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Modelling and Forecasting of Car Speed Using Detrended Inputs and Hybrid Multilayered Percepton Network

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Abstract

The study explores the capability of hybrid multilayered perceptron network (HMLP) trained using modified recursive prediction error (MRPE) algorithm as a nonlinear model for a speed of a car. This model is used for speed forecasting for a car in order to avoid speed limit on the road traffic. The injected fuel was measured from the experimented car and used as an input for the HMLP model. The input and output variables were recorded from the car sensors. The modeling performances are measured based on the correlation tests. The simulation result shows that preprocessing data using digital high-pass filter is better than the first differential to pass the correlation test. This preliminary result shows that this modeling system is capable to be used as an alternative speed- forecaster for cars.

Keywords: Car Speed, Injected Fuel, Hybrid Multilayered Perceptron Network, Deterended Input Signals

1 Introduction

Forecasting is a scientific process of using historic data to determine the direction of future trends. Every forecast is based on a selected model and by different approaches of dynamic variables it will have different strengths and weaknesses. Forecasting performance often fail to spot the result of 100 percent accuracy. However, they provide the best basis for scheduling available. Considering several variables is vital when developing model of forecasts [1]. Recently, neural network becomes more popular as an automotive engine diagnose or a specific engine activities forecasting. A number of researches have been carried out using different methodology on engine diagnose [2][3][4]. The current study proposed a modeling and forecasting of the car speed based on HMLP with MRPE as the training algorithm. After preliminary study, injected fuel (liter/hour) has been selected as neural network input, while the speed (km/h) is the output. With several dynamic combinations of input and output variables, they become an essential ingredient in the formation of unbiased and adequate modeling and forecasting.

2 Methodology

The current study use Proton Gen 2 with an automatic 1.6 litre CamPro engine which produced 110 maximum horsepower (82 kW) at 6,000rpm and 148Nm 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 located in Penang on the west-coast of Peninsular Malaysia. The methodology used to develop forecasting of speed includes; a) data preprocessing, b) data training and data testing, using HMLP network trained by MRPE algorithm. The datasets were sampled in every second. The first dataset consists of 770 data samples that were used to train the network and second data set consists of 460 data samples that were used for testing the fitted network model. The total complete data set consists of 1230 data of two data sets for input and output are shown in Figure 1 and Figure 2. Data recorded by online monitoring system is the speed of a car denoted as y and fuel consumption denoted as u. Two different types of detrend methods are a) First differential detrend (FDD) and b) Digital high pass filter(DHPF) which were adopted in this study [5]. The input and output signals (Figure 1 & 2) have been detrended by using these two method. The examples of detrended signals from these two methods are shown in Figure 3 and Figure 4.

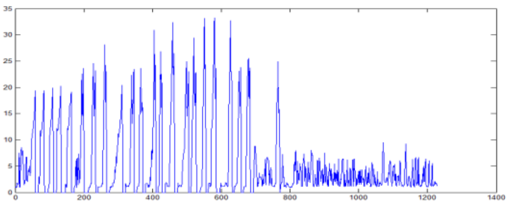

Fig 1. The engine fuel consumption (Liter/hour) as input signal (u)

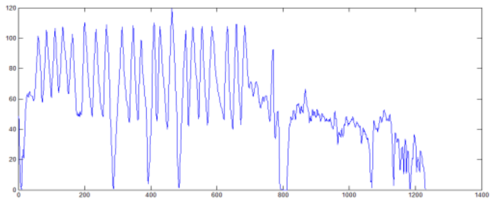

Fig 2. The speed of the car (Km/h) as output signal (y)

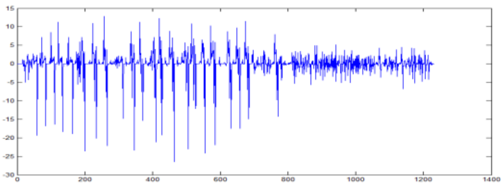

Fig 3. The detrended input signal with FDD

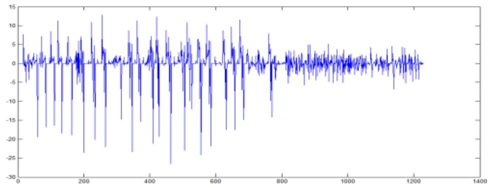

Fig 4. The detrended input signal with DHPF

3 Theoretical Background

3.1 Hybrid Multilayered Perceptron Network (HMLP)

HMLP network is produced from 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 with the nonlinear original MLP model. A HMLP network with one hidden layer is shown in Figure 5. These linear connections can be viewed as a linear model, which is in parallel to standard MLP network; hence, the projected network is called a hybrid multilayered perceptron network. In the present study, theoretical description of the network will be limited to one hidden layer only [6].

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

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

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

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 while $F(\bullet)$ 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:

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

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

In this study, 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]

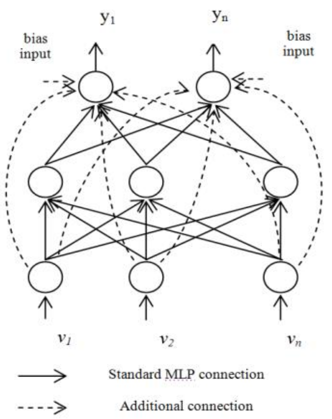

Fig 5. Hybrid Multilayered Perceptron Network

3.2 MRPE Learning Algorithm

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 x 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 RPE algorithm according to:

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

and

$$\alpha_g(t) = \alpha_g(0)(1-\alpha_m(t)) \tag{7}$$

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:

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

P(t) in Equation (3) is updated recursively according to:

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

where $\lambda(t)$ is forgetting factor, 0< $\lambda(t)$ <1, and updated using the following equation, [6]

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

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:

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

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

3.3 Modeling nonlinear system using HMLP network.

The NARMAX model can be expressed in terms of a nonlinear function expansion of lagged input, output and noise terms as follows [6][8]:

$$y(t) = f_s(y(t-1), \ldots, y(t-n_y), u(t-1), \ldots u(t-n_u), e(t-1), \ldots, e(t-n_e)) + e(t) \tag{12}$$

where $y(t)=[y_1(t)\ldots y_m(t)]^T$, $u(t)=[u_1(t)\ldots u_r(t)]^T$ and $e(t)=[e_1(t)\ldots e_m(t)]^T$ are the system outputs and input vectors respectively; n_y, n_u and n_e are the maximum lags in the output, input and noise vectors respectively. $f_s(\bullet)$ is the unknown non-linear function. It is normally constructed based on the observation of input and output data. In the present study, HMLP networks will be used to model the input-output relationship. In other words, $f_s(\bullet)$ will be approximated by using equation (1) where $F(\bullet)$ is selected to be a sigmoid function. The network input vector, $v(t)$ is formed from lagged input, which are donated as $u(t-1)\ldots u(t-n_u), y(t-1)\ldots y(t-n_y)$ and $e(t-1)\ldots e(t-n_e)$ respectively in equation (5).

The final stage in system identification is model validation. In the present study correlation test is used to evaluate the performance of the fitted models. The residual will be unpredictable from all linear and non linear combinations of past inputs and outputs. Billings and Voon [8], proved that for a certain class of non-linear systems the following conditions should hold if the fitted non-linear model is adequate:

$$\left.\begin{aligned}
&\Phi_{\varepsilon\varepsilon}(\tau)=E[\varepsilon(t-\tau)\varepsilon(t)]=\delta(\tau)\\
&\Phi_{\varepsilon(u\varepsilon)}(\tau)=E[\varepsilon(t)\varepsilon(t-1-\tau)u(t-1-\tau)]=0,\ \tau\geq 0\\
&\Phi_{\varepsilon u}(\tau)=E[u(t-\tau)\varepsilon(t)]=0, \qquad \forall\tau\\
&\Phi_{u^{2'}\varepsilon}(\tau)=E\left[\left(u^2(t-\tau)-\bar{u}^2(t)\right)\varepsilon(t)\right]=0, \quad \forall\tau\\
&\Phi_{u^{2'}\varepsilon^2}(\tau)=E\left[\left(u^2(t-\tau)-\bar{u}^2(t)\right)\varepsilon(t)^2\right]=0 \qquad \forall\tau
\end{aligned}\right\} \tag{13}$$

where $\bar{u}^2(t)$ and $E[\bullet]$ are the mean value of $u^2(t)$ and the expectation respectively. In practice, if the correlation tests lie within the 95% confidence limits, $\pm 1.96/\sqrt{N}$, then the model is regarded as adequate, where N is the number of data used to train the model [8].

4 Results and Discussion

In this section, the effectiveness of three variations of the models was compared. The performance comparison for speed 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 detrend method with the best forecasting performance that passes all the correlation tests. All the HMLP-MRPE models in this study were simulated by the following configuration base on the network node analysis:
v(t)=[u(t) u(t-1) u(t-2) u(t-3) y(t-1) y(t-2) y(t-3) e(t-1) e(t-2)] with bias input, number of hidden nodes n_h = 9 and P(0) = 1000I.

Correlation test as a result of the original data, FDD and DHPF Data are shown in Figure 6, Figure 7 and Figure 8 respectively. Correlation test for original data in Figure 6 is unsuccessful as not all of the correlation tests are within the 95% confidence limit. $\Phi\varepsilon\varepsilon$ plot are marginally outside the limit in the first lag and effected the $\Phi\varepsilon(u\varepsilon)$ plot which caused major fault in correlation test. However, the result for FDD and DHPF detrended data as shown in Figure 7 and Figure 8, both detrended method corrected the major fault that was caused by original data. The correlation tests for FDD are adequate, almost all the correlation tests are within the 95% confidence limits except for the $\Phi u\varepsilon$ and $\Phi\varepsilon(u\varepsilon)$ plots that are marginally outside the limits. Correlation tests for DHPF are slightly better than FDD, only $\Phi u\varepsilon$ plot that is marginally outside the limits. The $\Phi u^{2'}\varepsilon^{2}$ plot is outside 95% confidence limits at the step 16 for both FDD and DHPF which are too far from source, and therefore the error is negligible.

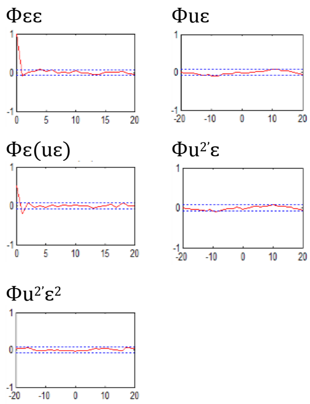

Fig. 6. Correlation tests for original data

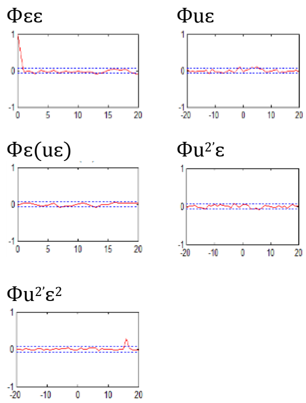

Fig. 7. Correlation tests for FDD

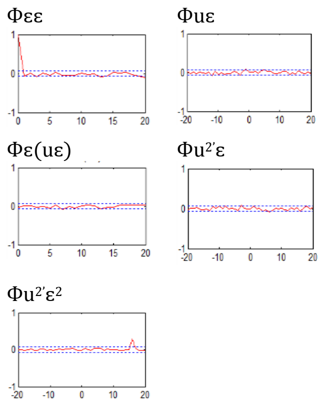

Fig. 8. Correlation tests for DHPF

5 Conclusion

In this work, modeling with HMLP network trained by MRPE algorithm has successfully been used to forecast the speed of a car. One type of vehicle data inputs namely injected fuel (litre/hour) was used. The only output is speed (km/h) has been used as HMLP network output data. From the results in the previous section, it has been proved that the HMLP network has successfully been modeled and validated. The model validations namely correlation test are used to evaluate the performance of the fitted models. The analyses have been proved by the significant information about the accuracy level of forecasting which is done by HMLP network. DHPF detrend method is selected as the best technique among the comparison to eliminate the dc shift effect that can cause major error in correlation test and forecasting. Correlation test results in this study demonstrate that the model is unbiased and adequate to represent the identified system.

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