Prediction of Driver's Accelerating Behavior in the Stop and Go Maneuvers Using Genetic Algorithm-Artificial Neural Network Hybrid Intelligence

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Abstract

Research on vehicle longitudinal control with a stop and go system is presently one of the most important topics in the field of intelligent transportation systems. The purpose of stop and go systems is to assist drivers for repeatedly accelerate and stop their vehicles in traffic jams. This system can improve the driving comfort, safety and reduce the danger of collisions and fuel consumption. Although there have been many attempts to model stop and go maneuver via traffic models, but predicting the future vehicle's acceleration in steps ahead has not been studied much in this models. The main contribution of this paper is in designing integrated genetic algorithm-artificial neural network (GA-ANN) which is a soft computing method to simulate and predict the future acceleration of the stop and go maneuver for different steps ahead based on US federal highway administration's NGSIM dataset in real traffic flow. The results of this study are compared with two methods, back propagation based artificial neural network model (BP-ANN) and standard time series forecasting approach called ARX model. The mean absolute percentage error (MAPE), root mean square error (RMSE) and coefficient of determination or R-squared (R2) are utilized as three criteria for evaluating predictions accuracy. The results showed the effectiveness of the proposed approach for prediction of driving acceleration time series. The proposed model can be employed in intelligent transportation systems (ITS), collision prevention systems (CPS) and driver assistant systems (DAS) such as adaptive cruise control (ACC) and etc. The outcomes of this study can be used for the automotive industries who have been seeking accurate and inexpensive tools capable of predicting vehicle speeds up to a given point ahead of time, known as prediction horizon, which can be used for designing efficient predictive controllers based on human behaviors.

***Keywords**: Stop and Go, Prediction of Acceleration, Hybrid Intelligence, Artificial Neural Network, Genetic Algorithm, and Vehicle*.

1. Introduction

Car accidents can be avoided through timely threat recognition and appropriate collision avoidance systems. This may be achieved by suitable warning to the driver or by automatic support to longitudinal or lateral control of the vehicle [1]. 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. Driver assistance systems (DAS) are being broadly utilized in view of the fact that driver workloads will be decreased in DAS-equipped vehicles [2]. Adaptive cruise control (ACC) with the capability of stop and go is one of intelligent transportation systems (ITS) which are highly used in modern vehicles. The goal of this system 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 and 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 and go system can follow other vehicles in dense traffic while keeping a safe distance in stop and go driving situations. The basic requirements for realizing a stop and go cruise control system have been discussed by Venhovens et al. [3].

Stop and 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 Figure 1 (a) and (b). The Follower Vehicle (FV) performs the stop and go maneuver in these cases [4].

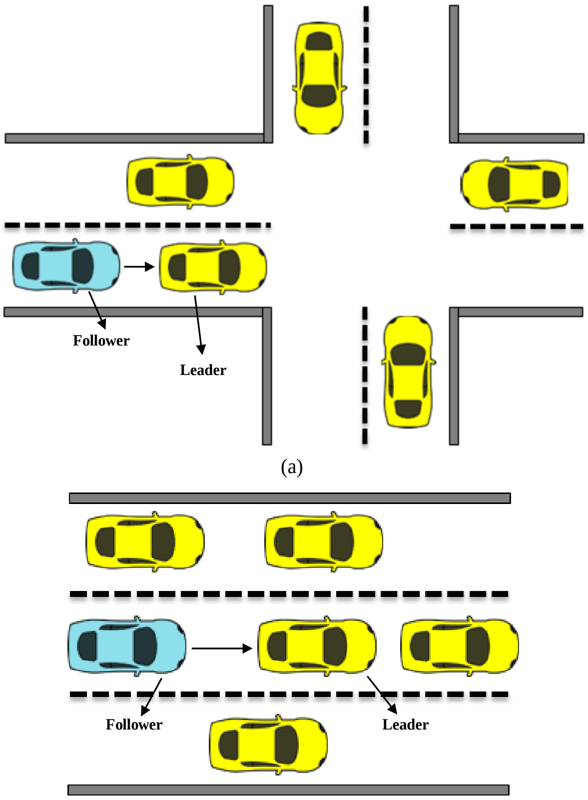


Fig1. Examples of situations that a stop and go maneuver may occur,(a) An intersection with traffic light, (b) Congested road

Driving behavior observed at traffic networks varies considerably depending on the type of road section. At signalized junctions, drivers are taught to moderate their speed, and to comply with the priority rules set by the traffic light. Therefore, vehicles stop and queue up during the red phase, and they leave the junction during the green and amber phases. During these operations, vehicles driving patterns vary significantly [5]. Driving behaviors differ among drivers. They differ in how they hit the gas and brake pedals, in the way they turn the steering wheel, and in how much distance they keep when following a vehicle [6]. Five major categories of factors influencing driver capability, performance and behavior are attitudes/personality, experience, driver state (impairment level), task demand (workload) and situation awareness [7].

Researchers use stop and go microscopic data for analyzing driving behavior, traffic impacts (instantaneous speeds, accelerations, car-following distances and relative speeds), calibration of traffic flow models and enhancing the ITS applications. So this data can be used to estimate or to derive safety measures like time-to-collision. In fact, to enhance the functionality of the vehicle [4] safety, intelligent tools should be used to predict the future vehicle speeds with respect to the real-time speed profile of a moving vehicle [8]. A similar approach has been pursued by Fotouhi et al. [8] to design an efficient power management controller for a HEV. Moreover, there are other investigations which demonstrate that intelligent tools can be used for the prediction of vehicle speeds. Park et al. [9] indicated that a back propagation-artificial neural network (BP-ANN) can be used for real time vehicle speed predictions and indicated the validity of their methodology. Similar approach proposed by Ghaffari et al. [4] for predicting the acceleration of vehicle in steps ahead. However the previous work, sound that using intelligent tools especially neural network for designing vehicle acceleration predictors at the heart of a predictive powertrain controller is a reasonable option; but it is acknowledged that BP based neural network has such problems as slow convergence and easily converging to local minimum that should be removed [10].

In this study, a soft computing idea is proposed to predict the stop and go behavior in the real traffic flow considering the effects of driver's behaviors. This idea is used to predict Driver-Vehicle-Unit

(DVU) acceleration using a hybrid intelligence approach called integrated genetic algorithm-artificial neural network (GA-ANN) predicator. This method can speed up the convergence and avoid local minimum of BP-ANN. This paper is organized as follows. A brief review on the stop and go behavior and the related works are presented in Section 2. In Section 3, it is explained that how the real traffic data are collected and prepared for the farther simulations. These stop and go data are obtained from US Federal Highway Administration's NGSIM dataset. In Section 4, GA-ANN models are designed to model and predict the DVU accelerating behavior in stop and go scenarios. GA-ANN models are designed based on real traffic data to predict the acceleration of the vehicle which performs a stop and go maneuver in different situations. These models predict the acceleration of 1, 2 and 3 steps ahead. Each step is equal to 0.1 second. In other words, these models can predict the acceleration of 0.1, 0.2 and 0.3 seconds ahead. Simulation results and discussions for the proposed GA-ANN models are given in Section 5. The mean absolute percentage error (MAPE), root mean square error (RMSE) and R-squared (R2) are utilized as three criteria for evaluation of predictions accuracy. In addition, the integrated genetic algorithm-artificial neural network predicator is compared with back propagation based artificial neural network model (BP-ANN) and standard time series forecasting method (ARX) as a reference for the prediction results. Lastly, conclusion is presented in Section 6.

2. STOP AND GO TRAFFIC MODEL

Conventional ACC systems only work in the range of 40 km/h to the highest speed, which makes them unable to perform stop and go operations. This is because these systems only automate the throttle of the vehicle so the speed is only reduced by the motor braking, which is not enough to stop a car in a typical situation like a traffic jam [11]. The stop and go cruise control system comprises at least the following functions [3]:

- 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

Adjust headway according to driver preference

Additional functions could be realized when a stop and go cruise control system is integrated with, for example, a vehicle navigation system which adjust headway and vehicle speed according to road class, road attributes (such as prevailing speed limits) and roadway curvature.

To date, ACC systems have been in market as an optional device for luxury vehicles, and such systems have been developed for highway driving assistance only at speeds above 40 km/h, whereas stop and go systems are employed to handle urban traffic situations at low speeds under 40 km/h. In particular, stop and go systems must deal with the following two difficulties encountered in ACC systems. One is sensing difficulty in complex urban; the front vehicle situation of cut-in and lane change are more frequency and the recognition pedestrian must be completely considered. The other is the frequent switching between acceleration and deceleration, and the smooth control for the driving stability and comfort at low speeds. The commercial systems achieve vehicle longitudinal dynamics control via integration engine management system (EMS) and anti-lock braking system (ABS). Acceleration control is applied by electronic throttle control and deceleration is performed using a smart booster besides using ABS modulator [12].

To simulate and analyzing the performance of the stop and go control systems, models of this maneuvers are needed to investigate the fairness of the designed controllers before applying them in real vehicles. Here, GA-ANN models of this behavior are proposed which simulate and predict the behavior of the follower vehicle performs the stop and go maneuver (as shown in Figure 1).

3. REAL TRAFFIC DATA COLLECTION AND PROCESSING

Traffic behavior can be modeled at macroscopic, mesoscopic and microscopic levels. Macroscopic models provide direct relationships between macroscopic variables (e.g. average speeds, flows, densities). In mesoscopic models traffic flow and performance variables are instead represented through probability distributions. Microscopic models have been developed with the main aim of simulating the movement of vehicles on the roads at the individual level i. e. each vehicle movement in the stop and go traffic condition [5].

As mentioned before, modeling and prediction of the microscopic behavior of vehicles will improve the ITS applications. In order to design GA-ANN prediction systems, a dataset of stop and go behavior is needed. To do this, real stop and go data from US Federal Highway Administration's NGSIM dataset is used [13]. The Federal Highway Administration of the U.S. Department of Transportation has originated the Next Generation SIMulation community (NGSIM) in order to improve the quality and performance of simulation tools, promote the use of simulation for research and applications, and achieve wider acceptance of validated simulation results. NGSIM data provides detailed vehicle trajectory data, wide-area detector data, and supporting data needed for behavioral algorithm research. As part of the program, a first data set has been collected at the Berkeley Highway Laboratory (BHL) in Emeryville by Cambridge Systematics and the California Center for Innovative Transportation at UC Berkeley. The BHL is a part of the I-80 at the east coast of the San Francisco Bay as shown in Figure 2.

I-80 highway has 9 lanes. Lane 1 is the farthest left lane; lane 6 is the farthest right lane. Lane 7 is the on-ramp at Powell Street, and Lane 9 is the shoulder on the right-side. Six cameras have been mounted on top of the 97m tall Pacific Park Plaza tower and recorded 4733 vehicles on a road section of approximately 900m length in a 30-minute period in December 2003. The result has been published as the "Prototype Dataset". As part of the California Partners for Advanced Highways and Transit (PATH) Program, the Institute of Transportation Studies at UC Berkeley further enhanced the data collection procedure [15] and in April 2005, another trajectory dataset was recorded at the same location using seven cameras (Figure 3) and capturing a total of 5648 vehicle trajectories in three 15-minute intervals (with resolution of 10 frames per second) on a road section of approximately 500m. These periods represent the buildup of congestion, or the transition between uncongested and congested conditions, and full congestion during the peak period [16]. This dataset was later published as the "I-80 Dataset".

Considering observations in real traffic are always affected by measurement errors, the data which is used to test the model should be smoothed like [17] and [18]. A moving average filter has been designed according to Equation (1) and applied to all data before any further data analysis. In this equation, $\boldsymbol{U}$ and $\boldsymbol{V}$ are original data and filtered data respectively, and $\boldsymbol{k}$ is length of window which contains data. A comparison of the unfiltered and filtered data of the acceleration of the follower vehicle in one maneuver is shown in Figure 4.

$$V[i] = \frac{1}{k}\sum_{j=0}^{k-1} U[i-j] \qquad (1)$$

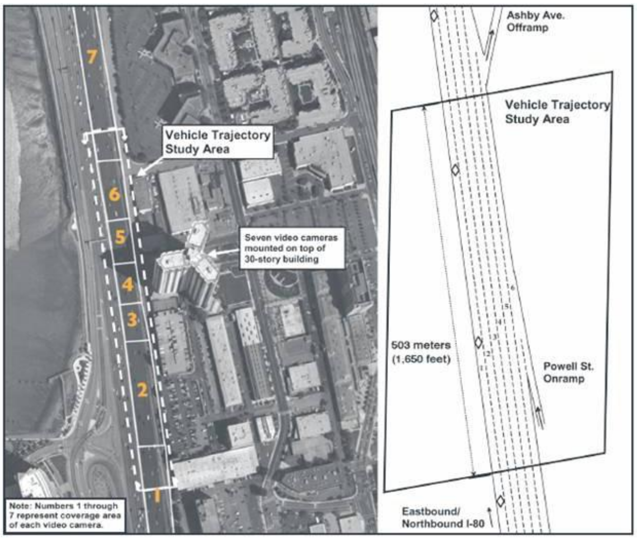


Fig2. A segment of eastbound I-80 in the San Francisco Bay area in Emeryville, California [14]

Fig3. A digital video camera mounted on top of a building that overlooks I-80 is recording vehicle trajectory data [14]

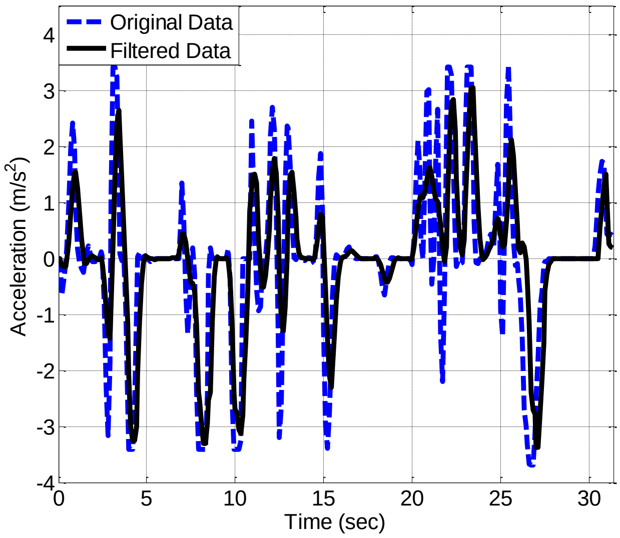


Fig4. Comparison of original and filtered acceleration

4. EVOLUTIONARY PREDICTION ALGORITHM

In this section, the procedure of designing neural network with multi-layer perceptron (MLP) which is integrated with genetic algorithm to predict DVU acceleration time series in a stop and go maneuvers is illustrated. Neural Networks (NNs) are based on early work of McCulloch & Pitts (1943), who built a first crude model of a biological neuron with the aim to simulate essential traits of biological information handling. The training algorithm of MLP is called back propagation method. In the back propagation learning method, a network learns a predefined set of input-output example pairs by using a two-phase propagate-adapt cycle. 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. MLP model consists of a single layer of S perceptron neurons connected to R inputs is demonstrated in Figure 5.

As mentioned before, back propagation method has some problems such as the longtime training, easy convergence to the local minimum points and low prediction precision due to use descent gradient algorithm as learning method. For overcoming this problems, evolutionary algorithms such as Artificial

Bee Colony (ABC) Algorithm [10] and Least Learning Machine (LLM) [19] are introduced for training MLP networks with tuning the connection weights and biases. Shojaeefard et al. [20], used NSGA-II as a multi-objective evolutionary algorithm to train neural network for optimizing heavy-duty diesel engine.

In this study, separate parts of driving data are used for training and testing GA-ANN. Designed predicator model has four inputs and one output, which inputs are velocity of FV at time step $\boldsymbol{i}$ ($\boldsymbol{v}[\boldsymbol{i}]$), acceleration of FV at time steps $\boldsymbol{i}$ and $\boldsymbol{i-1}$ ($\boldsymbol{a}[\boldsymbol{i}]$ and $\boldsymbol{a}[\boldsymbol{i-1}]$) and the relative velocity between FV and leader vehicle (LV) at time step i ($\boldsymbol{v_r}[\boldsymbol{i}]$). The output of the model is the acceleration of FV at time step $\boldsymbol{i+h}$ ($\boldsymbol{a}[\boldsymbol{i+h}]$), where $\boldsymbol{h}$ is step ahead. The ANN model designed here has a structure similar to one shown in Figure 6.

It is assumed that the applied ANN has three layers. The first layer which is known as the input layer has 2 neurons, the second one is the hidden layer with 5 neurons and the last one is the output layer with one neuron. For proposed model, a perceptron neuron with tangent-sigmoid transfer function is used (Figure 7). The governing function is shown in Equation (2).

$$\alpha = \frac{2}{(1+e^{-2\beta})} - 1 \qquad (2)$$

In the development of ANN prediction model, the available data are usually divided into two 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

$$GA_{Cost\ Function} = MSE(a_R[i+h] - a_P[i+h]) \qquad (3)$$

development of the model, is utilized to validate the performance of the trained model. For this paper, 75% of the master data set was used for training and testing purposes. The remaining 25% was set aside for model validation. Genetic algorithm is used to find optimal ANN model by tuning network parameters. This leads to the following evolutionary training cycle [21]:

1. Creation of the next population of ANNs by means of mutation, recombination and fitness-oriented selection of the weight matrices. (The initial population is randomly created.)
2. Evaluation of the fitness values of the ANNs.
3. If the desired result is obtained, then stop; otherwise go to step 1.

As shown in Equation (3), mean square error (MSE) criteria is used as the cost function of GA for optimizing ANN, which estimation error is difference between the real value and the predicted value of a FV acceleration time series. GA main parameters, mutation and cross-over are selected 0.35 and 0.5 respectively.

$$A_{Cost\ Function} = MSE(a_R[i+h] - a_P[i+h]) \qquad (3)$$

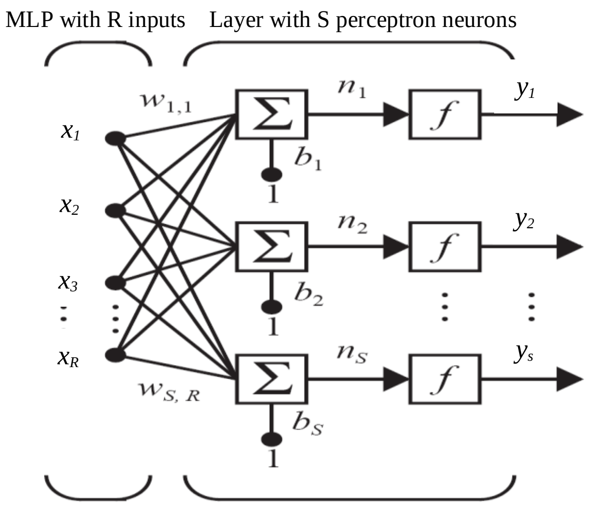


Fig5. A perceptron network consists of a single layer of S perceptron neurons connected to R inputs

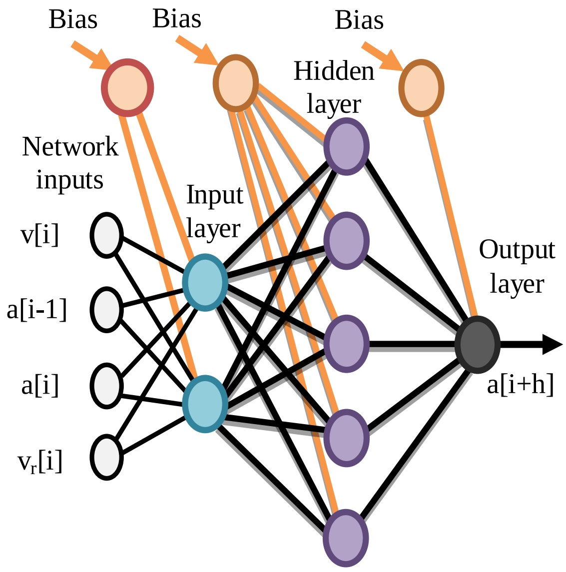


Fig6. Designed ANN model for car-following behavior prediction

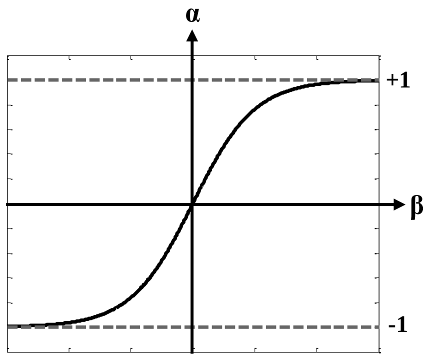


Fig7. A perceptron neuron with tangent-sigmoid function

5. EVALUATION OF RESULTS AND DISCUSSIONS

In order to verify the performance of GA-ANN model, the validation datasets are used. The matrix of the validation data is divided to two groups of 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. Both of these were illustrated in section 4 and were shown in Figure 6. Then the comparison of between the outputs of proposed model with real data and similar results of BP-ANN and ARX [22] models is investigated. Figure 8 shows the acceleration of FV during a stop and go maneuver predicted in one, two and three steps ahead (Each step is equal to 0.1 second. In other words, these models can predict the acceleration of 0.1, 0.2 and 0.3 seconds ahead).

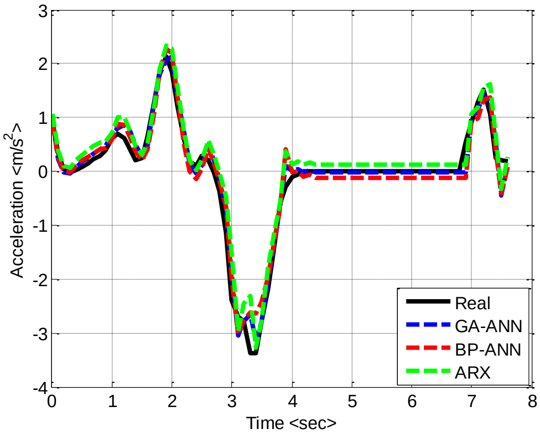
In order to have a better understanding of the performance of these models, errors between the outputs of the models and real data for each of the designed model are shown in Figure 9.

Three criteria used to measure the forecasting performance of proposed model. The mean absolute percentage error (MAPE), according to Equation (4) which shows the MAPE can be considered as a criterion to model risk to use it in real-world conditions. Root mean squares error (RMSE), according to Equation (5) is a criterion to compare error dimension in various models, and R-squared (R2), according to Equation (6) is a number that indicates how well data fit a statistical model. In these equations, z_i shows the real value of the variable being modeled (observed data), $\hat{\boldsymbol{z}}_i$ denotes the value of variable modeled by the predicator, $\bar{\boldsymbol{z}}_i$ is the real mean value of the variable and N is the number of test observations [23]. Errors of the designed predicator models for stop and go maneuvers considering three error criteria are summarized in Table 1.

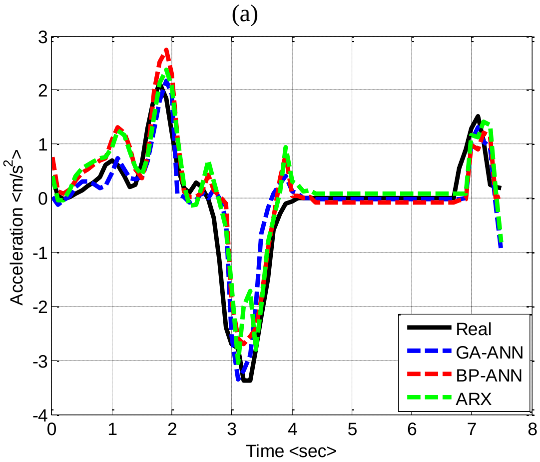
$$MAPE = \frac{100}{N}\sum_{i=1}^{N}\frac{|z_i - \hat{\boldsymbol{z}}_i|}{z_i} \tag{4}$$

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(z_i - \hat{z}_i)^2} \tag{5}$$

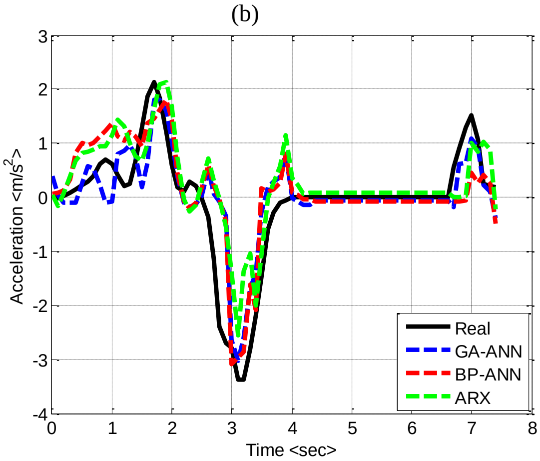
$$R^2 = 1 - \frac{\sum_{i=1}^{N}(z_i - \hat{z}_i)^2}{\sum_{i=1}^{N}(z_i - \bar{z}_i)^2} \tag{6}$$



(a)

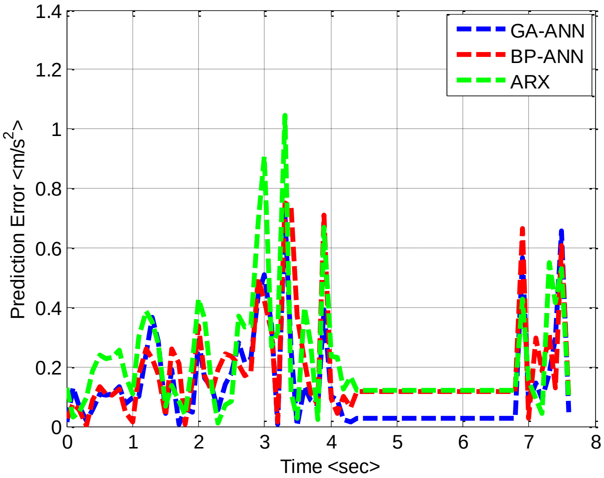


(b)

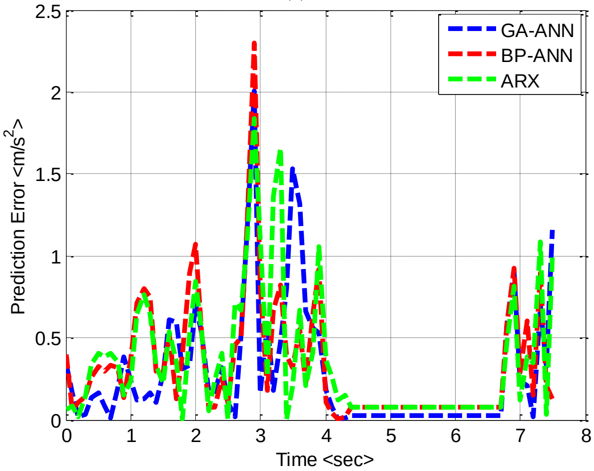


(c)

Fig8. Fig. 8. The acceleration prediction based on GA-ANN predicator and other models, (a) 0.1 second ahead model, (b) 0.2 second ahead model, (c) 0.3 second ahead model



(a)



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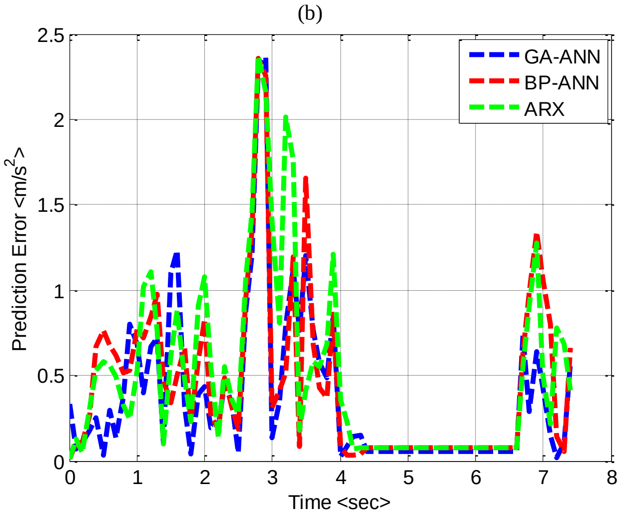

(c)

Fig9. Comparison between the errors of GA-ANN predictor with other models, (a) 0.1 second ahead model, (b) 0.2 second ahead model, (c) 0.3 second ahead model

The measures of predicting performance, MAP Error, RMS Error and R2 are demonstrated in bar graph in Figures 10 to 12.

The analysis confirms the ability of GA-ANN hybrid intelligence model to predict accelerating behavior of DVU in stop and go maneuvers. As seen in Figures 10 to 11, the measure of error is increasing directly by the prediction horizon for all the designed predicators. Presented results in Figure 12 shows that there is a small difference between the prediction performance of GA-ANN with BP-ANN and ARX

for 0.1 second ahead, but for longer prediction horizons the GA-ANN predicts better than BP-ANN and ARX models which is in agree with the previous results.

Table 1. Comparison results of predicator models according to MAPE, RMSE and R2 criteria

Prediction Horizon (sec)	MAP Error			RMS Error			R^2		
	GA-ANN	BP-ANN	ARX	GA-ANN	BP-ANN	ARX	GA-ANN	BP-ANN	ARX
1 second ahead	12.8	15.0	16.4	0.19	0.21	0.22	0.964	0.946	0.925
2 second ahead	29.0	33.2	35.5	0.48	0.50	0.53	0.788	0.773	0.746
3 second ahead	37.8	45.1	49.8	0.60	0.66	0.73	0.676	0.605	0.527

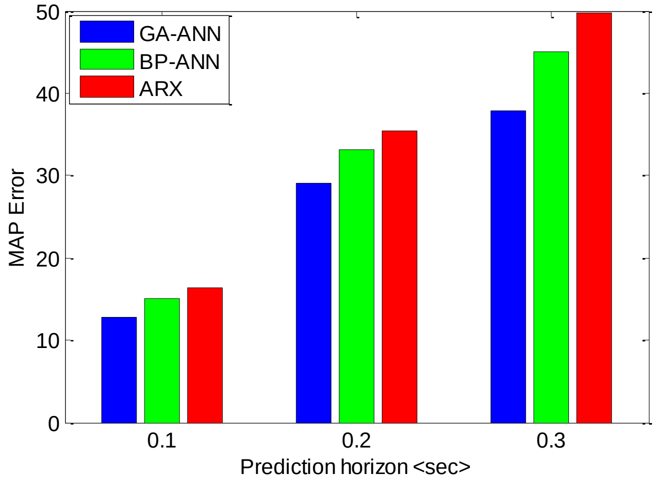

Fig10. MAP Error for GA-ANN predictor and other models

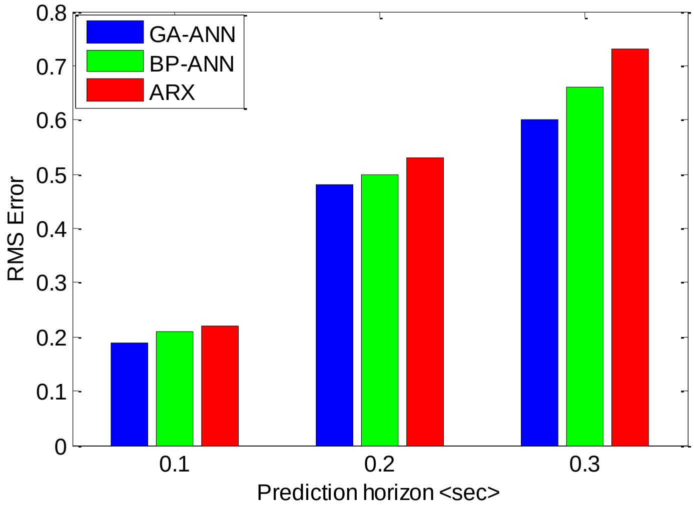

Fig11. RMS Error for GA-ANN predictor and other models

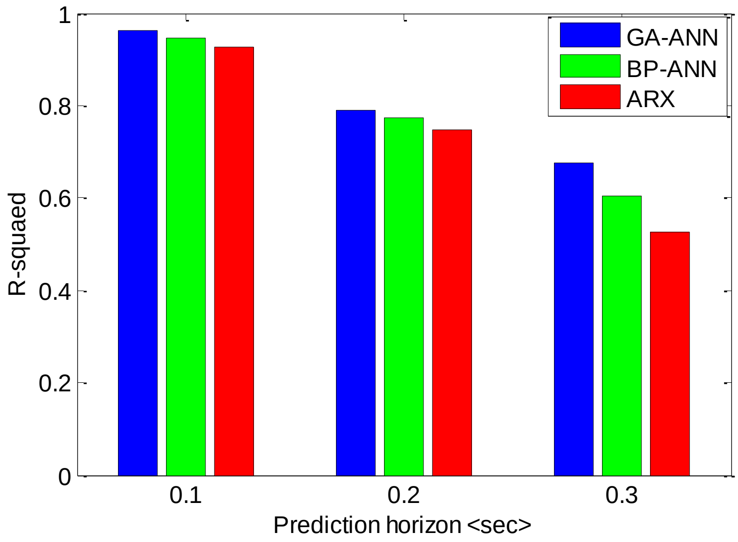

Fig12. R-squared criterion for GA-ANN predictor and other models

6. CONCLUSION

In this study, a hybrid intelligence method based on genetic algorithm and artificial neural network improved to predict the driver's accelerating behavior in the stop and go maneuvers. Main factors such as velocity and acceleration of the follower vehicle and relative velocity were used for development of proposed model. These models predict the acceleration of 1, 2 and 3 steps ahead. Each step is equal to 0.1 second. In other words, these models can predict the acceleration of 0.1, 0.2 and 0.3 seconds ahead. For investigating the forecasting performance of the proposed predicator, real stop and go data from US Federal Highway Administration's NGSIM dataset were used. Three criteria, MAPE, RMSE and R-squared utilized and the performance of GA-ANN compared with two predicator models; back propagation based artificial neural network (BP-ANN) and standard time series forecasting approach (ARX). Simulation results indicated that the GA-ANN model were highly accordant with real behaviors and has higher prediction accuracy and longer correct prediction steps than other models. The results of this study can be used by automotive engineers in industries to improve the smart vehicles, intelligent transportation systems (ITS), collision prevention systems (CPS) and driver assistant systems (DAS) which are very affected by human driving behavior. Future work will be development of a DAS system like adaptive cruise control, which is compensated by GA-ANN predicator and uses human driving behavior in feedback loop.

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