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Prediction of marine diesel engine performance by using artificial neural network model

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ABSTRACT

This study deals with an artificial neural network (ANN) modelling of a marine diesel engine to predict the output torque, brake power, brake specific fuel consumption and exhaust gas temperature. The input data for network training was gathered from engine laboratory testing running at various engine speeds and loads. An ANN prediction model was developed based on a standard back-propagation Levenberg–Marquardt training algorithm. The performance of the model was validated by comparing the prediction data sets with the measured experiment data and output from the mathematical model. The results showed that the ANN model provided good agreement with the experimental data with a coefficient of determination (R^2) of 0.99. The prediction error of the ANN model is lower than the mathematical model. The present study reveals that the artificial neural network approach can be used to predict the performance of a marine diesel engine with high accuracy.

Keywords: Artificial neural network; marine diesel engine; engine performance.

INTRODUCTION

Energy efficiency is always becoming an issue due to fuel depletion and higher demand [1, 2]. Combustion is still very important source of energy generation [3-6]. Marine diesel engines are very similar to the self-ignition engines in heavy-duty vehicles, but they are generally bulky, larger in size, equipped with more complex systems, and operate with higher efficiency. About 75% of all marine diesel engines are four-stroke engines and the remaining 25% are two-stroke engines [7]. Four-stroke marine diesel engines are gaining importance in not only inland but also marine shipping, primarily in smaller container and bulk carrier ships, whereas two-stroke engines are normally used to propel slow speed ships. Marine engines provide the major power sources for sea transportation. Marine diesel engines can be classified as slow, medium, and high-speed diesel engines based on their principle of operation. The performance of the marine engine depends not only on the principle of operation, but also on the type, size, power, load, speed, etc. The volatile situation in world oil prices lately has urged ship owners to improve the efficiency of their marine engine performance in order to reduce their operating costs [8-10]. To investigate this situation, a series of laboratory tests need to be carried out. However, testing a marine engine for the complete range of operating conditions can be time-consuming and very costly. As an alternative, a simulation model can be developed to predict the actual condition of engine performance by using the artificial neural network approach. ANN modelling has been chosen for its capability to solve complex and difficult problems where conventional modelling methods fail [11-14]. A well-trained ANN can be used as a predictive model for a specific application, and is a data-processing system inspired by biological neural systems. The predictive ability of an ANN results from the training on experimental data and then validation by independent data. The prediction by a well-trained ANN is normally much faster than conventional simulation programs or mathematical models as no lengthy iterative calculations are needed to solve differential equations using numerical methods [15-17], but the selection of an appropriate neural network topology is important in terms of model accuracy and model simplicity. The application of ANN models in engineering has grown rapidly lately. Some researchers have used ANN to predict internal combustion engine characteristics. Çelik and Arcaklioğlu [18] predicted the exhaust temperature, brake specific fuel consumption (BSFC), and fuel to air equivalence ratio in a diesel engine using an ANN back-propagation (BP) algorithm. Yücesu et al. [19] analysed the mathematical model and experimental results of a spark ignition engine's performance using an ethanol–gasoline blend of fuel. Zweiri et al. [20] studied a diesel engine to predict the indicated torque by means of a BP neural network. Najafi et al. [21] predicted the performance and exhaust emissions in a spark ignition engine fuelled with ethanol–gasoline blends with the application of an ANN. They reported that the ANN is one of the most well-known methods to predict the actual combustion period and can be used for experimental data validation and optimization.

Canakci et al. [22] studied a diesel engine fuelled with biodiesel produced from waste frying palm oil to predict the performance and exhaust emissions. Ghobadian et al. [23] analysed the diesel engine performance and exhaust emission analysis using waste cooking biodiesel fuel with an ANN and were able to predict the engine performance and exhaust emissions successfully. Ganapathy et al. [24] investigated the artificial neural modelling of a jatropha oil fuelled diesel engine for emission predictions. Obodeh et al. [25] predicted the NO emission, power, and SFC of diesel in a diesel engine using an ANN BP algorithm. Yusaf et al. [26] studied the compressed natural gas (CNG)-diesel engine performance and exhaust emission with the aid of an ANN. Srinivasa et al. [27] predicted the brake thermal efficiency (BTE), brake specific energy consumption (BSEC), T_{exh}, NOx, smoke, and HC of a diesel engine fuelled with a biodiesel blend using an ANN BP algorithm. Shanmugam et al. [28] modelled their ANN concept to predict the performance and exhaust emissions of a single-cylinder diesel engine operating with hybrid fuel under different load conditions. They discovered that the use of the developed ANN model was proven to accurately predict the performance and exhaust emissions of the diesel engine with a low root-mean-square error and a range between 0.975 and 0.999 for the correlation coefficient. Kökkülünk et al. [29] used an ANN to predict emissions and exhaust temperature for a direct injection marine diesel engine with emulsified fuel. Other ANN modelling and prediction works that relate to the engine performance and exhaust emissions of diesel engines with biodiesel are [30-34]. Based on the literature, many studies have been carried out in connection with automotive engines; however, the investigation of marine diesel engines is still limited and is considered new in both test and simulation. Therefore, this study aims to develop a prediction model for marine diesel engine performance by using the artificial neural network approach. In order to ensure the model performance, the simulation output was compared with the mathematical model data and actual laboratory testing data.

EXPERIMENTAL SETUP

In this study, the experiments were performed on a Cummins NT-855 marine diesel engine with 4-stroke-Inline-6 cylinder. The full engine setup and details of the engine specification are illustrated in Figure 1 and Table 1 respectively. A 250 kW SAJ SE-250 eddy-current dynamometer was attached to the engine to provide different load conditions, as illustrated in Figure 2. The operating conditions of the engine and the dynamometer brake are characterized by speed and torque. The engine speed is controlled by the throttle engine position lever. The dynamometer sizing is chosen to cover the full-load engine operation for the whole range of engine speeds as the characteristic parts of the engine curve must fall within the characteristic curve of the dynamometer.

Figure 1. Cummin NT-855 marine diesel engine Figure 2. Eddy-current dynamometer SE-250.

Table 1. Marine diesel engine specification.

Brand	Cummins NT-855
Engine type	4 cycle-Inline-6 cylinder
Bore x stroke	139 mm x 152 mm
Displacement volume	14 litre
Fuel consumption	52.0 litre/hr
Compression ratio	14.5
Maximum torque	1068 N.m
Maximum power	201 kW
Cooling system	Water cooling

The fuel consumption and air consumption rate were measured by a positive displacement type KOBOLD flowmeter and TAYLOR air flowmeter respectively. The engine control unit (ECU) used in this engine was a REO-DCA control system assisted by a Samsung HDMI user interface as shown in Figure 3. The ECU's function is to control the quantity of fuel, injection timing, ignition timing and engine speed by receiving signals from the sensors attached. Among these sensors are an oxygen sensor, knock sensor, manifold air pressure sensor, intake air temperature sensor, throttle position sensor, water temperature sensor and engine speed sensor. A multi-point fuel injection

(MPFI) system with top-feed injectors is used to inject the fuel into the combustion chamber. The ignition system was semi-static distributorless ignition (DLI). A schematic diagram of the whole experimental setup is shown in Figure 4. The experiment on the marine diesel engine was tested by using B5 biodiesel fuel which was available in the commercial market. The test was carried out at three different engine loads of 10%, 20%, and 30% and with a variable engine speed from 800 rpm to 1700 rpm. The output data for the brake power, torque, brake specific fuel consumption (bsfc), exhaust temperature, fuel and air mass flow rate were recorded. All of these data were used as input data for the ANN model training process.

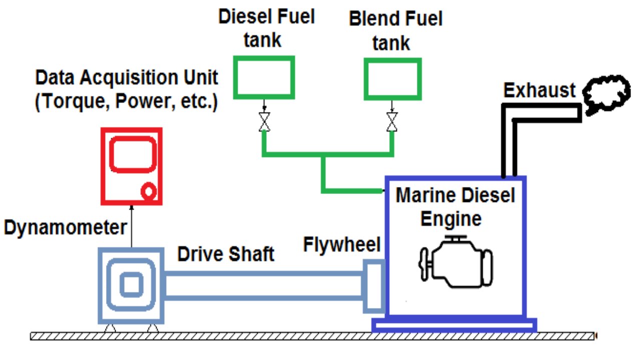

Figure 3. REO-DCA data acquisition unit   Figure 4. Schematic diagram of the experimental setup

ARTIFICIAL NEURAL NETWORK MODELLING

An artificial neural network (ANN) is a computational model based on the structure and functions of biological neural networks. ANNs are the preferred tool for many predictive data-mining applications because of their flexibility and ease of use. Furthermore, this technique is robust, powerful and suitable for nonlinear and complex processes. Since many phenomena in the industry have non-linear characteristics, ANN has been widely used. An ANN model can accommodate multiple input variables to predict multiple output variables. The network usually consists of an input layer, some hidden layers, and an output layer. A popular algorithm is the back-propagation neural network (BPNN), which has different variants. This algorithm uses the supervised training technique in which the network weights and biases are initialized randomly at the beginning of the training phase. The BPNN is based on the error correction learning rule. The operation of the neural network model can be divided into two main steps: forward computing and backward learning. In the forward computing, the input patterns applied to the neurons of the first layer are just a stimulus to the network. As illustrated in Figure 5, each neuron in the hidden layer determines a net input value based on all its input connections. These nodes are connected to each other so that the value of one node will affect the value of another. The relative influence that one node has on another one is specified by the "weight" that is assigned to each connection. The net input is calculated by summing the input values multiplied by their corresponding weight. Once the net input is calculated, it is converted to an activation value. The weight on the connection from the ith neuron in the forward layer to the jth neuron is indicated as w_{ij}. The output value of neuron j is computed by the following equations:

$$net_j = \sum_{i=0}^{n} w_{ij} x_j + x_0 \tag{1}$$

$$Y_j = f_{act}\left(net_j\right) \tag{2}$$

where net$j$ is the linear combination of each of the x_i values multiplied by w_{ij}, x_0 is a constant known as the bias, n is the number of inputs to the jth neuron, and f_{act} is the activation of neuron j.

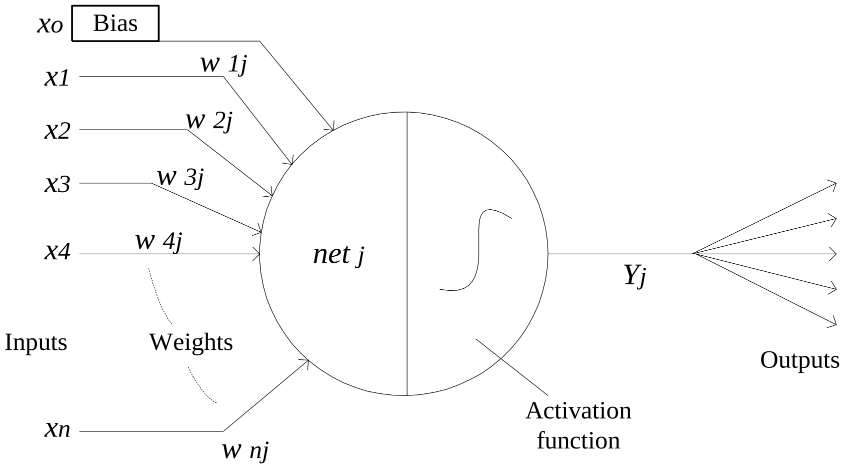

Figure 5. Architecture of an individual neuron in ANN.

In backward learning, the generated output of the network is compared to the desired output, and an error is computed for each output neuron. The error vector E between the desired values and the output value of the network is defined as:

$$E = \sum_j E_j = \sum_j \frac{1}{2}\left(T_j - Y_j\right)^2 \tag{3}$$

where Y_j is the output value of the jth output neuron and T_j is the desired value of the jth output neuron. Errors are then transmitted backwards from the output layer to each neuron in the forward layer. The process is repeated layer by layer and connection weights are updated by each neuron until the network is converged.

The development and the training of the network model in this study were carried out using MATLAB Neural Network Toolbox. The ANN modelling comprises two phases: the first phase is to train the network model, while the second phase is to validate the network model with new data which were not used for training. The flowchart of the neural network modelling procedure is shown in Figure 6. An ANN model for the marine diesel engine was developed using the data gathered in experiments as input data. In this model, 70% of the dataset was randomly selected as the training data, while the remaining 30% of data was used for the performance test and validation of the ANN model. The back propagation algorithm was chosen to calculate the weight values of the network. Choosing the optimum network architecture is one of the challenging steps in neural network modelling. The architecture of the ANN with back-propagation for the test engine is illustrated in Figure 7.

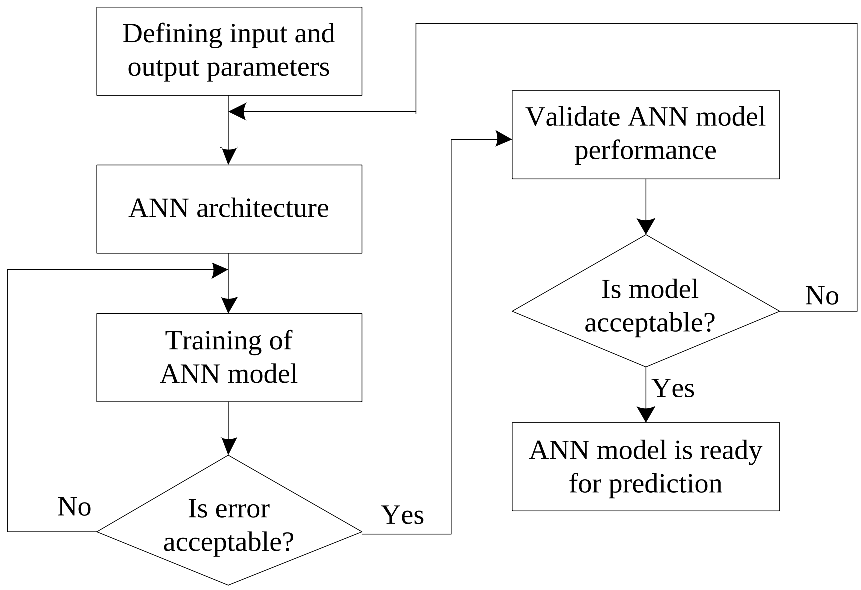

Figure 6. Neural network modelling procedure flowchart.

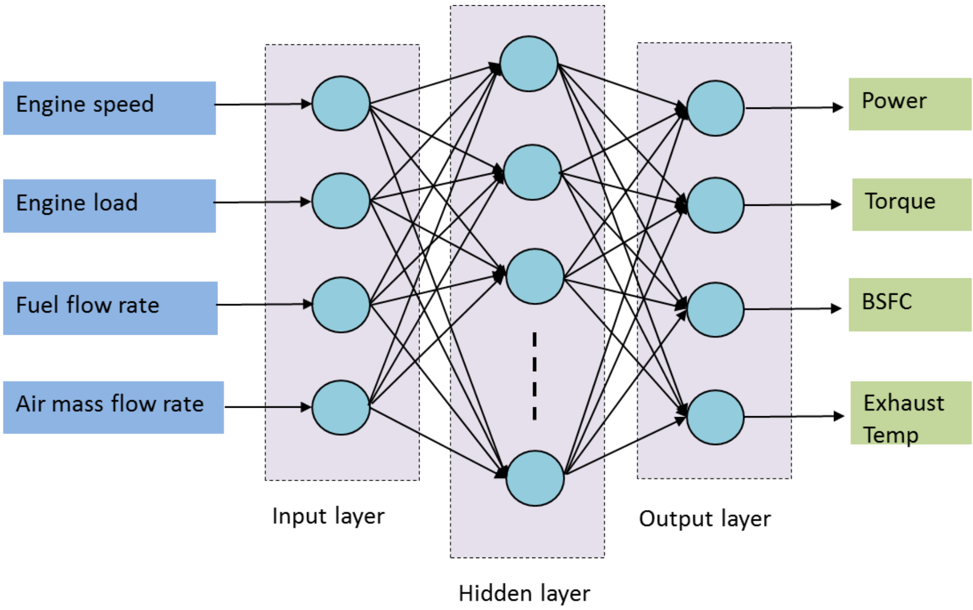

Figure 7. Neural network architecture.

The network has three layers: input layer, hidden layer and output layer. As there are four inputs and four outputs, the number of neurons in the input and output layer had to be set to 4 neurons each. In many ANN applications, the back-propagation architecture with one hidden layer is enough [18]. The neural network configuration for training was created and formulated according to the specification given in Table 2. The accuracy of the network was evaluated by the mean squared error (MSE) and the coefficient of determination (R^2). R^2 is a measure of how well the regression line represents the actual data sets. It can vary from 0 to 1. An R^2 value close to 1 indicates that the ANN model perfectly predicts the output. The MSE and R^2 can be defined by the following equations:

$$MSE = \frac{1}{N}\sum_{i=1}^{N}(y_i - y_k)^2 \tag{4}$$

$$R^2 = 1 - \frac{\sum_{i=1}^{N}(y_i - y_k)^2}{\sum_{i=1}^{N}(y_i - \bar{y})^2} \quad (5)$$

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

Table 2. Neural network configuration for the training

Parameter	Specification
No. of neurons in input layer	4
No. of neurons in hidden layer	10 to 34
No. of neurons in output layer	4
Training function	Levenberg–Marquardt
Performance function	Mean square error
Activation function	Tangent-sigmoid
Performance goal	1.0×10^{-3}
Normalized range	-1 to 1

In order to find an optimal architecture, different numbers of neurons in the hidden layer were considered and the prediction error for each network was calculated. Therefore the number of neurons in the hidden layer was varied from 10 to 34 neurons. As shown in Figure 8, the mean squared error (MSE) value is not directly proportional to the number of neurons in the hidden layer. Decreasing the number of neurons will reduce the performance of the network, whereas increasing the number of neurons beyond 22 gives no significant improvement to the training performance. The number of neurons for which the MSE is minimum and there is the maximum coefficient of determination (R^2) was selected as the number of neurons in the hidden layer. The best learning capability and minimum error were found when the number of neurons chosen was 22.

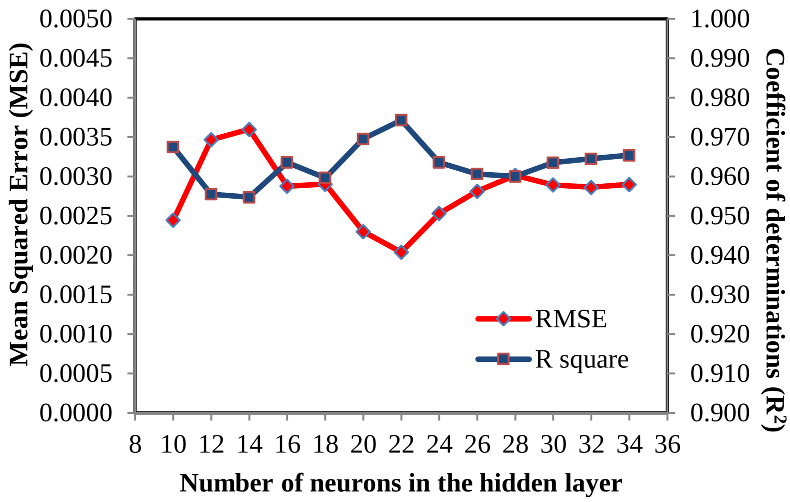

Figure 8. Variation of MSE and R^2 with the number of neurons in the hidden layer.

The network was trained with the Levenberg–Marquardt training algorithm. This training algorithm was chosen due to its high accuracy in similar function approximation. The adjustments of weights and biases are done according to the transfer function below:

$$\Delta w_{ij} = -\left(J^T J + \mu I\right)^{-1} J^T E \tag{6}$$

where J is the Jacobian matrix of derivation of each error, μ is a scalar and E is error function.

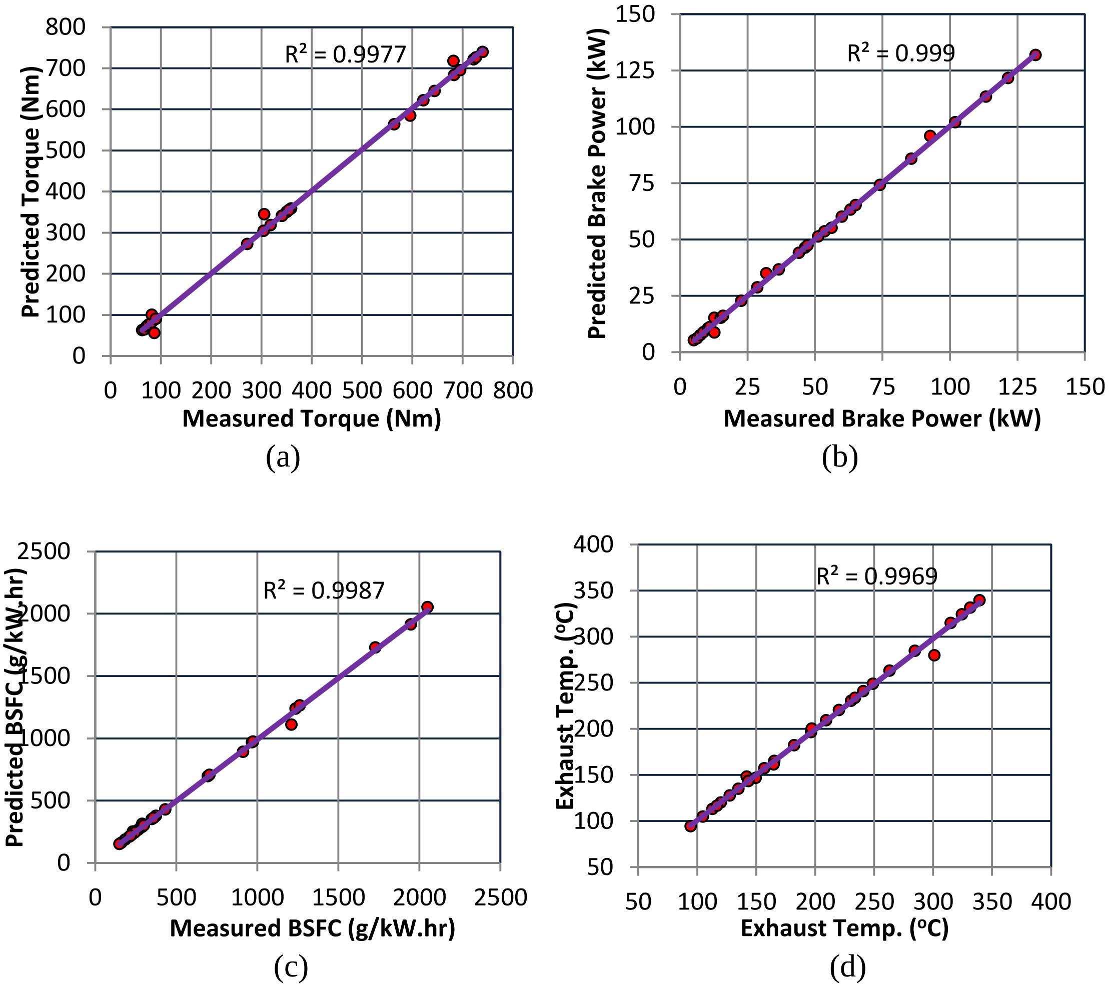

Figure 9. The relationships between measured and predicted data for (a) torque, (b) brake power, (c) BSFC, (d) exhaust temperature of ANN model.

RESULTS AND DISCUSSION

Neural Network Model

The prediction of marine diesel engine performance was carried out by using the ANN back-propagation model with the Levenberg–Marquardt training algorithm. The optimum architecture of the ANN model was constructed as a 4-22-4 architecture. The criteria of MSE and R^2 were selected to evaluate the networks with the optimum solution. A regression analysis between the network output and the corresponding targets was performed in order to investigate the network response in more detail. The results showed that the constructed model was sufficient to predict marine diesel engine performance at various engine speeds. Figure 9 shows the plot of experimental and ANN predicted values for torque, brake power, brake specific fuel consumption and exhaust temperature respectively. Its shows a good correlation between the experimental and ANN predicted values as indicated with higher values of R^2.

Mathematical Model

Mathematical models have been developed to predict the relationship between the input parameters and engine performance. The multiple regression technique was used to ascertain the relationship among variables. This is a linear statistical technique which is used for establishing the best relationship between variables using the least-squares method. The multiple regressions take the following form:

$$Y = a + b_1X_1 + b_2X_2 + b_3X_3 \dots\dots. + b_kX_k \tag{7}$$

where Y is the dependent variable, which is to be predicted. X_1, X_2, X_3,.....X_k are the k known variables on which the predictions are to be made. Meanwhile, a, b_1, b_2, b_3,.....b_k are the coefficients. The commercial statistical program IBM SPSS Statistics 21.0 was used to calculate the values of coefficients for different responses. The input dataset from the experiment was used as input data to the mathematical model. The prediction equations that resulted from the mathematical model are as follows:

$$Torque = -234.685 + 27.477\mathrm{L} - 0.126\mathrm{S} + 1.272\mathrm{FR} + 4.922\mathrm{AF} \tag{8}$$
$$Brake\ power = -32.724 + 3.022\mathrm{L} - 0.064\mathrm{S} + 0.467\mathrm{FR} + 2.516\mathrm{AF} \tag{9}$$
$$BSFC = 3456.786 - 83.068\mathrm{L} - 2.761\mathrm{S} + 38.881\mathrm{FR} + 42.797\mathrm{AF} \tag{10}$$
$$Exhaust\ temp. = -118.509 + 7.12\mathrm{L} + 0.142\mathrm{S} + 0.063\mathrm{FR} - 0.078\mathrm{AF} \tag{11}$$

where L is the engine load, S is the engine speed, FR is the fuel flow rate and AF is the air mass flow rate.

The performance of the mathematical model was assessed using regression analysis. Figure 10 compares the predicted value from the mathematical model and the actual measured value from the experiment. The efficiency and predictability of the developed ANN and mathematical model were measured by the absolute prediction error percentage according to Eq. (12).

$$E_e = \left| \frac{E_a - E_p}{E_a} \times 100 \right| \tag{12}$$

where E_e is the absolute prediction error, E_a and E_p represent the experimental and predicted data, respectively. The absolute prediction error of the neural network and the established mathematical model are listed in Table 3.

Table 3 shows that the prediction error for the ANN model is lower than the mathematical model. The ANN model prediction error ranged from 0.58 to 2.78%, while the prediction error for the mathematical model is 8.83 to 53.73%. Therefore, it can be stated that the efficiency of the prediction obtained from the ANN model produces better and more accurate results than the model developed using a mathematical method or a regression analysis. In addition, it is very difficult to establish the relationship between the process parameters and engine performance with the mathematical model because of the complex and nonlinear relationships among them. On the other hand, it is proved that the superiority of the neural network model to predict the engine performance with high precision is due to its high robustness and accuracy.

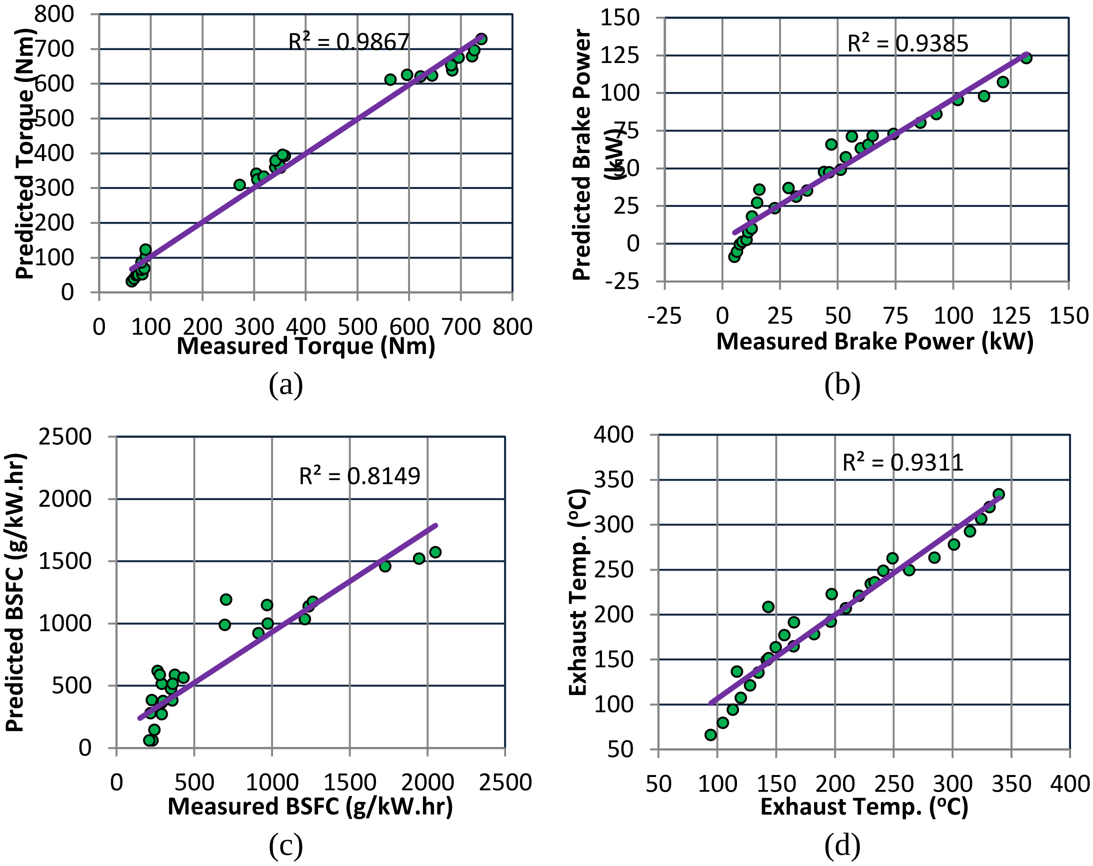

Figure 10. The relationships between measured and predicted data for (a) torque, (b) brake power, (c) BSFC, (d) exhaust temperature of mathematical model.

Table 3. Prediction error percentage of developed models

Engine Performance	ANN Model	Mathematical Model
Torque	2.78%	13.79%
Brake power	2.37%	40.25%
BSFC	1.01%	53.73%
Exhaust temp.	0.58%	8.83%

Next, the validation of the ANN and mathematical model with actual experimental data for marine engine prediction for torque, brake power, BSFC and exhaust temperature is presented in Figure 11. This shows that the distribution of data points predicted by the ANN model is very close to the experimental data, compared with the distribution of data points predicted by a mathematical model. The ANN model gives the best fit to the experimental results and produces a better prediction of the marine diesel engine.

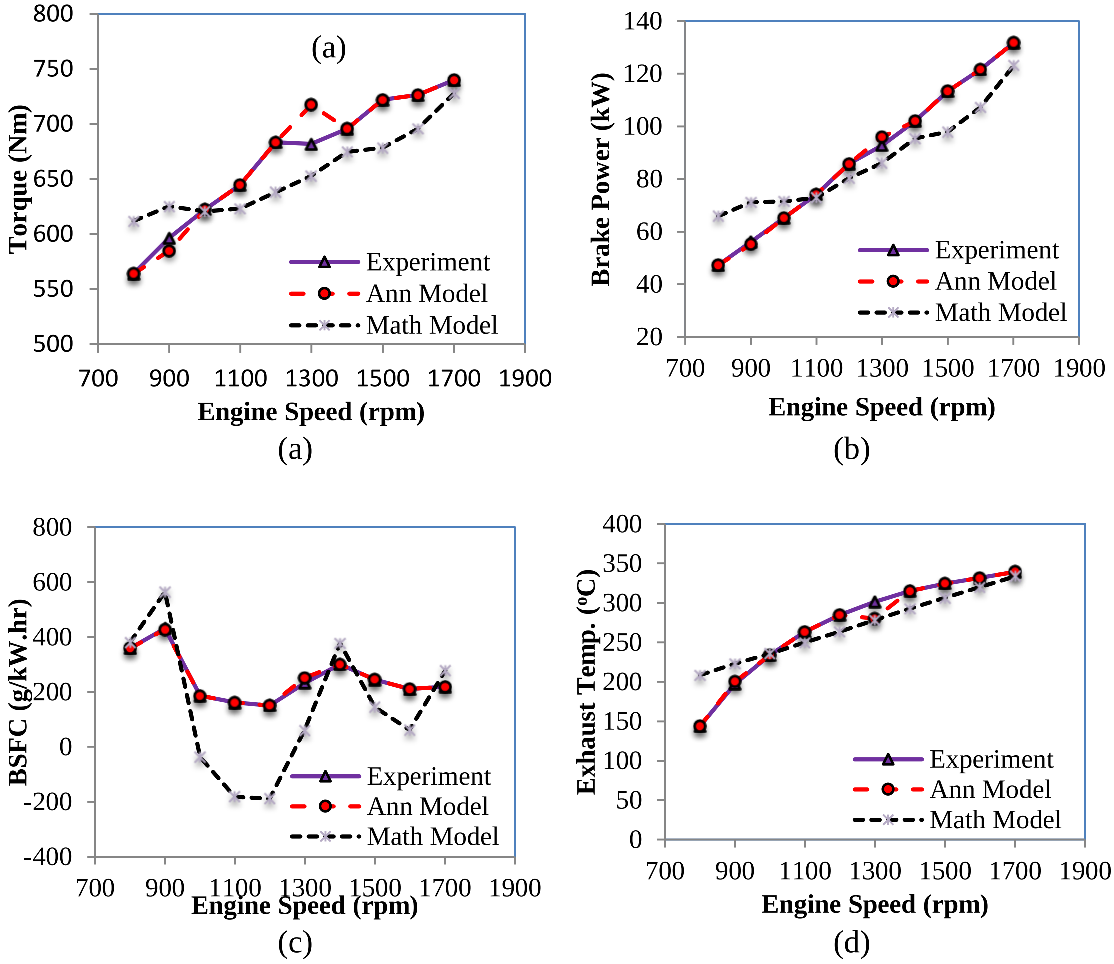

Figure 11. Validation of ANN and mathematical model predictions with experimental results for the (a) torque, (b) brake power, (c) BSFC, (d) exhaust temperature

CONCLUSIONS

An artificial neural model was successfully developed to predict the performance of a Cummins NT-855 marine diesel engine. The back-propagation ANN network with Levenberg–Marquardt training algorithm was used to train the data from engine laboratory testing. The ANN prediction results were compared with results from a mathematical model. The main conclusions from the present study are summarized as follows:

(i) The 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 for the ANN model is very similar and close to the actual experimental data with a coefficient of determination (R^2) of 0.99, while the R^2 for the mathematical model was slightly lower at 0.81 to 0.98. This indicated that the developed ANN model is capable of making a prediction that is in good agreement with the experiment data.

(iii) The developed ANN model is more accurate than the mathematical model. The prediction error percentage of the ANN model ranged from 0.58 to 2.78%, while the mathematical model was 8.83 to 53.73%.

(iv) The neural network is a powerful tool and is easy to use in nonlinear problems. The developed ANN model can be used reliably, successfully and very accurately for the prediction of marine diesel engine performance.

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