Proceedings of the 8th International
IEEE Conference on Intelligent Transportation Systems
Vienna, Austria, September 13-16, 2005

A Reactive Agent-Based Neural Network Car Following Model

Sakda Panwai and Hussein Dia

***Abstract*—This paper presents a car following model which was developed using reactive agent techniques based on a neural network approach for mapping perceptions to actions. The model has a similar formulation to the desired spacing models which do not consider reaction time or attempt to explain the behavioural aspects of car following. A number of error tests were used to compare the performance of the model against a number of established car following models. The results showed that simple back-propagation neural network models outperformed the Gipps and Psychophysical family of car following models. A qualitative drift behaviour analysis also confirmed the findings. For microscopic validation, speed and position of individual vehicles computed from the model were compared to field data. Macroscopic validation involved comparison of the field data and model results for trajectories, average speed, density and volume. Model validation at the microscopic and macroscopic levels showed very close agreement between field data and model results.**

I. Introduction

Microscopic traffic simulation tools are increasingly being applied by traffic engineers and transport professionals to deal with dynamic and operational traffic problems and to evaluate a range of new Intelligent Transport Systems (ITS) applications. There are many problems such as adaptive traffic management, traveller information and incident management systems which are difficult to evaluate using traditional analytical tools due to the complex nature of the underlying system dynamics in these applications. Microscopic traffic simulation tools provide an environment where different scenarios can be introduced and evaluated in a controlled setting without disrupting traffic conditions on the road. These traffic simulation tools are basically based on microscopic traffic behaviour such as car-following and lane-changing. Car following behaviour, in particular, has a significant impact on the accuracy of the simulation model in replicating traffic behaviour on the road.

This study develops a car following model using reactive agent techniques based on Artificial Neural Networks. The car following model explored in this study relates the follower vehicle's speed to the leader vehicle's speed and the relative distance between the two vehicles. The models are developed using speed data that were collected from a congested single lane road in Germany [1]. The paper also demonstrates the feasibility of interfacing advanced ANN models to a traffic simulator to replicate car-following behaviour. A comparative evaluation of the model developed in this study against established car following models is also carried out using a traffic simulator.

Sakda Panwai is a PhD Candidate in the Department of Civil Engineering, the University of Queensland, Australia.

Hussein Dia is Director, ITS Research Laboratory, Department of Civil Engineering, the University of Queensland, Australia. (phone: 07 3365 3517; fax: 07 3365 4599; e-mail: H.Dia@uq.edu.au).

II. Car Following Models

Car following behaviour, which describes how a pair of vehicles interact with each other, is an important consideration in traffic simulation models. A number of factors have been found to influence car following behaviour and these include individual differences of age, gender and risk-taking behaviour [2]. A study by Brackstone and McDonald [3] classified car following models into five groups as follows: Gazis-Herman-Rothery (GHR) model, Collision Avoidance model (CA), Linear model, Psychophysical or Action Point model (AP), and Fuzzy logic-based model. A detailed description of these models is outside the scope of this short paper.

III. Development of Reactive Agent-Based Car Following Model

A. Reactive Agent-Based Models

Agent structures are usually divided into two categories: reactive and cognitive. The reactive agent is based on a simple approach for mapping perceptions to actions. A cognitive agent, on the other hand, is a more complex structure endowed with reasoning capabilities and knowledge about its internal state and about the dynamics of the world [4]. The results reported in this paper are based on a reactive agent structure which was developed using Artificial Neural Networks (ANNs). The main advantages of ANNs include the ability to deal with complex non-linear relationship [5]; fast data processing [6]; handling a large number of variables [7] and fault tolerance in producing acceptable results under imperfect inputs [8]. ANNs are also suitable for this particular application because the behaviour of reactive agents is often described using rules, linking a perceived situation with appropriate action. 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 [9].

B. Data For Model Development and Evaluation

A number of studies on evaluating car following models are reported in the literature. The Robert Bosch GmbH

Research Group [1] collected speed data under stop-and-go traffic conditions during an afternoon peak on a single lane in Stuttgart, Germany. They used an instrumented vehicle to record the difference in speed and headway between the instrumented vehicle and the vehicle immediately in front. The response of the follower vehicle (the instrumented vehicle), in terms of acceleration or deceleration, was also recorded. This data was recorded in 100 millisecond intervals for a total duration 300 seconds. This data was used to evaluate a number of car following models [1, 10-12]. The models developed in this study are also based on the same time-series data.

C. Data Pre-Processing

The data used in this study consisted of speeds of the leader and follower vehicles, distance headway, and the follower's acceleration. Drivers' characteristics and road geometry are not included in model development. Of this data, only speeds of the vehicles and distance headways are used to model the reactive agent-based car following behaviour. The basic premise is that Driver-Vehicle-Units (DVUs) would select their individual speeds and maintain a desired distance headway based on particular driving conditions described by the leader vehicle's speed and headway between the two vehicles. Each DVU would then select a following speed based on the individual characteristics of the DVU. To develop the model, the time series data was first classified into five driving modes representing a range of driving conditions for which the model will need to be trained. These driving conditions are described below:

Free driving : situation where distance headway is greater than 60 meters (75 samples).

Approaching : situation where distance headway is between 10 to 60 meters and the speed difference between follower and leader is over +2 kph (754 samples).

Following I: situation where distance headway is between 10 to 60 meters and the speed difference between vehicles is within 2 kph. The driver then has to cautiously follow the leader vehicle (255 samples).

Following II: situation where distance headway is between 10 to 60 metres and the speed difference between follower and leader vehicles is greater than -2 kph (1022 samples).

Danger : situation where distance headway drops to below 10 meters (894 samples).

In the development of neural network models, the available data is usually divided into two randomly selected subsets. The first subset is known as the training and testing data set. This data set is used to develop and calibrate the model. The second data subset (known as the validation data set), which was not used in the development of the model, is utilised to validate the performance of the trained model. For this study, 70 per cent of the master data set was used for training and testing purposes. The remaining 30 per cent was set aside for model validation. Table 1 below shows the number of observations in each data set, formatted in 100 milliseconds.

TABLE 1
DATA SET FOR MODEL DEVELOPMENT AND VALIDATION

Driving Modes	Training and Testing	Validation	Total
Free driving	53	22	75
Approaching and shining away	528	226	754
Following I	178	77	255
Following II	715	307	1022
Danger	626	268	894
Total	**2100**	**900**	**3000**

D. Selection of ANN Architectures

The reactive agent-based car following models proposed in this study can be considered as a classification problem. Each DVU needs to classify the driving conditions into one of the five categories or driving modes presented in Table 1, before taking an appropriate action. Some of the ANN architectures typically used for classification problems include:

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.

The development of a neural network model also involves the selection of a suitable objective function, learning rule, and transfer function for each node. Classification rate (CR) was selected as the objective function in this study. It represents the percentage of correctly classified observations. A large number of learning rules and transfer functions were also explored. The parameters and CR results for the best performing model for each architecture considered in this study are shown in Table 2 below.

A number of experiments to refine the models were then carried out. These included the investigation of the impacts of the number of hidden units (Back Prop.), protons (RBFN), and mapping layers (Fuzzy ARTMAP). The performance of Fuzzy ARTMAP networks (in terms of CR) was improved to 98 per cent when 200 mapping layers were applied. Increasing the number of hidden units for Back Propagation network did not improve model performance. A total of 300 Protons were found satisfactory for RBFN networks. Using these values, both RBFN architectures approached a best CR performance around 96 per cent.

TABLE 2
BEST PERFORMANCE MODELS DURING TRAINING

Model No.	ANN Architecture	Learning Rule	Transfer Function	CR Training	CR Testing
1	Fuzzy ARTMAP Network	-	-	0.7674	0.9444
2	Back-Propagation Network	Delta Rule	TanH	0.9375	0.9475
3	Radial Basis Function Network	Nom-Cum-Delta	TanH	0.8750	0.9517
4	Radial Basis Function Network	Delta Rule	DNNA	0.8750	0.9510

E. Model Validation

The performance of the models presented in Table 2 was then evaluated using the validation data set which was not used in model development. The validation results are presented in Table 3 below. All models resulted in excellent classification rates exceeding 96 per cent. However, further examination of the results showed that the models' degrees of accuracy (represented by the R^2 measure between the observed and predicted speeds), is best for the Back Propagation and Fuzzy ARTMAP architectures.

TABLE 3
VALIDATION RESULTS

Model	Classification Rate	R^2
FuzzyARTMAP [a]	0.9645	0.9689
Back Propagation : Delta Rule-TanH	0.9656	0.9509
RBFN : Delta Rule-DNNA	0.9641	0.8094
RBFN : Nom-Com-Delta Rule -TanH	0.9634	0.7988

IV. MODEL IMPLEMENTATION AND EVALUATION IN MICROSCOPIC TRAFFIC SIMULATION

To test the performance of the developed model, the car-following field experiment was modelled using AIMSUN. The reactive agent-based model was then interfaced to AIMSUN as shown in Figure 1. A GETRAM Extension module was developed to override the leading vehicle speed behaviour according to the field observations which were stored in a database. In every time step, the GETRAM Extension communicated with the AIMSUN simulator using a DLL file. The follower behaviour was then modelled using the reactive agent-based model developed in this study. The traffic simulator was programmed to output three parameters: speed, time, and distance headways of both leader and follower vehicles.

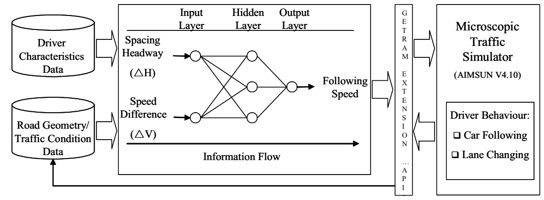


Fig. 1. A Framework to Interface the Agent-Based Car Following Model to AIMSUN

A. Simulation Results

Each of the four reactive agent-based models (Table 3) were interfaced to AIMSUN and simulated for five minutes. An error metric on distance (EM) and the RMS error were used as the key performance measures. The distance to the leader vehicle observed in the field (d_f) was compared to the values obtained from each traffic simulator (d_s). To avoid over-rating on discrepancies for large distance, the error metric was weighted by logarithm and squared, as shown below [1]:

$$EM = \sqrt{\sum_{n=1}^{N}\left(\log\frac{d_s}{d_f}\right)^2} \qquad 1)$$

The reactive agent-based models were also compared to the Gipps-based models implemented in AIMSUN and the results reported in Table 4. The EM showed that the two reactive agent-based models (Fuzzy ARTMAP and Back Propagation networks), performed better than the Gipps-based models.

TABLE 4
PERFORMANCE OF AGENT-BASED CAR FOLLOWING MODEL SIMULATED IN AIMSUN

Indicator	AIMSUN (v4.15) Gipps-Based Model [b]	Agent-Based Car Following Model: Fuzzy ARTMAP Network [a]	Back Propagation Network [a]	RBFN (1): Delta rule and DNNA	RBFN (2): Nom-Com-Delta and TanH
Error Metric (Em)	2.55	2.20	2.03	7.95	8.43
RMS Error	4.99	4.86	4.14	40.16	40.76

[a] best performance
[b] result obtained from previous study [12].

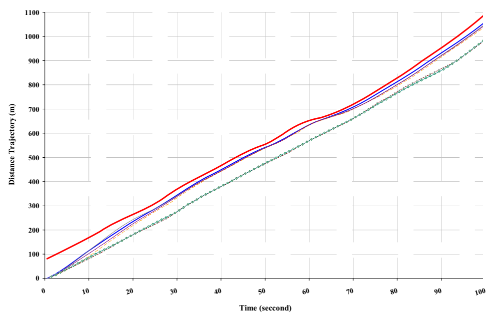
It should be pointed out that Panwai and Dia [12] also used the same time series data set to test the performance of car following models in three well-known traffic simulators: AIMSUN, VISSIM, and PARAMICS. The results are shown in Table 5 below.

TABLE 5
PERFORMANCE OF VARIOUS CAR FOLLOWING MODELS

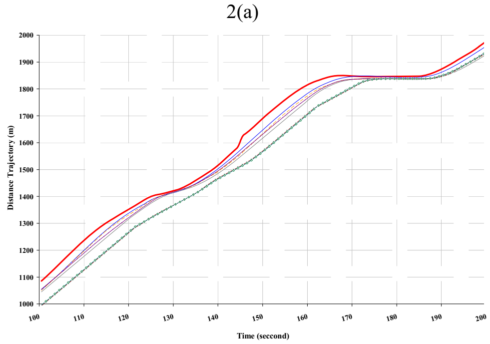
Simulator	AIMSUN (v4.15)	VISSIM (v3.70) Wiedemann74	VISSIM (v3.70) Wiedemann99	PARAMICS (v4.1)
Error Metric (Em)	2.55	4.78	4.50	4.68
RMS Error	4.99	5.72	5.05	10.43

B. Microscopic Evaluation.

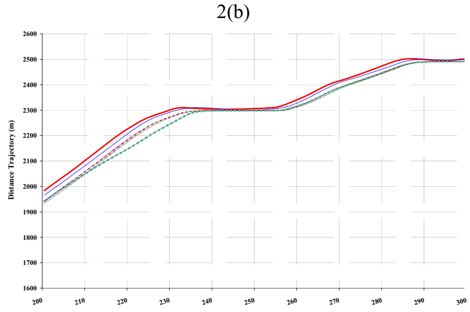
For microscopic validation, both speed and position of individual vehicles computed from the model, were compared to the field data. Trajectory profiles are presented in Figures 2(a), 2(b) and 2(c). The travel distance of the follower vehicle as replicated by each model was compared to the field following travel distance. It is clear from Figures 2(a)-2(c) that the two RBFN models had a lower degree of accuracy in predicting the follower speed. The results for the two agent-based models (Fuzzy ARTMAP and Back Prop.) and the Gipps-based model compared favourably with the field distance. This result is consistent with the statistical results reported in Table 4.



2(a)



2(b)



2(c)

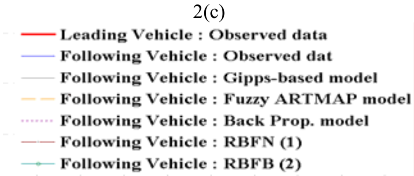


Fig. 2 Distance Trajectory of the Follower Vehicle Replicated by Each Model

Figures 3 and 4 show the distance headway and follower speed profiles, compared to field data, for each of the models. These results show that large oscillations in the follower speed profile reproduced by the Fuzzy ARTMAP model are not realistic, despite its very high CR.

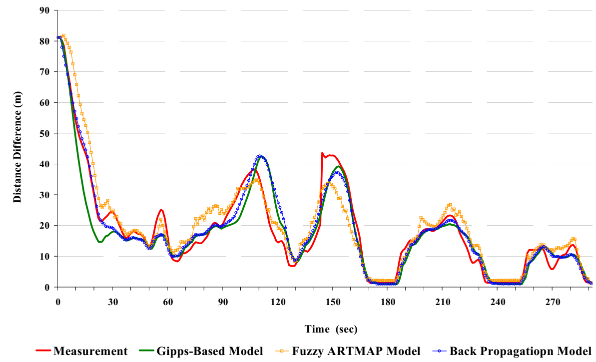


Fig. 3. Distance to leader profile as replicated by each model

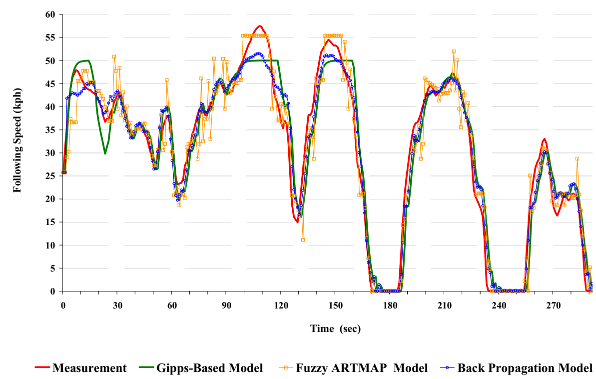


Fig. 4. Follower speed profile as replicated by each model

C. Macroscopic Evaluation

For this study, macroscopic traffic behaviour was evaluated using platoon concepts. The length of a platoon of vehicles and their average speed are used to describe the relationship between speed and density for a particular traffic condition. Traffic volumes can then be estimated as a function of speed and density from traffic flow theory. The length of a platoon is measured from centre of the leading vehicle to centre of the last following vehicle.

Figure 5 shows that both the Gipps and reactive agent model can accurately represent speed-flow-density relationships. The maximum flow rate was around 1900-2000 vehicles per hour. Both models produced a maximum density about 180 vehicles per kilometre whereas the observed value was about 170 vehicles.

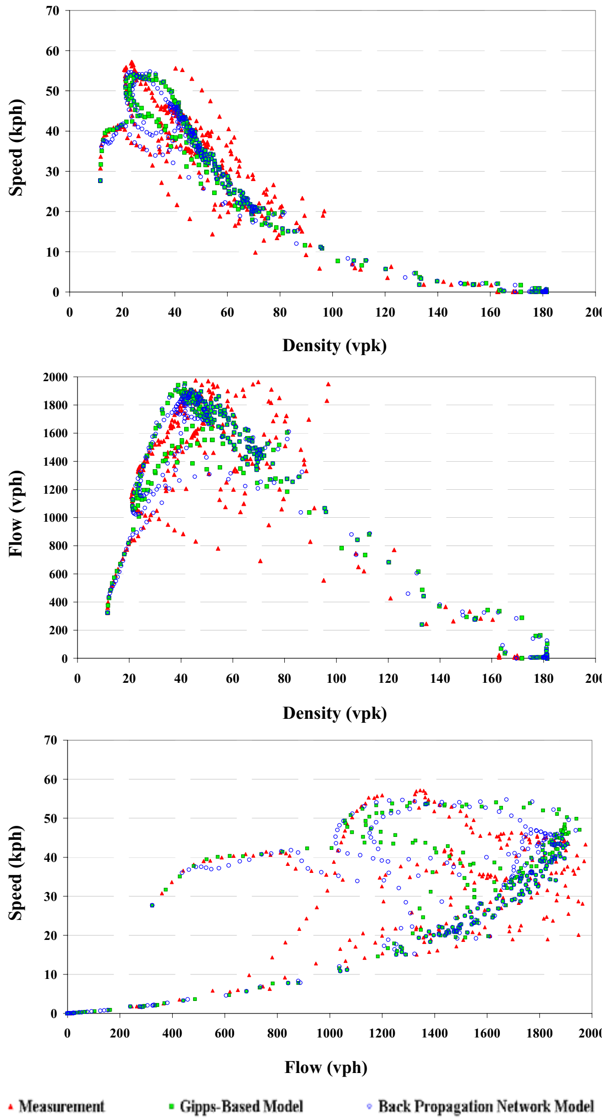


Fig. 5 Macroscopic traffic behaviour replicated by each model

D. *Qualitative Drift and Goal Seeking Behaviour*

The drift and goal seeking behaviour of a pair of vehicles is essentially related to how the distance headway between leader and follower vehicles oscillates (drifts) around what might be termed as a stable distance headway [13]. This behaviour occurs because the driver of the follower vehicle cannot judge the leader vehicle's speed accurately or cannot maintain their own speed precisely. Drift behaviour can be illustrated by plotting relative distance against relative speed, as shown in Figure 6 (a-d). The x-axis shows the relative speed of the vehicles while the y-axis represents the distance to the vehicle ahead. The data points appearing in the negative regions correspond to the follower vehicle travelling at speeds greater than the leader vehicle. These figures provide a qualitative measure of how each model replicates the field drift behaviour. It is clear from these figures that there were large fluctuations in the behaviour of the Fuzzy ARTMAP model when compared to the Back Prop and Gipps-based models.

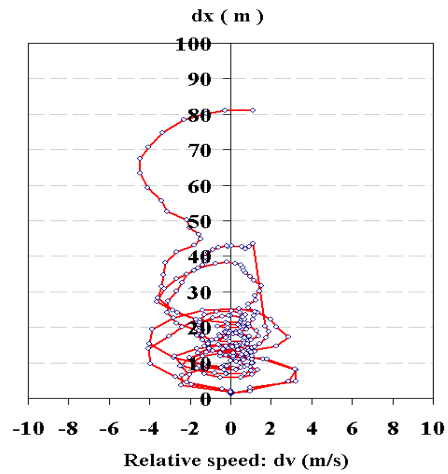


Fig. 6(a). Field drift and goal seeking behaviour

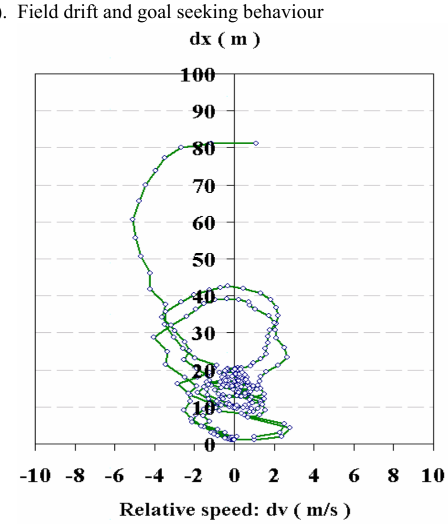


Fig. 6(b). Drift and goal seeking behaviour as replicated by AIMSUN

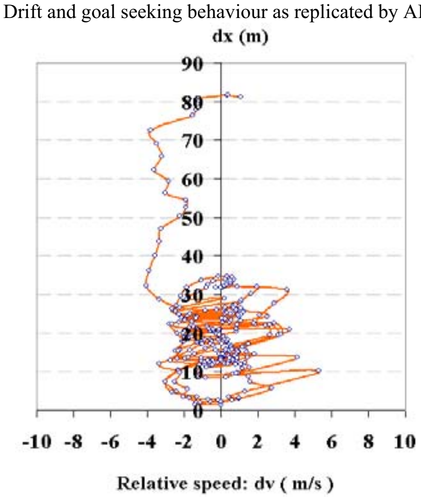


Fig. 6(c). Drift and goal seeking behaviour as replicated by Fuzzy ARTMAP

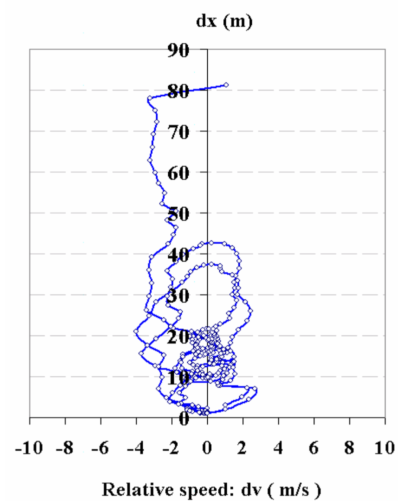


Fig. 6(d). Drift and goal seeking behaviour as replicated by Back Propagation Network

V. Conclusions and Future Research Directions

A number of reactive agent-based car following models that were developed using Artificial Neural Network techniques were reported in this paper. The models' performance was evaluated based on field data and compared to a number of existing car following models. The results showed that simple back-propagation neural network models performed substantially better than the Gipps and psychophysical family of car following models. The main limitation of the work reported in this study is the lack of large amounts of data for training and validating the neural network models for a wide range of driving conditions. Nevertheless, the performance results reported in this paper, which were based on a subset of 900 observations, are encouraging and demonstrate the feasibility of the approach. There is scope in future studies to collect more data and extend the evaluation framework to include car-following behaviour for critical driving situations (e.g. near on- and off-ramps on freeways). Obviously, the lane changing behaviour in each model is much more difficult to validate due to the difficulty of collecting relevant field data but it is hoped that with the advent of smart vehicle sensors and detection devices on the road infrastructure, such data collection efforts could be easier to complete.

Acknowledgement

The authors wish to thank the Robert Bosch GmbH Research Group in Germany for providing the radar speed data used in this study.

Disclaimer

This paper represents the opinions of the authors and does not necessarily represent the views or policy of the ITS Research Laboratory at the University of Queensland. The paper does not constitute a recommendation or standard.

References

[1] D. Manstetten, W. Krautter, and T. Schwab, "Traffic simulation supporting urban control system development," presented at 4th World Congress on Intelligent Transport System, Berlin, Germany, 1997.

[2] T. A. Ranney, "Psychological factors that influence car-following and car-following model development," *Transportation Research Part F: Traffic Psychology and Behaviour*, vol. 2, pp. 213-219, 1999.

[3] M. Brackstone and M. McDonald, "Car-following: a historical review," *Transportation Research Part F: Traffic Psychology and Behaviour*, vol. 2, pp. 181-196, 1999.

[4] R. J. F. Rossetti, R. H. Bordini, A. L. C. Bazzan, S. Bampi, R. Liu, and D. V. Vliet, "Using BDI agents to improve driver modelling in a commuter scenario," *Transportation Research Part C: Emerging Technologies*, vol. 10, pp. 373-398, 2002.

[5] K. Narendra and K. Paethasarathy, "Identification and control of dynamical systems using neural networks," *IEEE Trans. Neural Network*, vol. 1, pp. 4-27, 1990.

[6] A. J. Maren, C. T. Harston, and R. M. Pap, *Handbook of Neural Computing Applications*: Academic Press, Inc., 1990.

[7] L. Smith, "An Introduction to Neural Networks," *[Accessed September 2003], Available from http://www.cs.stir.ac.uk/~lss/NNIntro/InvSlides.html,*, 2003.

[8] R. Hecht-Nielsen, *Neurocomputing*: Addison-Wesley Publishing Company, Inc.: Reading, Mass., 1990.

[9] P. V. Palacharla and P. C. Nelson, "Application of fuzzy logic and neural networks for dynamic travel time estimation," *International Transactions in Operational Research*, vol. 6, pp. 145-160, 1999.

[10] J. Barceló, "Microscopic Traffic Simulation: A tool for the Analysis and Assessment of ITS Systems," presented at Highway Capacity Committee, Half Year Meeting, Lake Tahoe, 2002.

[11] J. Barceló and J. Casas, "Dynamic Network Simulation With AIMSUN," presented at International Symposium on Transport Simulation, Yokohama, Japan, 2002.

[12] S. Panwai and H. Dia, "Comparative Evaluation of Car Following Models," presented at Workshop on Traffic Simulation (Bridging Theory and Practice), Customs House, Brisbane, Queensland, Australia, 2004.

[13] P. Chakroborty and S. Kikuchi, "Evaluation of the General Motors based car-following models and a proposed fuzzy inference model," *Transportation Research Part C: Emerging Technologies*, vol. 7, pp. 209-235, 1999.