}$$

The number of drivers in the time slot is given by k, and the optimal capacity of the time slot is given by c. Below an optimal capacity value c, the reward of the time slot increases linearly with the number of drivers. When the number of drivers is above the optimal capacity level, the value of the time slot decreases quickly (asymptotically exponential) with the number of drivers. This reward models how drivers do not particularly care how much traffic is on a road until it is congested. This function is shown in Figure 1. In this problem the task of the system designer is to have the agents choose time slots that help maximize the system reward. To that end, agents have to balance the benefit of going at preferred time slots with the congestion at those time slots.

3.1.1 Driver Rewards

While as a system designer our goal is to maximize the system reward, we have each individual agent try to maximize a driver-specific reward that we select. The agents maximize their rewards through reinforcement learning, where they learn to choose time slots that have expected high reward. In these experiments, we evaluate the effectiveness

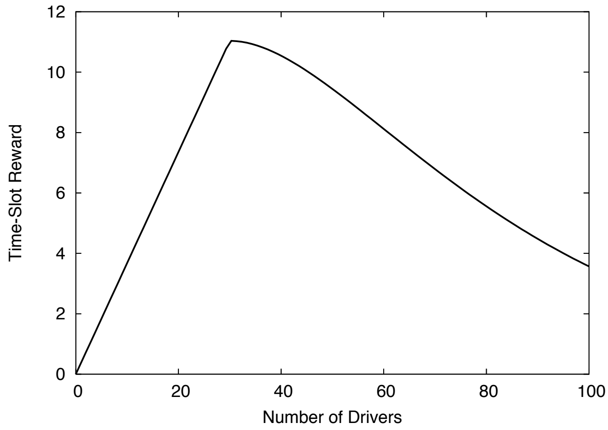

Figure 1: Reward of time slot with $c = 30$.

of three different rewards. The first reward is simply the system reward G, where each agent tries to maximize the system reward directly. The second reward is a local reward, L_i where each agent tries to maximize a reward based on the time slot it selected:

$$L_i(k) = w_i S(k_i) \ , \tag{6}$$

where k_i is the number of drivers in the time slot chosen by driver i. The final reward is the difference reward, D:

$$\begin{aligned} D_i &= G(k) - G(k_{-i}) \\ &= \sum_j L_j(k) - \sum_j L_j(k_{-i}) \\ &= L_i(k) - L_i(k_{-i}) \\ &= w_i k_i S(k_i) - w_i(k_i - 1)S(k_i - 1) \ , \end{aligned}$$

where k_{-i} represents the the driver counts when driver i is taken out of the system. Note that since taking away driver i only affects one time slot, all of the terms but one cancel out, making the difference reward simpler to compute than the system reward.

3.1.2 Results

In this set of experiments there were 1000 drivers, and the optimal capacity of each time slot was 250. Furthermore, the weighting vector was centered at the most desirable time slot (e.g., 5 PM departures):

$$w = [1\ 5\ 10\ 15\ 20\ 15\ 10\ 5\ 1]^T \ .$$

This weighting vector reflects a preference for starting a commute at the end of the workday with the desirability of a time slot decreasing for earlier and later times.

This experiment shows that drivers using the difference reward are able to quickly obtain near-optimal system performance (see Figure 2). In contrast, drivers that try to directly maximize the system reward learn very slowly and never achieve good performance during the time-frame of the experiment. This slow learning rate is a result of the system reward having low learnability to the agents' actions. Even if a driver were to take a system wide coordinated action, it is likely that some of the 999 other drivers would take uncoordinated actions at the same time, lowering the value of the system reward. A driver using the system reward typically does not get proper credit assignment for its actions, since the reward is dominated by other drivers.

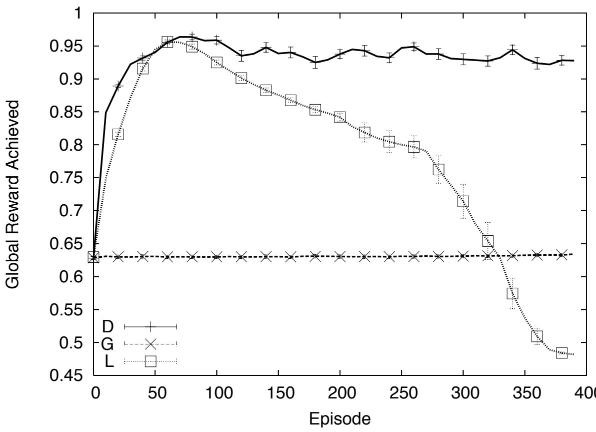

Figure 2: Performance on Single-Route Domain. Drivers using difference reward quickly learn to achieve near optimal performance (1.0). Drivers using system reward learn slowly. Drivers using non-factored local reward eventually learn counterproductive actions.

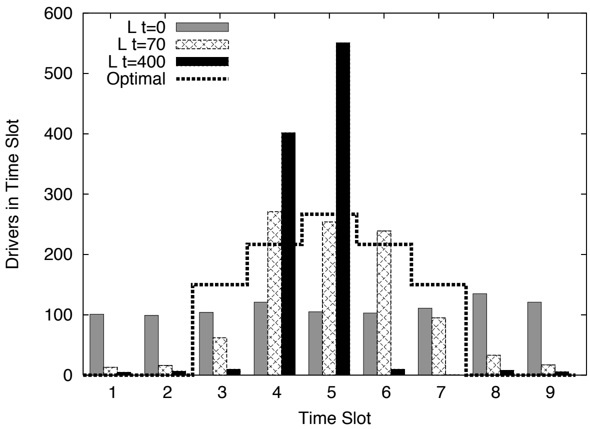

Figure 3: Distribution of Drivers using Local Reward. Early in training drivers learn good policies. Later in learning, the maximization of local reward causes drivers to over utilize high valued time slots.

The experiment where drivers are using L (a non-factored local reward) exhibit some interesting performance properties. At first these drivers learn to improve the system reward. However, after about episode seventy their performance starts to decline. Figure 3 gives greater insight into this phenomenon. At the beginning of the experiment, the drivers are randomly distributed among time slots, resulting in a low reward. Later in training agents begin to learn to use the time slots that have the most benefit. When the number of drivers reach near optimal values for those time slots, the system reward is high. However, all agents in the system covet those time slots and more agents start to select the desirable time slots. This causes congestion and system reward starts to decline. This performance characteristics is typical of system with agent rewards of low factoredness. In such a case, agents attempting to maximize their own rewards lead to undesirable system behavior. In contrast, because their rewards are factored with the system reward, agents using the difference reward form a distribution that more closely matches the optimal distribution (Figure 4).

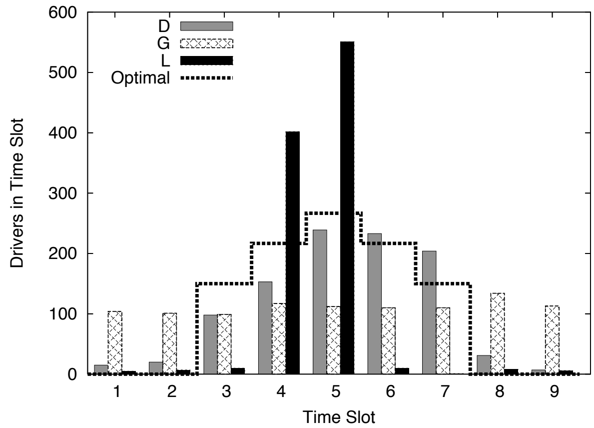

Figure 4: Distribution of Drivers at end of Training. Drivers using difference reward form distribution that is closer to optimal than drivers using system of local rewards.

3.2 Cascading Single-Route Congestion Model

The previous single-route model assumes that drivers enter and leave the same time slot. Here we introduce a more complex model, where drivers remain in the system longer when it is congested. This property modeled by having drivers over the optimal capacity, c stay in the system until they reach a time slot with a traffic level below c. When the number of drivers in a time slot is less than c the reward for a time slot is the same as before. When the number of drivers is above c the linear term k is replaced with c:

$$S(k) = \begin{cases} ke^{-1} & \text{if } k \leq c \\ ce^{-k/c} & \text{otherwise} \end{cases} \tag{7}$$

As before the system reward is a sum of the time slot rewards: $G = \sum_t S(k_t)$.

3.2.1 *Driver Rewards*

Again the local reward is the weighted time slot reward:

$$L_i = w_i S(k_i) \ , \tag{8}$$

where k_i is the number of drivers in the time slot chosen by driver i. However the difference reward is more difficult to simplify as the actions of a driver can have influence over several time slots:

$$\begin{aligned} D_i &= G(k) - G(k_{-i}) \\ &= \sum_j w_j S(k_j) - \sum_j w_j S(k_{-i_j}) \ , \end{aligned}$$

where k_{-i_j} is the number of drivers there would have been in time slot j had driver i not been in the system.

3.2.2 Results

Figure 5 shows the results for cascading traffic model. As previously, there are 1000 drivers and time slot capacities are 250. Drivers using the different rewards exhibit similar characteristics on this model than on the non-cascading one. Again drivers using the system reward are unable to improve their performance significantly beyond their initial random performance. In this model drivers using the local reward perform even worse once they become proficient at maximizing their own reward. The local reward here performs worse, because in this model a driver's choice of time slot can cause additional side-effects for other time slots, as drivers from a congested time slot remain in the system for future time slots. As a result, when drivers using the local reward cause congestion for their time slots, the congestion cascades as drivers spill into future time slots causing a significant decrease in performance.

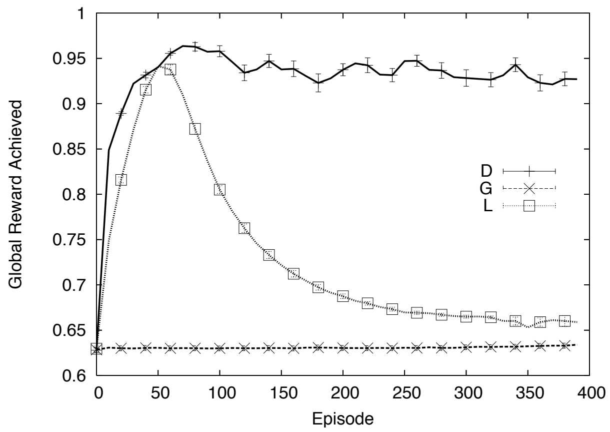

Figure 5: Performance on Cascading Single-Route Domain. In this domain drivers above the capacity in one time slot remain in system in future time slots. Drivers using difference reward quickly learn to achieve near optimal performance (1.0).

3.3 Multiple-Route Congestion Model

In this model instead of selecting time slots, drivers select routes. The main difference in this model is the functional form of the reward for a route as shown in Figure 6. In this model the objective is to keep the routes uncongested. The system reward does not care how many drivers are on a particular route as long as that route is below its congestion point. Each route has a different weight representing overall driver preference for a route. Furthermore, each route has its own capacity, modeling the realities that some routes having more lanes than others.

In this model the reward for an individual route is:

$$S(k,c) = \begin{cases} e^{-1} & \text{if } k \le c \\ e^{-k/c} & \text{otherwise} \end{cases} \quad (9)$$

The system reward is then the sum of all route rewards

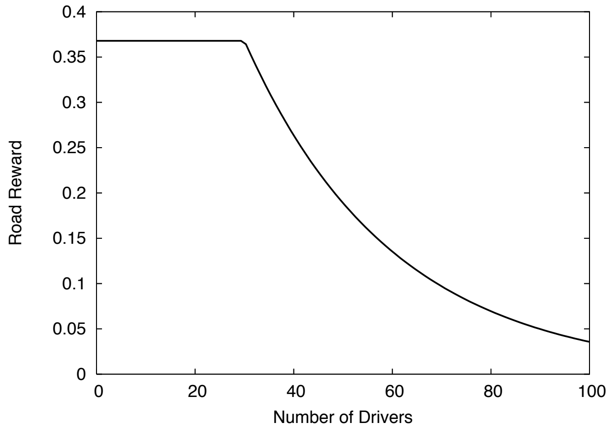

Figure 6: Reward of Road with $c = 30$.

weighted by the value of the route.

$$G = \sum_i w_i S(k_i, c_i) \ , \quad (10)$$

where w_i is the weighting for route i and c_i is the capacity for route i.

3.3.1 Driver Rewards

Again three rewards were tested: the system reward, the local reward and the difference reward. The local reward is the weighted reward for a single route:

$$L_i = w_i S(k_i, c_i) \ . \quad (11)$$

The final reward is the difference reward, D:

$$\begin{aligned} D_i &= G(k) - G(k_{-i}) \\ &= L_i(k) - L_i(k_{-i}) \\ &= w_i S(k_i, c_i) - w_i S(k_i - 1, c_i) \ , \end{aligned}$$

representing the difference between the actual system reward and what the system reward would have been if the driver had not been in the system.

3.3.2 Results

Here we show the results of experiments where we test performance of the three rewards in the multi-route model, where different routes have different value weightings and different capacities. There were 1000 drivers in these experiments and the route capacities were 333, 167, 83, 33, 17, 33, 83, 167, 333. Each route is weighted with the weights 1, 5, 10, 1, 5, 10, 1, 5, 10. Figure 7 shows that drivers using the system reward perform poorly, and learn slowly. Again drivers using the difference reward perform the best, learning quickly to achieve an almost optimal solution. Drivers using the local reward learn more quickly early in training than drivers using the system reward, but never achieve as high as performance as those using the difference reward. However in this domain the drivers using the local reward do not degrade from their maximal performance, but instead enter a steady state that is significantly below that of the drivers using the difference reward.

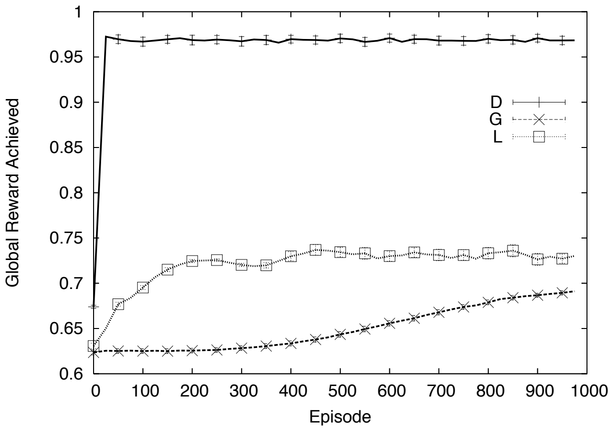

Figure 7: Performance on Domain with Multiple Routes. Best observed performance = 1.0 (optimal not calculated)

4. DISCUSSION

This paper presented a method for improving congestion in two different traffic problems. First we presented a method by which agents can coordinate the departure times of drivers in order to alleviate spiking at peak traffic times. Second we showed that agents can manage effective route selection and significantly reduce congestion by using a reward structure that penalizes greedily pursuing the routes with high capacity. Both results are based on agents receiving rewards that have high factoredness and high learnability (i.e., are both aligned with the system reward and are as sensitive as possible to changes in the reward of each agent). In both sets of experiments, agents using collective-based rewards produced near optimal performance (93-96% of optimal) whereas agents using system rewards (63-68%) barely outperformed random action selection (62-64%) and agents using local rewards (48-72%) provided performance ranging from mediocre to worse than random in some instances.

One issue that arises in traffic problems that does not arise in many other domains (e.g., rover coordination) is in ensuring that drivers follow the advice of their agents. In this work, we did not address this issue, as our purpose was to show that solutions to the difficult traffic congestion problem can be addressed in a distributed adaptive manner using intelligent agents. Ensuring that drivers follow the advice of their agents is a fundamentally different problem. On one hand, drivers will notice that the departure times/routes suggested by their agents provide significant improvement over their regular patterns. However, as formulated, there are no mechanisms for ensuring that a driver does not gain an advantage by ignoring the advice of his or her agent.

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