Jurnal Teknologi

Full Paper

ON-LINE MODELLING AND FORECASTING OF A MOVING CAR INFORMATION USING TD-HMLP NETWORK

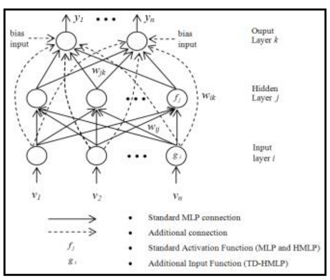
Article history
Received
1 June 2015
Received in revised form
13 July 2015
Accepted
20 August 2015

Z. Saad[a]*, M. Y. Mashor[b], Wan Khairunizam[b]

[a]Faculty of Electrical Engineering, Universiti Teknologi MARA, Malaysia, 13500 Permatang Pauh, Penang, Malaysia
[b]Electronic & Biomedical Intelligent Systems Research Group, School of Mechatronic Engineering, Universiti Malaysia Perlis, Pauh Putra Campus, 02600 Arau, Perlis, Malaysia

*Corresponding author
zuraidi570@ppinang.uitm.edu.my

Graphical abstract



Abstract

The study proposed a model called trend data hybrid multilayered perceptron network (TD-HMLP) coupled with a modified recursive prediction error (MRPE) training algorithm as a nonlinear modeling. An on-line model was used to forecast speed, revolution and fuel balanced in a Proton Gen2 car tank. The car measured the injected fuel from fuel injection sensor and become an input for the TD-HMLP model to forecast the speed, revolution and fuel balanced in tank. These forecasted variables were also measured from the car sensors. The criterions for performances are based on the one step ahead forecasting (OSA), multi-step ahead forecasting (MSA) and adjusted R^2. The forecasting result showed that TD-HMLP network is better than the conventional HMLP network to maintain higher value in adjusted R^2 and produce better step in multi-step ahead forecasting. These preliminary results show that the proposed modeling approach is capable to be used as an on-line information forecaster of a moving car.

Keywords: On-line modelling and forecasting, car speed, revolution, fuel balance in tank, injected fuel, trend data – hybrid multilayered perceptron network

Abstrak

Kajian ini mencadangkan model yang dinamakan trend data hibrid rangkaian perceptron berbilang lapisan (TD-HMLP) digabungkan dengan algoritma latihan ramalan rekursi yang diubahsuai (MRPE) sebagai model tak linear. Model dalam talian telah digunakan untuk meramalkan kelajuan, revolusi dan baki kandungan bahan api di dalam tangki kereta Proton Gen2. Suntikan bahan api dikira dari sensor suntikan bahan api untuk meramalkan kelajuan, revolusi dan baki kandungan bahan api di dalam tangki kereta. Kriteria untuk validasi model adalah berdasarkan kepada ramalan satu langkah kehadapan (OSA), ramalan pelbagai langkah kehadapan (MSA) dan R^2 terubah. Keputusan-keputusan ramalan menunjukkan bahawa rangkaian TD-HMLP adalah lebih baik daripada rangkaian HMLP konvensional untuk mengekalkan nilai R^2 terubah yang lebih tinggi serta dapat meramalkan beberapa langkah kehadapan (MSA) yang lebih baik. Hasil kajian menunjukkan bahawa pendekatan model yang dicadangkan mampu untuk digunakan sebagai peramal maklumat dalam talian dari enjin kereta yang bergerak.

Kata kunci: Pemodelan dan ramalan dalam talian, kelajuan kereta, revolusi, baki bahan api di tangki, suntikan bahan api, trend data hibrid rangkaian perceptron berbilang lapisan

1.0 INTRODUCTION

Excessive speed (driving faster than the posted limit or too fast for the prevailing conditions) has been found to contribute to a substantial number of crashes. It is predicted that, if the number of speeding drivers is reduced, both the likelihood and severity of a crash will be lowered. Therefore, early warnings of moving car information to reduce speed are considered essential to prevent road injuries. However, the dynamic of the speed, rpm and injected fuel flow of a car known to be highly nonlinear. Hence, the conventional linear model such as autoregressive with exogenous inputs (ARX) model, autoregressive moving average (ARMA) model or autoregressive integrated moving average with exogenous inputs (ARIMAX) model have failed to provide an adequate forecast. Neural networks with various architectures and trainings algorithms have been applied for nonlinear modelling and forecasting of car speed [1-2]. It has been shown that hybrid multilayered perceptron network (HMLP) trained using modified recursive prediction error (MRPE) algorithm with detrend data input has satisfied the entire correlation test in model validation[1].

Previous studies were based on off-line modelling technique of speed and fuel flow [1-2]. As the fuel flow and speed dynamic will change with time especially during car speeding and car breaking, the speed forecasting performance based on off-line model will be degraded with time [4-5]. This problem can be overcomed by using an on-line modelling technique. Mashor (2009) concluded that the HMLP network is suitable to be used for on-line nonlinear modelling and forecasting of streamflow which is to reduce hydrological risks due to streamflow, such as flood [3]. This model was adopted in this study by a simple modification of the HMLP input structure for the purposes of trend and highly dynamic data forecasting.

2.0 METHODOLOGY

2.1 Trend Data–Hybrid Multilayered Perceptron Network

HMLP network is modified from multilayered perceptron (MLP) network with some additional linear input connections. The network inputs are connected directly to the output nodes by means of some weighted connections to form the linear model in parallel to the nonlinear original MLP model. A HMLP network with one hidden layer is shown in Figure 1. These linear connections can be viewed as a linear model, which is in parallel to standard MLP network and additional input function is fixed at input layer as a data detrend function. These projected network is called a trend data hybrid multilayered perceptron network (TD-HMLP). In the present study, theoretical description of the network will be limited to one hidden layer only [6].

The output of TD-HMLP network with one hidden layer can be expressed by the following equation:

$$\hat{y}_k(t) = \sum_{j=1}^{n_h} w_{jk}^2 F_j\left(\sum_{i=1}^{n_i} w_{ij}^1 G_i\left(v_i^0(t)\right) + b_j^1\right) + \sum_{i=0}^{n_i} w_{ik}^l G_i\left(v_i^0(t)\right) \quad (1)$$

$$for\, 1 \le k \le m$$

where w_{ij}^1 denotes the weights that connect the input and the hidden layers; b_j^1 and v_i^0 represents the threshold in hidden nodes and input supplied to the network; w_{jk}^2 denotes the weights that connect the hidden and output layer; w_{ik}^l is the weights connection between input and output layer; n_i and n_h are the number of input nodes and hidden nodes; m represents the number of output nodes. G_i is an input function which is can be selected as digital high pass filter, first differential detrend or others function that is used to detrend the input signal. $F_j(\bullet)$ is an activation function which is normally selected as sigmoidal function. The weights w_{jk}^2, w_{ij}^1, w_{ik}^l and b_j^1 are unknown, and should be selected carefully in order to achieve minimum prediction error, defined as below:

$$\varepsilon_k(t) = y_k(t) - \hat{y}_k(t) \quad (2)$$

where $y_k(t)$ and $\hat{y}_k(t)$ are the actual and forecasted output.

In this study, TD-HMLP network is trained using Modified Recursive Prediction Error (MRPE) algorithm. MRPE algorithm is modified from Recursive Prediction Error (RPE) algorithm by varying the momentum and learning rate [6] compared to constant values applied in Chen *et al.* [7].

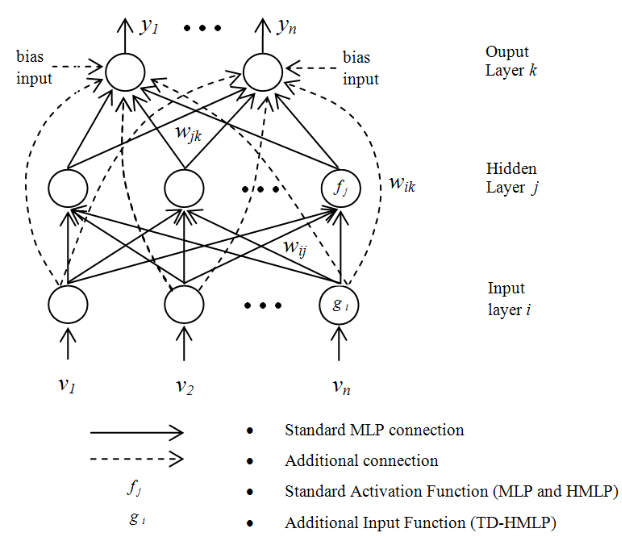


Figure 1 Trend data - hybrid multilayered perceptron network

2.2 Modified Recursive Prediction Error Algorithm

In this study the MRPE proposed by Mashor [6] is used for the on-line update of the tunable weights. Firstly, Chen *et al*. [7] modified the RPE algorithm to minimize the cost function given by:

$$J(\hat{\Theta}) = \frac{1}{2N}\sum_{t=1}^{N}\varepsilon^{T}(t,\hat{\Theta})\Lambda^{-1}\varepsilon(t,\hat{\Theta}) \tag{3}$$

The modified RPE algorithm is used to update the estimated parameter $\hat{\Theta}$ (consists of *ws* and *bs*), recursively using the Gauss-Newton algorithm:

$$\hat{\Theta}(t) = \hat{\Theta}(t-1) + P(t)\Delta(t) \tag{4}$$

and

$$\Delta(t) = \alpha_m(t)\Delta(t-1) + \alpha_g(t)\psi(t)\varepsilon(t) \tag{5}$$

where $\varepsilon(t)$ and Λ are the prediction error and *m* × *m* symmetric positive definite matrix respectively. Meanwhile, *m* is the number output nodes of the network; $\alpha_m(t)$ and $\alpha_g(t)$ can be assigned within the range of 0 and 1, and the typical values of $\alpha_m(t)$ and $\alpha_g(t)$ are varied to improve further the convergence rate of the MRPE algorithm by Mashor [6] according to:

$$\alpha_m(t) = \alpha_m(t-1) + \mathrm{a} \tag{6}$$

and

$$\alpha_g(t) = \alpha_m(t)(1-\alpha_m(t)) \tag{7}$$

where a is a small constant (typically a=0.01); $\alpha_m(0)$ and $\alpha_g(0)$ are the initial values of $\alpha_m(t)$ and $\alpha_g(t)$ that have the typical values of 0 and 0.5 respectively. $\psi(t)$ is the gradient of one step ahead predicted output with respect to the network parameters:

$$\psi(t,\hat{\Theta}) = \left[d\,\hat{y}(t,\hat{\Theta}) \big/ d\,\hat{\Theta} \right] \tag{8}$$

The error covariance matrix P(t) that define the search changes along the Gauss–Newton direction is stated in Equation (4). P(t) is updated recursively according to:

$$P(t) = \frac{1}{\lambda(t)}\Big[P(t-1) - P(t-1)\psi(t)\lambda(t)I + \psi^{T}(t)P(t-1)\psi(t))^{-1}\psi^{T}(t)P(t-1)\Big] \tag{9}$$

where $\lambda(t)$ is forgetting factor, 0< $\lambda(t)$ <1, and updated using the following Equation (10),

$$\lambda(t) = \lambda_o\lambda(t-1) + (1-\lambda_o) \tag{10}$$

where λ_o and the initial forgetting factor $\lambda(0)$ are the design values. The initial value of the P(t) matrix, P(0) is usually set to αI where *I* is the identity matrix and α is a constant, normally between 100 to 10 000.

The gradient matrix $\psi(t)$ can be adapted to accommodate the extra linear connections for a one-hidden layer HMLP network model by differentiating Equation (1) with respect to the parameters, θ_c, to yield:

$$\psi_k(t) = \frac{dy_k(t)}{d\theta_c} = \begin{cases} v_j^1 & \text{if} \quad \theta_c = w_{jk}^2 \quad 1 \le j \le n_h \\ v_j^0 & \text{if} \quad \theta_c = w_{ik}^l \quad 0 \le i \le n_i \\ v_j^1(1-v_j^1)w_{jk}^2 & \text{if} \quad \theta_c = b_j^1 \quad 1 \le j \le n_h \\ v_j^1(1-v_j^1)w_{jk}^2 v_i^0 & \text{if} \quad \theta_c = w_{ij}^1 \quad 1 \le j \le n_h, 1 \le i \le n_i \\ 0 & \text{otherwise} \end{cases} \tag{11}$$

The above gradient matrix is derivative of the sigmoid function; consequently, if other activation functions were used, the matrix has to be changed accordingly. The detailed explanation of MRPE for a one-hidden-layer HMLP network can be implemented as Mashor [6].

2.3 Model Validation

The performance of the OSA and MSA prediction models are indicated in terms of adjusted R² ($\bar{R}^2$) introduced by Ezekiel [8] to partially compensate the overfitting and the sizes effect in multiple regression analysis. Adjusted R² is given by:

$$\bar{R}^2 = 1 - \left(\frac{(1-R^2)(N-1)}{N-k-1}\right) \tag{12}$$

where R² is the coefficient of determination, N is the number of observation and k is the number of independent variables or the number of predictors.

2.4 Case Study – Proton Gen 2

The current study uses Proton Gen 2 with 1.6 litre CamPro engine (automatic transmission) which produced 110 maximum horsepower (82 kW) at 6,000 rpm and 148 Nm of maximum torque at 4,000rpm as a target vehicle. The data was experimentally sampled along the federal roads in Permatang Pauh, and expressways from Seberang Jaya to Jawi Toll Exit. The area is located in Penang on the west-coast of Peninsular Malaysia. The datasets were sampled in every second. The first dataset consists of 600 data samples that were used to train the network, while the second data set consists of 630 data samples that were used for testing the fitted network model. The total complete dataset consists of 1230 data of four data sets for input and output are shown in Figure 2 to Figure 5. The data were recorded by on-line monitoring system is the speed of the car denoted as *y1*, the revolution of the engine denoted as *y2*, the fuel balance in tank denoted as *y3* and fuel consumption denoted as *u*.

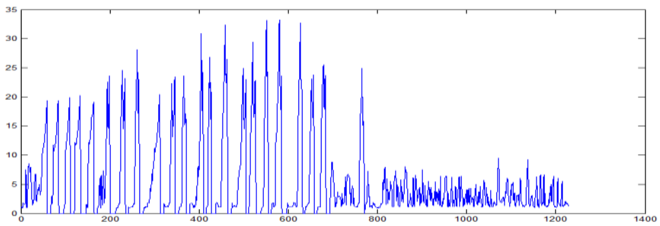


Figure 2 The engine fuel consumption (Liter/hour) as input signal (u)

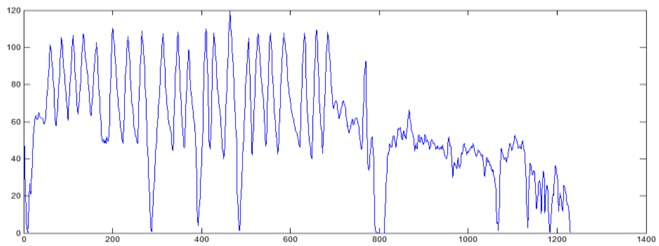


Figure 3 The speed of the car (Km/h) as output signal (y1)

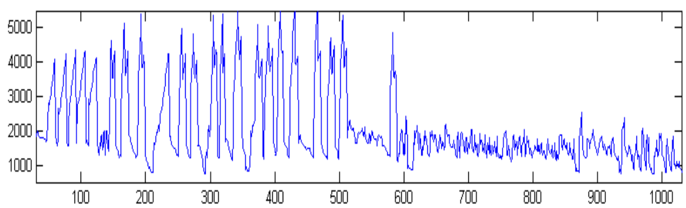


Figure 4 The revolution of the engine (r.p.m) as output signal (y2)

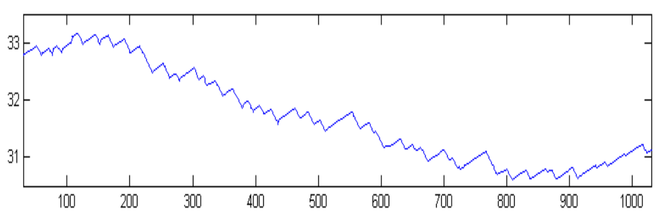


Figure 5 The fuel balance in tank (Liter) as output signal (y3)

3.0 RESULTS AND DISCUSSION

The performance of both HMLP and TD-HMLP networks trained using MRPE and RLS algorithms are compared. The performance comparison for speed, rpm and fuel balance forecasting are carried out by using the same conditions mentioned in the previous section, such as number of training set and testing set, respectively. To be fair, analysis were carried out in order to choose the best network with the best forecasting performance. All the models in this study were simulated by the following configuration base on the network node analysis:

v1(t+1) = [u(t) y(t) y(t-1) 1]; ..
v2(t+2) = [u(t) y_{nn1}(t+1) y(t) 1];
.. until .. v10(t+10,:) = [u(t) y_{nn9}(t+9) y(t+8) 1];

with bias input, number of hidden nodes n_h = 3 and P(0) = 1000I. v1 to v10 is the input configuration of the one step ahead model to the 10th step ahead model. u and y are the input output of the predicted signal. y_{nn1} to y_{nn10} is the output of TD-HMLP network at one step ahead model to the 10th step ahead model.

One step ahead forecasting, multi steps ahead forecasting and adjusted R^2 tests were used as model validation in this comparison. The conventional HMLP network was compared with proposed TD-HMLP for speed, revolution and fuel balanced in tank forecasting. These results can be visually analyzed in Table 1 to Table 3 and Figure 6 to Figure 11. The highlighted adjusted R^2 values in the Table 1 to Table 3 indicated generally that both results (multi step ahead and adjusted R^2 values that are > 0.5) are still in the good forecasting even though it keeps on decreasing with the number of step ahead forecasting.

Result of speed forecasting in Figure 6 and Figure 7 show that the forecasting quality of both conventional HMLP network and TD-HMLP network keep on decreasing as the number of step ahead is increased. The overall shape of the speed graph shows a good match where the forecasted speed matches the peak speeds, low speeds, rising limbs and recession limbs of the actual speed quite well. Conventional HMLP network maintains good forecast of the speed with speed graph matches until step 7 while TD-HMLP keep on maintaining with speed graph matches until step 9. Conventional HMLP network tends to lose the shape of speed graph up step 7 while TD-HMLP network maintains the shape of speed graph until step 9. The adjusted R^2 test in Table 1 showed that TD-HMLP network has three steps ahead forecasting better than conventional HMLP network. Maintaining the shape of the forecasted graph is the main criterion of the target model output. As the consequences of these results, the TD-HMLP network has been further investigated by coupling with other training algorithm namely recursive least square (RLS). The result in Table 1 show that the TD-HMLP network coupled with RLS can only maintained the speed graph matches until step 5. Due to RLS has a tendency to immediate decrease the performance in the lower step of forecasting (step 5), the following result will discuss only the TD-HMLP network coupled with MRPE training algorithm.

Result for revolution forecasting in Figure 8 and Figure 9 show that the forecasting quality of both conventional HMLP network and TD-HMLP network keeps on decreasing as the number of step ahead is increased. Conventional HMLP network maintain good forecast of the revolution with revolution graph matches until step 3 while TD-HMLP keep on maintaining with revolution graph matches until step 6. The adjusted R^2 test in Table 2 showed that TD-HMLP network has three steps ahead forecasting better than conventional HMLP network. These revolutions forecasting results give advantage for TD-HMLP network compared to the conventional HMLP network.

TD-HMLP network has maintained a good reputation compared to conventional HMLP to forecast a fuel balance in tank. Table 3 shows that TD-HMLP has significantly better adjusted R^2 values compared to the conventional HMLP. The conventional HMLP network can only maintained the good forecasting of remaining fuel until step 6 while the TD-HMLP network can maintain the good forecasting of remaining fuel until step 10 as showed in Figure 10 and Figure 11. At step 10 of TD-HMLP network, the remaining fuel flow graph is not so good where the forecasted remaining fuel flow fluctuate on the peak flows, low flows, rising limbs and recession limbs of the actual remaining fuel flow. However, the value of adjusted R^2 is still in an acceptable range (>0.5) and this problem will be reduced as the number of training data increases.

Table 1 Adjusted R^2 tests comparison between TD-HMLP and HMLP for speed (Km/h) forecasting

Step Ahead Forecasting	HMLP MRPE (Testing Data)	TD-HMLP MRPE (Testing Data)	TD-HMLP RLS (Testing Data)
1	**0.9867**	**0.9868**	**0.9868**
2	**0.9491**	**0.9737**	**0.9804**
3	**0.9470**	**0.9673**	**0.9536**
4	**0.8747**	**0.9456**	**0.8766**
5	**0.7626**	**0.9419**	0.4062
6	**0.6359**	**0.9019**	0.2945
7	**0.5490**	**0.8913**	0.1651
8	0.4939	**0.8396**	0.0143
9	0.2911	**0.6747**	0.0087
10	0.1388	**0.5746**	-0.0029

Table 2 Adjusted R^2 tests comparison between TD-HMLP and HMLP for revolution (r.p.m) forecasting

Step Ahead Forecasting	HMLP MRPE (Testing Data)	TD-HMLP MRPE (Testing Data)
1	**0.8053**	**0.8513**
2	**0.7190**	**0.8394**
3	**0.6733**	**0.7658**
4	0.4558	**0.7556**
5	0.2447	**0.7468**
6	0.0325	**0.6195**

Table 3 Adjusted R^2 tests comparison between TD-HMLP and HMLP for fuel balance (litre) forecasting

Step Ahead Forecasting	HMLP MRPE (Testing Data)	TD-HMLP MRPE (Testing Data)
1	**0.9943**	**0.9948**
2	**0.9848**	**0.9878**
3	**0.8701**	**0.9870**
4	**0.7793**	**0.9793**
5	**0.6617**	**0.9766**
6	**0.5182**	**0.9678**
7	0.4695	**0.9597**
8	0.3656	**0.8882**
9	0.1313	**0.7240**
10	0.0212	**0.6264**

A. On-line Nonlinear Modelling and Forecasting of Speed

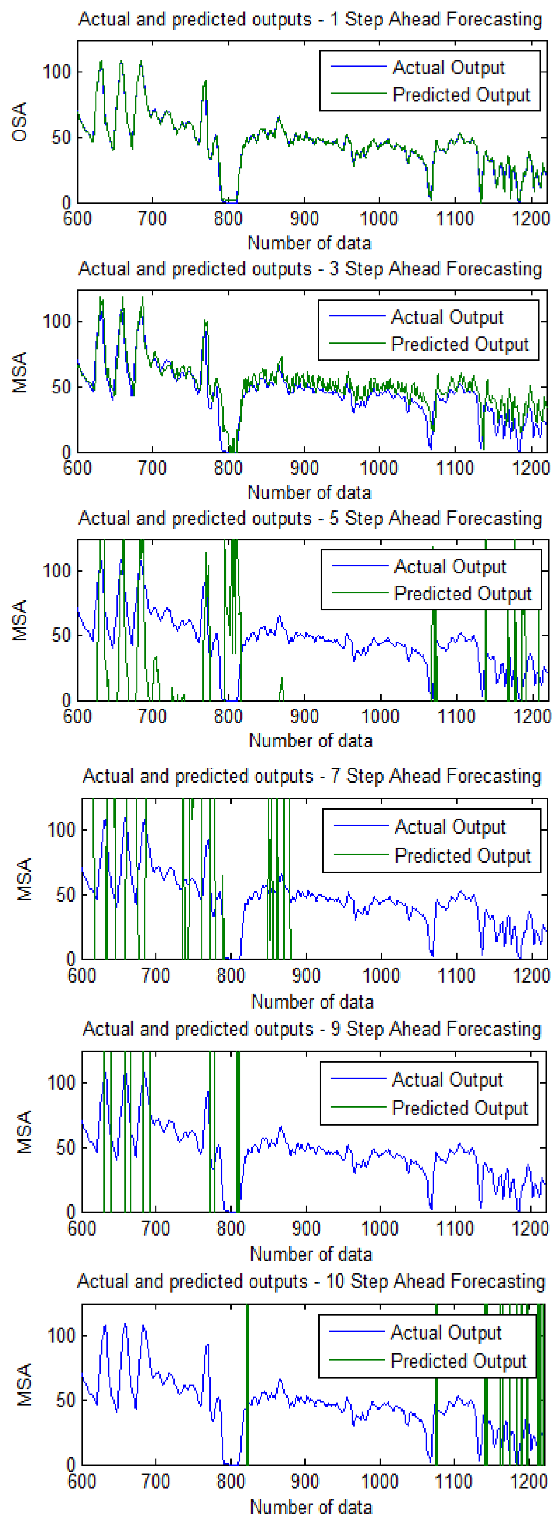


Figure 6 1 to 10 seconds ahead forecasting of speed with HMLP network

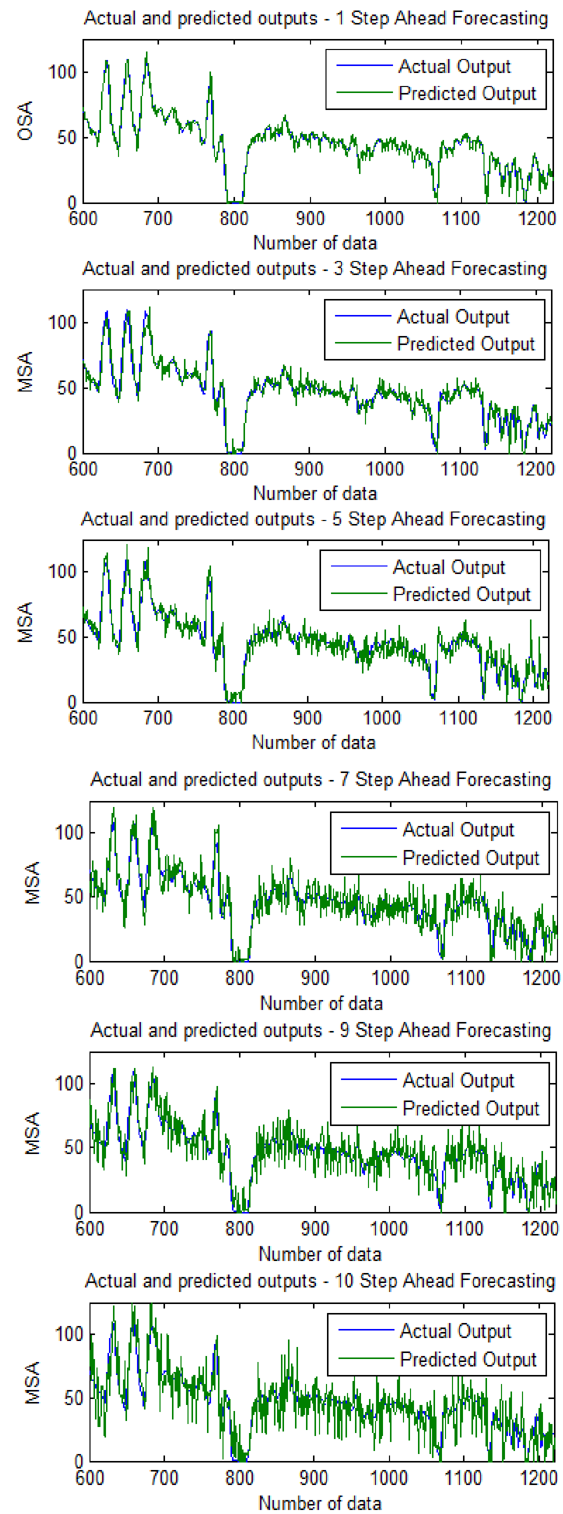


Figure 7 1 to 10 seconds ahead forecasting of speed with TD-HMLP network

B. On-line Nonlinear Modelling and Forecasting of Revolution

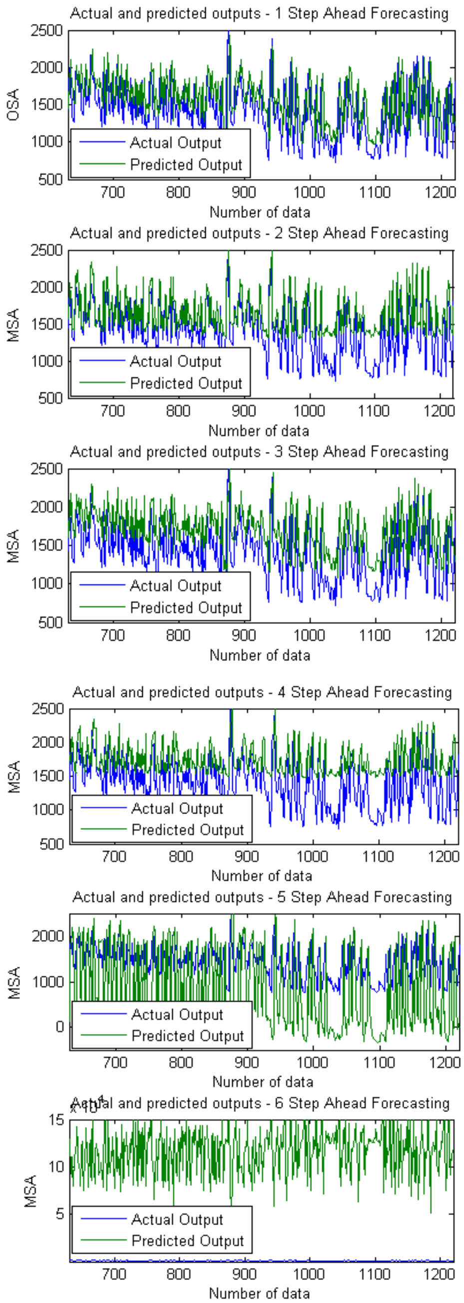


Figure 8 1 to 6 seconds ahead forecasting of revolution with HMLP network

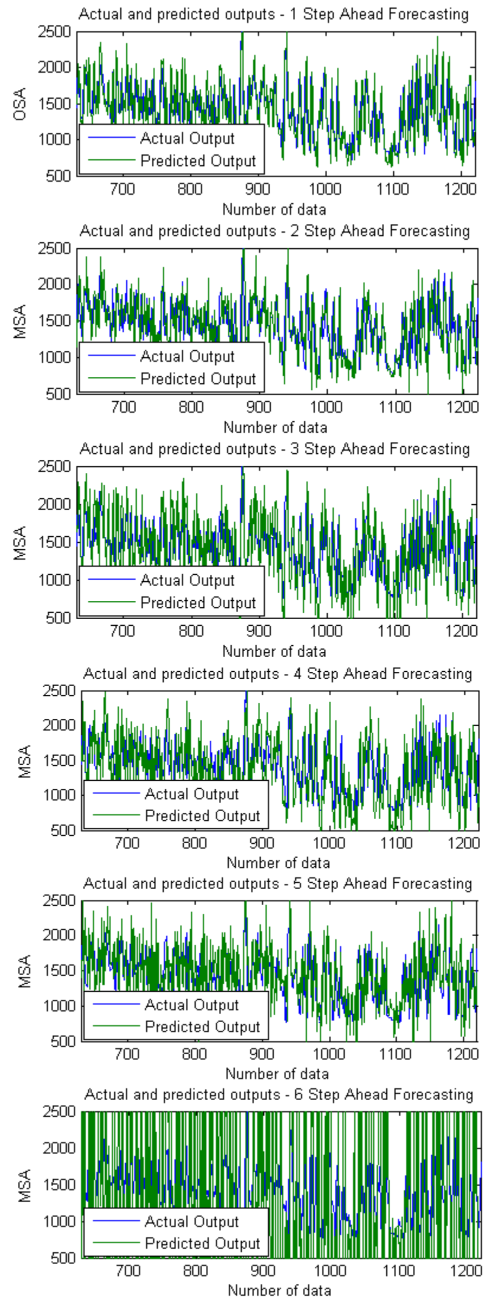


Figure 9 1 to 6 seconds ahead forecasting of revolution with TD-HMLP network

C. On-line Nonlinear Modelling and Forecasting of Fuel Balanced (FB) in the tank.

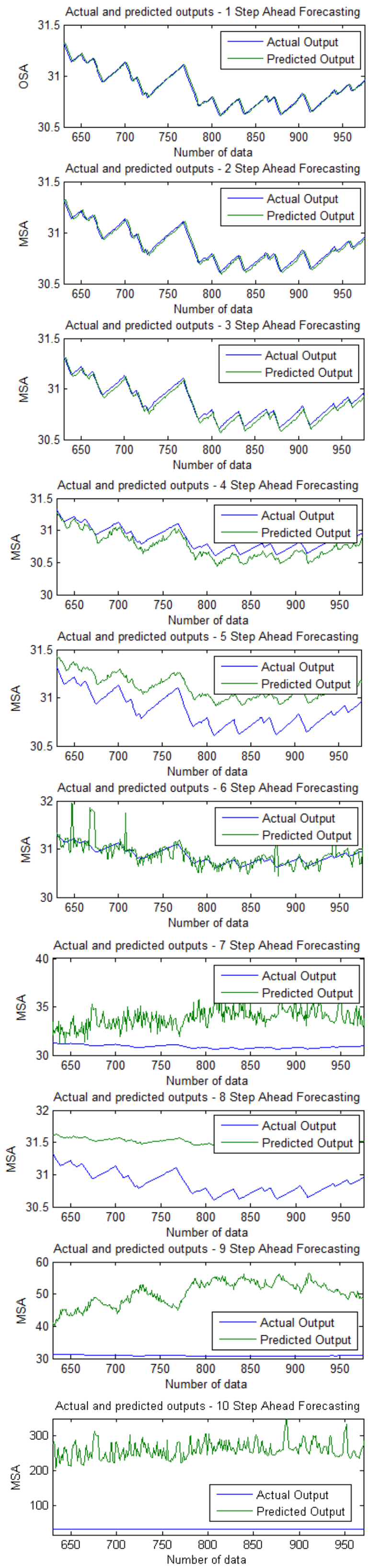


Figure 10 1 to 10 seconds ahead forecasting of fuel balance with HMLP network

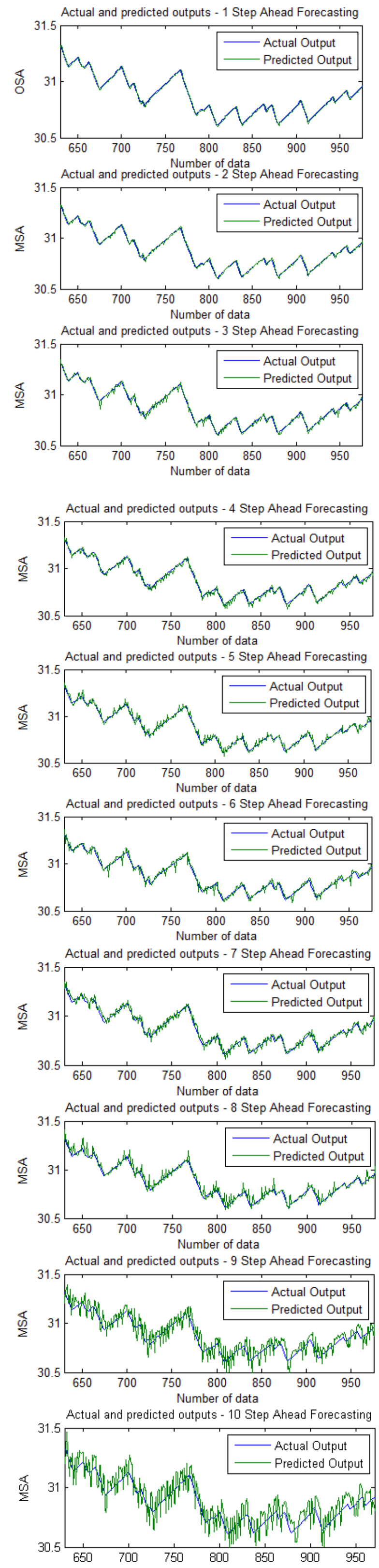


Figure 11 1 to 10 seconds ahead forecasting of fuel balance with TD-HMLP network

4.0 CONCLUSION

The TD-HMLP network has been proposed as an alternative to the on-line modelling and forecasting that are based on the MRPE training algorithm as nonlinear modelling. This on-line model was used to forecast a speed, revolution and fuel balanced in tank of a Proton Gen2 car. The car measures the injected fuel from the fuel injection sensor and selected it as an input variable for the TD-HMLP model in order to forecast the speed, revolution and fuel balanced inside the tank. The speed, revolution and fuel balanced were also selected as an output variable for the TD-HMLP model where it was measured from each particular sensor. The selection of input/output variable, training algorithm and modeling parameters and configuration has been made to acchieve the possible higher's performance of the design model. The criterions for performances are based on the one step ahead forecasting (OSA), multi-step ahead forecasting (MSA) and adjusted R^2. The forecasting result in section IV showed that the proposed TD-HMLP network is better than conventional HMLP network to maintain higher values in R^2 and get better step in multi step ahead forecasting with maintaining the shape of the forecasted flow graph. This preliminary result shows that these modelling systems with TD-HMLP network are capable to be used as an on-line information forecaster of a moving car.

Acknowledgement

The author would like to thank Ministry of Science, Technology and Innovation (MOSTI) for financial assistance while conducting this project (06-01-01-SF0339).

References

[1] Saad, Z., Osman, M. K., and Mashor, M.Y., 2014. Modelling and Forecasting of Car Speed using Hybrid Multilayered Neural Network, *Journal of Contemporary Engineering Sciences.* 7(13): 603-610.

[2] Saad, Z., Mashor, M. Y., 2013. Model Structure Selection for Speed Forecasting with Nonlinear Autoregressive with an Exogenoues Input. *The 4th International Conference on Intelligent Systems, Modelling and Simulation (ISMS2013)*.

[3] Mashor, M. Y., 2009. On-line Nonlinear Modelling and Forecasting of Streamflow Using Neural Network. *International Journal of The Computer, The Internet and Management.* 17(1): 44-54.

[4] Anant Bhaskar, G., Parag, D., and Mukesh, S. 2014. Artificial Neural Networks for Internal Combustion Engine Performance and Emission Analysis. *International Journal of Computer Applications*. 87(6): 23-27

[5] Taghavifar, H., Taghavifar, H., Mardani, A., and Mohebbi, A. 2014. Exhaust Emissions Prognostication for DI Diesel Group-Hole Injectors using a Supervised Artificial Neural Network Approach. *Fuel*. 125(1): 81-89.

[6] Mashor, M. Y., 2000. Hybrid Multilayered Perceptron Networks. *Int. Journal of Systems Science.* 31(6): 771-785.

[7] Chen, S., Cowan, C. F. N., Billings, S. A., and Grant, P. M. 1990. A Parallel Recursive Prediction Error Algorithm for Training Layered Neural Network. *Int. Journal of Control*. 51(6): 1215-122.

[8] Yin, P., and Fan, X. 2001. Estimating R2 Shrinkage in Multiple Regression: A Comparison of Analytical Methods. *The Journal of Experimental Education*. 69(2): 203-2.