

## SYSTEM IDENTIFICATION OF HAMMERSTEIN MODEL A QUARTER CAR PASSIVE SUSPENSION SYSTEMS USING MULTILAYER PERCEPTRON NEURAL NETWORKS (MPNN)

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**Abstract.** Recently, some researchers have focused on the applications of neural networks for system identification. In this paper, a Hammerstein model of a quarter car passive suspension system is identified using multilayer perceptron neural networks. Input and output data are acquired by driving a car on a special road event. The networks structure is based on system model. The network learning algorithm is based on Fisher's scoring method. Fisher information is given as a weighted covariance matrix of inputs and outputs of the network hidden layer. Unitwise, Fisher's scoring method reduces to the algorithm in which each unit estimates its own weights by a weighted least square method. The results show that the minimum mean square error (MSE) value of the training process was found with a short record.

*Keywords:* System identification, Hammerstein model, multilayer perceptron, weighted least square, Fisher information, Fisher's scoring

**Abstrak.** Sejak kebelakangan ini, ramai penyelidik telah memberi perhatian kepada aplikasi rangkaian neural untuk pengenalan sistem. Dalam penulisan ini, model Hammerstein untuk suspensi pasif kereta suku telah dikenal pasti menggunakan rangkaian perceptron neural anggapan berbilang lapis. Data masukan dan keluaran telah diperolehi dengan memandu sebuah kereta pada satu paras jalan yang khas. Struktur daripada rangkaian adalah berdasarkan kepada model daripada sistem. Rangkaian algoritma pembelajaran adalah berdasarkan kaedah pemarkahan Fisher. Maklumat Fisher ini diberikan sebagai pemberat matrix kovarian masukan dan keluaran lapisan rangkaian yang tersembunyi. *Unitwise* daripada kaedah pemarkahan Fisher berkurangan kepada algoritma di mana setiap unit menganggarkan sendiri pemberat pemberat dengan menggunakan kaedah pemberat kuasa dua terkecil. Hasilnya telah menunjukkan bahawa nilai ralat minimum punca kuasa dua proses pembelajaran diperolehi dengan satu lalaran yang singkat.

*Kata kunci:* Pengenalan sistem, model Hammerstein, rangkaian perceptron neural berbilang lapis, pemberat kuasa dua terkecil, maklumat Fisher, pemarkahan Fisher

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## 1.0 INTRODUCTION

Multilayer perceptrons have been applied successfully to solve some difficult and diverse problems by training them in a supervised manner. The highly popular training algorithm is known as the error backpropagation algorithm [1-3]. Squared error criterion is usually used as the cost function. The network weights are found by minimizing the cost function using the steepest descent method [4].

In this paper, the error is assumed to have a Gaussian distribution. The cost function is minimized by applying the maximum likelihood parameter estimation technique [5-7]. The iterative weighted least squares algorithm is derived from the cross entropy cost function by applying maximum likelihood estimation procedure [4]. A learning algorithm is presented based on Fisher's scoring method. The Hessian matrix is constructed using Newton Raphson method and Fisher's information matrix. The algorithm is presented as an iterative weighted least square method [4,8]. Fisher information is also given as the weighted covariance matrix of input output of hidden layer neuron. In this research, the weight increment is controlled to ensure that it changes smoothly.

The neural network developed in this research is used to identify the nonlinear model of a quarter car passive suspension system. The car model is derived using Hammerstein model. The Hammerstein cascade can be a useful model, especially when representing systems containing hard nonlinearities, such as the car suspension system dynamics, where functional expansions would be impractical [9]. The input and output data of the car were obtained in the experiment. The car was driven on the random type of artificial road surface.

The objectives of work are:

- (1) To design a neural network structure based on the nonlinear model of a quarter car passive suspension system. The network is a multilayer perceptron.
- (2) To design and implement the system identification algorithm using neural networks and weighted least square method. The algorithm is called Multilayer Perceptron Neural Networks (MPNN).
- (3) To identify the model parameters of the Hammerstein model of a quarter car passive suspension system.

## 2.0 A QUARTER CAR MATHEMATICAL MODEL

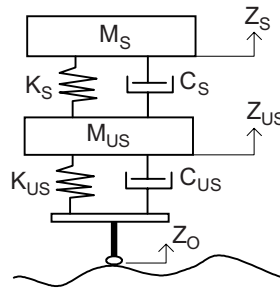
The main functions of the ground vehicle suspension are to: support the car weight, keep the wheel on the ground, minimize transient force to the body, maintain good ride comfort and enhance handling performance [10,11].

Suspension systems are influenced by the excitations due to the road unevenness and variable velocity. In earlier work on the analysis of car response, the car velocity

was considered as constant, since it was difficult to introduce the effect of variable velocity formulation of the model [12].

The physical constraint of the suspension system is the limited suspension travel. A basic passive suspension consists of a spring with a parallel damper at each wheel.

In this paper, a generic quarter car passive suspension model is used for analysis [13-19]. A quarter car system offers a quite reasonable representation of the actual suspension system [17]. The nonlinear components are affected by the suspension dynamics. The tyre is assumed to be linear. Figure 1 shows the schematic diagram of this model.



**Figure 1** A quarter car suspension schematic diagram

In the past decade, the car dynamics system suspension have been modeled using nonlinear formulae [13-16,18-21]. The dynamics of real suspensions are inherently nonlinear.

Assumed  $C_s$  and  $K_s$  are nonlinear as shown in [9]:

$$C_s = C_{s0} + C_{sn} (\dot{Z}_s - \dot{Z}_{us}) \quad (1)$$

$$K_s = K_{s0} + K_{sn} (Z_s - Z_{us}) \quad (2)$$

Using Newton's second law, the nonlinear dynamic equation of the masses yields:

$$\ddot{Z}_s = -\frac{K_{s0}}{M_s} (Z_s - Z_{us}) - \frac{C_{s0}}{M_s} (\dot{Z}_s - \dot{Z}_{us}) - \frac{K_{sn}}{M_s} (Z_s - Z_{us})^2 - \frac{C_{sn}}{M_s} (\dot{Z}_s - \dot{Z}_{us})^2 \quad (3)$$

$$\begin{aligned} \ddot{Z}_{us} = & -\frac{K_{s0}}{M_{us}} (Z_s - Z_{us}) + \frac{C_{s0}}{M_{us}} (\dot{Z}_s - \dot{Z}_{us}) - \frac{K_{us}}{M_{us}} Z_{us} - \frac{C_{us}}{M_{us}} \dot{Z}_{us} + \frac{K_{us}}{M_{us}} Z_o + \frac{C_{us}}{M_{us}} \dot{Z}_o \\ & + \frac{K_{s0}}{M_{us}} (Z_s - Z_{us})^2 + \frac{C_{s0}}{M_{us}} (\dot{Z}_s - \dot{Z}_{us})^2 \end{aligned} \quad (4)$$

where,  $Z_s$ ,  $Z_{us}$ ,  $Z_o$  are the displacement of sprung mass, wheel, and road surface elevation;  $M_s$ ,  $M_{us}$  are their respective masses. Between these masses,  $K_s$ ,  $K_{us}$  are the spring rates and  $C_s$ ,  $C_{us}$  are the damping rates as indicated.  $K_{so}$  and  $C_{so}$  are the linear coefficient and  $K_{sn}$  and  $C_{sn}$  are the nonlinear coefficient of the suspension spring and damping component.

Equations (3) and (4) have similar structure to the nonlinear Hammerstein mathematical model. The nonlinear Hammerstein structure has been widely used to formulate explanation [2,14,15,22-24]. The general form of nonlinear Hammerstein model of a quarter car passive suspension system are represented by Equations (5), (6) and (7).

$$Z_s(kT) A(q^{-1}) = B(q^{-1}) x(kT) \quad (5)$$

$$Z_{us}(kT) A(q^{-1}) = B(q^{-1}) z_o(kT) + B(q^{-1}) x(kT) \quad (6)$$

$$x(kT) = r_0 + r_{ng} Y^{ng}(kT) + \dots + r_{NG} Y^{NG}(kT), \quad ng = 1, 2, \dots, NG \quad (7)$$

where,  $A(q^{-1}) = a_0 + a_1 q^{-1} + \dots + a_n q^{-n}$ ,  $B(q^{-1}) = b_1 q^{-1} + \dots + b_m q^{-m}$ ,  $x(kT)$  is the static nonlinear part of the model.  $z_o(kT)$  is input variable,  $Y(kT)$  is output variable.  $q^{-1}$  is a unit delay,  $(n, m)$  is the order of linear part,  $ng$  is nonlinearity degree,  $T$  is sampling time.

In this study, the output variable of the system is the car suspension deflection  $Y(kT)$  and  $v(kT)$  is the noise measurement with the function shown below.

$$Y(kT) = d_1 Z_s(kT) - d_2 Z_{us}(kT) + v(kT) \quad (8)$$

The block diagram of a nonlinear Hammerstein structure of a quarter car passive suspension system is shown in Figure 2.

## 2.1 Multilayer Perceptron Neural Networks (MPNN) Structure

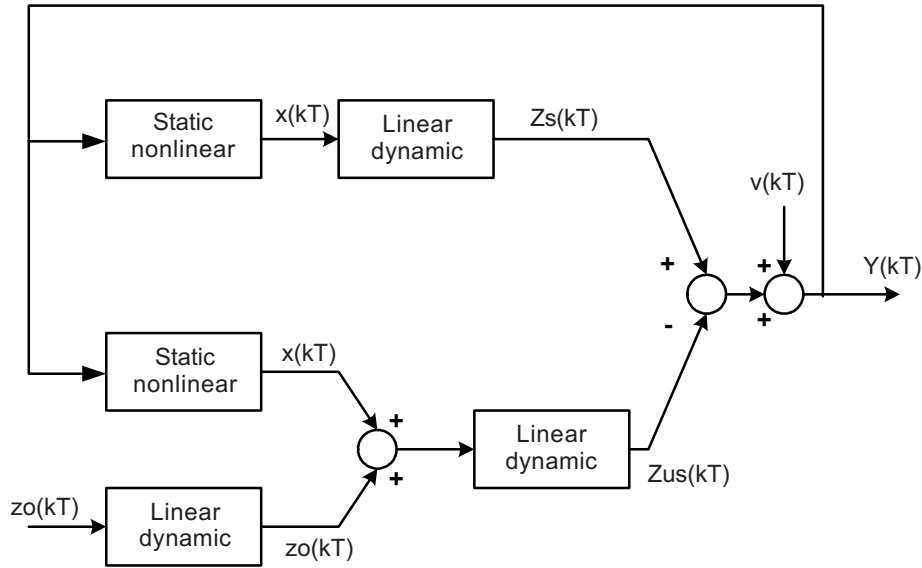
Model parameters are taken to be the neural networks weights. Input vector for each layer of the networks is written as the following:

- (1) First hidden layer neuron

$$x_1 = [Z_1((k-1)T), \dots, Z_1((k-n)T), Y^{ng}((k-1)T), \dots, Y^{ng}((k-m-1)T)] \quad (9)$$

- (2) Second hidden layer neuron

$$x_2 = [Z_2((k-1)T), \dots, Z_1((k-n)T), z_o(kT), \dots, z_o((k-m)T), Y^{ng}((k-1)T), \dots, Y^{ng}((k-m-1)T)] \quad (10)$$



**Figure 2** The block diagram of a nonlinear Hammerstein model of a quarter car passive suspension system dynamic

(3) Output layer neuron

$$Z = [Z_1(kT), Z_2(kT)] \quad (11)$$

## 2.2 Training Algorithm

The cost function in this research is formulated using the log likelihood formulation [4,7].

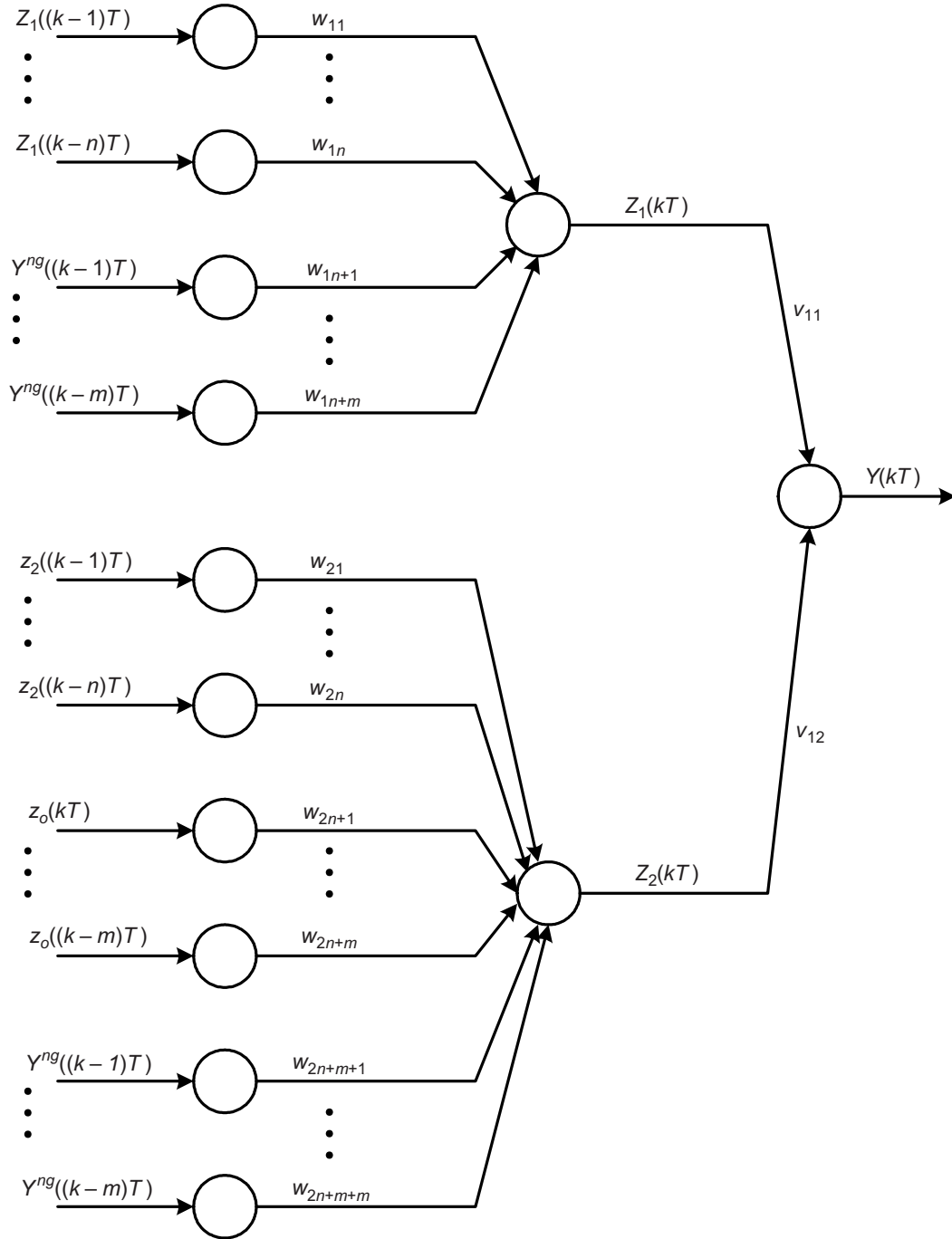
## 2.3 Likelihood

In this case, we assumed that:  $j = 1, 2, \dots, J$  are numbers of hidden layer neuron;  $k = 1, 2, \dots, K$  are numbers of output layer neuron;  $i = 1, 2, \dots, I$  are numbers of input layer neuron or unit input; and  $p = 1, 2, \dots, P$  are numbers of input data.  $x_p = (x_{p1}, \dots, x_{pI})$  is the networks input vector. The network block diagram is shown by Figure 3.

The output vector of the network in Figure 3,  $Y_p = [Y_{p1}, \dots, Y_{pK}]$  is determined for an input vector.

$$z_{pj}(\zeta_{pj}) = \frac{\exp(\zeta_{pj})}{1 + \exp(\zeta_{pj})}, \zeta_{pj} = \sum_{i=1}^I w_{ji} x_{pi} \quad (12)$$

$$y_{pk}(\eta_{pk}) = \frac{\exp(\eta_{pk})}{1 + \exp(\eta_{pk})}, \eta_{pk} = \sum_{j=1}^J v_{kj} z_{pj} \quad (13)$$



**Figure 3** MPNN structure

Let the set of learning samples be  $\{<x_{pi}, t_{pk}> | p = 1, 2, \dots, P\}$ ,  $P$  is a number of input variable.  $t_{pk}$  is the teacher's signal. The error is assumed to have Gaussian distribution. If each element of the output vector of the network is conditionally independent, then the log likelihood of the network for the set of learning samples is given by:

$$l = \sum_{p=1}^P \sum_{k=1}^K \left\{ -\frac{1}{2} \log(2\pi) - \frac{P}{2} \log(\sigma^2) - \frac{1}{2\sigma^2} (t_{pk} - y_{pk})^2 \right\} \quad (14)$$

## 2.4 Fisher Information

In this network, Fisher Information for hidden layer is calculated explicitly [17,26]. The first and second derivative of Equation (11) are given as:

(1) The first derivatives

$$\frac{\partial l}{\partial w_{ji}} = \sum_{p=1}^P \sum_{k=1}^K \omega_{pk} \sigma_{pj} v_{pj} x_{pi} \quad (15)$$

$$\frac{\partial l}{\partial v_{kj}} = \sum_{p=1}^P \delta_{pk} \omega_{pk} z_{pj} \quad (16)$$

where,  $\sigma_{pj} = \sum_{k=1}^K \delta_{pk} v_{kj}$ ,  $\delta_{pk} = (t_{pk} - y_{pk})$ ,  $\omega_{pk} = \frac{1}{\sigma^2} \Omega_{pk}$ ,  $\Omega_{pk} = y_{pk} (1 - y_{pk})$ , and

$$v_{pj} = z_{pj} (1 - z_{pj})$$

(2) The second derivatives

$$\frac{\partial^2 l}{\partial w_{ml} \partial w_{ji}} = \begin{cases} \sum_{p=1}^P x_{pl} \delta_{pk} (1 - 2y_{pk}) \chi_{pjj} v_{pj} v_{pj} x_{pi} & \text{if } j = k \\ -\sum_{p=1}^P x_{pl} \Omega_{pk} \chi_{pjj} v_{pj} v_{pj} x_{pi} & \\ \sum_{p=1}^P x_{pl} \delta_{pk} (1 - 2y_{pk}) \chi_{pmj} v_{pj} v_{pm} x_{pi} & \text{otherwise} \\ -\sum_{p=1}^P x_{pl} \Omega_{pk} \omega_{pk} v_{pm} v_{km} x_{pi} & \end{cases} \quad (17)$$

$$\frac{\partial^2 l}{\partial w_{ml} \partial v_{kj}} = \begin{cases} \sum_{p=1}^P x_{pl} \delta_{pk} (1 - 2y_{pk}) \omega_{pk} v_{pj} v_{kj} z_{pj} \\ - \sum_{p=1}^P x_{pl} \Omega_{pk} \omega_{pk} v_{pj} x_{pi} & \text{if } j = k \\ \sum_{p=1}^P x_{pl} \sigma_{pm} (1 - 2y_{pk}) \omega_{pk} v_{pm} z_{pj} \\ - \sum_{p=1}^P x_{pl} \Omega_{pk} \omega_{pk} v_{pm} v_{km} x_{pi} & \text{otherwise} \end{cases} \quad (18)$$

$$\frac{\partial^2 l}{\partial v_{nm} \partial w_{ji}} = \begin{cases} \sum_{p=1}^P x_{pi} \sigma_{pk} (1 - 2y_{pk}) \omega_{pk} v_{pj} z_{pm} \\ - \sum_{p=1}^P x_{pi} v_{pj} \omega_{pk} \Omega_{pk} v_{kj} z_{pm} & \text{if } j = k \\ \sum_{p=1}^P x_{pi} \sigma_{pk} (1 - 2y_{pk}) \omega_{pm} v_{pj} z_{pm} \\ - \sum_{p=1}^P x_{pi} \Omega_{pk} v_{kj} \omega_{pm} v_{pj} z_{pm} & \text{otherwise} \end{cases} \quad (19)$$

$$\frac{\partial^2 l}{\partial v_{bn} \partial v_{kj}} = \begin{cases} \sum_{p=1}^P z_{pm} \delta_{pk} (1 - 2y_{pk}) \omega_{pk} z_{pj} & \text{if } j = k \\ 0 & \text{otherwise} \end{cases} \quad (20)$$

where  $\chi_{pmj} = \sum_{k=1}^K v_{km} \omega_{pk} v_{kj}$ ,  $\delta_p = \sum_{k=1}^K \delta_{pk}$ ,

Minimization of the criteria function is given by:

$$0 = E \left( \frac{\partial l}{\partial Y} \right) = \frac{E(t_{pk}) - y_{pk}}{y_{pk} (1 - y_{pk})} \quad (21)$$



Fisher Information related for each weight vector of network is written as the following

$$F_{w_m w_{j_i}} = \sum_{p=1}^P x_{p_i} \delta_{p_k} (1 - 2y_{p_k}) \chi_{p_m j} v_{p_j} v_{p_m} x_{p_i} - \sum_{p=1}^P x_{p_i} \Omega_{p_k} \chi_{p_m j} v_{p_j} v_{p_m} x_{p_i} \quad (22)$$

$$F_{w_m v_{k_j}} = \sum_{p=1}^P x_{p_i} \sigma_{p_m} (1 - 2y_{p_k}) \omega_{p_k} v_{p_m} z_{p_j} - \sum_{p=1}^P x_{p_i} \Omega_{p_k} \omega_{p_k} v_{p_m} v_{k_m} x_{p_i} \quad (23)$$

$$F_{v_{n_m} w_{j_i}} = \sum_{p=1}^P x_{p_i} \sigma_{p_k} (1 - 2y_{p_k}) \omega_{p_m} v_{p_j} z_{p_m} - \sum_{p=1}^P x_{p_i} \Omega_{p_k} v_{k_j} \omega_{p_m} v_{p_j} z_{p_m} \quad (24)$$

$$F_{v_{n_m} v_{k_j}} = \begin{cases} \sum_{p=1}^P z_{p_m} \delta_{p_k} (1 - 2y_{p_k}) \omega_{p_k} z_{p_j} & \text{for } j = k \\ 0 & \text{otherwise} \end{cases} \quad (25)$$

## 2.5 Iterative Weighted Least Squares Algorithm

The weight update learning algorithm is done by minimizing Equation (11). We apply steepest decent optimization method using the first derivative of objective function [17,25,26]. Assume the current estimate of the weights is  $W$ . Then the estimate is repeatedly updated by:

$$W^* = W - \alpha \nabla l \quad (26)$$

If weights are updated to each set of learning sample, Equation (23) can be modified to be:

$$W^* = W - \alpha \nabla l_p \quad (27)$$

where  $\nabla l_p$  is the first derivative to the sample  $(x_p, t_p)$  and the relation  $\nabla l = \sum_{p=1}^P \nabla l_p$  hold. This is called steepest descent method.

In this case, Fisher's scoring algorithm is developed which uses Fisher's information. The estimated is repeatedly changed by

$$W^* = W + \delta W \quad (28)$$

where the increment  $\delta W$  is calculated by solving the following equation.

$$F \delta W = \nabla l \quad (29)$$

This is called Fisher's scoring method.

## 2.6 Unitwise Iterative Weighted Least Squares Algorithm

Fisher's information related with the weights from input layer to hidden layer are given by [10].

$$\begin{aligned} F_{wj} &= \sum_{p=1}^P x_{pl} \delta_{pk} (1 - 2y_{pk}) \chi_{pmj} v_{pj} v_{pm} x_{pi} - \sum_{p=1}^P x_{pl} \Omega_{pk} \chi_{pmj} v_{pj} v_{pm} x_{pi} \\ &= X^T Q_{wj} X \end{aligned} \quad (30)$$

where,  $Q_{wj} = \text{diag} ((\delta_{pk}(1 - 2y_{pk}) - \omega_{pk}\Omega_{pk}) v_{pj}\chi_{pij}v_{pj})$  and  $j$  is the number of hidden neuron. This is a weighted covariance matrix of input vectors. Using Equations (26) and (27), the normal equation of weighted least squares estimation to obtain the current estimates of the weights  $W_{wj}^*$  as the following

$$X^T Q_{wj} X W_{wj}^* = X^T Q_{wj} (\zeta_j + Q_{wj}^{-1} \delta_{wj}) \quad (31)$$

where,

$$\delta_{wj} = \left( \sum_{k=1}^K \omega_{1k} \sigma_{1j} v_{1j}, \dots, \sum_{k=1}^K \omega_{pk} \sigma_{pj} v_{pj} \right) \quad (32)$$

$$\zeta_j = (\delta_{j1}, \dots, \zeta_{pj})^T \quad (33)$$

Similarly, Fisher's information for output layer weights and corresponding normal equation are written as:

$$F_{vk} = [z_{pm} \delta_{pk} (1 - 2y_{pk}) \omega_{pk} z_{pj}] = Z^T Q_{vk} Z \quad (34)$$

and

$$Z^T Q_{vk} Z V_{vk}^* = Z^T Q_{vk} (\eta_k + Q_{vk}^{-1} \delta_{vk}) \quad (35)$$

where,

$$Z^T = (z_1, z_2, \dots, z_p) \quad (36)$$

$$Q_{vk} = \text{diag} (\delta_{pk} (1 - 2y_{pk}) \omega_{pk}) \quad (37)$$

$$\eta_k = (\eta_{1k}, \dots, \eta_{pk})^T \quad (38)$$

$$\delta_{v_k} = (\delta_{1k}\omega_{1k}, \dots, \delta_{pk}\omega_{pk})^T \quad (39)$$

The estimates  $\{W_{w_j} | j = 1, \dots, J\}$  and  $\{V_{v_k} | k = 1, \dots, K\}$  are repeatedly updated by solving normal equation. This method is called Unitwise Fisher's scoring method. In this algorithm each neuron weights unit of the networks is estimated by the iterative weighted least squares algorithm.

Next we will consider the recursive formulation to solve these normal equations for the weighted least squares. This reveals the close relation between the proposed Unitwise Fisher's Scoring algorithm and the back propagation learning algorithm.

The optimal estimate parameters respect to the set of earlier learning samples and the new learning samples. The recursive equation is written as:

$$w_{w_j}^N = w_{w_j}^{N-1} + R_{w_j}^N x_N \omega_N \sigma_{Nj} v_{Nj} \quad (40)$$

where the matrix  $R_{w_j}$  gives the estimates of the inverse of the weighted covariance matrix  $^{(N)}X^T(^{N})Q_{w_j}(^{N})X$  and its recursive formula is given by:

$$R_{w_j}^N = R_{w_j}^{N-1} - \frac{(\delta_N (1 - 2y_N) - \omega_N \Omega_N) v_{Nj} \chi_{Njj} v_{Nj} R_{w_j}^{N-1} x_N x_N^T R_{w_j}^{N-1}}{1 + (\delta_N (1 - 2y_N) - \omega_N \Omega_N) v_{Nj} \chi_{Njj} v_{Nj} x_N^T R_{w_j}^{N-1} x_N} \quad (41)$$

In the same way the recursive formula for the estimate  $v_{v_k}$  is given by:

$$v_{v_k}^N = v_{v_k}^{N-1} + R_{v_k}^N z_N \delta_{Nk} \omega_{Nk} \quad (42)$$

$$R_{v_k}^N = R_{v_k}^{N-1} - \frac{\delta_{Nk} (1 - 2y_{pk}) \omega_{Nk} R_{v_k}^N z_N z_N^T R_{v_k}^{N-1}}{1 + \delta_{Nk} (1 - 2y_{pk}) \omega_{Nk} z_N^T R_{v_k}^{N-1} z_N} \quad (43)$$

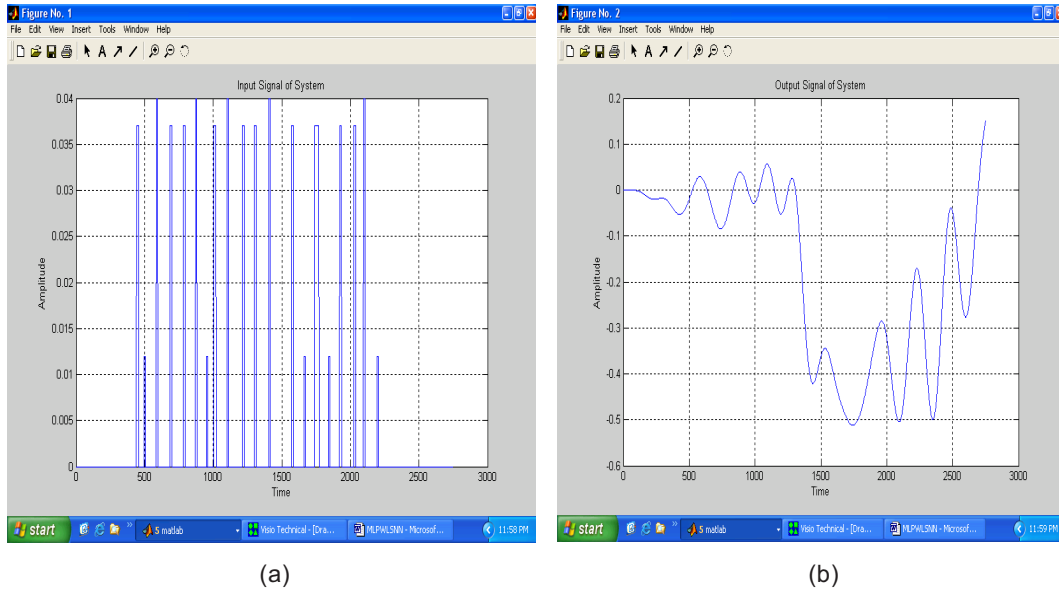
### 3.0 MODEL VALIDATION AND SYSTEM IDENTIFICATION RESULT

Model validation is needed to verify that the identified model fulfills the modeling requirement according to the subjective and objective criteria of good model approximation. In this paper, several criteria are applied among [14,21,26]:

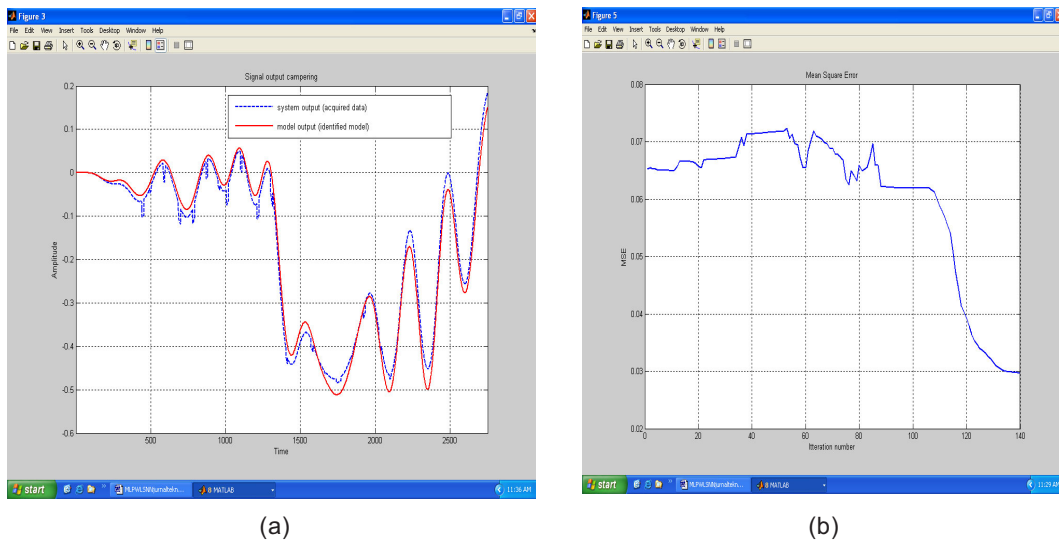
- (1) Compare between the signal graph of system output and estimated model output.
- (2) Residual analysis: auto correlation and cross correlation, and test statistic.
- (3) Percent Variance Accounted For (% VAF).

The data sampling ( $T$ ) is assumed to be 1 second.

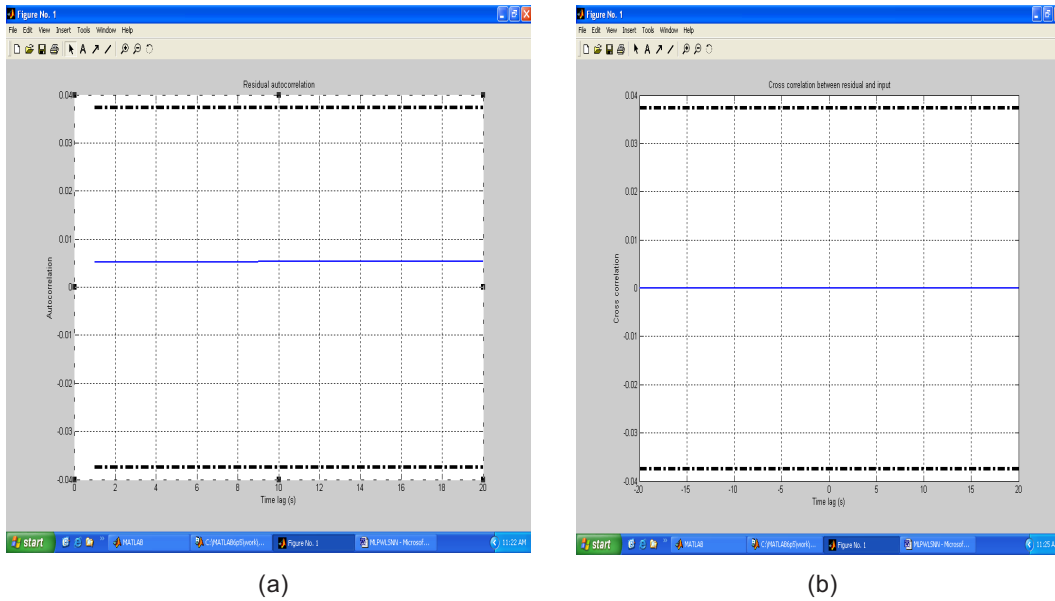
The graph of input signal and output signal of system are shown in Figures 4(a) and 4(b).



**Figure 4** (a) Random type of artificial road surface and (b) The signal graph of output system



**Figure 5** (a) The output comparing between system and estimate model and (b) MSE value



**Figure 6** (a) Autocorrelation residual with 99% confidence interval and (b) Cross correlation between residual and input with 99% confidence interval

Figure 5(a) shows the comparison between the system and the model output. The output model trend is similar with the output system. A typical training is shown in Figure 5(b). The MSE on the training set is shown as a function of the number of iterations. A standard way to present the decision problem in the case of interactive system identification is to show a diagram of residual autocorrelation. Figure 6(a) shows the residual autocorrelation with 99% confident interval limit. A test for the independence of input and residual is based on the cross correlation covariance function. Figure 6(b) shows the residual cross correlation with 99% confident interval limit.

The best identified model has  $n = 2$ ,  $m = 1$  and  $ng = 3$ . The MSE minimum value is defined at iteration numbers 143 as shown in Figure 5(b). From statistical analysis, we defined the value of the autocorrelation test statistic is 0.0273 and cross correlation test statistic is 0 (for  $m = 20$  theses value must be less than 37.6). Loss function and %VAF are respectively 0.0006 and 90.4%.

#### 4.0 DISCUSSION

Determination of the nonlinear model of a quarter car suspension system has been discussed. The model is formulated using nonlinear Hammerstein model which is then used to design the neural network structure. The network structure is defined as a Multilayer Perceptron. The networks training algorithm is written down applying Fisher's information and Fisher's scoring algorithm. The algorithm is interpreted as

iterations of weighted least square method. The system input and output data are achieved from a known parameter of nonlinear model of a quarter car passive suspension system simulation. The development algorithm is examined using those data. A detailed description of the taken to perform the modeling, i.e. the data acquisition and application of neural network structures and algorithm, is given and the results are displayed.

## 5.0 CONCLUSION

In this paper, system identification technique for a quarter car suspension systems dynamic has been developed. The neural network weight update is done using weighted least squares method. The weighted least square works as a function for tuning the network weights. The system identification algorithm is used to identify the nonlinear model of a quarter car passive suspension system. The results show that the trend of output signal of estimate model is nearly similar with the output signal of the system. The networks can converge at the short iteration number as shown in Figure 5(b). The autocorrelation graph of residual and cross correlation graph between residual and input signal is laying in 99% confident limit. The value of Percent Variance Accounted For (%AVF) and loss function are acceptable.

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