International Journal of Innovative Computing, Information and Control
Volume **14**, Number **3**, June **2018**
ICIC International ©2018 ISSN 1349-4198
pp. 959–969

COMPARATIVE STUDY OF ARTIFICIAL NEURAL NETWORK AND MATHEMATICAL MODEL ON MARINE DIESEL ENGINE PERFORMANCE PREDICTION

Che Wan Mohd Noor[1,2,*], Rizalman Mamat[1] and Ali Najah Ahmed[3,4]

[1]Faculty of Mechanical Engineering
Universiti Malaysia Pahang
Pekan 26600, Pahang Darul Makmur, Malaysia
*Corresponding author: che.wan@umt.edu.my; rizalman@ump.edu.my

[2]School of Ocean Engineering
Universiti Malaysia Terengganu
Kuala Terengganu 21030, Terengganu, Malaysia

[3]College of Engineering
[4]Institute for Energy Infrastructures
Universiti Tenaga Nasional
Jalan Ikram Uniten, Kajang 43000, Selangor, Malaysia
mahfoodh@uniten.edu.my

Received May 2017; revised November 2017

Abstract. *The investigation of marine diesel engines is still limited and considered new in both: physical testing and prediction. Therefore, this study deals with an artificial neural network (ANN) modeling for a marine diesel engine performance prediction such as the brake power (BP), brake specific fuel consumption (BSFC), brake thermal efficiency (BTE), volumetric efficiency (VE), exhaust gas temperature (EGT) and nitrogen oxide (NO_X) emissions. Input data for network training was gathered from laboratory engine testing operated at various speed, load and fuel blends. ANN prediction model was developed based on standard back-propagation with Levenberg-Marquardt training algorithm. The performance of the model was validated by comparing the prediction data sets with the experimental data and the output from the mathematical model. Results showed that the ANN model provided a good agreement to the experimental data with the coefficient of determinations (R^2) of 0.99. Mean absolute prediction error (MAPE) of ANN and the mathematical model is between 1.57-9.32% and 4.06-28.35% respectively. These values indicate that the developed ANN model is more reliable and accurate than the mathematical model. The present study reveals that the ANN approach can be used to predict the performance of marine diesel engine with high accuracy.*

Keywords: Artificial neural network, Mathematical model, Marine diesel engine, Engine performance

1. **Introduction.** Marine transportation activities are mostly driven by marine diesel engines due to their efficiency and robustness. Marine diesel engine is nearly identical to land-based automotive. Generally it is larger in size and is equipped with fairly complicated system to operate in a higher efficiency [1]. Marine engines provide the major power sources for sea transportation. Marine diesel engine can be classified into slow, medium, and high speed diesel engines based on their principle of operation. Performance of the marine engine not only depends on the principle of operation, but also on the type, the size, the power, the load, the speed, etc. However, emissions from marine engines are considered as one of the major sources of air pollution which can seriously threaten the environment [2]. Study by Eyring et al. and Corbett et al. reported, about 14-31%, 4-9%,

and 3-6% of global emissions of NO_X, SO_X, and CO_2, respectively, are from combustion process of marine engines [3,4].

On the other hand, increasing energy demand, volatile of crude oil prices, depleting oil reserves and environmental pollution problems associated with the use of fossil fuels has urged ship owners to improve the efficiency of their marine engine performance. In order to carry out further investigations on engine efficiency, intensive laboratory study on marine engines must be taken. Nevertheless, testing marine diesel engine for the complete range of operating conditions and fuel cases consumes a lot of time and money. As an alternative, the artificial neural network (ANN) and mathematical model can be used to determine engine performance and exhaust emissions. ANNs technique was a well-known evolutionary computation method, which ensures the prediction of the system variables without requiring mathematical expressions [5]. ANN modelling has been chosen by its ability to solve complex and difficult problem where the conventional methods fail. The prediction by a well-trained ANN is normally much faster than the conventional simulation programs as no lengthy iterative calculations are needed to solve differential equations. However, instead, the selection of appropriate neural network topology is important in terms of model accuracy and model simplicity. The application of the ANN model in determining the performance of the internal combustion engine has grown rapidly in recent years.

Oğus et al. predicted the performance of biofuel in compress ignition engine using ANN model [6]. They revealed that the model reliability value was 99.94% in predicting the engine performance parameters. Kapusuz et al. investigated the various alcohol-gasoline blends in a spark-ignition engine using neural network model [7]. The results yield a higher regression value, such as 0.9906, 0.997, and 0.9312 for torque, brake power and brake specific fuel consumption, respectively. Evaluating the linear regression model against artificial neural network in predicting diesel engine exhaust gas emissions was carried out by Tosun et al. [8]. The model was set up in multi-layer feedforward networks and trained by back propagation algorithm. In recent work, Gürgen et al. predict the cyclic variation in the diesel engine operated with diesel-butanol blends [9]. The results reveal that the ANN model can predict with a high overall accuracy. The correlation coefficient value is between 0.858-0.983 and the predicted error value is below 9%. Syed et al. utilized an ANN model as a tool to investigate the performance of hydrogen fuel in diesel engine [10]. The model was trained with 16 sets of data and seven training algorithms. The authors concluded back propagation algorithm is the best among other algorithms with regression coefficient ranging between 0.9869-0.9996. There are more studies using ANN models in predicting the characteristics of internal combustion engines [11-18].

Based on the literature, many studies have been carried out in connection with automotive engines; however, investigation of marine diesel engines is still limited and considered new in both: physical testing and prediction. Therefore, the aim of this study is to predict the performance parameters of marine diesel engine by using artificial neural network and compared with mathematical approach. This study involves two stages, where in the first stage, performance tests are performed on the marine diesel engine while in the second stage the data from the experiments will be used for training and prediction of the ANN models. ANN's prediction outputs were validated with the mathematical model and other experimental data.

2. Methodology.

2.1. Experimental setup.

The experiment was conducted using direct injection, 4-stroke six-cylinder marine diesel engine. The engine was fully instrumented and connected to the data acquisition system. The full setup and detailed specification of the test engine are presented in Figure 1 and Table 1 respectively. A 250 kW eddy-current dynamometer was attached to the engine to measure engine brake power and torque. Fuel consumption and air flow rate were measured using positive displacement KOBOLD flowmeter and TAYLOR air flowmeter respectively. The engine was equipped with K-type thermocouples and resistance temperature detectors (RTD) for temperature measurement. The exhaust stream of the engine was diverted to KANE gas analyzer (as shown in Figure 2) from which exhaust emissions were measured. The schematic diagram of whole experimental setup is given in Figure 3.

Figure 1. Full setup of marine diesel engine

Figure 2. KANE gas analyzer

Table 1. Marine diesel engine specification

Engine model	Cummins NT-855
Engine type	4-stroke, 6-cylinder
Bore × stroke	139 mm × 152 mm
Displacement volume	14 litre
Compression ratio	14.5
Maximum torque	1068 Nm
Maximum power	201 kW
Cooling system	Water cooling

The experiments were carried out by using the different blends of biodiesel-diesel fuel: B0, B5 (5% biodiesel + 95% diesel), B10 and B15. The test fuels were prepared by mixing pure diesel (B0) with certified local palm oil biodiesel. Biodiesel is commonly recognized as an alternative fuel for industry [22]. The tests were carried out under steady-state condition at 50% engine loads and various engine speeds ranging from 800-1600 rpm. Before each test, the engine was warmed up at idling condition until the cooling water temperature reached at 80-85°C. The desired parameters such as engine speeds, torque, brake power, fuel consumption, exhaust gas temperature and emissions were measured, while the brake specific fuel consumption, brake thermal and volumetric efficiency were computed later.

2.2. **ANN model.** ANN model is a computational model based on the structure and functions of biological neural networks. ANN is the preferred predictive tool for many applications because of their ability to work with complex and nonlinear model [23]. The model network usually consists of an input layer, hidden layers, and an output layer. Back

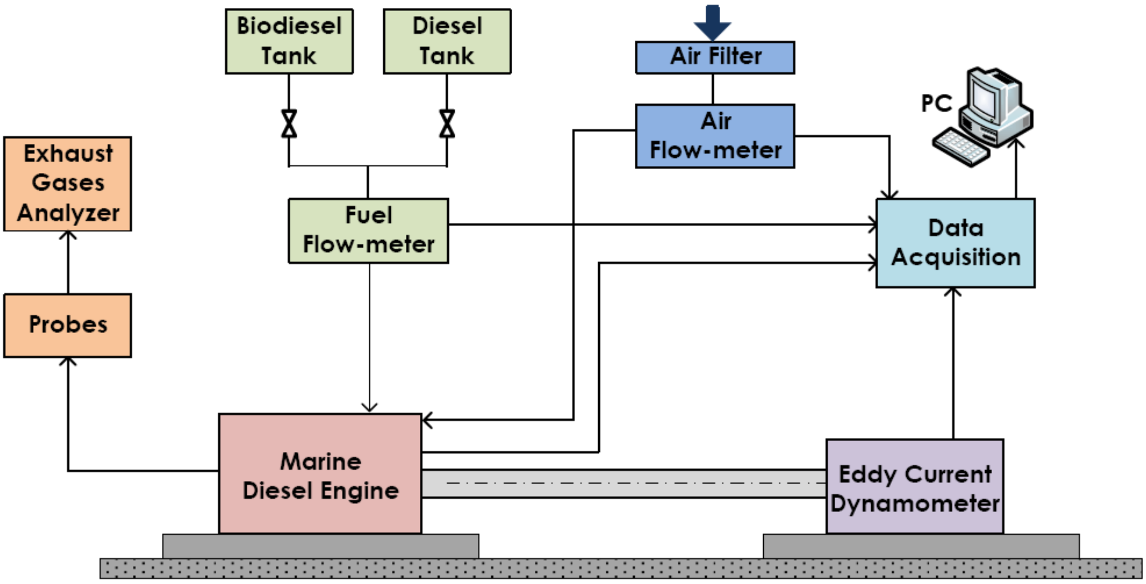

FIGURE 3. Schematic diagram of the experimental setup

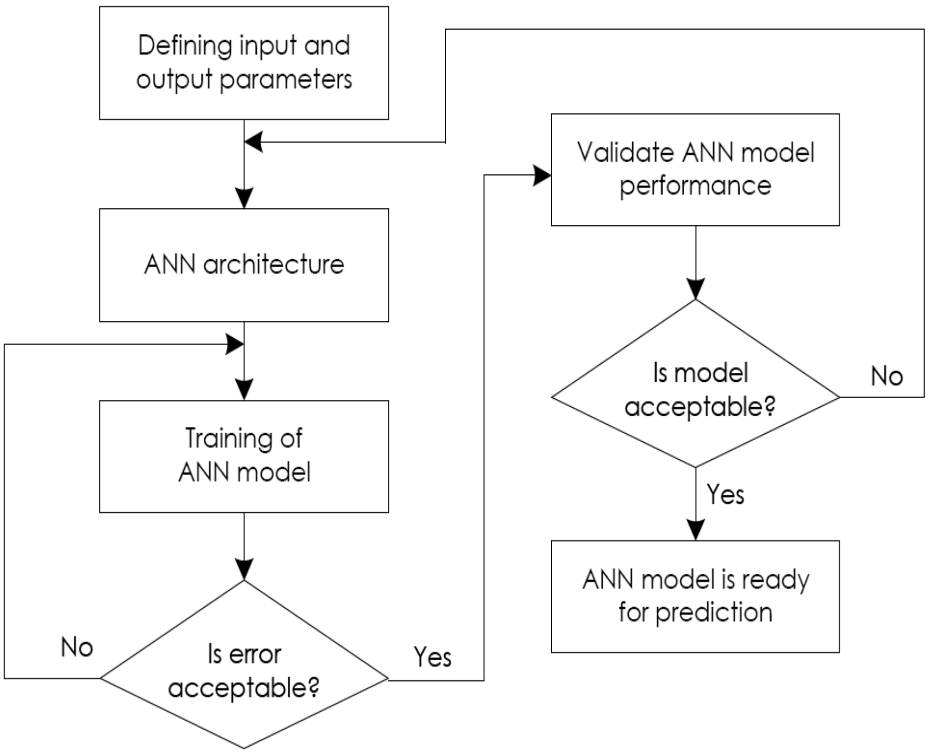

FIGURE 4. ANN model flowchart

propagation neural network (BPNN) is a popular algorithm used to supervise training as the network weights and biases are initialized randomly at the initial phase. The details about ANN theory can be found in [23-25]. The model was developed using Matlab neural network toolbox as accordance to the flowchart shown in Figure 4. The results of the engine test were collected as an input data where 70% of the datasets were randomly selected as training data, while the remaining 30% of data was used for model validation. This prediction model is based on multilayer perceptron (MLP) of one hidden layer architecture, to reduce local minima and improve the prediction accuracy. MLP

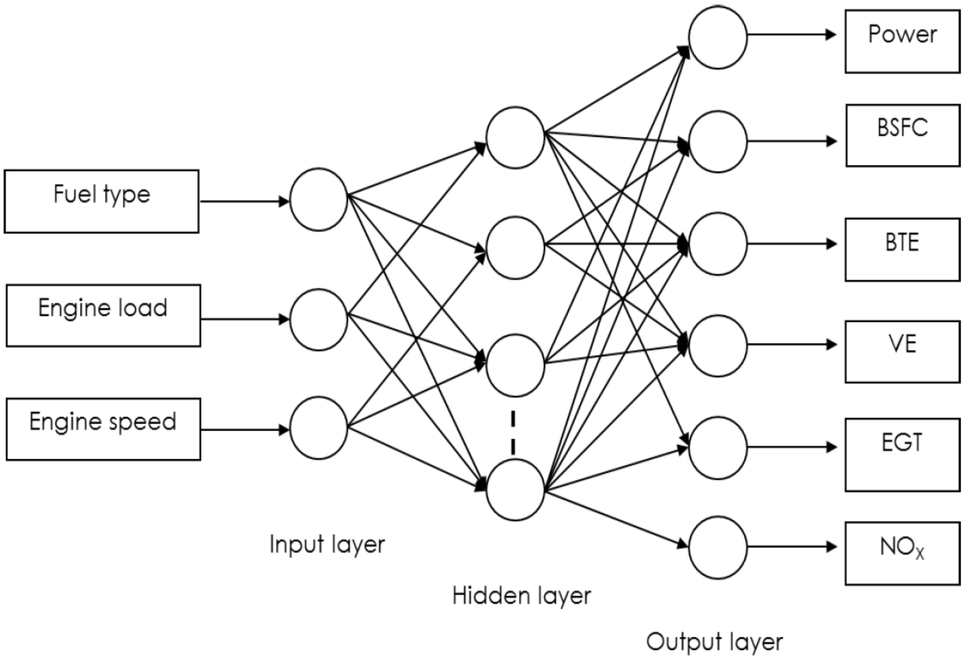

FIGURE 5. ANN model structure

TABLE 2. ANN configuration for model training

Parameter	Specification
Input layer neurons	3
Hidden layer	22
Output layer neurons	6
Training function	Levenberg-Marquardt
Performance function	Mean square error
Activation function	Log-sigmoid, Linear
Performance goal	1.0×10^{-3}

shows the most promising performance compared to the other types of ANN's models [26].

The prediction model structure comprises three input layers, one hidden layer and six output layers as shown in Figure 5. Back propagation architecture with one hidden layer is sufficient enough for many ANN modelling [27]. The model configuration for data training was based on specification in Table 2. Choosing the optimum network architecture is one of the challenging steps in neural network modelling. In order to find an optimal architecture, different numbers of neurons in the hidden layer were varied between 10-26 neurons by trial and error method to avoid large number of weights in the training process. Training results show that the values of root mean square error (RMSE) are not directly proportional to the number of neurons in the hidden layer. It is found that the reduction in the number of neurons will reduce the network performance, while the increase in the number of neurons beyond 22 does not have a significant increase in the training performance. Therefore, the number of 22 neurons was selected as the optimum neurons in the hidden layer. The final configuration comprises three neurons in the input layer, twenty-two neurons in hidden layer and six neurons in the output layer. Log-sigmoids and linear activation functions have been selected because they work well in nonlinear phenomena such as in assessing the relationship between marine engine input and output parameters. The Levenberg-Marquardt training algorithm has been used to calculate the weight and bias value as it provides the fastest training speed and convergence time for the backpropagation model [28]. Performance goals have been set as 1.0×10^{-3} to improve the accuracy of prediction model.

In order to avoid complicated ANN learning process caused by large input values, all inputs and outputs are normalized between 0 and 1 for minimum and maximum values according to Equation (1).

$$X_n = \frac{X - X_{\min}}{X_{\max} - X_{\min}} \tag{1}$$

where X_n is the normalized value of a variable X (real value in a parameter), and $X_{\max}$ and $X_{\min}$ are the maximum and minimum values of X, respectively.

The accuracy and quality of the prediction model are evaluated by the criteria of root mean squared error (RMSE), coefficient of determinations (R^2) and mean absolute prediction error (MAPE). RMSE represents the average difference between the predicted and the experiment data. Meanwhile, R^2 is a measure of how well the regression line represents the actual dataset. It can vary between 0-1, where R^2 close to 1 indicates the perfect ANN prediction model. MAPE parameter shows the prediction error in the ANN model. All these parameters can be determined based on the following equations:

$$\mathrm{RMSE} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(y_i - y_k)^2} \tag{2}$$

$$\mathrm{R}^2 = 1 - \frac{\sum_{i=1}^{N}(y_i - y_k)^2}{\sum_{i=1}^{N}(y_i - \bar{y})^2} \tag{3}$$

$$\mathrm{MAPE} = \frac{1}{N}\sum_{i=1}^{N}\left|\frac{y_i - y_k}{y_i}\right| \tag{4}$$

where y_i and y_k are the actual and predicted data of the ith output neuron respectively, $\bar{y}$ is the actual mean value and N is the total number of data.

2.3. **Mathematical model.** The mathematical model based on multiple regression techniques has been developed to predict the relationship between the input and output parameters of the marine diesel engine. This technique gives the best prediction between the variables by adopting the least square method approach. The multiple regression equation is based on the following equation:

$$Y = a + b_1X_1 + b_2X_2 + b_3X_3 + \cdots + b_kX_k \tag{5}$$

where Y is the predicted dependent variable. X_1, X_2, X_3, …, X_k are the known variables on which the prediction is to be made and a, b_1, b_2, b_3, …, b_k are the coefficients.

The coefficient of mathematical model equations has been calculated using the SPSS commercial statistics program. The dataset from the experimental results is used as input data to the model and the final prediction equation has been developed as follows:

$$\mathrm{BP} = -37.660 + 0.007F + 1.249L + 0.032S \tag{6}$$

$$\mathrm{BSFC} = 1244.122 + 8.468F - 17.427L - 0.226S \tag{7}$$

$$\mathrm{BTE} = -5.462 - 0.198F + 0.601L + 0.008S \tag{8}$$

$$\mathrm{VE} = -26.018 + 0.021F + 0.095L + 0.061S \tag{9}$$

$$\mathrm{EGT} = 11.597 + 0.294F + 2.478L + 0.085S \tag{10}$$

$$\mathrm{NO_X} = 63.422 + 1.371F + 8.219L - 0.075S \tag{11}$$

where BP is brake power, BSFC is brake specific fuel consumption, BTE is brake thermal efficiency, VE is volumetric efficiency, EGT is exhaust gas temperature, NO_X is nitrogen oxide, F is fuel type, L is the engine load and S is the engine speed.

3. **Results and Discussion.** Prediction for marine diesel engine performance has been performed by using ANN back-propagation trained with the Levenberg-Marquardt algorithm. The optimum architecture of the built ANN model is 3-22-6. Criteria R^2 and MAPE have been selected to evaluate network accuracy. Regression analysis between the corresponding network output and target was performed to investigate the network's response in more detail. The results show that the model is sufficient to predict the performance of marine diesel engines at different engine speed, load and ratio of fuel blends ratio. Relations of ANN model predictions with experimental data on engine performance parameters are illustrated in Figure 6. It shows a good correlation between the model and the experiment as indicated by the higher value of R^2 which is close to unity. The

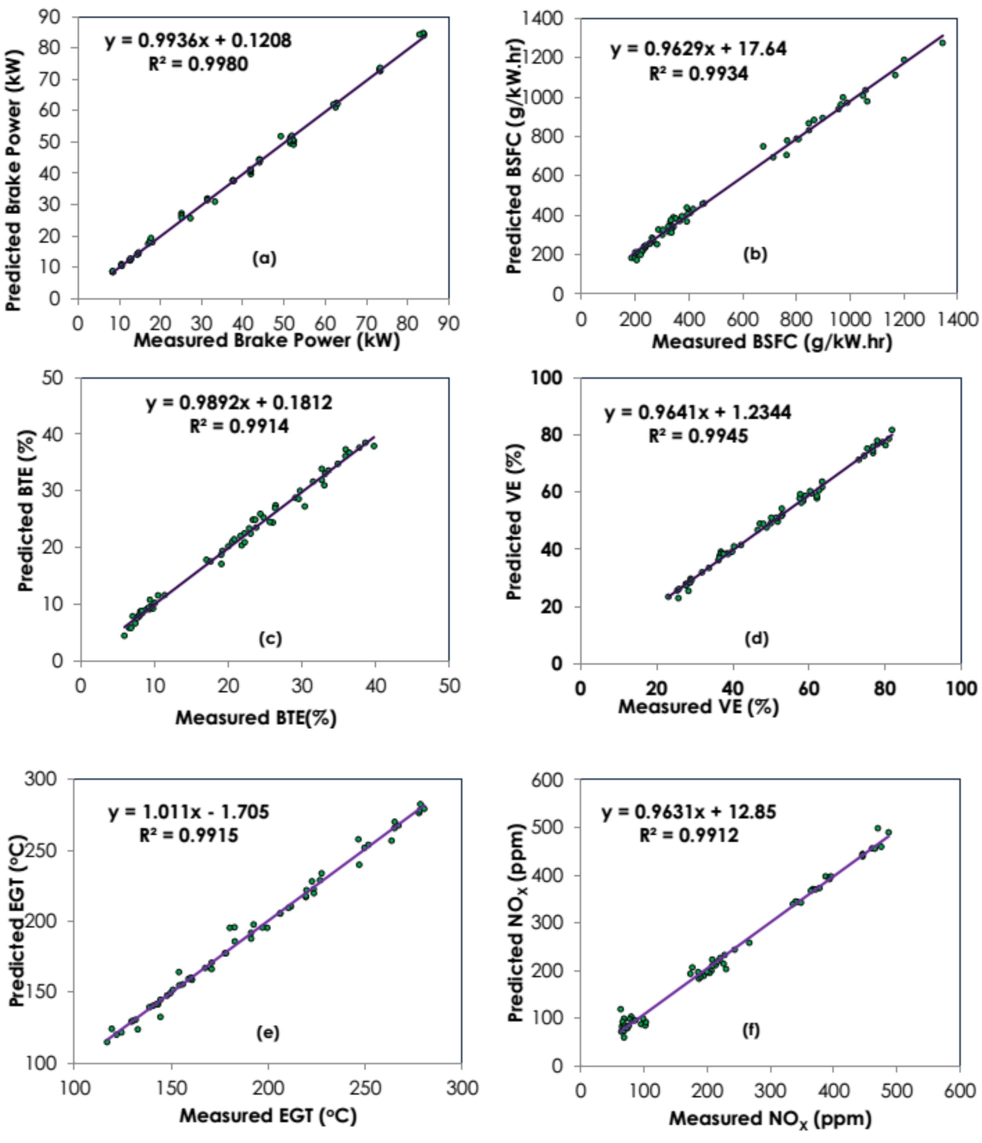

FIGURE 6. The relationships between predicted and actual measured data for (a) BP, (b) BSFC, (c) BTE, (d) VE (e) EGT and (f) NO_X

TABLE 3. Summarized R^2 value of ANN and mathematical model

Outputs	R^2	
	ANN model	Mathematical model
Brake Power	0.9980	0.9556
BSFC	0.9934	0.8455
BTE	0.9914	0.9751
VE	0.9945	0.9823
EGT	0.9915	0.9638
NO_X	0.9912	0.9590

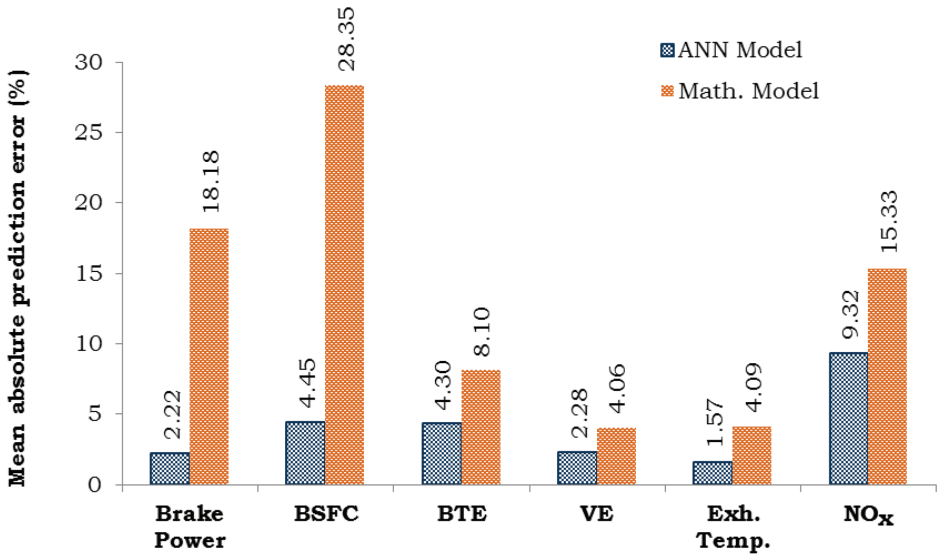

FIGURE 7. Mean absolute prediction error for ANN and mathematical model

ANN predictions for (a) brake power, (b) brake specific fuel consumption, (c) brake thermal efficiency, (d) volumetric efficiency, (e) exhaust gas temperature and (f) nitrogen oxide yield a coefficient of determinations (R^2) of 0.9980, 0.9934, 0.9914, 0.9945, 0.9915 and 0.9912 respectively. Meanwhile, the R^2 values of mathematical model for the same output parameters are 0.9556, 0.8455, 0.9751, 0.9823, 0.9638 and 0.9590. ANN model produces higher R^2 compared to the mathematical model, thus indicating ANN predictions are more accurate. The summary of R^2 for both models is summarized in Table 3.

The efficiency and predictability of the developed ANN and mathematical model were compared by the difference in MAPE values as shown in Figure 7. From the figure, the ANN model has a relatively low predicted error compared to the mathematical model. MAPE value of ANN model for (a) brake power, (b) brake specific fuel consumption, (c) brake thermal efficiency, (d) volumetric efficiency, (e) exhaust gas temperature and (f) nitrogen oxide was 2.22%, 4.45%, 4.30%, 2.28%, 1.57% and 9.32% respectively. Instead, the MAPE value for the mathematical model is 18.18%, 28.35%, 8.10%, 4.06%, 4.09% and 15.33% for the same output. Hence, it can be concluded that the results obtained from the ANN model are better and more accurate than mathematical model. In addition, it is very difficult to establish a relationship between process parameters and engine performance with mathematical models due to complex and non-linear relationships between them. The validation of ANN and mathematical model against the experimental data is shown

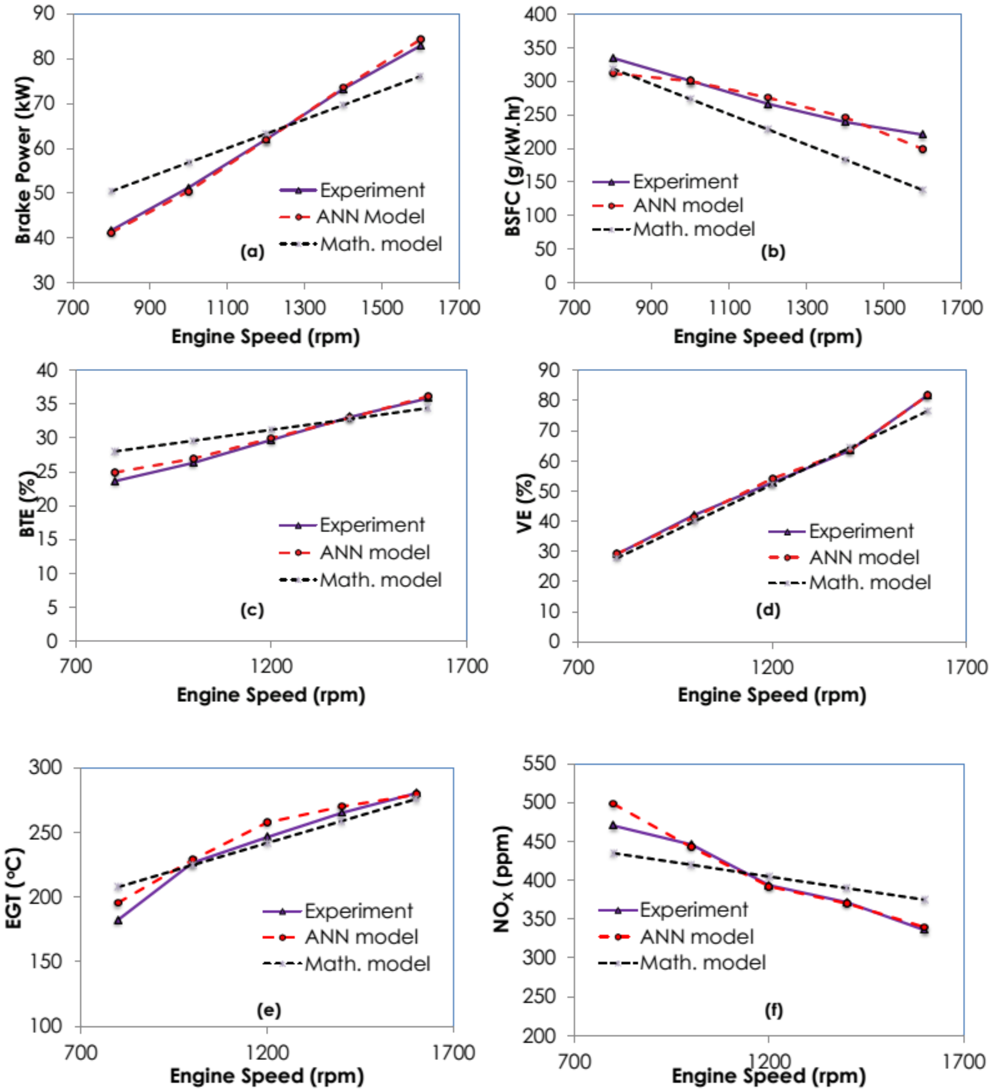

FIGURE 8. Experimental versus ANN and mathematical model for (a) brake power, (b) BSFC, (c) BTE, (d) VE, (e) EGT, (f) NO_X

in Figure 8. It shows the distribution of ANN prediction data points is almost close to the experimental data as compared with the mathematical data points. The ANN prediction provides the best fit to the experimental results and produces a better prediction of the marine diesel engine performance.

4. **Conclusions.** An artificial neural network model has been successfully developed to predict the performance of the Cummins NT-855 marine diesel engine. The ANN back-propagation model with the Levenberg-Marquardt algorithm is used to train the input data. The ANN prediction results have been compared with the mathematical model and the actual data of the experiments. The main conclusions of this study can be summarized as follows.

(i) Prediction result of the ANN model which has 22 neurons in the hidden layer was found to be in good agreement with the experimental data.

(ii) The distribution of data points of ANN model was almost similar and close to the actual experimental data with a coefficient of determinations (R^2) of 0.99. Meanwhile, the R^2 for the mathematical model was slightly lower between 0.85-0.98. This indicated the developed ANN model is capable of making the prediction with good agreement to experimental data.

(iii) The ANN model produced more accurate prediction than the mathematical model. Mean absolute prediction error (MAPE) of ANN model is between 1.57-9.32%, while MAPE for the mathematical model was between 4.06-28.35%.

(iv) Artificial neural network is a powerful tool and is easy to use in non-linear problems. The developed ANN model can be used to predict marine diesel engine performance and emission with reliable and acceptable accuracy.

Acknowledgment. The authors would like to express their deep gratitude to Department of Marine Technology, Universiti Malaysia Terengganu for providing facilities and support to carry out this research. Thanks to the Ministry of Education, Malaysia for sponsoring the main author with a scholarship under the SLAB scheme. The third author would like to acknowledge the Universiti Tenaga Nasional for the financial support under Bold Grant 10289176/B/9/2017/14.

REFERENCES

[1] M. Palocz-Andresen, *Decreasing Fuel Consumption and Exhaust Gas Emissions in Transportation*, Springer-Verlag Berlin Heidelberg, 2013.

[2] C. Wang, J. J. Corbett and J. Firestone, Improving spatial representation of global ship emissions inventories, *Environ. Sci. Technol.*, vol.42, no.1, pp.193-199, 2008.

[3] V. Eyring, H. W. Köhler, J. van Aardenne and A. Lauer, Emissions from international shipping: 1. The last 50 years, *J. Geophys. Res.*, vol.110, 2005.

[4] J. J. Corbett, C. Wang, J. J. Winebrake and E. Green, Allocation and forecasting of global ship emissions, *Clean Air Task Force*, 2007.

[5] M. Canakci, A. N. Ozsezen, E. Arcaklioglu and A. Erdil, Prediction of performance and exhaust emissions of a diesel engine fueled with biodiesel produced from waste frying palm oil, *Expert Systems with Applications*, vol.36, pp.9268-9280, 2009.

[6] H. Oğus, I. Sarıtas and H. E. Baydan, Prediction of diesel engine performance using biofuels with artificial neural network, *Expert Systems with Applications*, vol.37, pp.6579-6586, 2010.

[7] M. Kapusuz, H. Ozcan and J. Ahmad, Research of performance on a spark ignition engine fueled by alcohol-gasoline blends using artificial neural networks, *Appl. Therm. Eng.*, vol.91, pp.525-534, 2015.

[8] E. Tosun, K. Aydin and M. Bilgili, Comparison of linear regression and artificial neural network model of a diesel engine fueled with biodiesel-alcohol mixtures, *Alexandria Engineering Journal*, vol.55, pp.3081-3089, 2016.

[9] S. Gürgen, B. Ünver and Ż Altın, Prediction of cyclic variability in a diesel engine fueled with *n*-butanol and diesel fuel blends using artificial neural network, *Renew Energy*, pp.1-7, 2017.

[10] J. Syed, R. U. Baig, S. Algarni, Y. V. V. S. Murthy, M. Masood and M. Inamurrahman, Artificial neural network modeling of a hydrogen dual fueled diesel engine characteristics: An experiment approach, *International Journal of Hydrogen Energy*, vol.42, no.21, pp.14750-14774, 2017.

[11] B. Bahri, M. Shahbakhti and A. A. Aziz, Real-time modeling of ringing in HCCI engines using artificial neural networks, *Energy*, vol.125, pp.509-518, 2017.

[12] J. M. Luján, H. Climent, L. M. García-cuevas and A. Moratal, Volumetric efficiency modelling of internal combustion engines based on a novel adaptive learning algorithm of artificial neural networks, *Appl. Therm. Eng.*, vol.123, pp.625-634, 2017.

[13] S. Dharma, M. H. Hassan, H. C. Ong, A. H. Sebayang, A. S. Silitonga, F. Kusumo et al., Experimental study and prediction of the performance and exhaust emissions of mixed Jatropha curcas-Ceiba pentandra biodiesel blends in diesel engine using artificial neural networks, *J. Clean Prod.*, vol.164, pp.618-633, 2017.

[14] C. W. M. Noor, R. Mamat, G. Najafi, W. B. W. Nik and M. Fadhil, Application of artificial neural network for prediction of marine diesel engine performance, *IOP Conf. Ser. Mater. Sci. Eng.*, vol.100, 2015.
[15] G. Kökkülünk, E. Akdogan and V. Ayhan, Prediction of emissions and exhaust temperature for direct injection diesel engine with emulsified fuel using ANN, *Turkish J. Electr. Eng. Comput. Sci.*, vol.21, pp.2141-2152, 2013.
[16] H. Sharon, R. Jayaprakash, M. K. Selvan, D. R. S. Kumar, A. Sundaresan and K. Karuppasamy, Biodiesel production and prediction of engine performance using SIMULINK model of trained neural network, *Fuel*, vol.99, pp.197-203, 2012.
[17] P. Shanmugam, V. Sivakumar, A. Murugesan and M. Ilangkumaran, Performance and exhaust emissions of a diesel engine using hybrid fuel with an artificial neural network, *Energy Sources, Part A: Recovery, Utilization, and Environmental Effects*, vol.33, pp.1440-1450, 2011.
[18] Shivakumar, P. S. Pai and B. R. S. Rao, Artificial neural network based prediction of performance and emission characteristics of a variable compression ratio CI engine using WCO as a biodiesel at different injection timings, *Appl. Energy*, vol.88, pp.2344-2354, 2011.
[19] P. Shanmugam and V. M. A. Sivakumar, Performance and exhaust emissions of a diesel engine using hybrid fuel with an artificial neural network, *Energy Sources, Part A: Recovery, Utilization, and Environmental Effects*, vol.33, pp.1440-1450, 2011.
[20] M. K. Kiani, B. Ghobadian, T. Tavakoli, A. M. Nikbakht and G. Najafi, Application of artificial neural networks for the prediction of performance and exhaust emissions in SI engine using ethanol-gasoline blends, *Energy*, vol.35, pp.65-69, 2010.
[21] A. N. Ahmed, C. W. M. Noor, M. F. Allawi and A. El-Shafie, RBF-NN-based model for prediction of weld bead geometry in shielded metal arc welding (SMAW), *Neural Computing and Applications*, vol.29, no.3, pp.889-899, 2018.
[22] Z. A. Majid, R. Mohsin and A. H. Shihnan, Engine performance and exhaust emission of diesel dual fuel engine fuelled by biodiesel, diesel and natural gas, *Jurnal Teknologi – Sciences Eng.*, vol.78, pp.59-67, 2016.
[23] S. Haykin, *Neural Networks: A Comprehensive Foundation*, Macmillan, New York, 1999.
[24] A. Abraham, *Artificial Neural Networks. Handb. Meas. Syst. Des.*, John Wiley & Sons, Ltd., 2005.
[25] Y. H. Hu and J.-N. Hwang, *Handbook of Neural Network Signal Processing*, CRC Press, London, 2002.
[26] Z. Hassan, S. Shamsudin and S. Harun, Minimum input variances for modelling rainfall-runoff using ANN, *Jurnal Teknologi – Sciences Eng.*, vol.69, pp.113-118, 2014.
[27] R. Sarala, M. Rajendran and B. Sutharson, Exhaust emission analysis using nakthamala oil biodiesel fuel in a IC engine with ANN, *Int. J. Res. Environ Sci. Technol.*, vol.2, pp.48-53, 2011.
[28] N. M. Nawi, A. Khan and M. Z. Rehman, A new Levenberg Marquardt based back propagation algorithm trained with cuckoo search, *Procedia Technol.*, vol.11, pp.18-23, 2013.