# Predicting the Future State of a Vehicle in a Stop&Go Behavior Based on ANFIS Models Design


Ali Ghaffari
Mechanical Engineering Department
K. N. Toosi University of Technology
Tehran, Iran
ghaffari@kntu.ac.ir

Alireza Khodayari
Mechanical Engineering Department
K. N. Toosi University of Technology
Tehran, Iran
khodayari@ieee.org

Fatemeh Alimardanii
Mechatronics Engineering Department
K. N. Toosi University of Technology
Tehran, Iran
f.alimardani@ee.kntu.ac.ir



*Abstract*— **Stop&go cruise system is an extension to ACC which is able to automatically accelerate and decelerate the vehicle in city traffic. There have been attempts to model stop&go waves via microscopic and macroscopic traffic models. But predicting the future state of the maneuver has not attracted much attention. The purpose of this study is to design adaptive neuro-fuzzy inference system (ANFIS) models to simulate and predict the future state of the stop&go maneuver in real traffic flow for different steps ahead. These models are designed based on the real traffic data and model the acceleration of the vehicle which performs a stop&go maneuver. Using the field data, the performance of the presented models is validated and compared with the real traffic datasets. The results show very close compatibility between the model outputs and maneuvers in real traffic flow.**



***Keywords: Intelligent Automation; Stop&go maneuver; neuro-fuzzy inference system; modeling.***


## I. INTRODUCTION

Intelligent Transportation Systems (ITS) are being developed and deployed to improve the efficiency, productivity, and safety of existing transportation facilities and to alleviate the impact of transportation on the environment. These systems exploit currently available and emerging computer, communication, and vehicle-sensing technologies to monitor, manage, and control the highway transportation system. The success of ITS deployment depends on the availability of advanced traffic analysis tools to predict network conditions and to analyze network performance in the planning and operational stages. Many ITS sub-systems are heavily dependent on the availability of timely and accurate wide-area estimates of prevailing and emerging traffic conditions. Therefore, there is a strong need for a Traffic Estimation and Prediction System (*TrEPS*) to meet the information requirements of these subsystems and to aid in the evaluation of ITS traffic management and information strategies [1].

Microscopic models are increasingly being used by transportation experts to evaluate the applications of new ITS. A variety of applications including car navigation systems, adaptive cruise control systems, lanes keeping assistance systems and collision prevention systems directly use the microscopic traffic flow models [2].

To develop a microscopic traffic simulation of high fidelity, researchers are often interested in imitating human's real driving behavior at a tactical level. In other words, without describing the detailed driver's actions, driver-vehicle units (DVUs) in the simulation are modeled to replicate their states in reality, i.e., the profiles of vehicle position, velocity, acceleration, and steering angle. Fig. 1 indicates the model structure of a DVU, in which the detailed driver's actions become internal. A number of factors have been found to influence car-following behavior, and these include individual differences of age, gender, and risk-taking behavior [3].

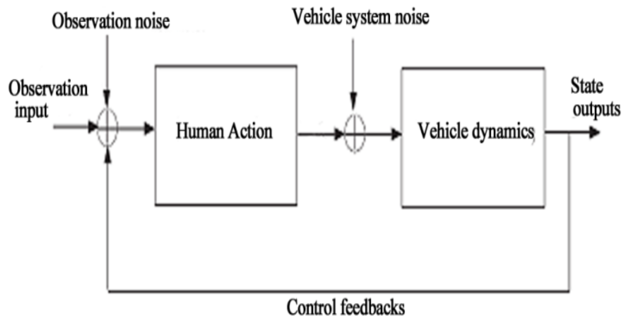
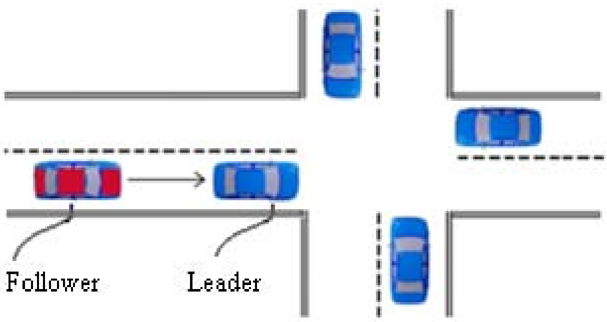



Figure 1. Structure of a DVU model [3].

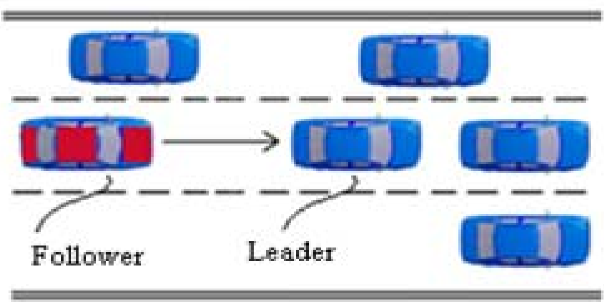
Humans play an essential role in the operation and control of human–machine systems such as driving a car. Modeling driver behavior has transferred human skills to intelligent systems, e.g., the adaptive cruise control (ACC) system, intelligent speed adaption (ISA) system, and autonomous vehicles. Human driving models are also indispensable for the performance evaluation of transportation systems. With advances in emerging vehicle-based ITS technologies, it becomes even more important to understand the normative behavior response of drivers and changes under new systems [1]. Based on Rasmussen's human–machine model as shown in Fig. 2 [3], driver behavior can also be separated into a hierarchical structure with three levels: the strategic, tactical, and operational level. At the highest or strategic level, goals of each driver are determined, and a route is planned based on these goals. The lowest operational level reflects the real actions of drivers, e.g., steering, pressing pedal, and gearing. In the middle tactical level, certain maneuvers are selected to achieve short-term objectives, e.g., interactions with other road users and road infrastructures. The behavior at this level is dominated by the most recent situations but is also influenced by drivers' goals at the higher level.

Stop&go maneuver can happen in different situations in traffic flow. The necessity to reduce the velocity of a vehicle may be due to traffic light in an intersection, congestion in traffic flow, a passing pedestrian, etc. Two examples of these situations are shown in Fig. 3 (a) and (b). The follower vehicle (FV) performs the stop&go maneuver in these cases.


Figure 2. Rasmussen's human–machine model




(a)




(b)

Figure 3. Examples of situations that a stop&go maneuver may occur, (a) An intersection with traffic light, (b) Congested road.

The highly nonlinear nature of the stop&go behavior necessitates the development of intelligent algorithms to describe, model, and predict this phenomenon. Neuro fuzzy models, such as adaptive neuro fuzzy inference system (ANFIS), are combinations of artificial neural networks (NNs) and fuzzy inference systems (FIS), simultaneously using the advantages of both methods. Integration of human expert knowledge expressed by linguistic variables, and learning based on the data are powerful tools enabling neuro fuzzy models to deal with uncertainties and inaccuracies [4].

In this paper, we have focused on the ANFIS model design to predict the stop&go behavior in the real traffic flow, considering the effects of driver's behaviors. This paper is organized as follows. A brief review of the stop%go behavios and its features is presented in Section II. In Section III, the ANFIS models are proposed to model and predict the DVU behavior in stop&go behavior scenarios. Four ANFIS models are designed based on real traffic datasets to predict the acceleration of the vehicle which performs a stop&go maneuver in different situations. These models predict the acceleration of 1, 2, 4 and 6 step ahead. Each step is equal to 0.1 second. In other words, these models can predict the acceleration of 0.1, 0.2, 0.4 and 0.6 seconds ahead. Some numerical simulation results for the proposed ANFIS models are given in Section V. Lastly, conclusions is presented in Section VI.

## II. STOP&GO MANEUVER AND FEATURES

Ordinary cruise control systems for passenger vehicles are becoming less and less meaningful because the increasing traffic density rarely makes it possible to drive at a preselected speed. Driver assistant systems currently under development by most automotive manufacturers around the world and recently commercialized by several companies are intelligent cruise control (ICC) systems and stop&go cruise control systems. The goal of stop&go is a partial automation of the longitudinal vehicle control and the reduction of the workload of the driver with the aim of supporting and relieving the driver in a convenient manner in busy urban traffic. ICC and stop&go systems control both speed and distance in relation to preceding vehicles and can both improve the driving comfort and reduce the danger of rear-end collisions. Vehicles with a stop&go system can follow other vehicles in dense traffic while keeping a safe distance in stop&go driving situations. Although there has been a lot of research conducted on ICC, relatively few publications have appeared on SG control. The basic requirements for realizing a stop&go cruise control system have been discussed by Venhovens et al. [5].

Stop and go control is meant to reduce driver workload in suburban areas where ACC systems are practically ineffective. Due to the more complex driving environment and more stringent sensory requirements in lower speeds, the challenges in developing stop and go systems are more than ACC systems. Stop&go cruise control must take into consideration a much broader view of the driving environment compared with an ICC system with a low level of acceleration [6]. Although stop&go is no longer limited to the simple task of following a vehicle immediately in front of the stop&go vehicle, vehicle speed and vehicle-to-vehicle distance control is one of the key features of the stop&go systems. The brake and throttle controls should be gently applied so that the driver feels comfortable and is not surprised by the control actions, while the speed control error and the errors between the desired headway distance and the actual vehicle-to-vehicle distance are kept within acceptable limits. Improving transportation systems is about more than just adding road lanes, transit routes, sidewalks and bike lanes. It is also about operating those systems efficiently. Not only does congestion cause slow speeds, it also decreases the traffic volume that can use the roadway; stop&go roads only carry half to two-thirds of the vehicles as a smoothly flowing road [7].

## III. ANFIS STOP AND GO MODELS DESIGN

In this section, input-output models based on ANFIS are presented to estimate acceleration of the vehicle which performs a stop&go maneuver. In order to design ANFIS prediction systems, a dataset of stop&go behavior is needed. So, real stop&go data from US Federal Highway Administration's NGSIM dataset is used to train the ANFIS prediction model [8]. Researchers for the NGSIM program collected detailed vehicle trajectory data on Lankershim Boulevard in the Universal City neighborhood of Los Angeles, CA, on June 16, 2005. The study area, which consisted of bidirectional data of the three to four lane arterial segments and complete coverage of three signalized intersections, was approximately 500 meters (1,600 feet) in length. These data were collected using five video. NG-VIDEO, a customized software application developed for the NGSIM program, transcribed the vehicle trajectory data from the video. This vehicle trajectory data provided the precise location of each vehicle within the study area every one-tenth of a second, resulting in detailed lane positions and locations relative to other vehicles. A total of 30 minutes of data are available in the full dataset, which are segmented into two 15-minute periods (8:30 a.m. to 8:45 a.m. and 8:45 a.m. to 9:00 a.m.). These periods represent primarily congested conditions on the arterial. This dataset has been published as the Lankershim Dataset, as shown in Fig. 4. Any measured sample in this dataset has 24 features of each driver-vehicle unit in any sample time, such as longitudinal and lateral position, velocity, acceleration, time, number of road, vehicle class, front vehicle and etc [9].

The other dataset was published as the Peachtree Dataset. Researchers for the NGSIM program collected detailed vehicle trajectory data on a segment of Peachtree Street in Atlanta on November 8, 2006. Aggregate summaries of flow and speed of the vehicles, number of lane changes, headway and gap analysis, and an input-output analysis of flows are provided. The results are aggregated by time and intersection. The speed limit on the Peachtree Street is 35 mph. Fig. 5 provides an aerial image of the location with the camera coverage. Video data were collected using eight video cameras. Complete vehicle trajectories were transcribed for two 15 minute periods – one from 12:45 p.m. to 1:00 p.m. and the other from 4:00 p.m. to 4:15 p.m. – for a total of 30 minutes at a resolution of 10 frames per second [10].


Figure 4. Lankershim Boulevard in the Universal City neighborhood of Los Angeles, CA [9].

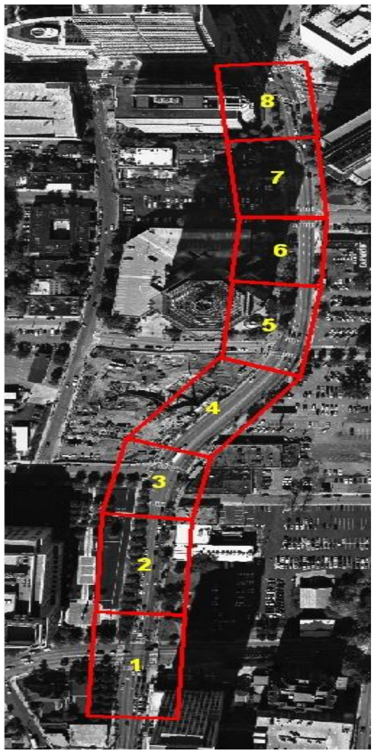



Figure 5. A segment of Peachtree Street, in Atlanta, Georgia [10].

The data extracted from the datasets, seem to be unfiltered and exhibit some noise artifacts, so these data must be filtered like [11, 12]. A moving average filter has been designed and applied to all data before any further data analysis. In the model designed in this study, the acceleration of the follower vehicle is simulated. So, at first, comparison of the unfiltered and filtered data of the acceleration of the follower vehicle is shown in Fig. 6.

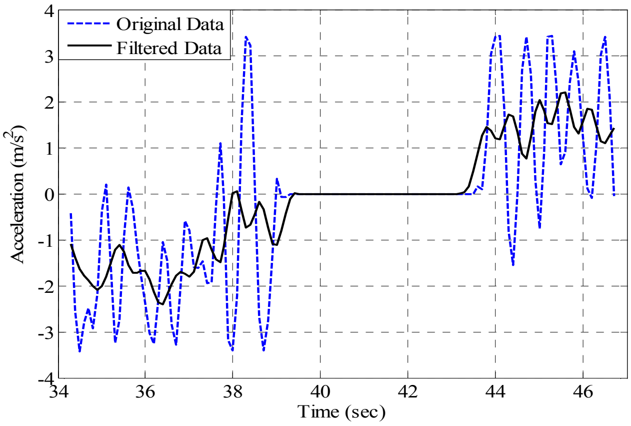



Figure 6. Comparison of unfiltered and filtered acceleration.

To design ANFIS model, it is assumed that the fuzzy inference system applied for prediction model has four inputs and one output, which inputs are relative speed, relative distance, acceleration and velocity of FV, and output is acceleration of FV in next steps. There are three dsigmf membership functions for each input. The rule base contains 81 fuzzy if-then rules of Takagi-Sugeno's type [13] and hybrid algorithm is used to train this model.

In the development of ANFIS prediction models, the available datasets are divided into two randomly selected subsets. The first subset is known as the training subset which is used to develop and calibrate the model. The second one is the testing subset (also known as the validation one). This subset, which was not used in the development of the model, is utilized to validate the performance of the trained model. For this paper, 70% of the master data set was used for training and testing purposes. The remaining 30% was set aside for model validation [14].

## IV. Discussion and Results

To assess the performance of the ANFIS models, the validation datasets are used to evaluate the proficiency of the model. The output of the models is compared to the real data. The comparisons of the output of the four ANFIS models with real data and are shown below. Fig. 7 shows the acceleration of FV during a stop&go maneuver predicted in one, two, four and six steps ahead. Notice that the validation datasets are composed of the data of several stop&go maneuvers. Here, the output of one stop&go maneuver for one test vehicle is shown from the four designed models. In order to have a better understanding of the performance of these models, errors between the outputs of the models for the same test vehicles for each designed model is shown in Fig. 8.

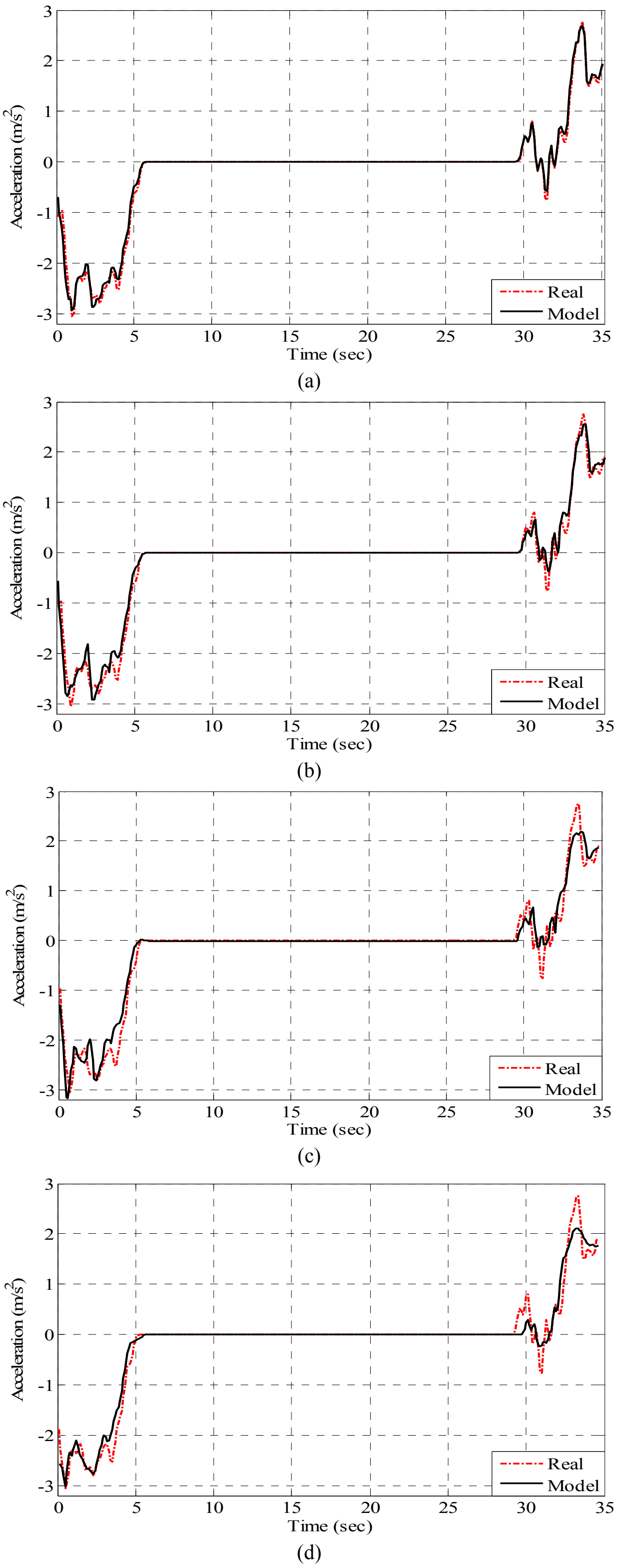



Figure 7. Comparison of the output of ANFIS models and real data, (a) 0.1 second ahead model, (b) 0.2 second ahead model, (c) 0.4 second ahead model, (d) 0.6 second ahead model.

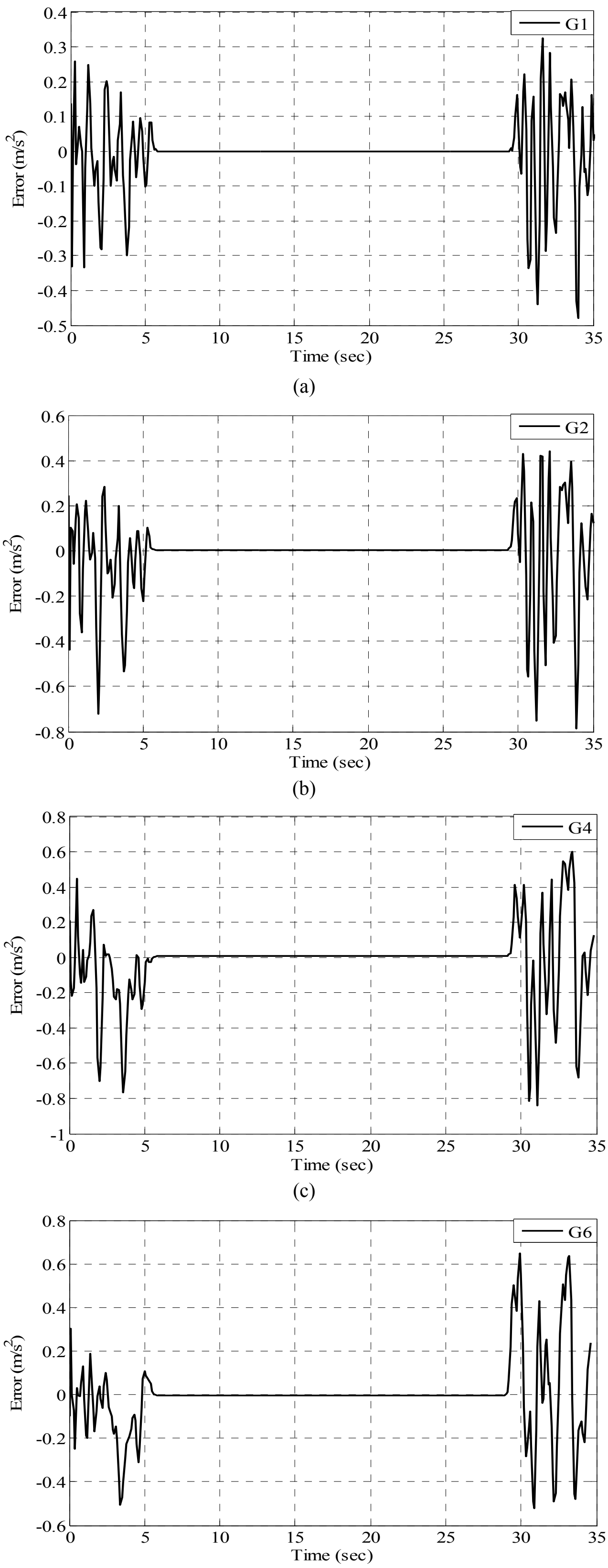



Figure 8. Comparison of errors for the same test vehicles of Fig. 7 , (a) 0.1 second ahead model, (b) 0.2 second ahead model, (c) 0.4 second ahead model, (d) 0.6 second ahead model.

To examine the performance of the developed models, various criteria were used to calculate errors. The criterion mean absolute percentage error (MAPE), according to Equation (1), shows the mean absolute error that can be considered as a criterion to model risk to use it in real-world conditions. Root mean squares error (RMSE), according to Equation (2), is a criterion to compare error dimension in various models. In these equations, $x_i$ shows the real value of the variable being modeled (observed data), $\hat{x}$ denotes the real value of variable modeled by the model, $\bar{x}$ is the real mean value of the variable, and $N$ is the number of test observations [15].

$$MAPE = \frac{100}{N}\sum_{i=1}^{N}\frac{\left|x_i - \hat{x}_i\right|}{x_i} \tag{1}$$

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(x_i - \hat{x}_i)^2} \tag{2}$$

Errors in modeling of four designed ANFIS stop&go models by considering MAPE and RMSE are summarized in Table I for the test vehicles that was used for Fig. 7 and Fig. 8. Table II shows these error values for another test vehicle.

TABLE I. RESULT OF ERROR FOR ANFIS STOP&GO MODELS FOR TEST VEHICLE 1

| ANFIS STOP&GO MODELS | Error Criteria | |
|---|---|---|
| | MAPE | RMSE |
| Model which predicts 0.1 second ahead | 2.8404 | 0.0940 |
| Model which predicts 0.2 second ahead | 4.7954 | 0.1556 |
| Model which predicts 0.4 second ahead | 5.8833 | 0.1873 |
| Model which predicts 0.6 second ahead | 6.8876 | 0.1954 |

TABLE II. RESULT OF ERROR FOR ANFIS STOP&GO MODELS FOR TEST VEHICLE 2

| ANFIS STOP&GO MODELS | Error Criteria | |
|---|---|---|
| | MAPE | RMSE |
| Model which predicts 0.1 second ahead | 1.6368 | 0.0795 |
| Model which predicts 0.2 second ahead | 2.4273 | 0.2128 |
| Model which predicts 0.4 second ahead | 2.9455 | 0.3603 |
| Model which predicts 0.6 second ahead | 4.9371 | 0.4369 |

As shown in Table I and Table II, ANFIS stop&go models have low error values. The results show that these proposed models have a strong capability to predict the future state behavior of follower vehicle.

## V. CONCLUSION

In this study, four ANFIS models were designed to predict the future state behavior of stop&go maneuver based on real traffic datasets. These models considered important factors such relative velocity, relative distance, acceleration and velocity of the follower vehicle in stop&go maneuver. These models can predict the future state of FV in four different steps ahead. These steps are 1, 2, 4 and 6 steps ahead which each step is equal to 0.1 second. It means that these models can predict the acceleration of 0.1, 0.2, 0.4 and 0.6 seconds ahead.

Using the instantaneous value of the variables is the prominent aspect of the proposed models. Evaluation of the designed models was investigated through simulation and comparing the outputs of the models with behaviors of human drivers from real traffic datasets. Comparison showed that the designed models were highly accordant with real behaviors. In addition, different error criteria were used to evaluate the performance of these models numerically. Low rates of errors also proved the high compatibility of the desired models with real traffic flow. The proposed models can be recruited in driver assistant devices, safe distance keeping observers, collision prevention systems and other ITS applications.

## ACKNOWLEDGMENT

The authors extend their thanks to US Federal Highway Administration and Next Generation SIMulation (NGSIM) for providing the data set used in this paper.

## REFERENCES

[1] X. Ma, I. Andréasson, .Behavior Measurement, Analysis, and Regime Classification in Car Following., *IEEE Transactions on Intelligent Transportation Systems*, vol. 8, no. 1, pp. 144-156, 2007.

[2] A. Khodayari, A. Ghaffari, R. Kazemi, and Reinhard Braunsting, “A Modified Car-Following Model Based On a Neural Network Model of the Human Driver Effects”, *Accepted for publication in IEEE Transactions on Systems, Man, and Cybernetics*, *Part A-Systems and Humans*, 2011.

[3] A. Khodayari, A. Ghaffari, R. Kazemi, N. Manavizadeh, “ANFIS Based Modeling and Prediction Car Following Behavior in Real Traffic Flow Based on Instantaneous Reaction Delay,” *13th International IEEE Annual Conference on Intelligent Transportation,* Madeira Island, Portugal, Sep 19-22, 2010.

[4] A. Khodayari, F. Alimardani, A. Ghaffari, H. Sadati, ‘Overtaking Maneuver Behaviour Modeling Based on Adaptive Neuro-Fuzzy Inference System’, *IEEE International Conference on Intelligent Computing and Intelligent Systems* (ICIS 2011), China, 2011.

[5] P. Venhovens, K. Naab, B. Adiprasito, “Stop and Go Cruise Control”, *FISITA World Automotive Congress*, Seoul, Korea, June 12-15, 2000.

[6] S. Tsugawa, Sh. Kato, T. Matsui, H. Naganawa, and H. Fujii, “An Architecture for Cooperative Driving of Automated Vehicles”, *IEEE Intelligent Transportation Systems Conference Proceedings Dearborn* (MI), USA, 2000.

[7] K. Yi1, J. Hong and Y. D. Kwon, “A vehicle control algorithm for stop-and-go cruise control”, *Proceedings of the Institution of Mechanical Engineers, Part D: Journal of Automobile Engineering*, 2001.

[8] US Department of Transportation, “NGSIM - Next Generation Simulation”, ngsim.fhwa.dot.gov (2009).

[9] The Federal Highway Administration website. Available: http://www.fhwa.dot.gov/publications/research/operations/07030/index.cfm.

[10] The Federal Highway Administration website. Available: http://www.fhwa.dot.gov/publications/research/operations/06137/index.cfm.

[11] C. Thiemann, M. Treiber, A. Kesting, “Estimating Acceleration and Lane-Changing Dynamics Based on NGSIM Trajectory Data”, Transportation Research Record: Journal of the Transportation Research Board, Vol. 2088, pp. 90-101 (2008).

[12] A. Ghaffari, A. Khodayari, S. Arvin, F. Alimardani, “ANFIS Based Modeling for Overtaking Maneuver Trajectory in Motorcycles and Autos”, IEEE International Conference on Control System, Computing and Engineering (ICCSCE 2011), Malaysia (2011).

[13] J. S. R. Jang, C.T. Sun, and E. Mizutani, Neuro-Fuzzy and Soft Computing: A Computational Approach to Learning and Machine Intelligence, *Prentice Hall*, 1996.

[14] A. Ghaffari, A. Khodayari, S. Arvin, F. Alimardani, “ANFIS Based Modeling for Overtaking Maneuver Trajectory in Motorcycles and Autos”, IEEE International Conference on Control System, Computing and Engineering (ICCSCE 2011), Malaysia (2011).

[15] J. R. Taylor, “An introduction to error analysis: the study of uncertainties in physical measurements”, University Science Books, Mill Valley, CA, 1982.