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Identification of Aerodynamic Coefficients of Ground Vehicles Using Neural Network

Nabilah Ramli, Shuhaimi Mansor, Hishamuddin Jamaluddin, and Waleed Fekry Faris

Abstract—**The purpose of this paper is to demonstrate the application of a combination of neural network and an oscillating model facility as an approach in identification of aerodynamic coefficients of ground vehicle. In literature study, a method for estimating transient aerodynamic data has been introduced and the aerodynamic coefficients are extracted from the measured time response by means of conventional approach. The potential of neural network as an alternative method is explored. For simplicity, only the damped oscillation considered in this analysis while neglecting any unsteadiness or buffeting load. Two feedforward neural networks are constructed to estimate the damping ratio and natural frequency, respectively, from the measured time response recorded during the dynamic wind tunnel test. These two parameters are used to calculate the aerodynamic coefficients of the ground vehicle model. To validate the network approach, the resulted coefficients are compared with the ones retrieved conventionally. By simulating the system's transfer function, the response generated from neural network results were found to be closer to the measured time response compared to the response generated using the conventionally estimated coefficients.**

I. Introduction

VEHICLE stability is one of the major measures for vehicle performance, and it means the ability of the vehicle to maintain its course upon subjected to any external disturbance [1]. These disturbances can be due to many external forces, one of them is the aerodynamic force and this is known in the automotive aerodynamic literature as "cross-wind" effect [2], [3]. The interest in this field started around the seventies, when the vehicles started to have considerable speeds on the high ways and the application grows steadily in other types of ground vehicles like trains [4]. One of the major tasks in this area is to estimate the aerodynamic coefficients required to calculate the aerodynamic moments and forces. Currently two main approaches are available, namely, the wind tunnel testing and the theoretical predictions. The experimental approach is still superior to the theoretical and CFD approaches till now [3]. In the experimental approach, one major challenge is estimating the aerodynamic derivatives which is the subject of this paper.

Parameters identification is becoming an indispensable tool for many applications, the range of identification techniques is quietly wide ranging from conventional approaches which depend on the theoretical framework of the problem at hand to neural networks and similar modern approaches.

Parameter identification in aerodynamics is taking steady steps in aerospace applications since sometime [5] and specifically neural network which is gaining more popularity [6].

Neural networks have emerged as one of the promising tools in the area of system identification of nonlinear systems. The popularity of neural networks is due to their ability to learn from its environment in supervised as well as unsupervised ways, plus the universal approximation property of neural networks that makes them highly suited for solving difficult signal processing problems.

In automotive aerodynamics, identification is still new [7] and in this work neural network is used for the first time in getting the aerodynamic derivatives for simple automotive bodies.

II. Methodology

A method for estimating the transient aerodynamic data from dynamic wind tunnel tests have been proposed and employed by Mansor [7] to investigate the unsteady response of simple automotive type bodies. The experimental setup consists of the test model mounted to the oscillating model facility and subjected to a single degree of freedom of pure yawing motion.

The oscillating rig is mounted on the roof of the 1.9 × 1.3 m low speed wind tunnel in the Department of Aeronautical and Automotive Engineering at Loughborough University. The oscillator mechanism is mounted to a rigid support structure outside the working section and the circular section steel rod, of 20 mm diameter, passes through a clearance hole in the ceiling. Fig. 1 shows the model setup in wind tunnel test section. The model is mounted to the end of the support rod and is free to rotate in yaw. The angular position of the model is recorded using a low friction potentiometer mounted to the top of the support rod. The combination of the tunnel flow and model oscillation then represents an

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N. Ramli is with the Universiti Teknologi Malaysia, Skudai, 81310 Johor, Malaysia (phone: 6012-9011345; email: nabilah@iiu.edu.my).

S. Mansor is with the Universiti Teknologi Malaysia, Skudai, 81310 Johor, Malaysia (email: shuhaimi@fkm.utm.my).

H. Jamaluddin is with Universiti Teknologi Malaysia, Skudai, 81310 Johor, Malaysia (phone: 6075537782; email: hishamj@fkm.utm.my)

W. F. Faris is with International Islamic University Malaysia, Jalan Gombak, 53100 Kuala Lumpur, Malaysia (email: waleed@iiu.edu.my)

unsteady wind input.

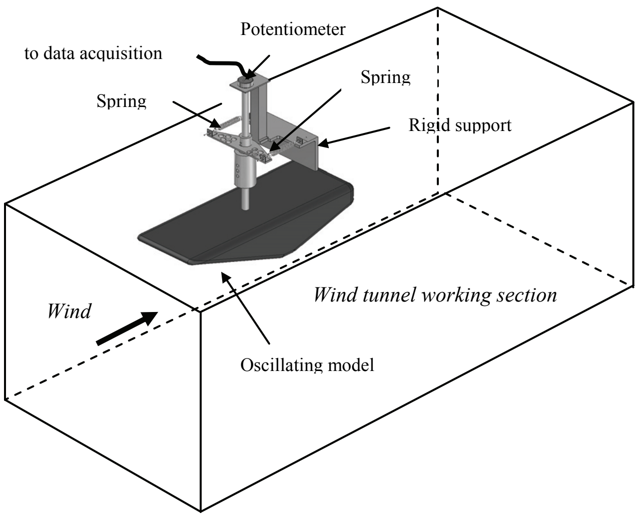

Fig. 1. Oscillating model in the wind tunnel working section [7]

The model employed in the study is a simplified bluff body that represents a road vehicle shape, a Davis model. The model is approximately 1/6 scale of an average road car. The detailed model specifications for 20° rear slant angle are given in Table I [7].

TABLE I. SPECIFICATION OF DAVIS MODEL

Parameters	
Width (m)	0.225
Height (m)	0.160
Length (m)	0.625
Ground Clearance (m)	0.040
Frontal Area (m^2)	0.036
Side Area (m^2)	0.063
Mass (model + oscillating mechanism) (kg)	4.689
Moment Inertia (kgm^2)	0.11
Material	GRP/ Composite

The moment of inertia of the system (model and support system) is determined experimentally from the wind-off free oscillation tests. The moment of inertia is given by the relationship between the natural frequency and torsional stiffness for a series of different spring stiffness.

$$I_{zz} = \frac{K_r}{\omega_n^2} \quad (1)$$

The characteristic of the series of different springs used in the study is shown in Table II.

TABLE II. SPRINGS TORSIONAL STIFFNESS AND THE CORRESPONDING MEASURED OSCILLATION FREQUENCY

Spring Number	Torsion Stiffness (Nm/rad)	Measured frequency (Hz)
1	0.98	0.4915
2	2.38	0.7749
3	4.28	1.0667
4	6.12	1.3167
5	16.12	2.0333
6	21.02	2.3083
7	35.02	2.8167
8	44.84	3.3917
9	51.88	3.5917
10	67.98	4.1407

A graph is plotted for a series of K_r against ω_n and the moment of inertia is given by the gradient of the graph.

The yaw motion was measured at 1 kHz sampling frequency. The experiment was carried out in two modes; wind-off oscillation and wind-on oscillation [7]. For a one degree of freedom system, the equation of motion to represent the dynamic response with pure yawing motion is given by:

$$I_{zz}\ddot{\beta} + C_r\dot{\beta} + K_r\beta = \sum N_a(t) \quad (2)$$

Where β, $\dot{\beta}$ and $\ddot{\beta}$ are yaw angle, yaw rate and yaw acceleration respectively while I_{zz}, C_r and K_r representing model yaw inertia, mechanical damping and mechanical stiffness. The term in the right-hand side of the equation, $\sum N_a(t)$ is the total aerodynamic yaw moment representing the input function. For simplicity, only the dynamic yaw moment are considered as the input function. The stiffness and damping approach is adapted to estimate the unsteady aerodynamic derivatives. The dynamic yaw moment can be written as:

$$N_a(t)_{dynamic} = K_a\beta + C_a r \quad (3)$$

The K_a that is in phase with the displacement of motion is regarded as the aerodynamic stiffness while C_a that is in phase with the velocity of the motion is considered as an aerodynamic damping. The aerodynamic damping and aerodynamic stiffness, respectively is given by:

$$K_a = \frac{1}{2}\rho V^2 AlC_{n\beta} = N_\beta \quad (4)$$

$$C_a = \frac{1}{2}\rho V^2 AlC_{nr}\frac{l}{V} = N_r \quad (5)$$

where ρ, V, A and l represents the air density, wind runnel speed, frontal model area and characteristic model length respectively. $C_{n\beta}$and C_{nr} are the yaw moment derivative and the yaw damping derivative.

Combining equation (2) and (3) and rearrange it, the system's characteristic equation is presented as:

$$\ddot{\beta} + \frac{(C_r - C_a)}{I_{zz}}\dot{\beta} + \frac{(K_r - K_a)}{I_{zz}}\beta = 0 \tag{6}$$

The expression $\left(-\frac{K_a}{I_{zz}}\right)$ is termed as the normalized aerodynamic yaw moment, $\hat{N}_\beta$ and the aerodynamic yaw damping, $\hat{N}_r$ is given by $\left(-\frac{C_a}{I_{zz}}\right)$.

A. Conventional Approach for Aerodynamic Coefficient Estimation

From the measured time response data, the transient aerodynamic loads were extracted by means of a conventional method where the frequency of oscillation was obtained through power spectral density and the time to half amplitude was calculated from the rate of decay of the peak amplitude.

The two parameters are used to calculate the aerodynamic damping and stiffness by using Eq. (7) and (8).

$$\hat{N}_\beta = -\left\{4\pi^2 f_o^2\left(\left[\frac{f}{f_o}\right]^2 - 1\right) + 0.6931^2\left(\frac{1}{(t_{1/2})^2} - \frac{1}{(t_{1/2})_o^2}\right)\right\} \tag{7}$$

$$\hat{N}_r = -1.3863\left[\frac{1}{(t_{1/2})} - \frac{1}{(t_{1/2})_o}\right] \tag{8}$$

The symbol f represents the damped frequency and $t_{1/2}$ is the time to half amplitude. The subscript o denotes the wind-off condition. Through equation (4) and (5), the non-dimensional aerodynamic derivatives of $C_{n\beta}$ and C_{nr} are obtained.

However, the existence of nonlinearity in the real system makes the conventional linear method less appropriate. In the next chapter, Neural Network is introduced as an alternative technique to estimate the aerodynamic coefficients.

B. Neural Network Approach for Aerodynamic Coefficient Estimation

The system's characteristic equation in (6) is similar to the standard second order dynamic system equation.

$$s^2 + 2\zeta\omega_n s + \omega_n^2 = \Delta s \tag{9}$$

Comparing equations (6) and (9),

$$\left(\frac{C_r}{I_{zz}} - \frac{C_a}{I_{zz}}\right) = 2\zeta\omega_n \tag{10}$$

and

$$\left(\frac{K_r}{I_{zz}} - \frac{K_a}{I_{zz}}\right) = \omega_n^2 \tag{11}$$

The mechanical terms, i.e. $\frac{K_r}{I_{zz}}$ and $\frac{C_r}{I_{zz}}$ can be determined from wind-off test while the aerodynamic terms can be evaluated by extracting the mechanical terms from equations (10) and (11).

The estimation of the aerodynamic coefficients is carried out based on the recorded time series data. Thus, a construction of a static neural network to represent this dynamic system is adequate. Multilayer feedforward neural network (MFNN) is utilized to determine the damping ratio, ζ and natural frequency, ω_n of the oscillation. The structure of the network is selected based on trial and error approach.

Two MFNNs are constructed, each to determine the ζ and ω_n respectively. The first network is a 100-5-5-1 network with the time response data as the input and ζ as the output. The second network's structure is 2-2-5-1 with ζ and the period-of-3 cycles, t_3, as the input, and ω_n as the output.

For this static network, batch training is used where the weights and biases are only updated after all of the inputs and targets are presented, The data was first preprocessed before it is fed to the network since the training of the network can be more efficient if certain preprocessing steps are performed on the network inputs and outputs. The time response data are normalized and with zero mean. For the second network input, the mean is also removed and it has unity standard deviation. These steps are very useful so that the data always fall within a specified range before using it for training the network.

III. Neural Network Training and Validation

Since the estimation of the aerodynamic derivatives in [7] was based on a conventional standard second order dynamic system, a set of data can be generated from the standard normalized time response of a second order transfer function:

$$G(s) = \frac{\omega_n^2}{s^2 + 2\zeta\omega_n + \omega_n^2} \tag{12}$$

The network was trained using a set of impulse response of the transfer function for various ζ and ω_n values. The y-axis was normalized such that the maximum amplitude is 1 and the x-axis is the value of $\omega_n t$.

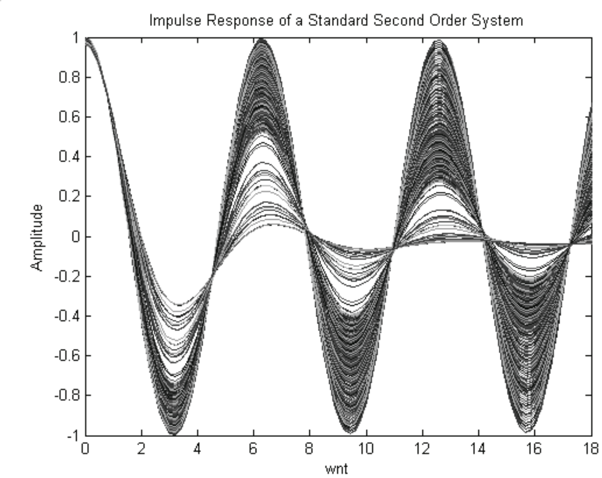

Fig. 2. Standard plot for impulse response of standard second order system

Only the first complete three cycles is used as the input to the first network as shown in Fig. 2. The training data covers the damping ratio range of 0.001-0.35 and the ω_n ranges from 0.4-26 rad/s. The range of the training data was selected based on the resulted natural frequency and damping ratio from the conventional method. For the second network, the resulted ζ and t_3 were used as the inputs. The inputs were scaled with appropriate scaling factor before feeding it to the second network. The outputs then were scaled back to give the estimated ω_n value.

The networks were trained using backpropagation (BP) algorithm. The BP algorithm is a basic and the most effective weight updating method of MFNN [8]. However, BP algorithm has an issue in determining the optimal number of input and hidden neurons as well as the hidden layers, and usually they have to be determined by trial and error.

Sometimes, overfitting may occur during training the network. The error of the training set is driven to a very small value, but when a new data is presented to the network, a large error is produced. The network managed to memorize the training examples but yet, failed to learn to generalize new situations.

Generalization may be achieved by the network by means of regularization. This involves modifying the performance function, which is normally chosen to be the sum of squares of the network errors on the training set. The network error, *e*, is defined as the difference between the target output, *t*, and the network output, *a*. A typical performance function that is used for training feedforward neural networks is the sum of squares of the network errors.

$$F_e = \sum_{i=1}^{N} \left(e_i\right)^2 = \sum_{i=1}^{N} \left(t_i - a_i\right)^2 \qquad (13)$$

It is possible to improve generalization if the performance function is modified by adding a term that consists of the sum of squares of the network weights and biases, *w*.

$$F_{reg} = \gamma F_e + (1-\gamma) F_w \qquad (14)$$

where γ is the performance ratio, and

$$F_w = \frac{1}{n} \sum_{j=1}^{n} w_j^2 \qquad (15)$$

Using this performance function will cause the network to have smaller weights and biases, and this will force the network response to be smoother and less likely to overfit [9].

The weight and bias values are updated according to Levenberg-Marquardt optimization. It minimizes a combination of squared errors and weights and, then determines the correct combination so as to produce a network which generalizes well. The process is called Bayesian regularization.

The Bayesian framework of David MacKay [9] is an approach used to determine the optimal value of the performance ratio in an automated fashion. In this framework, the weights and biases of the network are assumed to be random variables with specified distributions. The regularization parameters are related to the unknown variances associated with these distributions. These parameters can be estimated using statistical techniques. Detailed of the Bayesian regularization, in combination with Levenberg-Marquardt training, can be reviewed in [10].

After proper training, the networks were tested with another set of data. Fig. 3 shows the errors produced by the network when the networks were simulated with another set of training data, a set of generated data that were not used during network training. The error between the estimated damping ratio and natural frequency and the corresponding target value were calculated. From the percentage error plot, it shows that the networks are capable to give a very close estimation with the real value.

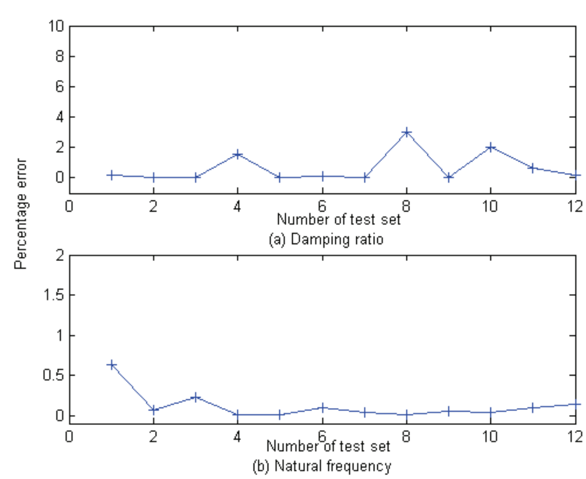

Fig. 3. Error from neural network estimation (a) damping ratio, (b) natural frequency

For validation, the networks were simulated with the measured time response data. With the resulted ζ and ω_n, another response was generated from the system transfer function:

$$G(s)=\frac{s+2\zeta\omega_n}{s^2+2\zeta\omega_n+\omega_n^2} \tag{16}$$

and compared with the measured data as shown in Fig. 4 and the magnified view in Fig. 5.

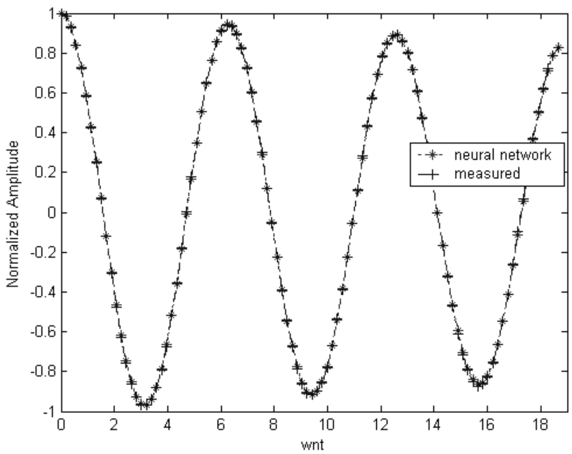

Fig. 4. Comparison between the measured time response data and the response generated based on networks results

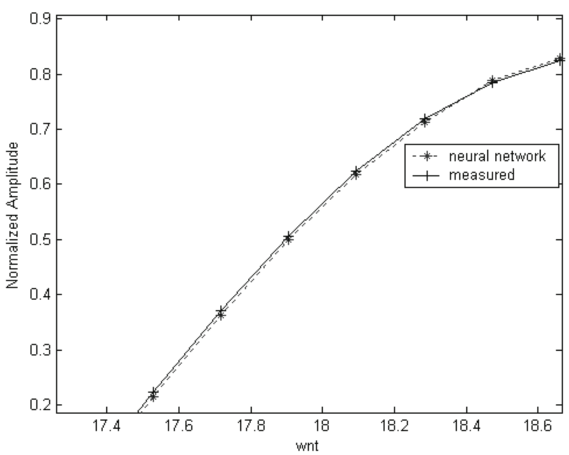

Fig. 5. Magnified view of Fig. 4

The result shows that the response that was generated based on the neural network results are close to the original measured time response. However, when the networks were simulated with the following 3 cycles consecutively from the same measured time response, the results varies especially the ζ value as summarized in Table III. This variation indicates the inherent nonlinearity in the system.

TABLE III. VARIATION IN THE RESULTS AS THE FOLLOWING 3 CYCLES CONSECUTIVELY ARE RUN THROUGH THE NETWORK

Cycle sequence	ζ	ω_n
1^{st} 3 cycle	0.0091	12.4332
2^{nd} 3 cycle	0.0086	12.4992
3^{rd} 3 cycle	0.0079	12.5074
4^{th} 3cycle	0.0074	12.5658
5^{th} 3 cycle	0.0059	12.5570
6^{th} 3 cycle	0.0056	12.5654
7^{th} 3 cycle	0.0065	12.5824
8^{th} 3 cycle	0.0065	12.6331

Here it is clearly shown that the representation of 3 complete cycles from the measured time response does not accommodate the whole response due to nonlinearity. However, the choice of feeding 3 complete cycles to the network is justifiable for the network can work on a wider range of ζ.

Due to the nonlinearity, the average value of ζ and ω_n will be used to calculate the stability derivatives for solving case in hand.

IV. APPLICATION OF NEURAL NETWORK

By subtracting the mechanical terms i.e. that are evaluated from the wind-off test, from equation (10) and (11), the normalized aerodynamic yaw moment $\hat{N}_\beta$ and normalized aerodynamic yaw damping $\hat{N}_r$ are obtained.

The non-dimensional aerodynamic derivatives of $C_{n\beta}$ and C_{nr} are given by the following expressions:

$$C_{n\beta}=\frac{\hat{N}_\beta I_{zz}}{\frac{1}{2}\rho V^2 Al} \tag{17}$$

$$C_{nr}=\frac{\hat{N}_r I_{zz} V}{\frac{1}{2}\rho V^2 Al^2} \tag{18}$$

Table IV compares the aerodynamic derivatives estimated via neural network and the conventional method. The results from neural network are close to the results obtained from the conventional method.

TABLE IV

	Cn_{β}	Cn_{r}
Derivatives obtained from Neural Network	0.4719	-0.1033
Derivatives obtained from Conventional method	0.49519	-0.11397

Fig. 6 shows the time response plot based on estimated $C_{n\beta}$ and C_{nr} between conventional method and neural network, and the measured time response. It is shown that the plot from neural network estimation is closer to the measured response. However, both estimated aerodynamic derivatives either from the conventional method or the neural network approach are based on the average values of the damping ratio and natural frequency of the response.

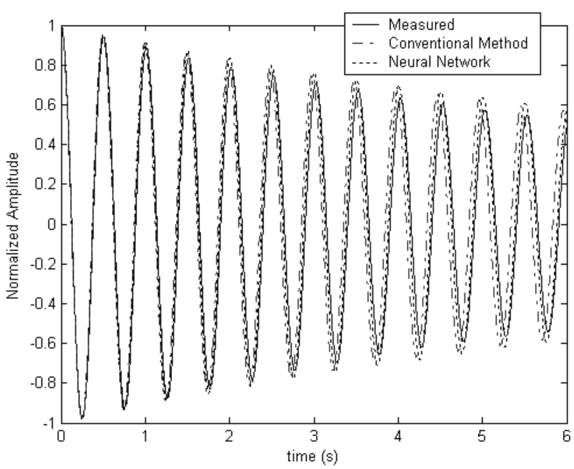

Fig. 6. Comparison of time response plot based on estimated $C_{n\beta}$ and C_{nr} between conventional and neural network, and measured data

V. CONCLUSION

In this study, the combination of Neural Network and an oscillating model facility as a novel approach in estimating the aerodynamic derivatives of simple automotive bodies is used. The technique was compared with conventional approach which was used earlier in the literature for the same test data and the results were in favor of the neural network. This could be resulted from the inherent nonlinear nature of the problem which the conventional methods, that are linear in nature, can not accommodate properly. However the ability of neural network in estimating aerodynamic derivatives for a nonlinear response will require further research.

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