Vehicle's Velocity Time Series Prediction Using Neural Network

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Abstract

This paper presents the prediction of vehicle's velocity time series using neural networks. For this purpose, driving data is firstly collected in real world traffic conditions in the city of Tehran using advance vehicle location devices installed on private cars. A multi-layer perceptron network is then designed for driving time series forecasting. In addition, the results of this study are compared with the auto regressive (AR) method. The least root mean square error (RMSE) and median absolute percentage error (MDAPE) are utilized as two criteria for evaluation of predictions accuracy. The results demonstrate the effectiveness of the proposed approach for prediction of driving data time series.

Keywords: *vehicle, velocity, time series, prediction, neural networks.*

1. INTRODUCTION

Hybrid vehicles are vehicles equipped with at least two different sources of energy. In the specific case of Hybrid Electric Vehicles (HEVs), one of the power sources is electrical. The architecture of a HEV includes an Internal Combustion Engine (ICE) with an associated fuel tank and an electric machine with its associated energy storage system (i.e. battery). Using this architecture, HEVs combine the benefits of ICE and electric motors to obtain different objectives such as improved fuel economy or additional auxiliary power for electronic devices and power tools.

In order to use the two power sources of HEV in an effective manner, a control strategy is necessary. Because of the influence of traffic conditions on the HEV power management system, applying an adaptive control strategy is essential. This approach suggests that a HEV requires high ability to adapt itself to traffic conditions to minimize fuel consumption and exhaust emissions. In fact, HEV is more sensitive to traffic conditions than a conventional vehicle. Thus, the use of traffic information in the adaptive HEV power management system has become one of the most important applications in the area of driving patterns and traffic condition analysis which has attracted a lot of interest recently among the researchers [1] to [8].

Driving condition prediction is a computational algorithm used in the HEV control unit in order to predict the driving data for the near future. One mechanism for having information about the short-term traffic flow is vehicle telematics [9] used in intelligent transportation systems (ITS). The navigation system and ITS can provide traffic information such as congested routes and arrival time for the driver in order to choose the best route. Although vehicle telematic systems have many advantages, they suffer from some limitations including equipments needed as infrastructure. In addition, the traffic information must be updated in very short time intervals for HEV application. Moreover, taking into account the target of this study which is the use of driving data in intelligent HEV control, it is essential for the telematic system to cover all regions where vehicle moves. However, the infrastructure required for a telematic system is not provided in many cities or regions. As a result, other approaches based on the analysis of the history of vehicle's motion may be applicable for HEV control. One of these approaches is velocity time series forecasting.

Albeit time series forecasting has been studied in previous studies in many areas such as market forecasting and climate prediction, only few studies have been undertaken for prediction of driving data time series [10] to [12]. In [12], short-term "traffic flow" prediction is studied to predict the traffic volume during daytime hours on an expressway for the next 15-minute interval using neural networks. In that study, three fixed points on a single expressway are considered during daytime hours on weekdays in order to measure and store traffic flow. These studies are not applicable for HEV control because traffic flow is predicted in a place instead of velocity time series of a moving vehicle.

In this paper, velocity time series prediction is presented based on the history of vehicle’s motion using neural networks. For this purpose, driving data is firstly collected using Advance Vehicle Location (AVL) systems and therefore real driving time series are used for the investigations. Multi-layer perceptron (MLP) networks are then designed for driving data prediction where two separate parts of driving data are used for training and testing of the neural networks. Taking the application of this study in intelligent HEV control into account, prediction horizon is considered 10 seconds ahead in velocity time series. Finally, the least root mean square error (RMSE) and median absolute percentage error (MDAPE) are utilized as two criteria for evaluation of predictions accuracy. In addition, the neural networks are compared with Auto Regressive (AR) method as a reference for the prediction results.

The structure of the paper is as follows. In section 2, intelligent control strategy for HEV based on driving condition prediction is introduced. Section 3 explains driving data gathering. In section 4, neural network is described. The vehicle’s velocity time series prediction is presented in section 5. Finally in section 6, the results are analysed.

2. DRIVING CONDITION PREDICTION FOR HEV CONTROL

As mentioned in the introduction section, HEVs are able to apply the driving condition information in order to improve vehicle's performance. A driving cycle can be represented as a sequence of traffic conditions. It is believed that by analyzing the driving data, useful information is provided to predict the traffic conditions. By recognition and prediction of traffic conditions, fuel-consumption and emissions reduction may be possible using an intelligent control algorithm in HEVs [7] and [8]. Figure 1 shows a schematic representation of driving condition prediction system. As presented in the figure, the predictor part predicts velocity time series in prediction horizon based on history of vehicle’s motion.

Figure 2 illustrates a schematic of adaptive HEV control based on driving time series prediction. In this approach, the prediction horizon is 10 seconds and

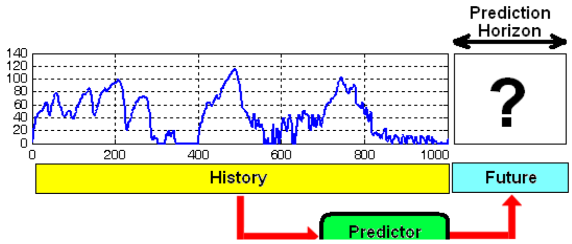

Fig. 1. Schematic of a driving pattern prediction system

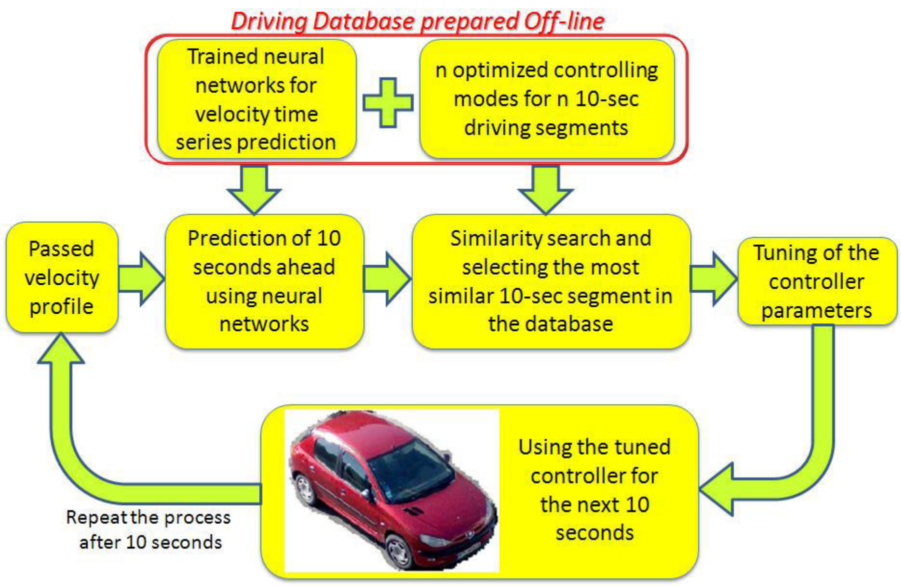

Fig. 2. schematic of an adaptive HEV control based on driving time series prediction

prediction is repeated after 10 seconds using an on-line approach. The last driving data is used as inputs of neural networks. Then velocity time series is predicted from 1 second to 10 second ahead. The control unit has an off-line database containing many 10-sec segments and corresponding optimized controllers of that segments. After prediction in each step, the most similar 10-sec driving segment in the database to the predicted segment is selected, and its controller is used for the next 10 second. This process is repeated each 10 seconds during motion.

3. DRIVING DATA

In this study, driving data are collected in the real world traffic condition in order to provide a real database including the vehicle's velocity. For this purpose, data gathering has been performed in the city of Tehran using Advance Vehicle Location (AVL) systems installed on private cars. The AVL system, depicted in Figure 3, operates on the basis of Global Positioning System (GPS) which is a satellite-based navigation system. The X8 model AVL system has been used in this study. The data which is recorded every second includes some information such as date/time, number of the satellites, longitude, latitude, speed and altitude of the vehicle.

Fig. 3. The X8 AVL system

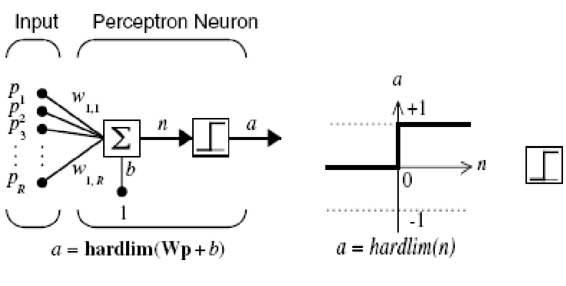

Fig. 4. A perceptron neuron with hard-limit function

4. NEURAL NETWORKS

In this study, neural networks have been used for driving time series prediction. The process of driving time series prediction and the results are discussed in the following parts. In this section, a brief explanation about the structure of neural networks used in this study is presented. Multi-layer perceptron (MLP) networks have been utilized in this work for driving time series prediction. Rosenblatt [13] created many variations of the perceptron. One of the simplest was a single-layer network whose weights and biases could be trained to produce a correct target vector when presented with the corresponding input vector. In this study, separate parts of driving data are used for training and testing neural networks. The discussion of the perceptrons in this paper is brief and for a more thorough discussion see references [13],[14]. A perceptron neuron, which uses the hard-limit transfer function, is shown in Figure 4 and a perceptron network consists of a single layer of S perceptron neurons connected to R inputs is demonstrated in Figure 5.

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. After an input pattern has been applied to

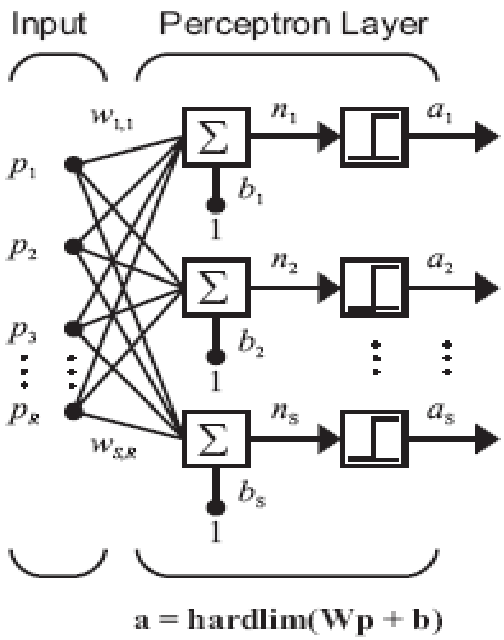

Fig. 5. A perceptron network consists of a single layer of S perceptron neurons connected to R inputs

the first layer of network units, it is propagated through each upper layer until an output is generated. This output pattern is then compared to the desired output and an error signal is computed for each output unit. The error signals are then transmitted backward from the output layer to each node in the intermediate layer that contributes directly to the output. However, each unit in the intermediate layer receives only a portion of the total error signal, based roughly on the relative contribution the unit made to the original output. This process repeats, layer by layer, until each node in the network has received an error signal that describes its relative contribution to the total error. Based on the error signal received, connection weights are then updated by each unit to cause the network to converge toward a state that allows all the training patterns to be encoded [15].

5. VELOCITY TIME SERIES PREDICTION

In this section, ability of MLP networks to predict the velocity time series in the near future is investigated. In this case, the inputs of the network are velocity values in the past seconds $(v_t, v_{t-1}, v_{t-2}, \ldots, v_{t-n})$ and the outputs are velocity values in next seconds $(v_{t+1}, v_{t+2}, v_{t+3}, \cdots)$. Separate networks have been designed for each output. The number of inputs for each network is determined by trial and error based on the accuracy of the predictions of testing data. The least root mean square error (RMSE) and median absolute percentage error (MDAPE) are utilized as two criteria of prediction accuracy as follows:

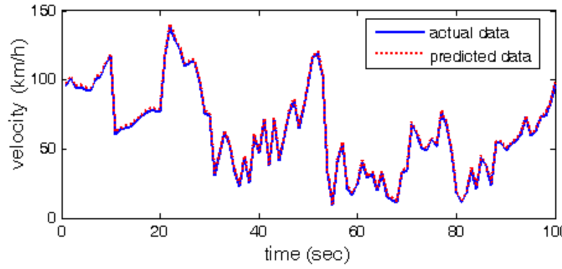

Fig. 6. Actual and predicted values of velocity in 1 second ahead using NN method

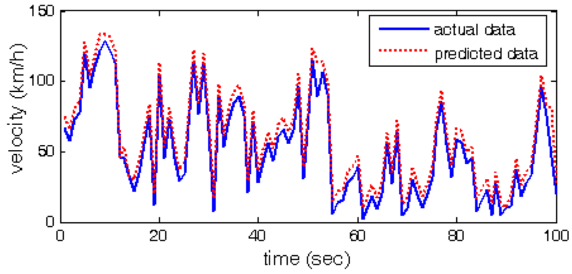

Fig. 7. Actual and predicted values of velocity in 5 seconds ahead using NN method

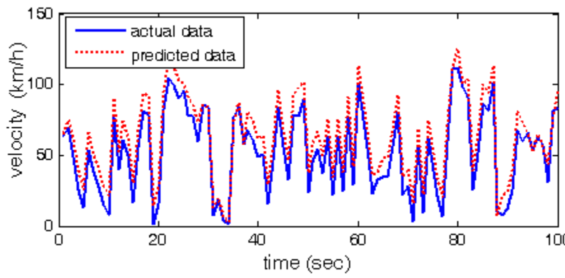

Fig. 8. Actual and predicted values of velocity in 10 seconds ahead using NN method

Table 1. structure of the best designed neural networks

Number of seconds ahead	Neural network (RMSE criterion)	Neural network (MDAPE criterion)
1	5 - 4 - 1	8 - 3 - 1
2	3 - 8 - 1	5 - 9 - 1
3	6 - 7 - 1	3 - 1 - 1
4	2 - 10 - 1	3 - 5 - 1
5	3 - 4 - 1	3 - 1 - 1
6	6 - 10 - 1	4 - 2 - 1
7	3 - 3 - 1	5 - 4 - 1
8	9 - 10 - 1	2 - 3 - 1
9	7 - 5 - 1	7 - 9 - 1
10	5 - 3 - 1	9 - 4 - 1

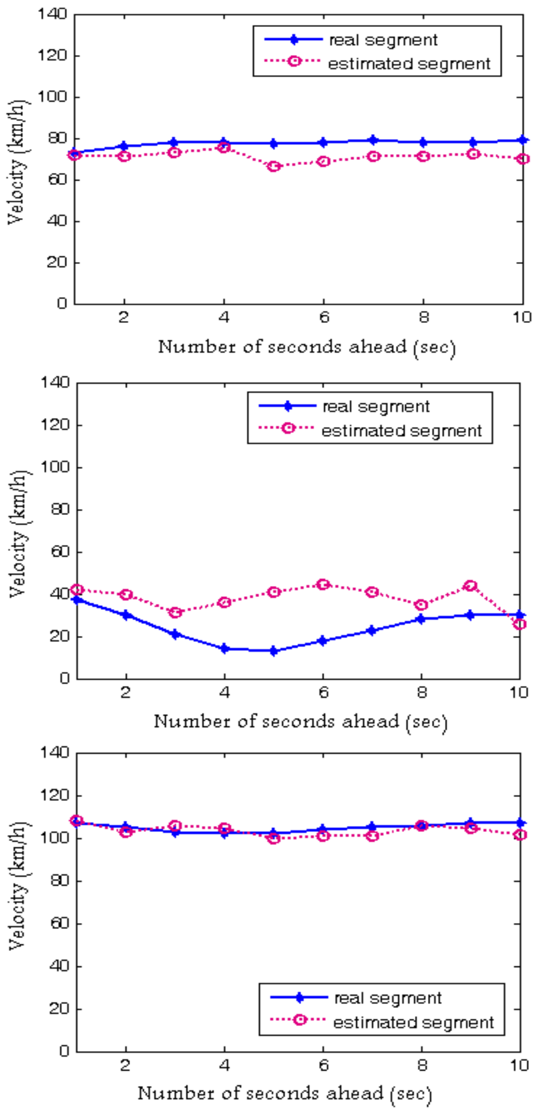

Fig. 9. three sample 10-sec segments predicted using neural networks

$$RMSE = \left(\frac{1}{Q}\sum_{k=1}^{Q} e(k)^2\right)^{1/2} = \left(\frac{1}{Q}\sum_{k=1}^{Q}\left(t(k)-a(k)\right)^2\right)^{1/2} \quad (1)$$

$$MDAPE = Median\left(\left|\frac{t(k)-a(k)}{t(k)}\right| \times 100\right) \quad (2)$$

where t(k) and a(k) are the target and predicted values of the velocity respectively and Q is the number of testing data points.

The results demonstrate that increasing the number of inputs of networks does not essentially lead to an improvement in prediction errors. This is because of the short-term characteristics of the traffic data. Indeed, these kinds of systems do not have a long memory against the dynamic systems. The number of neurons of the networks

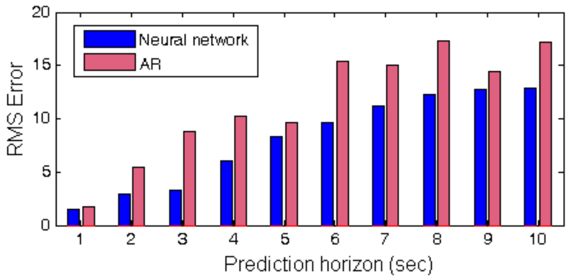

Fig. 10. RMS error of NN and AR for different prediction horizons

is selected sufficiently high in all cases. Increasing the number of neurons may be useful until a limit and after that we only increase the training time but the testing error remains almost constant.

The best configurations of MLP networks using different number of inputs and different number of neurons are presented in table 1 based on RMSE and MDAPE prediction errors. In the first row of the table, 5-4-1 means 5 inputs, 4 neurons in the hidden layer of network and 1 output. In other words, the 5-4-1 structure leads to the best prediction results for one second ahead based on RMSE criterion. Similarly, the 8-3-1 structure leads to the best prediction results for one second ahead based on MDAPE criterion and so on.

Figures 6 to 8 present the real and predicted values of the vehicle's velocity time series of the testing data in 1, 5 and 10 seconds ahead respectively using the best designed neural networks. As expected, increasing the prediction horizon leads to decrease in prediction accuracy. Prediction precision is investigated in next section based on least root mean square error (RMSE) and median absolute percentage error (MDAPE).

Figure 9 presents three sample 10-sec segments predicted using the designed neural networks. The figure demonstrate that although the two real and predicted driving segments are not the same exactly, the predicted segment get us an estimation about the next segment.

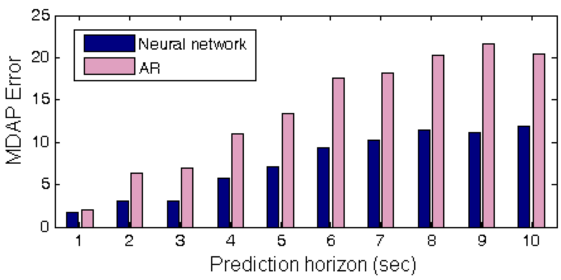

Fig. 11. MDAP error of NN and AR for different prediction horizons

For using in intelligent HEV control unit, after the prediction process a similarity search is performed in order to find the most similar driving segment in the database to the predicted one. By this way the accuracy of the predictions is improved. In other words, the controller parameters are optimized for a lot of different 10-sec driving segments in off-line condition and then the database is utilized in on-line applications. The similarity search means finding the most similar segments to the predicted segment in the database. After the similarity search, the optimized controller parameters of the estimated segment (funded segment in database) are used for the real segment. Although the off-line optimized parameters are not optimized for the real segment, the controller works as a semi-optimized controller.

All of the computations including the prediction and the similarity search and tuning of the HEV controller parameters are done during a time less than one second. The controller is used for 10 seconds ahead and prediction, similarity search and tuning are repeated each 10 seconds.

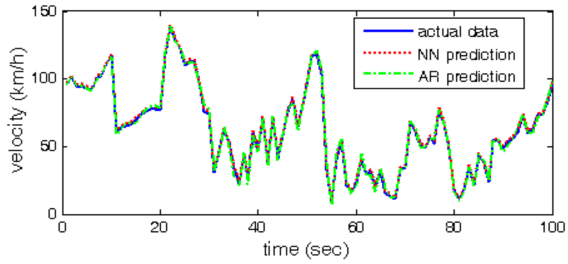

Fig. 12. Actual and predicted values of velocity in 1 second ahead using AR and NN methods

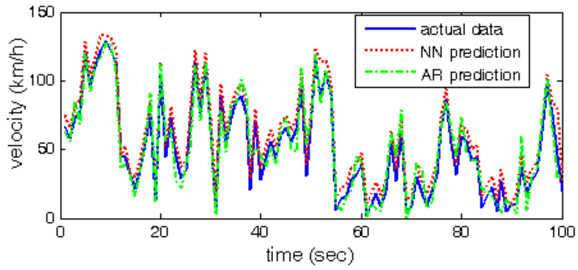

Fig. 13. Actual and predicted values of velocity in 5 seconds ahead using AR and NN methods

6. RESULT ANALYSIS

In this section, the neural networks prediction results are evaluated by a standard time series forecasting approach called Auto Regressive (AR) [16] and [17]. Table 2 presents the comparative results of AR and NN methods based on RMSE and MDAPE criteria. The results demonstrate that neural network act more perfectly than the AR models for different prediction horizons and also for the both error criteria. The errors are also presented in Figure 10 and Figure 11. The errors increase directly by the prediction horizon. NNs act better than AR models based on both errors especially based on MDAPE.

The actual and predicted values of three samples of time series for 1, 5 and 10 seconds ahead are also presented in Figure 12 to Figure 14 respectively. As seen in the figures, the difference between actual values and prediction results increases directly by length of prediction horizon. In addition, difference between predicted time series using AR and NN methods is negligible for one second ahead but for

Table 2. Comparison of AR and NN methods according to RMSE and MDAPE criteria

Prediction horizon (sec)	RMSE		MDAPE	
	AR	NN	AR	NN
1	1.78	1.52	2.02	1.7
2	5.43	2.97	6.32	3.02
3	8.76	3.24	6.96	3.14
4	10.28	6.04	11.03	5.71
5	9.62	8.28	13.45	7.05
6	15.38	9.64	17.56	9.34
7	15.08	11.16	18.2	10.18
8	17.36	12.26	20.23	12.45
9	14.44	12.75	26.61	11.1
10	17.22	12.87	18.48	11.88

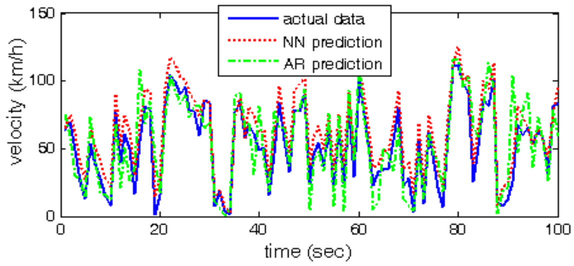

Fig. 14. Actual and predicted values of velocity in 10 seconds ahead using AR and NN methods

longer prediction horizons the neural networks predict better than AR models which is in agree with the previous results.

7. CONCLUSION

In this paper, application of neural networks for prediction of driving data time series is presented. The results demonstrate that neural networks perform efficiently as a prediction method comparing to other methods such as AR. In addition, the effect of prediction horizon on the performance of predictors is studied. Two criteria of prediction accuracy are used including the least root mean square error (RMSE) and median absolute percentage error (MDAPE). According to the results, the predictors can be used as a subsystem in HEV control unit in order to improve fuel economy and exhaust emission.

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