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Neural-Network-Based Modeling and Prediction of the Future State of a Stop&Go Behavior in Urban Areas

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Abstract— **The goal of Stop&Go systems is to assist drivers in traffic jams by reducing the need for them to repeatedly accelerate and/or stop their vehicles. There have been attempts to model Stop&Go waves via microscopic and macroscopic traffic models. But predicting the future state of the behavior of a Driver-Vehicle-Unit (DVU) in this maneuver has not been studied much. The purpose of this study is to design neural-network-based 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. The models were validated at the microscopic level, and the results showed very close agreement between field data and models output. The proposed models can be employed in ITS applications, Drier Assistant devices, Collision Prevention systems and etc.**

I. INTRODUCTION

The concept of assisting the driver in the task of longitudinal vehicle control has been a major focal point of research at many companies and institutes in the past decade. 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. Stop&Go systems control speed and distance in relation to preceding vehicles and can 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. The basic requirements for realizing a Stop&Go cruise control system have been discussed by Venhovens et al. [1].

Stop&Go maneuver can occur in different situations in traffic flow. The necessity to reduce the velocity of a vehicle may be due to traffic light, congestion in traffic flow, a passing pedestrian, etc. Two examples of these situations are shown in Fig. 1 (a) and (b). The follower vehicle (FV) performs the Stop&Go maneuver in these cases. Microscopic models are increasingly being used by transportation experts to evaluate the applications of new ITS.

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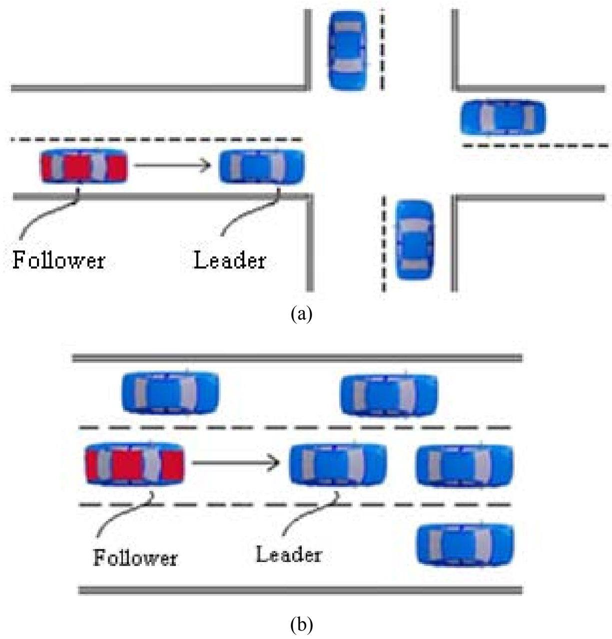

Fig. 1. Examples of situations that a Stop&Go maneuver may occur, (a) An intersection with traffic light, (b) Congested road.

A variety of applications including car navigation systems, adaptive cruise control systems, lane keeping assistance systems and collision prevention systems directly use the microscopic traffic flow models [2].

In this paper, we have focused on the Neural Network (NN) models 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 on the Stop&Go behavior and the related works on it are presented in Section II. In Section III, NN models are designed to model and predict the DVU behavior in Stop&Go behavior scenarios. Four NN models are designed based on real traffic data to predict the acceleration of the vehicle which performs a Stop&Go maneuver in different situations. These models predict the acceleration of 1, 2, 3 and 5 steps ahead. Each step is equal to 0.1 second. In other words, these models can predict the acceleration of 0.1, 0.2, 0.3 and 0.5 seconds ahead. Numerical simulation results for the proposed NN models are given in Section V. Lastly, conclusions is presented in Section VI.

II. STOP&GO MANEUVER

The Stop&Go cruise control system comprises at least the following functions: remain safe distance from preceding vehicle(s), slow down behind decelerating vehicle, eventually make a full stop, slow down and stop behind stopped vehicles, autonomous “go” when stopped behind vehicle, “go” when initiated by driver in case no preceding vehicles are present, control vehicle speed (up to set speed) when no preceding vehicles are present, manage standstill condition even on slopes, manage near cut-ins from adjacent lanes comfortably, recognize and manage lane changes initiated by the driver, harmonize perturbed traffic flows, inform driver when system limits are reached, switch off when brake pedal is activated, limit vehicle speed when set-speed has been reached, and also adjust headway according to driver preference. Additional functions could be realized when a Stop&Go cruise control system is integrated with, for example, a vehicle navigation system which adjusts headway and vehicle speed according to road class, road attributes (such as prevailing speed limits) and roadway curvature. Functions that a first generation Stop&Go cruise control system will not be able to cope with are: react to cross traffic from side streets, react to traffic signals and signs, and avoid a collision under every circumstance [1].

Stop&Go control is meant to reduce driver workload in suburban areas where Adaptive Cruise Control (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&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 ACC system with a low level of acceleration [3]. 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 [4]. Adaptive Cruise Control with Stop&Go function ensures that your vehicle remains a predefined distance away from the vehicle ahead, reducing the velocity to zero if necessary. When the traffic begins to move again, the system accelerates your vehicle - up to your preferred cruising speed if possible. Active Cruise Control (ACC) with Stop&Go function is primarily intended to serve as a driver assistant on freeways and highways. ACC with Stop&Go makes driving both more relaxing and safer. The main feature of such systems is that there is adaptation to a user-preset speed and, if necessary, speed reductions to keep a safe distance from the vehicle ahead in the same lane of the road, whatever the speed [5].

To simulate and investigate the performance of the Stop&Go control systems, models of this behavior are needed to investigate the fairness of the designed controllers before applying them in real vehicles. Here, NN models of this behavior are proposed which simulate and predict the behavior of the follower vehicle performs the Stop&Go maneuver (as shown in Fig. 1).

III. Neural Network Stop& Go Models Design

In this study, four NN models are proposed to simulate the Stop&Go behavior of the follower vehicle in this maneuver. The neural network theory is frequently used to model human driver's behaviors. The proposed NN architecture, datasets, implementation, and the results are discussed in the following sections. The NN models are able to model complex behaviors. Several studies explored the NN approach to model different driving behaviors. One contribution of this study is development of NN architecture to model the complex driving behavior during a Stop&Go behavior. Neural network resembles the biological network of the human brain. In a neural network, nodes or neurons are arranged in layers, beginning with an input layer, and ending with the final output layer with a hidden layer in between. Each hidden layer will be having more than one node passing information from the input layer to the output layer. The nodes in one layer are connected to nodes in the next layer and strength of these connections is measured by connection weights. Each node in a layer receives the weighted inputs from the previous layer, converts the weighted sum of the inputs to a single output using an activation function. The connection weights between nodes are optimized through training to produce outputs closest to the measured values. The most commonly used network is a feed-forward network. A multi-layer feed-forward network with back propagation is used in the present study. A feed-forward back propagation NN is the most commonly used network and the working principle of this network is as follows. First, the effect of the input is passed forward through the network, then the error between targets and predicted output is estimated at output layers, and then propagated back towards the input layer through each hidden node to adjust the connection weight. One complete forward and backward process is known as an iteration (or epoch). This process is repeated until the error between the predicted and measured values falls below a pre-specified error goal or until the number of epochs reaches a pre-determined maximum value. A multi-layer feed-forward network will have one or more hidden layers between the input and output layers. Each hidden layer consists of number of nodes passing information from the input layer to the output layer, and vice-versa in the case of a back propagation network [6]. To design the NN models presented in this study, real Stop&Go data is needed.

In order to design NN 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 NN prediction model [7]. 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. 2. 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 [8].

Fig. 2. Lankershim Boulevard in the Universal City neighborhood of Los Angeles, CA [8].

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, Georgia collected between 4:00 p.m. and 4:15 p.m. 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. 3 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 [9].

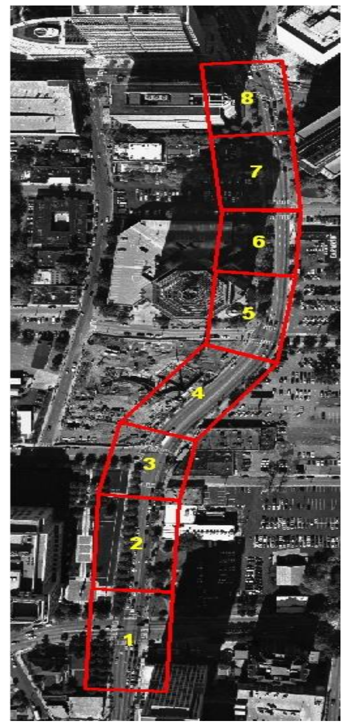

Fig. 3. A segment of eastbound I-80 in the San Francisco Bay area in Emeryville, California [9].

The data extracted from the datasets, seem to be unfiltered and exhibit some noise artifacts, so these data must be filtered like [10, 11]. A moving average filter has been designed and applied to all data before any further data analysis. A comparison of the unfiltered and filtered data of the acceleration of the follower vehicle in one maneuver is shown in Fig. 4.

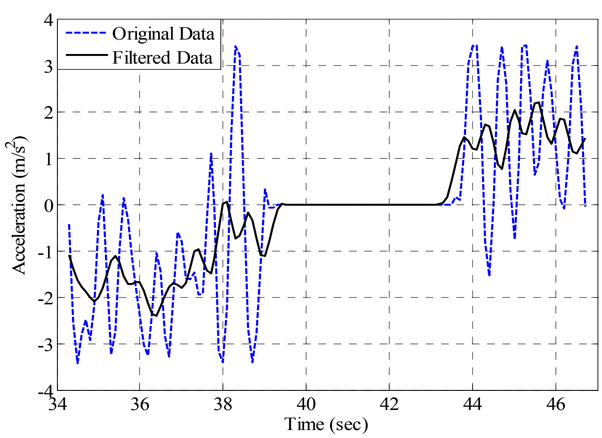

Fig. 4. Comparison of unfiltered and filtered acceleration.

To design the NN models, it is assumed that the models applied for prediction has four inputs and one output, which inputs are relative velocity, relative distance (spacing), acceleration and velocity of FV and the output of each model is the acceleration of FV in the next steps. The NN models designed here has a structure similar to one shown in Fig. 5. It is assumed that the applied NN has three layers. The first layer which is known as the input layer has 4 neurons, the second one is the hidden layer with 10 neurons and the last one is the output layer with one neuron. These models are based on Feed-Forward Back propagation network. Levenberg marquardt algorithm which is a kind of descent gradient algorithm is chosen as the training function [12].

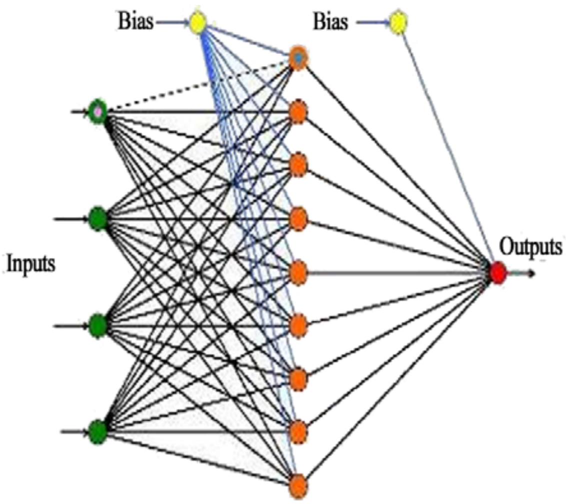

Fig. 5. Designed ANN model for car-following behavior.

In the development of NN prediction models, the available data are 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 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 [13].

IV. Discussion and Results

To assess the performance of the NN models, the validation datasets are used to evaluate the proficiency of the model. The matrix of the validation data is divided to two groups, the input columns and the output columns. The input columns are fed as the inputs of the models. Then, the output of the models is compared to the real output, which are the output columns of the validation data. The comparisons of the output of the four NN models with real data and are shown below. Fig. 6 shows the acceleration of FV during a Stop&Go maneuver predicted in one, two, three and five steps ahead (Each step is equal to 0.1 second. In other words, these models can predict the acceleration of 0.1, 0.2, 0.3 and 0.5 seconds 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.

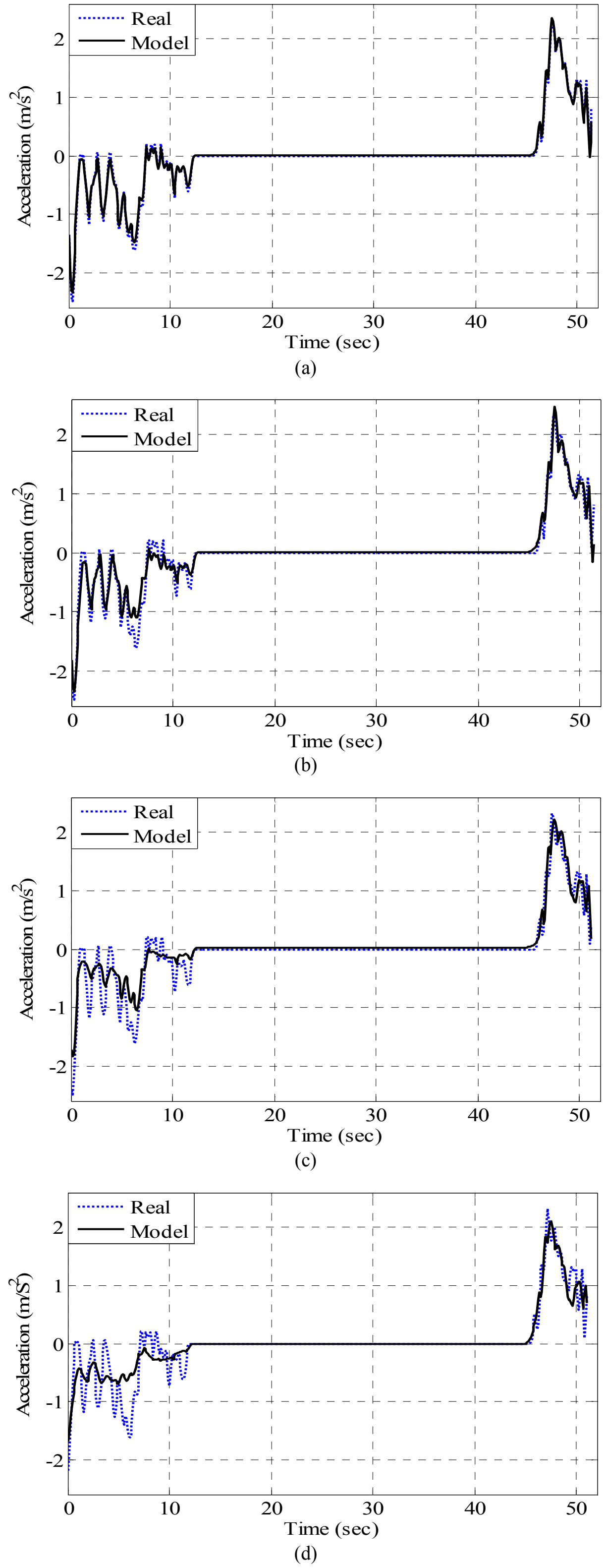

Fig. 6. Comparison of the output of NN models and real data, (a) 0.1 second ahead model, (b) 0.2 second ahead model, (c) 0.3 second ahead model, (d) 0.5 second ahead model.

In order to have a better understanding of the performance of these models, errors between the outputs of the models and real data for the same test vehicles used in Fig. 6 for each of the designed model are shown in Fig. 7.

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. Standard deviation error (SDE), according to equation (3), indicates the persistent error even after calibration of the model. 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 [14]. Errors of the designed NN Stop&Go models considering these error criteria are summarized in Table I for the test vehicles used in Fig. 6 and Fig. 7.

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

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

$$SDE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(\frac{|x_i - \hat{x}_i|}{x_i} - \frac{MAPE}{100}\right)^2} \tag{3}$$

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

NN STOP&GO MODELS	Error Criteria	
	MAPE	RMSE
0.1 second prediction	3.0905	0.0448
0.2 second prediction	8.4610	0.1262
0.3 second prediction	14.8704	0.2002
0.5 second prediction	13.2850	0.3463

We could not show the error table for all the test vehicles since we had over 500 vehicles in the test dataset. Therefore we provided the error table below to show the mean value of each error for the different models designed.

TABLE II
RESULT OF THE MEAN VALUE OF ERROR CRITERIA FOR NN STOP&GO MODELS FOR ALL TEST VEHICLES IN THE TEST DATASET

NN STOP&GO MODELS	Mean Value of Error Criteria	
	MAPE	RMSE
0.1 second prediction	2.3410	0.0487
0.2 second prediction	5.9835	0.1217
0.3 second prediction	10.5120	0.2119
0.5 second prediction	12.3110	0.3100

As shown in Table I and Table II, NN 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.

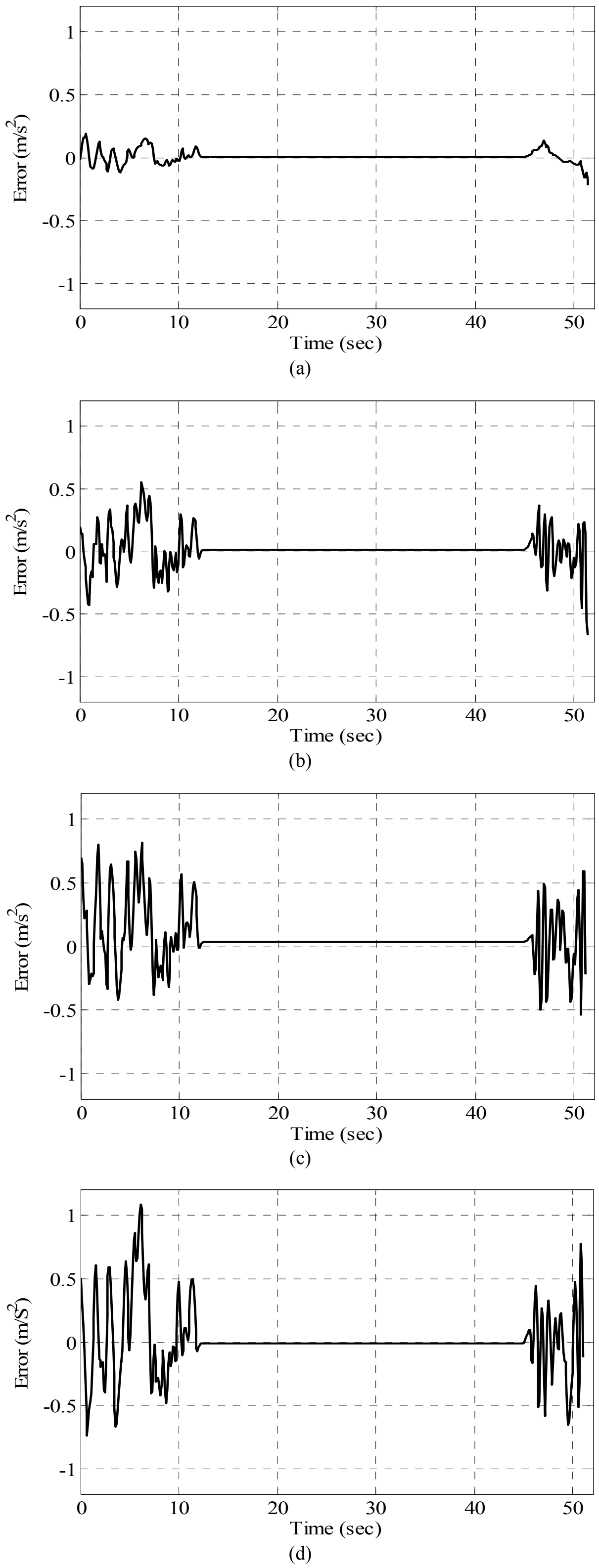

Fig. 7. Comparison of errors for the same test vehicles of Fig. 6, (a) 0.1 second ahead model, (b) 0.2 second ahead model, (c) 0.3 second ahead model, (d) 0.5 second ahead model.

As mentioned before, modeling the Stop&Go behavior has not been studied much, so to evaluate the performance of the designed models, since there is no other input/output based microscopic model for comparison, real traffic data and different error criteria are used instead. These models can be employed as future state predictive models for traffic estimation systems.

V. Conclusion

In this study, four NN models were improved 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, 3 and 5 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, 0.3 and 0.5 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.

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