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Research paper

Characterizing Spring Durability for Automotive Ride Using Artificial Neural Network Analysis

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Abstract

This paper presents the establishment of a relationship between coil spring fatigue life and automotive vertical vibration using neural network. During an automotive suspension design process, the suspension components are designed with the consideration of structure strength and fatigue life as well as the effects toward automotive ride. Hence, it is important to have a functional mathematical model to predict the fatigue life and automotive life simultaneously. To build the mathematical model, a multibody kinematic quarter model of suspension system was constructed to simulate force and acceleration time histories from the suspension system and the sprung mass of the vehicle model. The force time histories were used to predict the fatigue life of the coil spring while the acceleration time histories were converted into ISO vertical vibration index. A neural network model was created and used to fit the spring fatigue life and vehicle vertical vibration into a mathematical function. The neural network with 1 hidden layer and 2 neurons has shown a good fitting of the data with coefficient of determination as high as 0.88, 0.98, 0.96 for training, validation and testing, respectively. This constructed neural network serves to predict the vehicle vertical vibration using the spring fatigue life and suspension natural frequencies as input, and hence reduce the automotive suspension design process.

Keywords: *Spring Fatigue; Vertical Vibration, Curve Fitting, Neural Network*

1. Introduction

Automotive suspension design process involves many stages, such as selecting the appropriate target or suitable architecture, choosing the hard points, designing the spring and dampers, analysing the structure integrity and vehicle dynamics of the resulting designs [1]. To obtain a good suspension design, repeated processes of analysis were required because it promise a good ride quality of the vehicle and able to withstand required repeated cyclic loadings. Hence, many researches have been focused on automotive ride [2, 3] and suspension coil spring fatigue [4, 5]. For objective ride analysis, the vehicle was usually modelled with road excitation input.

For vehicle ride analysis, Hassaan [2] analysed the design of a Macpherson suspension system using a quarter car model. The responses of vehicle cross several bumps with different speeds were studied and linked to the ISO ride standard. Čorić et al. [3] optimised the vehicle ride comfort through a quarter car model and a collocation-type control variable optimisation method. They used road characteristics in cases of bump, pothole and bump for full vehicle and root mean square (RMS) acceleration as indicator for vehicle ride comfort. Putra et al. [5] performed a fatigue analysis on coil spring using the collected strain signals on a spring with different road conditions. Based on these works, it has shown that the fatigue life and ride quality assessments of a vehicle possessed a similarity which was the interaction of movement of the spring and vehicle body to the road excitations.

Hence, many researches [6] were focused on regenerating road profiles with minimum cost. For example, artificial neural network was used to reconstruct the road defects and road roughness for ride comfort and vehicle handling [6]. The data generated from simulation were used to train the network while the measured data from a real vehicle was used for validation. Meanwhile, adaptive neural network was used to develop the controller for an automotive suspension system [7]. The controller was used for magneto rheological active suspension system to control the vehicle body acceleration. The adaptive neural network controller had shown superior performance in terms of peak values of tyre displacement, body acceleration and control signal.

Feedforward neural networks were also used for remaining useful life prediction of an automotive bearing through using suspension history [8]. The age and degradation progression reflected in monitoring condition were used as input while the remaining life was the output of the model. Ali et al. [9] proposed a development of neural network using Weibull failure features as input for the automotive bearing remaining useful life prediction. Neural network was also found to be used in predicting fatigue life of an automotive subframe with multiaxial loading as input [10]. However, up to the extent of authors knowledge, there is no literature reported on modelling of automotive ride with fatigue characteristics as an input.

In this work, artificial neural network (ANN) was used to construct a durability model for automotive ride prediction. Applica-

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tion of neural network in fatigue life assessment field is new, the results of the current study are expected to provide a new knowledge on the applicability of durability and ride model in automotive industries. This constructed model aims to reduce the lengthy design period of automotive suspension design process. With the spring fatigue life as input, the vertical vibration of the vehicle could be estimated. It was hypothesised that the method successfully created a new prediction model which could provide objective indication of vehicle vertical vibration with sole fatigue parameter as input.

2. Methodology

The methods to create the model were classified into four steps which were road signal collection, construction of vehicle quarter car simulation model, characterisation of spring fatigue and vehicle vibration parameters and neural network modelling. The overall process flow of the analysis procedures is listed in Figure 1. The acceleration signal was collected using an accelerometer at the lower arm as shown in Figure 2(a). The other end of the accelerometer was connected to data acquisition system as illustrated in Figure 2(b). The vehicle was then driven on different road conditions to collect the acceleration signals. The sampling rate was determined to be 1000 Hz where this sampling rate is enough to capture the road condition, as reported by Wang et al. [11]. Wang et al. suggested that the minimum sampling rate of acceleration time history for automotive components durability analysis should be at least of 1000 Hz based on the relevant standards, such as SAE 2380, ECE regulation 100.

To obtain the signal for fatigue and vibration analysis, a vehicle quarter car model was modelled using commercial object-oriented simulation software. The 3D diagram view of the suspension system in shown in Figure 3. This suspension model consists of a spring and damper connected to vehicle mass. The other end of damper strut was connected to a wheel via a rigid wheel carrier. The masses of each components were assigned and the measured vibration signals were applied on the wheel of the simulation model. The force time histories were extracted from the spring element and acceleration signals were extracted from the connected vehicle mass of the model. The initial spring stiffness was determined to be 20 N/mm and damping coefficient was 15,564 Ns/m [12]. The spring stiffness variants were set from 14 N/mm to 32 N/mm to ensure the natural frequency of the suspension lie within 0.8 to 1.5 Hz which was the most suitable frequency region for passenger cars [13]. The vehicle sprung mass was 350 kg for the model with consideration of four passengers and vehicle weight was distributed equivalently to all four wheels.

The acceleration signal and force time history extracted from different sets of spring stiffness were converted into ISO vertical vibration and fatigue life respectively. For the vertical weighted acceleration, one-third octave band of the acceleration signal was required. The weighted vertical acceleration can be obtained as follows [14]:

$$a_w = \sqrt{\left[\sum_i (W_i a_i)^2\right]} \tag{1}$$

where a_w is the frequency weighted root mean square (r.m.s) acceleration, W_i is the weighting factor for the ith octave band given by ISO 2631, a_i is the r.m.s acceleration for the ith octave band. The used weighting factor was proposed by ISO 2631-1 [14] where the frequency range covered from 0.1 to 80 Hz to include passenger motion sickness at lower frequency.

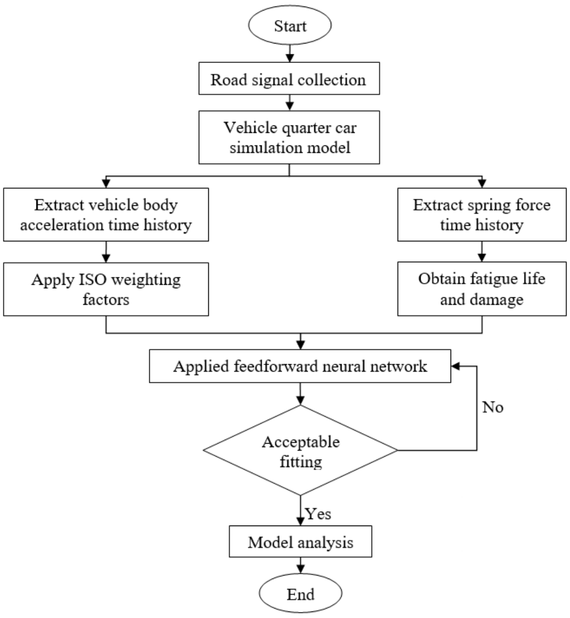

Figure 1: Process flow of an artificial neural network model generation

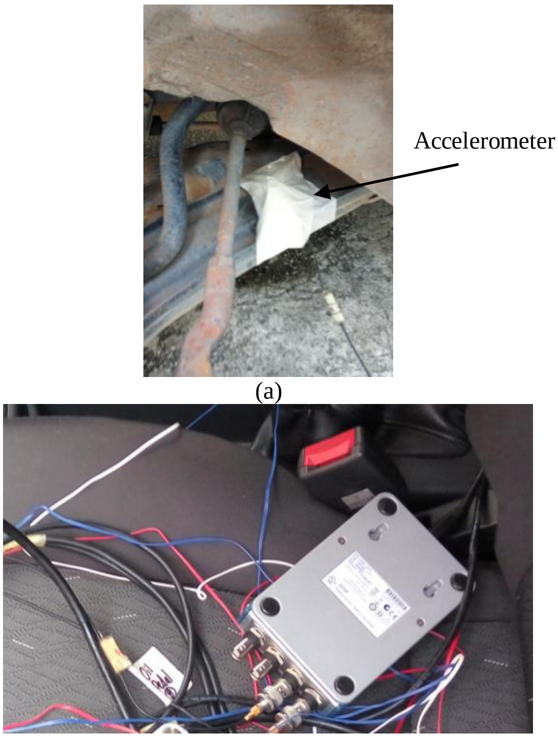

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Figure 2: Experimental setup for acceleration measurement: (a) accelerometer at lower arm, (b) data acquisition system

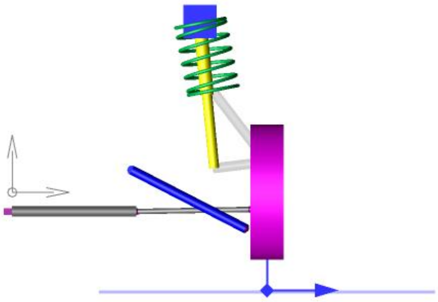

Figure 3: A 3D diagram view of a suspension model

On the other hand, the extracted force time histories from spring element were used for fatigue life prediction. The procedures for fatigue life prediction using force time histories are listed in Figure 4. FE spring models with force time steps were scaled according to the force time histories. The example of spring CAD model is shown in Figure 5. A total of 9227 nodes and 7170 elements were applied in the model. In durability analysis, material cyclic properties, loading signals and geometric were used as input to fatigue model for life prediction. The required SAE 5160 spring steel material cyclic properties are listed in Table 1. In this analysis, the Smith-Watson-Topper (SWT) strain life model was applied because of its suitability of fatigue life prediction for steel under cyclic loadings [15]. The SWT model can be defined as follows, as mentioned by Ince & Glinka [15]:

$$\sigma_{max}\varepsilon = \frac{(\sigma_f')^2}{E}(2N_f)^{2b} + \sigma_f'\varepsilon_f'(2N_f)^{b+c} \qquad (2)$$

where σ'_f is the fatigue strength coefficient, N_f is the number of cycles to failure for a stress range, b is the fatigue strength exponent, ε'_f is the fatigue ductility coefficient and c is the fatigue ductility exponent.

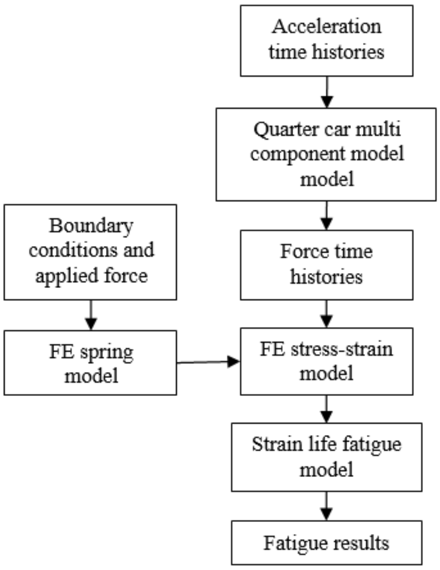

Figure 4: Procedures of spring durability analysis using extracted force time histories

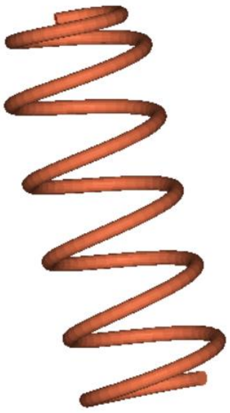

Figure 5: CAD model of the spring

Table 1: Properties of the SAE 5160 carbon steel [16]

Properties	Value
Yield strength (MPa)	1,487
Ultimate tensile strength (MPa)	1,584
Material modulus of elasticity (GPa)	207
Fatigue strength coefficient	2,063
Fatigue strength exponent	-0.08
Fatigue ductility coefficient	9.56
Fatigue ductility exponent	-1.05
Cyclic strain hardening exponent	0.05
Cyclic strength coefficient	1,940
Poisson ratio	0.27

To train a neural network model, Levenberg-Marquardt algorithm was widely adopted, especially for nonlinear analysis. The Levenberg-Marquardt algorithm adaptively varied the parameter updates between the gradient descent update and the Gauss Newton update as follows [17]:

$$[J^TWJ + \lambda I]h_{lm} = J^TW(y - \hat{y}) \qquad (3)$$

where J is the Jacobian matrix, h_{lm} is the perturbation, W is the weighting matrix, I is the identity matrix, λ is an algorithmic parameter result of Gauss-Newton update, y is the vector with i^{th}-component respectively. Marquardt updated the function as follows:

$$[J^TWJ + \lambda\, diag(J^TWJ)]h_{lm} = J^TW(y - \hat{y}) \qquad (4)$$

The Levenberg-Marquardt nonlinear curve fitting was used to train the neural network model with suspension natural frequency and spring fatigue life as input. The output of the neural network was vehicle ISO weighted vertical vibration which indicates how good the vehicle ride quality.

3. Results and Discussions

The collected acceleration signals from two different road conditions are shown in Figure 6. The signals were collected from residential area and rural area respectively where this two road conditions were commonly used. As observed from Figure 6(a), there were a few peaks in the signal during the time of 13 s, 57 s, 74 s and 98 s and the signal possessed approximate zero mean value. The kurtosis value of the acceleration signal was 9.68 and the acceleration signal was classified as non-stationary signal because of kurtosis value was higher than 3 [18]. These peaks were created when the vehicle was negotiating with a speed bump in residential area. The rural area acceleration signal had less significant peaks and this signal was consisted also zero mean value and a kurtosis value of 4.02. The kurtosis value of rural area acceleration signal was lower than the kurtosis value of residential area. Even the road roughness of rural road was coarser than residential road, the speed bump of residential area had created peaks which were leading to high kurtosis value. The kurtosis value indicates the spikiness of the data. For univariate data, the kurtosis could be obtained using the equation as follows:

$$kurtosis = \frac{1}{n(r.m.s)^4}\sum_{j=1}^{n}\left(x_j - \bar{x}\right)^4 \qquad (5)$$

where n is the number of data point, $\bar{x}$ is the mean value of the sample data. The power spectral densities of the acceleration time histories are plotted into Figure 7. As observed from Figure 7, both the peak of the acceleration PSD was founded at frequency range of 1 to 2 Hz. The same peak in acceleration PSDs was reported by Lu et al. [19] where the road excitation on the wheel occurs at low frequency range.

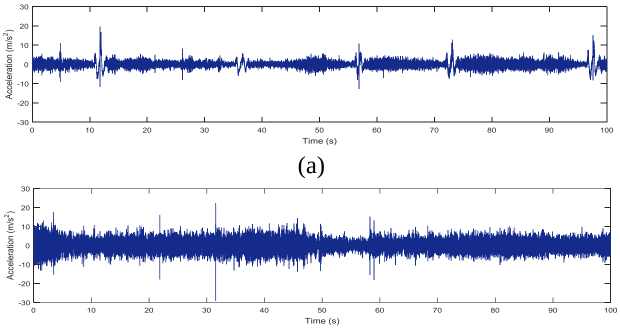

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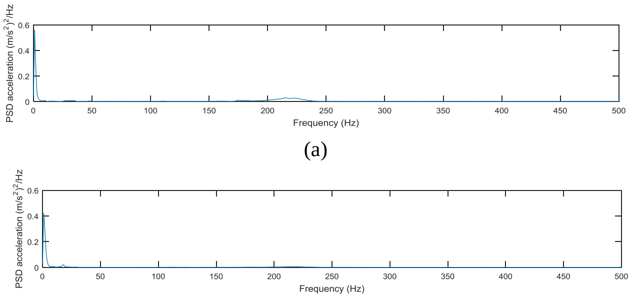
Figure 6: Measured acceleration time histories: (a) residential area, (b) rural area



(a)

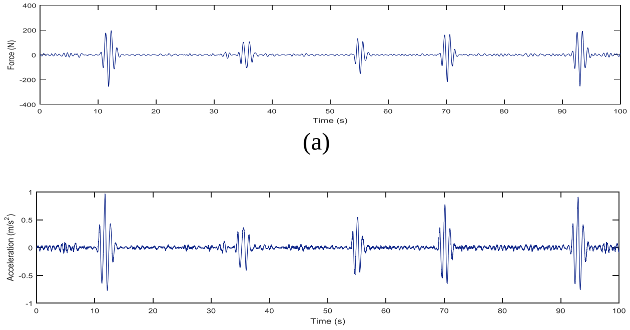
(b)

Figure 7: PSD of measured acceleration time histories: (a) residential area, (b) rural area

The acceleration signals from both residential and rural road were used as input to vehicle quarter car model to simulate the suspension and sprung mass behaviour. The acceleration response of sprung mass and the force time history of the spring were extracted. The examples of an extracted force and acceleration time histories are shown in Figure 8. The force time histories were used to predict the fatigue life of coil spring while the extracted acceleration time histories were used for vehicle vertical vibration analysis. Through utilising different spring stiffness, the corresponding weighted vertical vibration and spring fatigue life were obtained and listed into Table 2. The FE spring analysis of every single spring variants were required for fatigue life prediction. The example of a FE spring with stress-strain is shown in Figure 9. The spring stiffness was converted into suspension natural frequency using the following equation [20]:

$$f_n = \frac{1}{2\pi}\sqrt{\frac{k}{m}} \tag{6}$$

where f_n is the natural frequency, k is the stiffness of the spring, m is the sprung mass of the vehicle. These parameters were used as input and target for neural network model training. The weighted vertical acceleration was calculated using Equation 1 while the fatigue lives were obtained using SWT strain life fatigue model as listed in Equation 2.



(a)

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Figure 8: Examples of extracted time histories for analysis: (a) force time histories from spring, (b) acceleration time history from vehicle mass

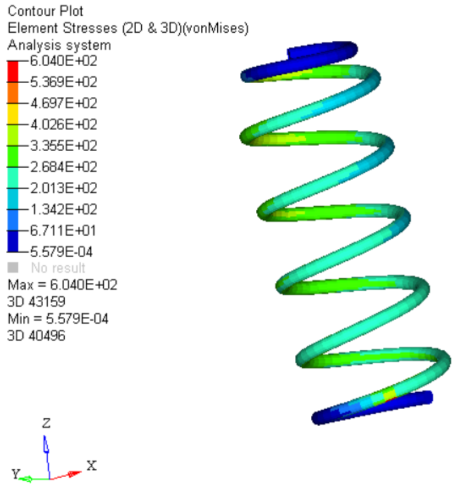


Figure 9: An example of spring FE model with stress-strain information

Prior to the modelling, the suitable architecture of neural network was determined with consideration of number of hidden layers and neurons. One-layer neural network architecture was applied because one-layer neural network was sufficient to solve most of the problems, as mentioned by Heaton [21]. The number of neurons was decided according to the general rule of thumb where it was the mean of the neurons in input and output layer. Hence, the customised architecture of the neural network was with 2 neurons in a single hidden layer as shown in Figure 10. Initially, the suspension natural frequencies and spring fatigue life data set were input to the hidden layer. The data were multiplied with calculated weighting factor in the hidden layer. Then, the weighted values were transferred to output layer and converted to a single targeted output. In this case, the output was the weighted acceleration. The weighting factors were repeatedly calculated to satisfy the target value with acceptable error value. In this analysis, a total of 67 iterations have been performed and the best iteration was found in the 61th iteration as depicted in Figure 11. The model of 61th iteration have shown the smallest mean square error (MSE) in validation process.

Table 2: Vertical vibration and spring fatigue with different spring Stiffness variant

f_n (Hz)	Residential		Rural	
	WA (m/s^2)	Fatigue life (blocks to failure)	WA (m/s^2)	Fatigue life (blocks to failure)
0.92	0.504	8.47×10^5	0.274	8.33×10^8
1	0.574	1.25×10^5	0.298	1.02×10^7
1.06	0.610	9.43×10^4	0.312	4.13×10^6
1.13	0.610	1.37×10^4	0.325	5.41×10^4
1.19	0.662	4.12×10^3	0.337	8.20×10^4
1.24	0.682	1.28×10^3	0.350	1.30×10^4
1.3	0.699	1.05×10^3	0.363	9.43×10^3
1.35	0.713	7.37×10^2	0.376	5.62×10^3
1.4	0.724	6.97×10^2	0.389	5.21×10^3
1.45	0.731	4.92×10^2	0.401	4.93×10^3

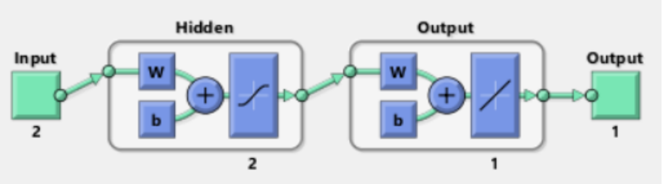


Figure 10: Selected neural network architecture

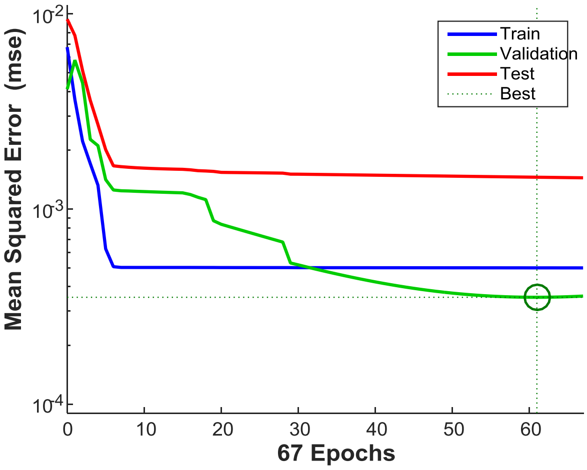


Figure 11: Epochs performance validation of neural network models

The model of neural network is illustrated in Figure 12. Since the neural network model has two neurons, two weightings of each neuron were obtained. The weightings of A and B for *k* were 0.991 and -20.021 respectively while the weightings for *N* were -4.421 and -1.749. When a weighting value is less significant, the value could approximate to zero. Meanwhile, there is no limit of maximum weighting value [21]. Hence, the obtained weighting values were considered as acceptable value. In this analysis, *k* is the vehicle natural frequency and *N* is the spring fatigue life which were served as input to the weighting factors. The output (a_w) was the estimated vehicle vertical vibration. The applied sigmoid transfer function was hyperbolic tangent sigmoid transfer function (tansig) and can be written as follows:

$$tansig\ (n) = \frac{2}{(1 + \ e^{-2n}) - 1} \tag{7}$$

Hyperbolic tangent sigmoid transfer function is suitable for non-linear function fitting with one hidden layer [22].

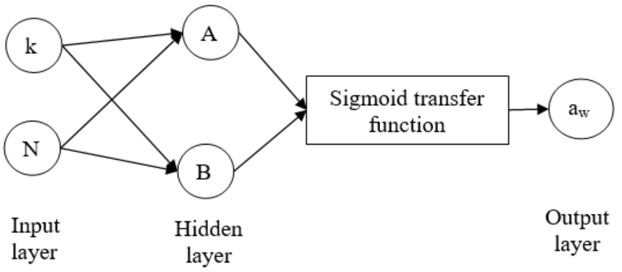


Figure 12: A schematic layout of an artificial neural network durability model

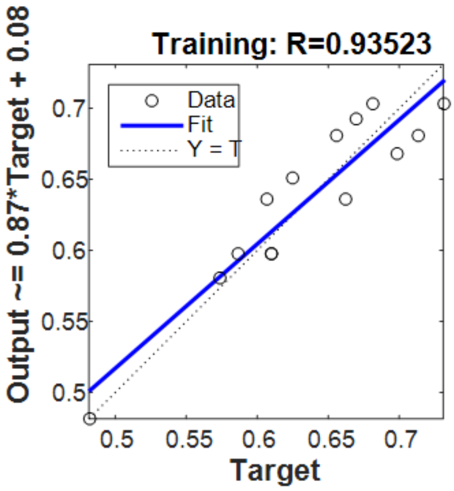
For the model fitting, 14 data were used to train the neural network while a total of 6 data were used for validation and test purpose. The results of the neural network model fitting are shown in Figure 13. The training set was used to set up the model where the sample correlation coefficient (*r*) of 0.94 was obtained. Based on the sample correlation coefficient, the coefficient of determination (R^2) up to 0.88 was obtained. As suggested by Sivák and Ostertagová [23], R^2 value of 0.9 or above is very good, a value above 0.8 is good. A value of R^2 above 0.6 was considered as acceptable. Hence, the data were fitted good with the model. For the validation, a set of three data was used to find the “optimal” number of hidden units or determine a stopping point for the back-propagation algorithm. The validation process possessed of a *r* value as high as 0.99 where a R^2 value of 0.98 was obtained. An optimised model among 67 iterations was selected with the highest correlation.

The validation set of data was needed to verify the optimised model after all the nine iterations. To avoid bias, the model selected from validation was further verified using this set of test data. In this case, three data were used to verify the final model. The test data have been well fitted into the model with *r* value as high as 0.98. Therefore, a R^2 value of 0.96 was achieved. This final neural network model was proved to have good performance for weighted vertical vibration prediction. Subsequently, the error for each data was plotted into Figure 14. The errors of each data were obtained through the difference between the targets and outputs of the model through relationship as follows:

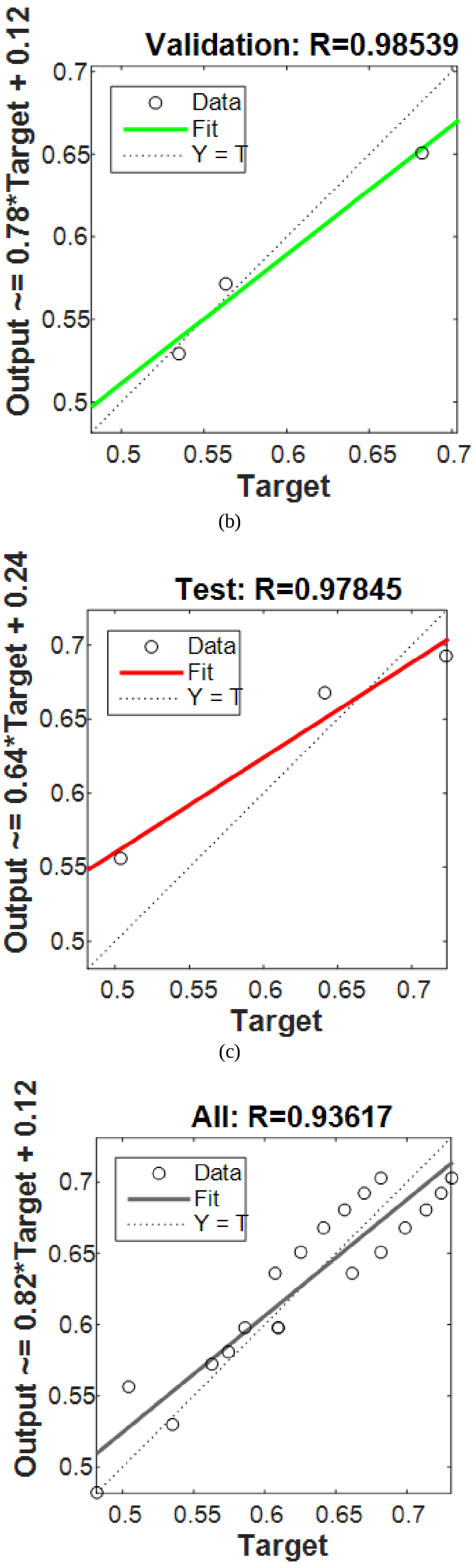
$$Error = Targets - Output \tag{8}$$

where the targets were the independent parameter used to train the model, the output were the results of the neural network model predictions. The error of prediction ranges from -0.05 to 0.03. The range of error is relatively small when compared to the target value with the range of 0.274 to 0.731 m/s^2. Hence, the neural network model has shown to provide good estimations.

In automotive suspension industry, the development process is very time consuming. Due to this reason, there is a need to have a well-established model for immediate vertical vibration estimation and thus, the model could reduce unnecessary trials. Therefore, the neural network model to provide prediction for these parameters were established. The procedures and relationship of the neural network model for vehicle vibration is shown in Figure 15. However, the reliability and accuracy of the established model is significance for automotive application. In future, more validation data could be used to validate this neural network model. The main challenge of this analysis is the characteristic of the data, whether they possess linear or non-linear relationship. When inappropriate method was used, low correlation values were obtained. Therefore, the neural network method was chosen after considered the fitting capability of nonlinear data. Neural network approach is more feasible when compared to multiple linear regression method [24]. Meanwhile, neural network has performed the optimisation to find the optimal model using a set of validation data set.



(a)



(b)

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Figure 13: Neural network fitting model of vehicle vertical vibration

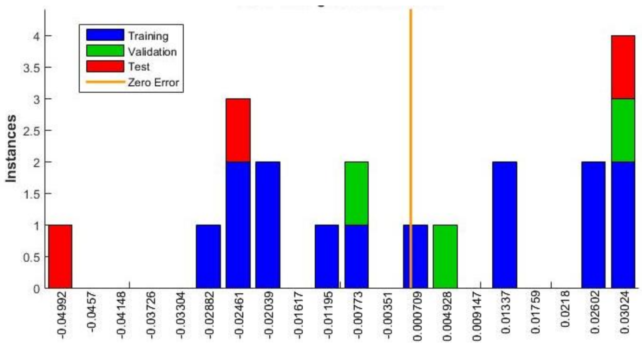

Figure 14: Error histogram of data of the neural network model

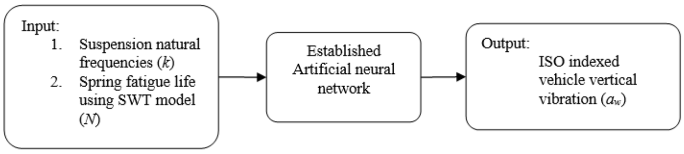

Figure 15: Procedures of utilizing established durability neural network model for vehicle vertical vibration prediction

4. Conclusion

A neural network spring fatigue model for vehicle vertical vibration estimation has been successfully established using Levenberg-Marquadt algorithm. The fatigue life of an automotive coil spring was predicted using force signals extracted from quarter car simulation model while the ISO 2631 vehicle vertical vibrations were obtained through acceleration signals extracted from the vehicle mass. A set of spring stiffness variants was applied to generate the data for suspension variants. For the model construction, a customized neural network was created to fit the vehicle vertical vibration and fatigue life data. The proposed neural network model has been successfully fitted training data with R^2 value as high as 0.88. The optimised trained model was selected using validation data out of nine iterations. A R^2 value as high 0.98 was obtained from the validation results. Lastly, the optimised model was tested using a set of test data for final validation to avoid bias. The optimised model has shown a good correlation of the test data with R^2 value of 0.96. Based on the correlation results, the proposed neural network provides good estimation of vehicle vertical vibration using fatigue life as input. This model intended to shorten the automotive suspension design process.

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