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To cite this article: C W Mohd Noor et al 2015 IOP Conf. Ser.: Mater. Sci. Eng. **100** 012023

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Application of artificial neural network for prediction of marine diesel engine performance

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Abstract. This study deals with an artificial neural network (ANN) modelling of a marine diesel engine to predict the brake power, output torque, brake specific fuel consumption, brake thermal efficiency and volumetric efficiency. The input data for network training was gathered from engine laboratory testing running at various engine speed. The prediction model was developed based on 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. Results showed that the ANN model provided good agreement with the experimental data with high accuracy.

1. Introduction

Simulation approaches such as artificial neural networks (ANN) model are widely used by researchers to solve a variety of problems in science and engineering, particularly for some areas where the conventional modelling methods fail [1]. An ANN model can accommodate multiple input variables to predict multiple output variables. The prediction by a well-trained ANN is normally much faster than the conventional simulation programs or mathematical models as no lengthy iterative calculations are needed to solve differential equations using numerical methods but the selection of an appropriate neural network topology is important in terms of model accuracy and model simplicity. On the other hand diesel engine laboratory performance testing are time consuming and very costly which include budget expenditure for the engine test set up. As an alternative method, diesel engine testing simulation can also be conducted to simulate the actual condition of the engine performance with different inputs and outputs. The application of ANN approach in automotive engineering could be progressed a very impressive rate in recent years. Some researchers used ANN to predict internal combustion engine characteristics. The predictive ability of an ANN results from the training on experimental data and then validation by independent data. ANN approach has been used by Xu, Xie [2], in forecasting engine systems reliability, Yuanwang, Meilin [3], analysed the effect of cetane number on exhaust emissions from engine, Korres, Anastopoulos [4], predict diesel lubricity, Lucas, Duran [5], setup ANN model for diesel particulate emission, Hafner et al.[6], for diesel engine control design, Shayler and Goodman [7], adapted ANN in automotive engine management systems and Tan [8], model the intake manifold and throttle body processes in an automotive engine. Najafi, Ghobadian [9] reported that artificial neural network (ANN) is among some of the most well-known methods to predict the actual combustion period and can be used for the experimental data validation and optimization. Mustafa Canakci and Erdil [10] and Arcaklioglu et al. [11] demonstrated that ANN can be an optimum tool for predicting the performance and exhaust emissions. Shanmugam and P.V. [12] has modelled his ANN concept to predict the performance and exhaust emissions of the single cylinder diesel engine operating with hybrid fuel under different load conditions. His report

discovered that the use of the developed ANN model has proven to 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 accurately. Wang, Zhang [13] used Ann radial basis function technique to predict emission parameters from marine diesel engine. Other ANN modelling and prediction works that related to the engine performance and exhaust emissions of diesel engine with biodiesel are Sharon H, Jayaprakash [14], Patil RC and S.U. [15], Sarala R and Rajendran [16] and Kökkülünk, Akdoğan [17]. According to these papers, it is important to have accurate experimental test data in order to give excellent and reliable ANN prediction results. In the existing literatures also stated that the ANN is a powerful modelling tool that has the ability to identify complex relationships between input–output data. However, there is still less investigation on marine diesel engine appears to have been published in the literature to date. Therefore, the present work intends to investigate the applicability of ANN method to predicting the marine diesel engine performance parameters. In this study, the prediction results were validated with the actual laboratory testing data.

2. Experimental Setup

2.1. Marine engine testing

In this research, the experiments were performed on a Cummins NT855 marine diesel engine with 4 stroke-Inline-6 cylinder. The full engine setup and details of engine specification are illustrated in figure 1(a) and Table 1 respectively. The eddy-current dynamometer SAJ SE-250 was attached to the engine to provide different load condition as illustrated in figure 1 (b). The operating conditions of the engine and the dynamometer brake are characterized by speed and torque. 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 engine curve must fall within the characteristic curve of dynamometer. The maximum output power for this dynamometer is 250 kW.
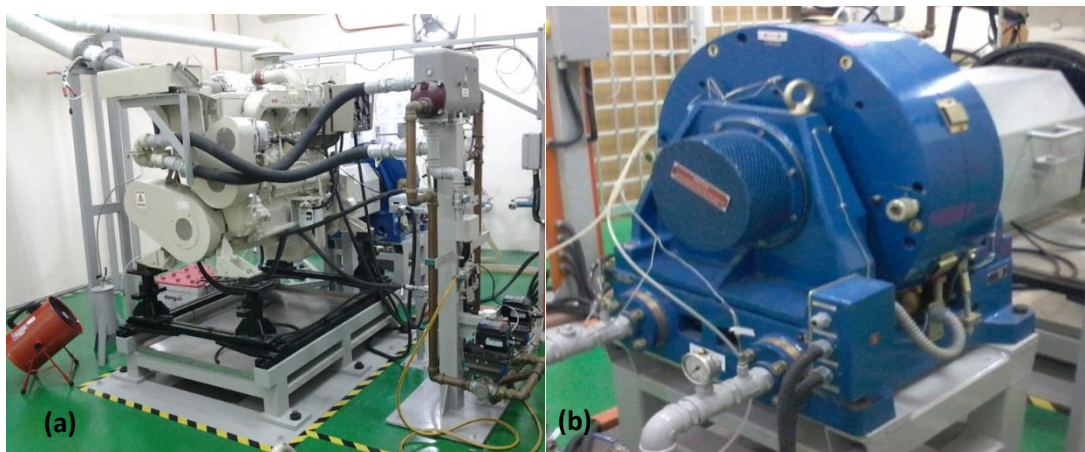

Figure 1. (a) Cummin NT855 marine diesel engine and (b) Eddy Current dynamometer SE-250.

Fuel consumption rate was measured by KOBOLD positive displacement type flow-meter. Air consumption was measured using an air flow-meter. Two separate fuel tanks were fitted to the engine and these contained diesel and the biodiesel blends. The engine control unit (ECU) used in this engine was REO-DCA control system with assisted of Samsung HDMI user interface as shown in figure 2(a). ECU function is to control the quantity of fuel, injection timing, ignition timing and engine speed by receiving signals from sensors. These sensors are 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 distributor less ignition (DLI). A schematic diagram of the whole experimental setup is shown in figure 2(b). The marine diesel engine was fuelled by B-5 biodiesel. The engine speeds, brake power, torque and fuel

consumption were measured, while the brake specific fuel consumption (bsfc), brake thermal efficiency and volumetric efficiency was computed later.

Table 1: Marine diesel engine specification.

| Brand	Cummins NT855
Engine type	4 cycle-Inline-6 cylinder
Firing order	1-5-3-6-2-4
Bore x stroke (mm)	139 x 152
Displacement volume (litre)	14
Compression ratio	14.5
Maximum torque (N.m)	1068
Maximum power (kW)	201
Maximum speed (rpm)	2100
Cooling system	Water cooling
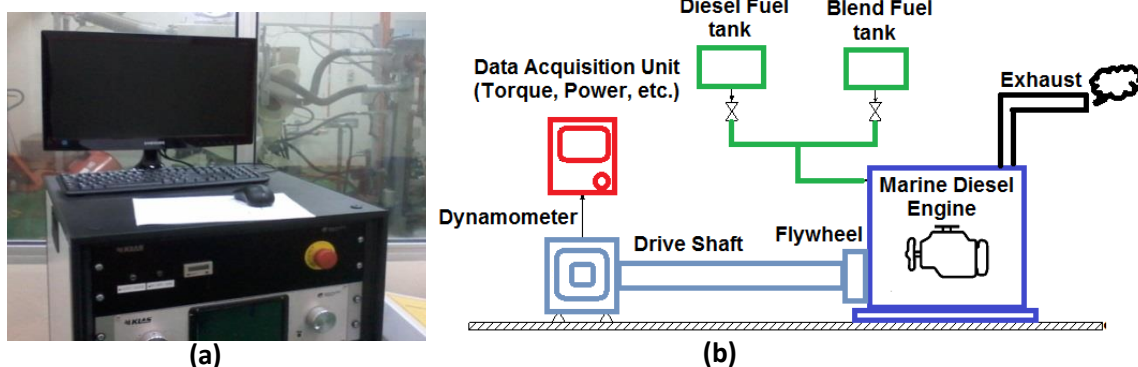
Figure 2. (a)REO-DCA data acquisition unit and (b) Schematic diagram of the experimental setup.

2.2. Neural network modelling

The development and the training of the network model were carried out using Neural Network Toolbox of MATLAB software. The ANN modeling comprises of 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 flow of neural network modeling procedure is shown in figure 3. Choosing the optimum network architecture is one of the challenging steps in neural network modeling. Figure 4(a) shows the neural network architecture with back-propagation neural network model (BPNN) employed in this study. The network has three layers: input layer, hidden layer and output layer. As there are one input and five outputs, the numbers of neurons in the input and output layer had to be set to 1 and 5, respectively. In many ANN applications, the back propagation architecture with one hidden layer is enough. In order to find an optimal architecture, different numbers of neurons in the hidden layer were considered and prediction error for each network was calculated. 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. In fact, there is no computation in the input layer. As illustrated in figure 4(b), 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.
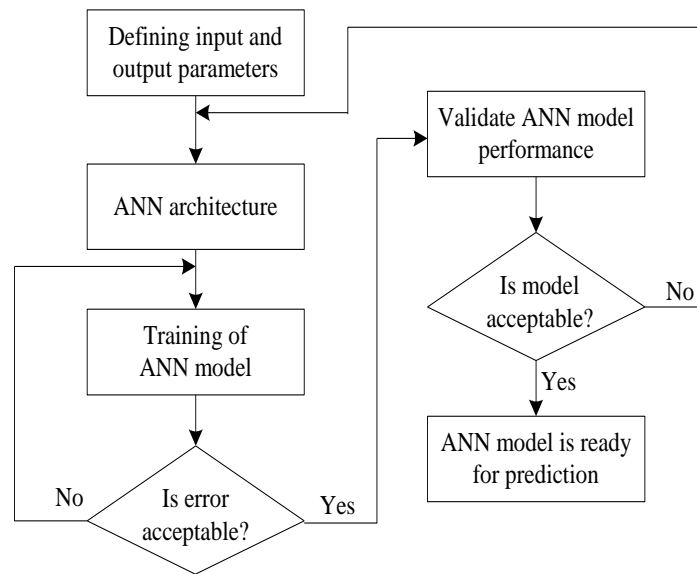
Figure 3. Neural network modeling procedure.
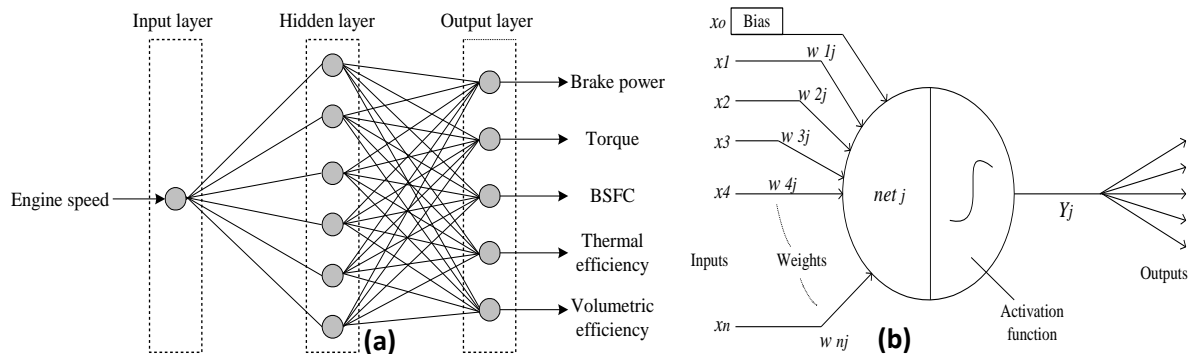
Figure 4. (a) Neural network architecture and (b) Architecture of an individual neuron.

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 equation:

$$net_j = \sum_{i=0}^{n} w_{ij}x_j + x_0, \quad Y_j = f_{act}\left(net_j\right) \tag{1}$$

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. In this study, the hidden layer with log-sigmoid (S-shaped curves) activation function is used for the prediction of weld bead geometry. The log-sigmoid activation function is given below:

$$Y_j = \frac{1}{1+\exp\left(-net_j\right)} \tag{2}$$

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 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 backward from the output layer to each neuron in the forward layer. The process is repeated layer by layer. Connection weights are updated by each neuron to cause the network to converge. 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 transfer following function:

$$\Delta w_{ij} = -\left(J^T J + \mu I\right)^{-1} J^T E \tag{4}$$

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

The input and output parameters data sets could not be trained by neural network in their original form due to the wide range of values among them. In order to become feasible neurons, all the values in the input neurons had to be preprocessed by normalizing and transformed within the range of -1and +1. The normalized value (X_i) for each raw input and output data set (d_i) was calculated as follows:

$$X_i = \frac{2}{d_{max} - d_{min}}\left(d_i - d_{min}\right) - 1 \tag{5}$$

Where d_{max} and d_{min} are the maximum and minimum values of the raw data, respectively.

The back-propagation neural networks model were trained using data sets from laboratory experiment results. They are randomly divided into tree data sets which 70% of data were used for training, 15% for testing and remaining 15% for validation. The neural network configuration for training was created and formulated according to specification given in table 2. In order to identify the optimum network architecture, it is essential to determine the number of neurons in the hidden layer. Therefore, the number of neurons was chosen from 4 to 28 neurons in a hidden layer. The accuracy of the network was evaluated by the mean squared error (MSE) and the coefficient of multiple determinations, R^2. As can be seen in table 3, the MSE in the training process is not directly related to increasing number of neurons. It can be noted that where there is a small number of neurons in the hidden layer, the output training performance of network is not satisfactory. However, the increasing number of neurons beyond 22 has no-significant improvement to the performance of the networks. It can be conclude that the network with 22 neurons in hidden layer shows give better results of minimum MSE and higher R^2 value.

Table 2. Neural network configuration for the training.

| Parameter	Specification
No. of neurons in input layer	1
No. of neurons in hidden layer	4 to 28
No. of neurons in output layer	5
Training function	Levenberg-Marquardt (trainlm)
Performance function	Mean square error (MSE)
Activation function	Log-sigmoid
Performance goal	1.0×10^{-3}
Normalized range	-1 to 1

Table 3. Training performance of different network architecture.

| Network architecture	MSE	R^2
1-16-5	0.00352	0.95989
1-18-5	0.00383	0.95435
1-20-5	0.00773	0.95094
1-22-5	0.00153	0.96222
1-24-5	0.00416	0.95232
1-26-5	0.01453	0.92544
1-28-5	0.02499	0.91357

## 3. Results and discussion

3.1. Experimental results

Engine performance testing was carried out by using Cummins NT855 Marine diesel engine with B-5 biodiesel as a fuel. Figure 5(a) and 5(b) show the variation of brake power and output torque at different engine speed respectively. The brake power is increased steadily with the increasing of speed until it reaches maximum point of 170 kW at 1700 rpm. On the other hand the torque value declined after speed of 1400 rpm. The maximum output torque of 1030 Nm was produced at about 1200-1400 rpm. Figure 5(c) shows the nature of fuel consumption (BSFC) of marine engine with varying speeds. Fuel properties such as density, viscosity and calorific value are normally will influence BSFC value. Optimum fuel consumption was observed at speed of 1200 rpm. Brake thermal efficiency appraises how efficiency an engine can transform the supplied fuel energy into useful work. Most of the supplied fuel will be lost as heat with the engine cooling water, lubricating oil and exhaust gas. As display in figure 5(d) the maximum brake thermal efficiency was around 55% at engine speed of 1000 rpm. The volumetric efficiency specifies the quantity of inflow air mass remaining in the cylinder relative to the theoretical air mass. Figure 5(e) shows the volumetric efficiency increase with increases of engine speed.
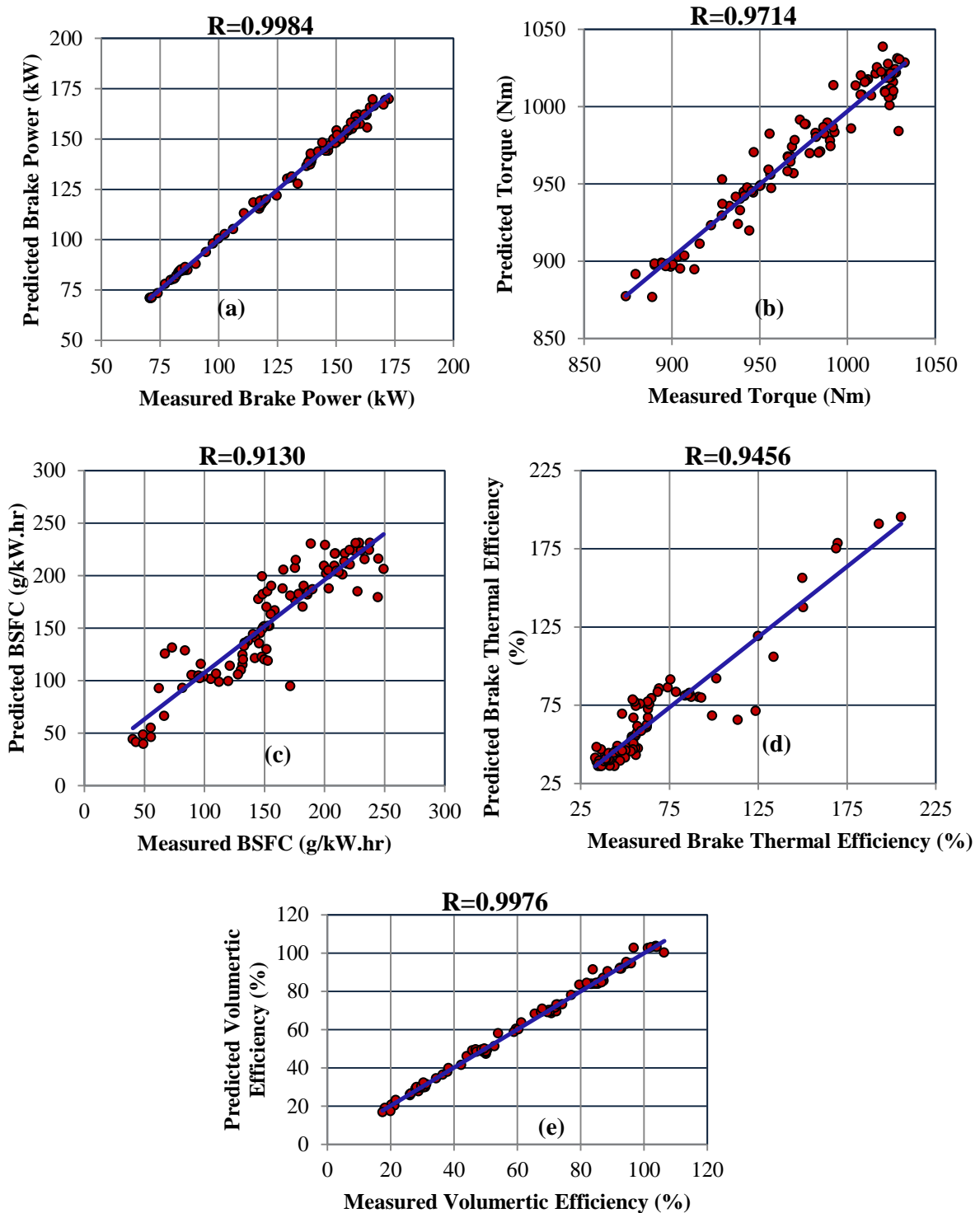

(a)

(b)

(c)

(d)

(e)
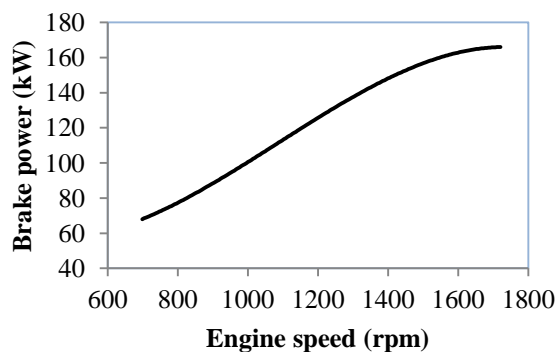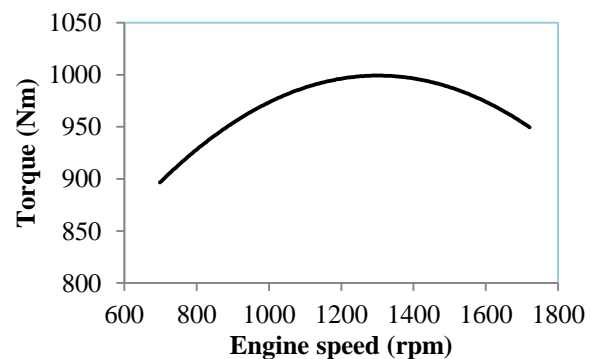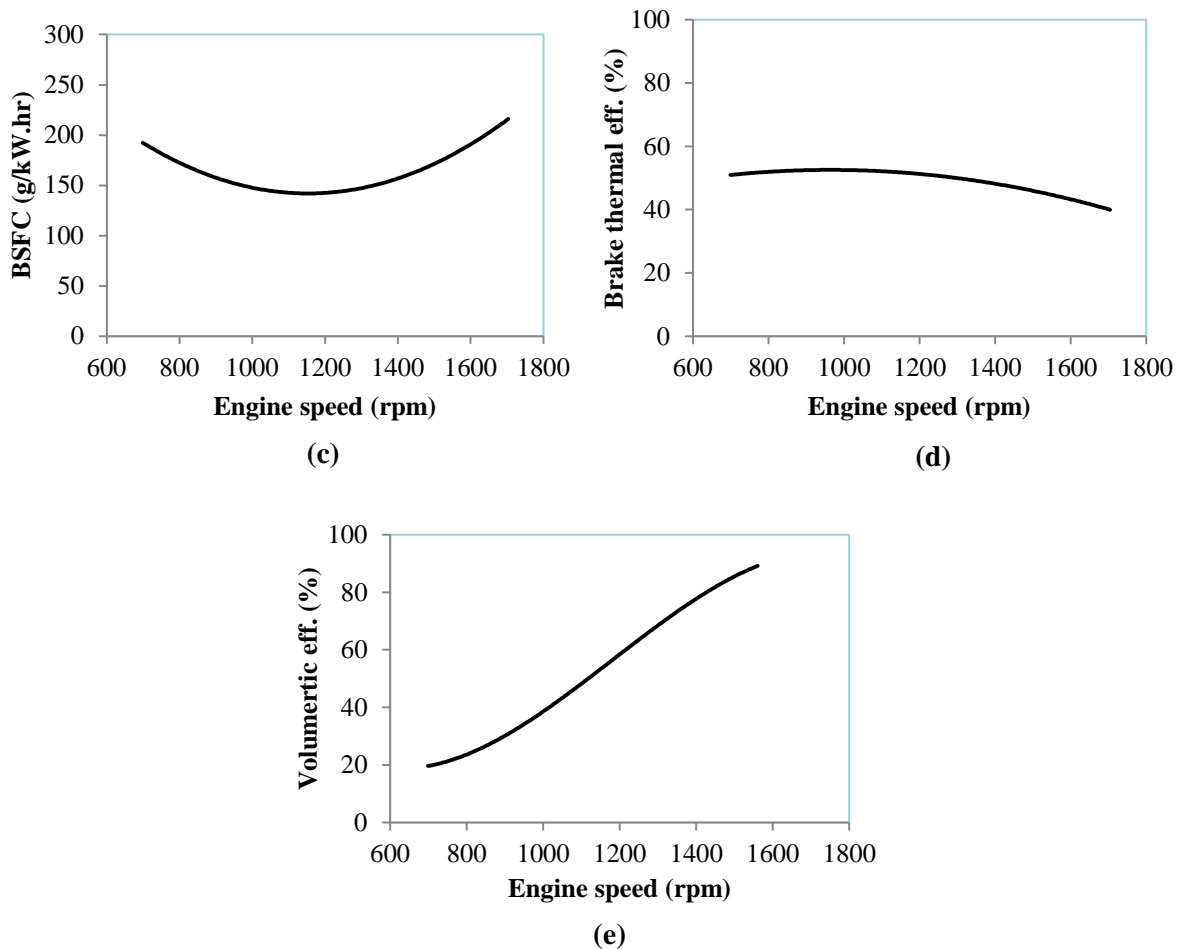
Figure 5. Experimental results of (a) brake power, (b) torque, (c) bsfc,
(d) thermal efficiency and (e) volumetric efficiency.
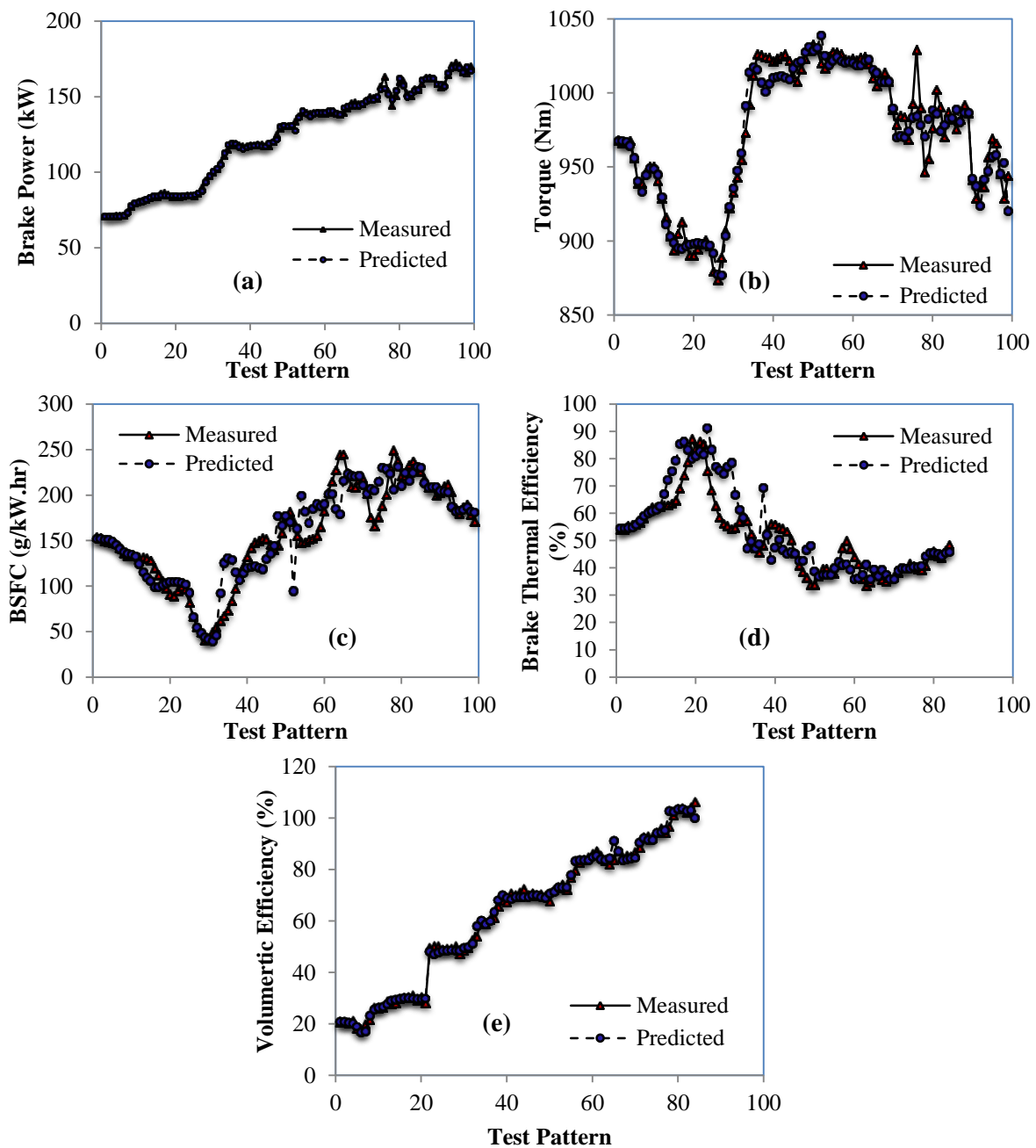
3.2. ANN prediction results

The prediction of marine engine performance was carried out by using ANN with back-propagation model with Levenberg-Marquardt training algorithm. The number of neuron in each layer can be determined by the complexity of the problem and data sets. In this study, the network was decided to consist of 22 neurons in the hidden layer. The criterion of MSE and R^2 was selected to evaluate networks with 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 predicting marine diesel engine performance at various engine speeds. The ANN predicted outputs versus experimental values are indicated in figure 6. The ANN predictions for the (a) brake power, (b) torque, (c) brake specific fuel consumption, (d) brake thermal efficiency and (e) volumetric efficiency yield a correlation coefficient (R) of 0.9984, 0.9714, 0.9130, 0.9456 and 0.9976, respectively. This indicated high correlation between predicted model and experiment data.

Figure 6. The ANN prediction for the (a) brake power, (b) torque, (c) bsfc,
(d) thermal efficiency and (e) volumetric efficiency versus experimental values.

A comparative presentation of the error during model testing by ANN and experimental results is shown in figure 7. The test pattern consists of 5 pairs of results data set. It was observed that the ANN model can predict marine engine performance accurately with close agreement to actual experiment data.

Figure 7. Comparisons of experimental results and the ANN predictions for the (a) brake power, (b) torque, (c) bsfc, (d) thermal efficiency and (e) volumetric efficiency for various test patterns.

4. Conclusion

An artificial neural model was successfully developed to predict the Cummins NT855 marine diesel engine performance. The back propagation ANN network with Levenberg-Marquardt training algorithm was used to train the data from engine laboratory testing. The main conclusions obtained in this study are as follows:

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

(ii) The distribution of data points for neural network model almost similar and close to the actual experimental data with correlation coefficient (R) in range in range of 0.9 - 1.0. This indicated the developed neural network model is capable of making the prediction with reasonable accuracy.

(iii) Neural network is a powerful tool and is easy to use in complex or non-linear problems. The developed neural network models are reliable and able to predict marine diesel engine performance parameter with reasonable accuracy.

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