Neural-Network Based Modeling for Stop&Go Behavior in Real Traffic Flow

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Abstract—**The first step towards an autonomous vehicle is adaptive cruise control (ACC) and stop&go maneuver systems since these kinds of systems adapt the speed of a vehicle to that of the preceding one (ACC) and get the vehicle to stop if the lead vehicle stops. There have been attempts to model stop&go waves via microscopic and macroscopic traffic models. But modeling the maneuver itself is presented only in a few studies. The purpose of this study is to design two neural network models for stop&go maneuver. These models are designed based on the real traffic data and model the velocity and longitudinal distance (spacing) with the front vehicle for 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.**

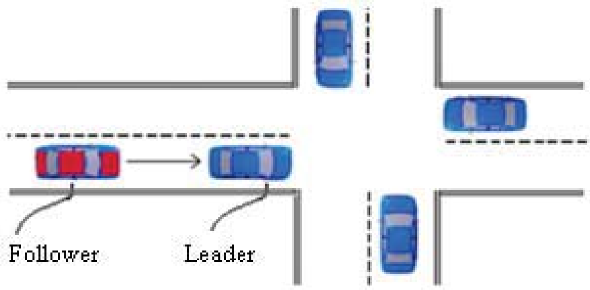
Keywords: Intelligent Automation; Stop&go maneuver; neural network; modeling.

I. INTRODUCTION

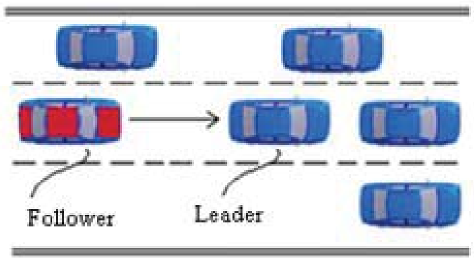
In spite of well-planned road management schemes, sufficient infrastructures, and traffic rules for safe driving, modern societies still face the problem of traffic congestion due to the ever-increasing traffic demand, which in turn results in loss of time, fuel, and money. Building new roads could be a solution, but it is less feasible due to political and environmental concerns. An alternative would be to make efficient use of the existing infrastructure. In this context advanced technologies in the field of telecommunication and information systems offer an excellent opportunity to implement a next generation traffic control and management approach. This has led to the emergence of a new paradigm called "Intelligent Transportation Systems" (ITS). ITS incorporate intelligence in both roadways and vehicles, and aim at improving the traffic flow. Possible performance measures in this context are throughput, travel times, safety, fuel consumption, reliability of travel times, robustness, etc. One way to improve traffic flow and safety of the current transportation systems is to apply automation and intelligent control methods to roadside infrastructure and vehicles. This gave rise to Automated Highway Systems (AHS), a component of advanced vehicle control systems that distributes the intelligence over the vehicles and the roadside infrastructure for better coordination of traffic network activities [1].

Research on adaptive cruise control (ACC) with stop&go maneuvers is presently one of the most important topics in the field of intelligent transportation systems. The main feature of such controllers is that there is adaptation to a user-preset speed and, if necessary, speed reduction to keep a safe distance from the vehicle ahead in the same lane of the road, whatever the speed. The extreme case is the stop&go operation in which the lead vehicle stops and the vehicle at the rear must also do so [2]. The goal that a vehicle be driven autonomously is far in the future and probably unreachable, but as a first step in that direction, adaptive cruise control (ACC) and stop&go maneuver systems are being developed. These kindس of controllers adapt the speed of a vehicle to that of the preceding one and get the vehicle to stop if the lead vehicle stops [3].

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. 1 (a) and (b).



(a)



(b)

Figure 1. Examples of situations that a stop&go maneuver may occur, (a) An intersection with traffic light, (b) Congested road.

In this paper, two neural network (NN) models for stop&go maneuver are designed based on real traffic datasets to simulate this maneuver in different situations. The first model simulates the velocity of a vehicle which performs this maneuver and the second model simulates the relative longitudinal distance between a follower vehicle with its lead vehicle during a stop&go maneuver. For simplicity, this distance is called the "Spacing distance" in the remaining parts of this study. In Fig. 1. spacing distance is the relative longitudinal distance between the follower vehicle and its preceding vehicle (the safe vehicle-to-vehicle distance to avoid collisions).

This study continues with an overview on stop&go maneuver and its features in section II. In section III, the design of the two NN models is described and the evaluation of the performance of these models is presented in section IV. At the end, the conclusion is stated in section V.

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 is related 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. The basic requirements for realizing a stop&go cruise control system have been discussed by Venhovens et al. [4]. In the case of stop&go driving situations, the bandwidth of the longitudinal vehicle control system should be increased significantly to reduce the spacing distance and to be meaningful on the busy urban traffic high way [5].

III. NEURAL NETWORK STOP&GO BEHAVIOR MODEL DESIGN

In this study, two neural network (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 neural network architecture, datasets, implementation, and the results are discussed in the following sections.

A. *Neural Networks*

The neural network models are able to model complex behaviors. Several studies explored the neural network approach to model different driving behaviors. One contribution of this study is development of neural network 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 multilayer feed forward network with error back propagation learning algorithm is used in the present study. A feed-forward back propagation neural network 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 neural network presented in this study, real stop&go data is needed.

B. *Datasets*

Real stop&go data from US Federal Highway Administration's NGSIM dataset is used to train the neural network model [7]. The NGSIM datasets represent the most detailed and accurate field data collected to date for traffic micro simulation research and development.

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].

Figure 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 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].

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. Models improved in this study simulate the velocity and spacing distance of the follower vehicle. Comparison of the unfiltered and filtered data of the velocity and spacing distance of the follower vehicle are shown in Fig. 4.

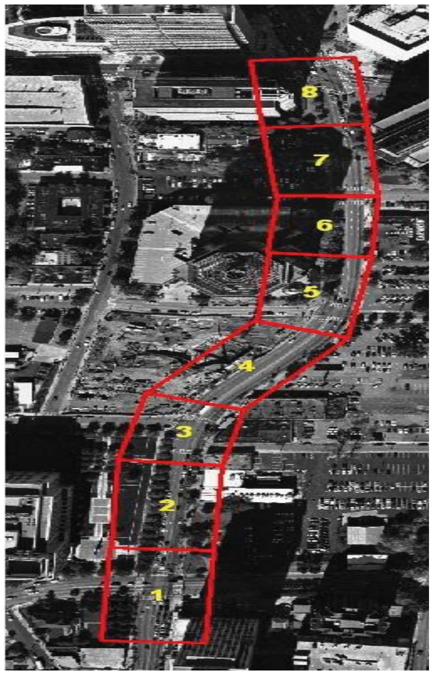


Figure 3. A segment of Peachtree Street, in Atlanta, Georgia [9].

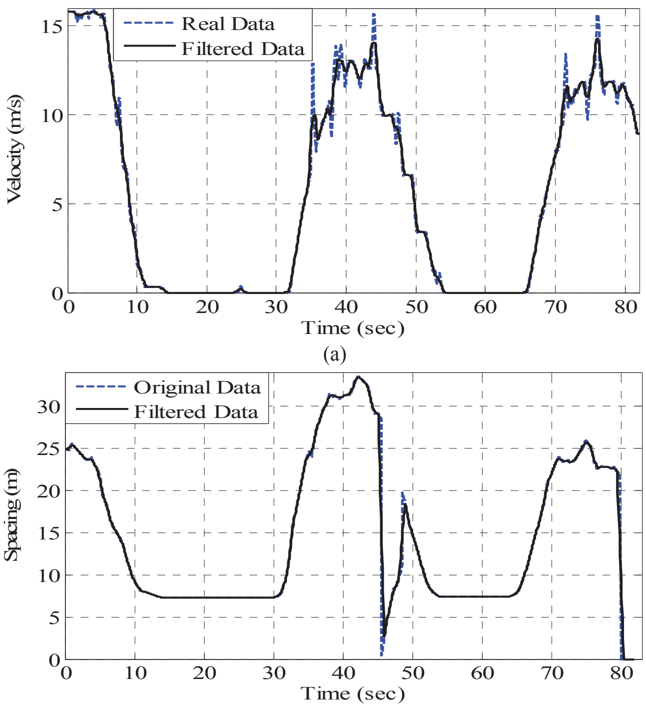


Figure 4. Comparison of unfiltered and filtered data, (a) Velocity, (b) spacing distance.

C. *Neural Network Models Design*

In the development of Neural Network model, the first step is defining the inputs and outputs of the model. These two models simulate the velocity and spacing distance of the follower vehicle. For the first model, acceleration, relative velocity, spacing distance and the velocity of the previous step are chosen as the inputs of the model and the velocity of the follower vehicle is chosen as the output. Notice that in the datasets the sample time of recording data is 0.1 second which means the data for the previous step is the data for 0.1 second before the current instant. In the second model, the velocity, relative velocity, acceleration and the spacing distance of the previous step are chosen as the inputs of the model and the spacing distance is chosen as the output. TABLE I and II show these variables.

TABLE I. INPUTS AND OUTPUTS OF THE FIRST MODEL

Type	Parameter Name	Symbol
input	Acceleration	$a(t)$
input	relative velocity	$\Delta V(t)$
input	Spacing	$\Delta R(t)$
input	velocity of the previous step	$V\ (t-0.1)$
output	Velocity	$V\ (t)$

TABLE II. INPUTS AND OUTPUTS OF THE SECOND MODEL

Type	Parameter Name	Symbol
input	Velocity	$V\ (t)$
input	relative velocity	$\Delta V\ (t)$
input	Acceleration	$a(t)$
input	spacing distance of the previous step	$\Delta R\ (t-0.1)$
output	Spacing	$\Delta R\ (t)$

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 dataset was used for training and testing purposes. The remaining 30% was set aside for model validation [12, 13]. To design the NN model 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.

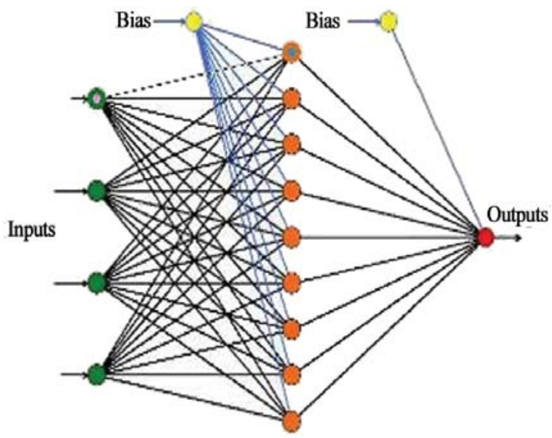


Figure 5. Designed ANN model for car-following behavior.

IV. DISCUSSION AND RESULTS

To assess the competence of the neural network model, the designed models are simulated in simulink in MATLAB. Then, the testing (validation) datasets are used to evaluate the proficiency of the model. The outputs of the models are compared to the real data, which are the output columns of the validation data. The comparisons of the output of the two neural network model with real data and are shown below. Fig. 6 (a) and (b) show the velocity and spacing distance of the follower vehicle during a stop&go maneuver. Notice that the validation datasets are composed of the data of several stop&go maneuvers. Here, the output of only one stop&go maneuver are shown. Each figure is composed of two subplots. The first subplot shows the difference between the model output and real data. The second subplot shows the error between the two diagrams shown in the first subplot. In order to have a better understanding of the performance of these models, errors between the outputs of the models for 4 test vehicles for each designed model is shown in Fig. 7 (a) and (b).

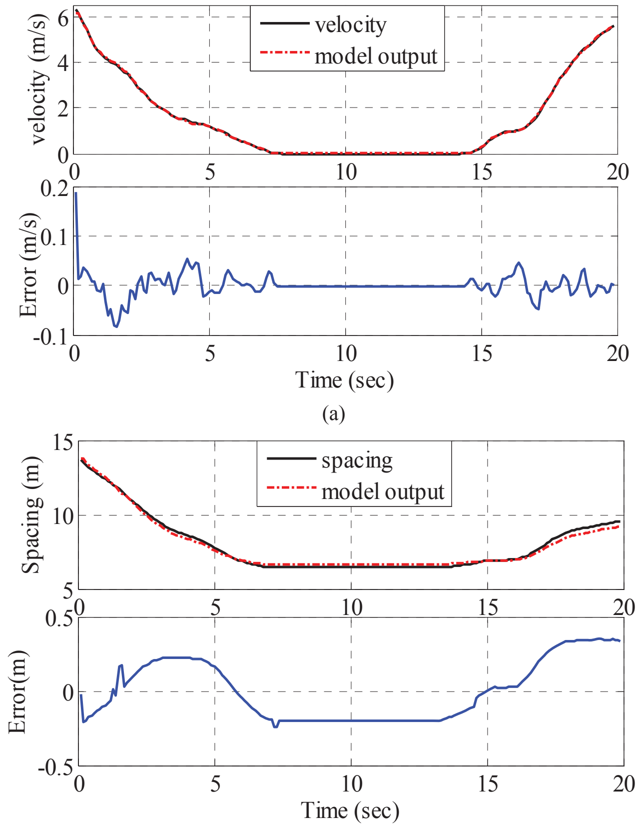
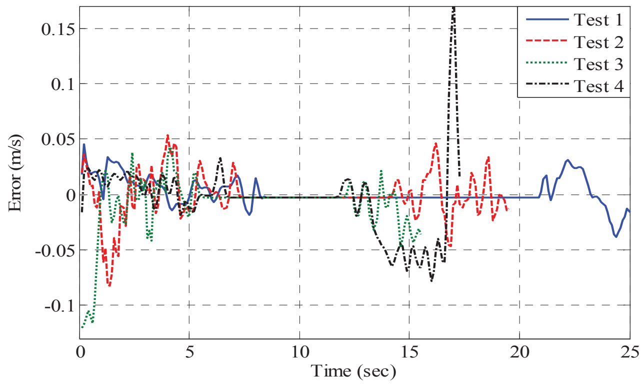
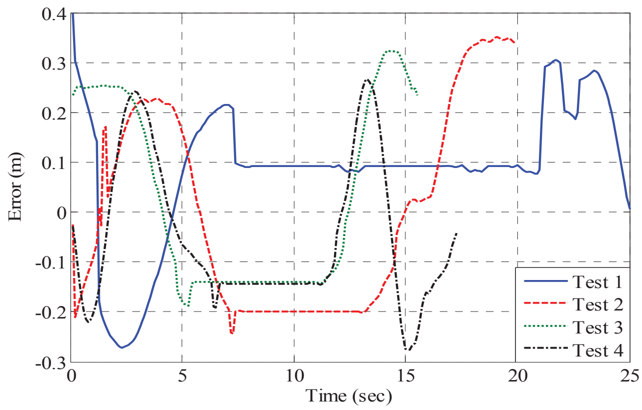


Figure 6. Comparison of the outputs of NN models and real data, (a) velocity model, (b) spacing distance model.



(a)



(b)

Figure 7. Comparison of errors for 4 test vehicles, (a) velocity model, (b) spacing distance model.

To examine the performance of the developed models, various criteria are used to calculate errors. The Mean Absolute Percent Error (MAPE) according to equation (1), is a very popular measure that corrects the 'canceling out' effects and also keeps into account the different scales at which this measure can be computed and thus can be used to compare different predictions. In general a MAPE of 10% is considered very good, a MAPE in the range 20% - 30% or even higher is quite common. Root mean squares error (RMSE), according to equation (1), is a criterion for comparing error dimension in various models. The mean absolute error (MAE), according to equation (2), is a quantity used to measure how close forecasts or predictions are to the eventual outcomes. The Mean Error (ME), according to equation (4), is the arithmetic average of all prediction errors. In these equations, x_i shows the real value of the variable being modeled (observed data), $\hat{x}_i$ shows the real value of variable modeled by the model and $\bar{x}$ is the real mean value of the variable and N is the number of test observations [14, 15].

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

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

$$MAE = \frac{1}{N}\sum_{i=1}^{N}|\hat{x}_i - x_i| \tag{3}$$

$$ME = \frac{1}{N}\sum_{i=1}^{N}(\hat{x}_i - x_i) \tag{4}$$

Errors in modeling the velocity output and the spacing distance output considering these criteria are summarized in TABLE III and IV. The last column of tables shows the mean value of each error criteria.

TABLE III. RESULT OF ERROR FOR NN VELOCITY MODEL

Vehicle	Test 1	Test 2	Test 3	Test 4	Mean
MAPE	1.2404	3.7253	4.3497	4.1218	3.3593
RMSE	0.0145	0.0240	0.0347	0.0297	0.0257
MAE	0.0098	0.0139	0.0217	0.0163	0.0154
ME	-5.9e-4	-3.4e-4	-0.006	-0.009	-0.0044

TABLE IV. RESULT OF ERROR FOR NN SPACING DISTANCE MODEL

Vehicle	Test 1	Test 2	Test 3	Test 4	Mean
MAPE	1.5900	2.3299	1.5232	2.2356	1.9197
RMSE	0.2885	0.1998	0.1662	0.1930	0.2119
MAE	0.1665	0.1790	0.1409	0.1758	0.1656
ME	0.0460	0.0035	0.0442-	0.0389	0.0419

V. CONCLUSION

In this study, two NN models were designed for stop&go maneuver based on real traffic datasets. These models considered important factors such as velocity and acceleration of the follower vehicle in stop&go maneuver. 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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