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DETERMINATION OF BIO-DIESEL ENGINE COMBUSTION PRESSURE USING NEURAL NETWORK BASED MODEL

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Abstract

Combustion pressure analysis is an important aspect to be studied in the research and development of internal combustion engines. However, measurements of in-cylinder combustion pressure for a complete range of testing are time-consuming and costly, as it required high accuracy pressure sensor systems. Alternatively, a simulation model based on the computer program can be used to retrieve those parameters. This study focused on developing the prediction model to determine the combustion pressure of diesel engines by employing artificial neural network methods. Input data for training, testing, and validation of the model were obtained from laboratory engine testing. The biodiesel blends percentage, engine loads, engine speeds and crank angle position were selected as the input parameters. The performance of the ANN model was validated against the experimental data. The results show that the developed model successfully predicted the engine combustion pressure with a higher correlation coefficient (R-value) between 0.99968-0.99973, means that the model produces 99% of prediction accuracy. In addition, the prediction errors occurred within a small range of values. This study revealed that the neural network approach is able to predict the combustion pressure of the diesel engine with high accuracy.

Keywords: Artificial neural network, Engine combustion pressure, Marine diesel engine, Palm biodiesel.

1. Introduction

Engine in-cylinder pressure data is an important parameter for combustion analysis of an internal combustion engine. Its magnitude relies on the correlation between several significant input parameters, such as fuel type, engine speed, engine load, and engine operating state. In general, engine testing is performed in laboratories to determine those parameters. This demands complex control, data acquisition systems and sensors. A complete range of engine testing is not only time-consuming but also costly as a comprehensive testing plan is required prior to setting up such facilities. As an alternative, prediction models based on computer simulations can be used to identify the combustion parameters for the engine. In this case, the ANN model was employed as an effective solution because this method is applicable to both intricate and non-linear problems without incorporating mathematical differential equations. In addition, the ANN model was employed to evaluate the correlations between the various input variables to predict the output variables without demanding much information regarding its system.

The study in the field of neural networks was initiated in 1943 when McCulloch and Pitts developed a computer model by applying the logical threshold algorithm [1]. This technique has been widely used in many areas, such as functional approximation, pattern recognition, identification, optimization, prediction, evaluation, classification, and control of complex systems. A substantial number of studies have estimated the performance of diesel engines fuelled by biodiesel using ANN models. Cirak and Demirtas [2] predicted the engine torque using the multilayer ANN model, where the R-values are close to one and the MSE value of 0.007 proving that ANN model is a great tool for solving complex problems.

Mohammadhassani et al. [3] utilized the combination of ANN and Ant Colony Optimization (ACO) algorithm, by employing a feed-forward multi-layer perceptron network for modelling and reducing diesel engine exhaust emissions. The obtained results reveal that the ANN can appropriately model the NO_X and soot emissions with the R-values of 0.98 and 0.96, respectively. Dharma et al. [4] estimated the engine exhaust temperature, brake specific fuel consumption, torque, brake power, thermal efficiency and exhaust emissions using the back-propagation algorithm. The model provides an accurate result with the R^2 is more than 98% for all parameters. They concluded that the ANN method has superb generalization capability and could predict the engine performance accurately. In addition, Rao et al. [5] employed the ANN model to evaluate diesel engine performance parameters fuelled by rice bran methyl ester biodiesel.

The embedded back-propagation algorithm has been found to be the best technique for model training that results in higher correlation coefficients. Syed et al. developed ANN model to investigate the performance of hydrogen dual fuelled diesel engine [6]. The model was trained by the BFGS Quasi-Newton algorithm and tan-sig transfer function. The output results of RMSE and MAPE were between 0.0055-2.8557 and 0.52-4.34%, respectively. The ANN prediction results precisely matched with the experimental data. Cay [7], Kapusuz et al. [8], and Kumar et al. [9] reported their engines study that employed an ANN-based modelling approach. Although many studies on diesel engines employ ANN models research that focuses on combustion characteristics prediction model is still lacking. In this study, engine-testing data using different palm biodiesel-diesel blends percentage had been used to train, test, and validate the developed models. The outcomes derived from the ANN methods provide a good agreement with the experimental results. Finally, the prediction equations for engine combustion pressure are successfully generated from the simulation models.

2. Experimental Procedures

The laboratory engine testing was performed on the Cummins diesel engine. Such an engine is commonly used as an electric power generator or auxiliary engine. The engine was completely instrumented and connected to the data acquisition system as shown in Fig. 1.

The details of engine specification are given in Table 1. The engine is coupled with the eddy-current dynamometer to give a certain braking load. The combustion cylinder pressure is instantaneously measured by using Optrand fibre-optic pressure transducer with a capacity that ranges between 0-200 MPa. The transducer was installed on the first cylinder of the test engine as illustrated in Fig. 2.

An Optrand fibre-optic pressure sensor operates using the principle of light, reflection from a flexible metal diaphragm, which exposed to combustion pressure in the engine cylinder. The pressure transducer is coupled to the signal conditioner through the fibre-optic cable to convert input analogue into a digital signal. The signal from the pressure transducer cylinder and crankshaft encoder is sent to the amplifier before being transferred to the data acquisition system.

Table 1. Engine specifications.

Engine Model	**Cummins NT-855M**
Type	Four strokes, 6 cylinders, DI
Bore *x* stroke	139 mm × 152 mm
Displacement	14 litre
Maximum torque	1068 Nm @ 1500 rpm
Maximum power	201 kW @ 1800 rpm
Cooling system	Water-cooled

Fig. 1. Engine test setup.

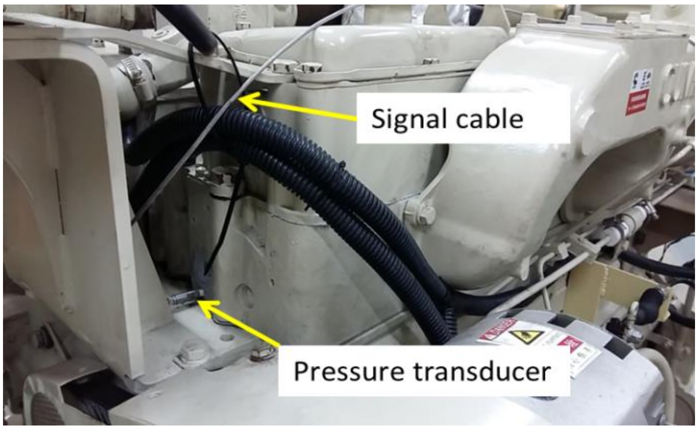

Fig. 2. Pressure transducer.

3. Artificial Neural Network (ANN) Architecture

ANN refers to a computational program that is inspired by the human brain systems [10]. The simplified neural network model is comprised of a group of artificial neurons that both interconnect and interact with each other, similar to the ways of the biological neural network [11], as illustrated in Fig. 3. On top of that, the weighted inputs in the ANN models are similar to dendrites in the biological neural networks. Besides, summation and activation function works as a cell body, which contains both summation and threshold units. Meanwhile, the output unit corresponds to the axon that generates an output signal to the synapses.

The most widely used ANN type is the Feed-Forward Neural Network (FFNN) model, which consists of single or multiple hidden layer neurons between input and output layers. The input layer is comprised of artificial neurons that receive input data for the network learning process. On the other hand, the hidden layer neurons are connected to a previous layer through adaptable weights and bias. Neurons refer to the information processing units that are fundamental to the operation of nerve networks. Figure 4 presents a block diagram that illustrates a simple neuron. All neuron within the hidden layer decides the net input value based on their input connections. Subsequently, the net input value is calculated by multiplying the input product with the assigned weight. In addition, the bias parameter is included to generate an output with a non-zero value. The threshold, next, is set by the activation function to obtain the desired output. The weight of the ith neuron in connection to jth neurons is depicted as w_{ij}. The summation of Net_j value is calculated based on Eqs. (1) and (2) [13].

$$Net_j = \sum_{i=0}^{N} w_{ij} \cdot x_j + b \tag{1}$$

$$Y_j = \varphi(Net_j) \tag{2}$$

where net_j is a linear combination of each input and weight value, xi refers to the input value, w_{ij} denotes weight value, b reflects constant bias value, φ is model activation function, Y_j refers to the output signal, and N reflects the number of inputs value.

Several algorithms can be employed for network training. The most popular learning algorithm is known as back-propagation (BP) [14]. The learning process of BP is comprised of two stages, which are: feedforward and back-propagation. As for the feed-forward process, the input data are introduced to the network and their effects are transmitted through all the network layers. In this step, the generated network output value and the desired target are compared so as to identify the network error as illustrated in Fig. 5. On the other hand, at the back-propagation phase, the error is propagated backwards from the output layer to all neuron in the front layer. The weight of all neuron connections are renewed at each alteration until the convergence output value is attained. BP uses a gradient descent approach to decrease the error between the network output value and the target value. Such error is typically expressed by the statistical parameter of Mean Square Error (MSE) [6]. Nevertheless, the training process is discontinued when the MSE value begins to increase, instead of decreasing.

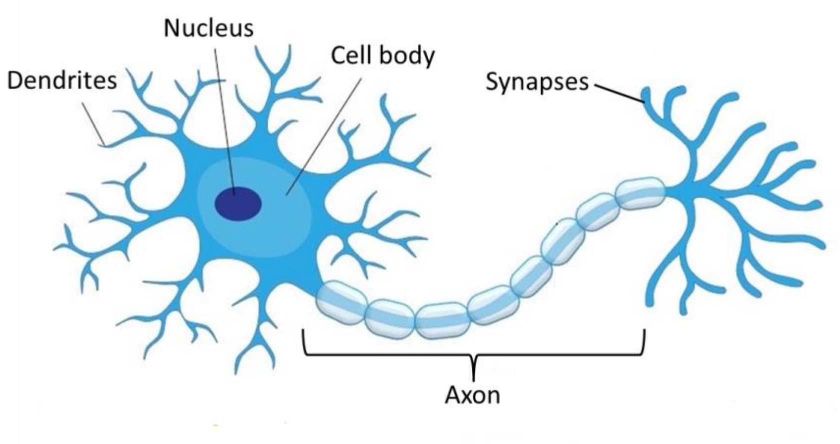

Fig. 3. Biological neural network systems [12].

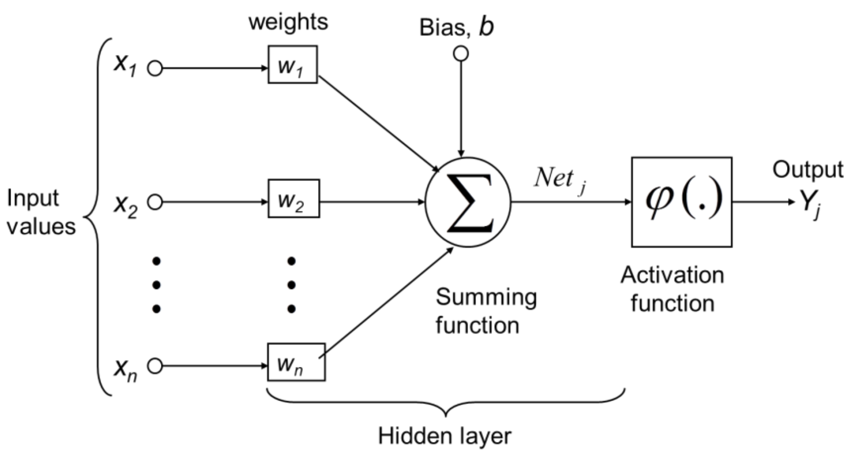

Fig. 4. Block diagram of a simple neuron model.

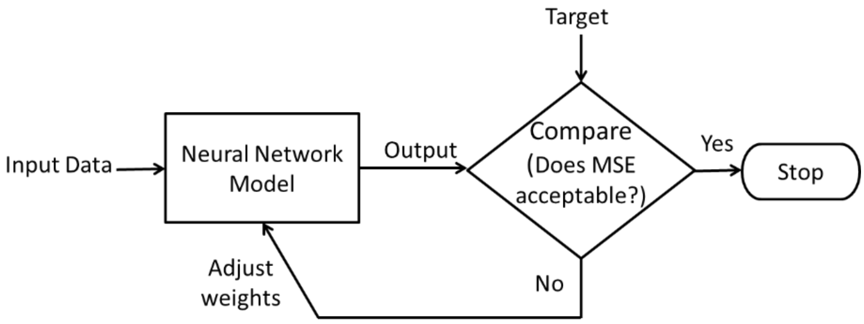

Fig. 5. Back-propagation learning process.

4. Results and Discussion

The combustion pressure prediction model was developed by employing the MATLAB software. The structure of an ANN architecture is illustrated in Fig. 6, which presents four input and one output parameters in the model. The input variables refer to the percentages of palm biodiesel, engine load, and crank angle position; whereas the output variable was the combustion pressure. The accuracy of the network was determined by the parameters of MSE and the coefficient of correlation (R-value*)*. The R-value is an indicator of the correlation between output and target. If *R* is equivalent to 1, an exact linear relationship is displayed between output and target. On the other hand, when *R* is close to zero, no linear relationship is exhibited between output and target. Both the MSE and the R-values can be identified by using Eqs. (3) and (4), respectively.

$$MSE = \frac{1}{N}\sum_{i=1}^{N}(t_i - o_i)^2 \quad (3)$$

$$R = \sqrt{1 - \frac{\sum_{i=1}^{N}(t_i - o_i)^2}{\sum_{i=1}^{N}(t_i - \bar{t})^2}} \quad (4)$$

where t denotes the target value, $\bar{t}$ is the target mean value, o refers to the output value, and N reflects the total number of data.

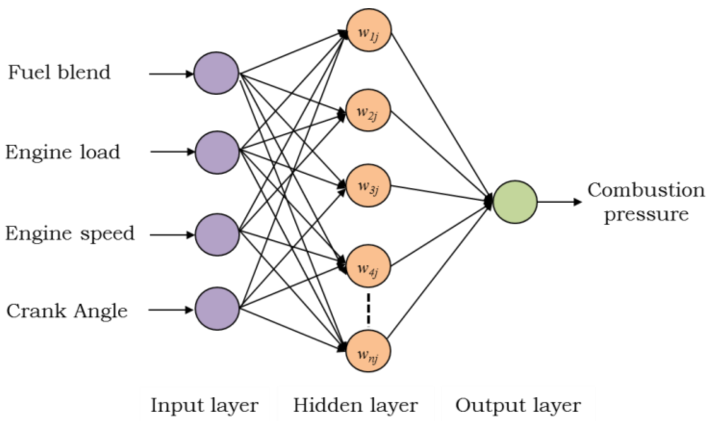

Fig. 6. Structure of artificial neural network prediction model.

The number of neuron embedded in the hidden layer has been determined by the trial-and-error procedure in order to identify the optimum network architecture. When too many neurons are employed, the network generalisation may decrease, while too few neurons may reduce the ability of the network to accurately learn the pattern. Therefore, the number of neurons in the hidden layer was varied between 2-18 neurons. The model training results illustrated in Fig. 7 indicates that the network accuracy increases when the neurons were increased. Nevertheless, when the number of neuron exceeded 16 neurons, MSE values were noted to rise. On top of that, the R-value was also optimized at that amount of neurons. The proposed ANN network has one hidden layer due to its adequate capability to train the input data. The ANN model having 4-16-1 architecture was selected for modelling as they provide the best learning capability with the minimum errors.

The data input for ANN models were derived from the results of the laboratory diesel engine test by employing varied ratios of palm biodiesel-diesel blends. Seventy percent of the data were selected for network training, while the remaining 30% were applied for testing and validation of the simulation model. The network has been trained by the Levenberg-Marquardt algorithm, since they have been acknowledged to be the fastest supervised algorithm in generating a moderate-sized feedforward model [15], even though it demands more computer memory, in comparison to other algorithms. The details of the ANN training configuration are illustrated in Fig. 8. As for the training process, both weights and biases were adjusted by the model to optimize the performance of the network based on the gradient descent technique. In addition, the tangent-sigmoid and the pure-linear were applied as a transfer function in hidden and output layers, respectively. The huge variances between the input and target values were eliminated by normalizing them in the range between −1 and +1 prior to the training process. The related tangent-sigmoid function can be derived according to Eqs. (5) and (6).

The weight and bias values between input and hidden layers for all prediction parameters are tabulated in Table 2.

$$F_j = \frac{2}{1+Exp^{(-2NET_j)}} - 1 \tag{5}$$

$$NET_j = (w_{1i} \times Fuel\ blend) + (w_{2i} \times Engine\ load) + (w_{3i} \times Engine\ speed) + (w_{4i} \times Crank\ angle) + b_{1i} \tag{6}$$

where w is the weight value and b is the bias value of the prediction model.

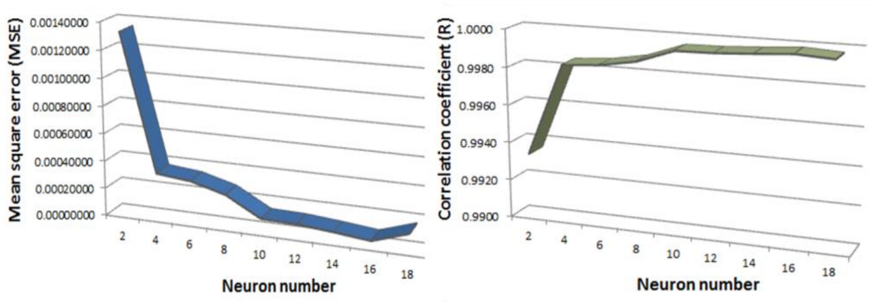

Fig. 7. Performance of trained artificial neural network model.

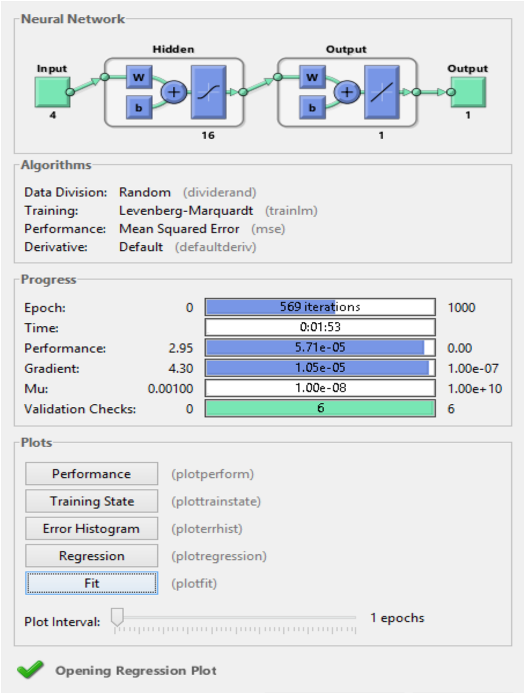

Fig. 8. Artificial neural network training configuration.

Table 2. Weight and bias of the prediction model.

i	w_{1i}	w_{2i}	w_{3i}	w_{4i}	b_i
1	19.32932	-0.05087	-1.74473	17.45133	-22.17653
2	0.17414	-0.09740	-0.07928	12.12394	-0.24941
3	-0.01196	0.36006	-0.04379	3.42552	-0.54531
4	0.00165	-0.01461	-0.14898	35.40187	-0.94912
5	-0.01269	0.42544	-0.02356	3.39657	-0.44622
6	-8.23658	-13.27445	10.02614	-9.40579	8.27650
7	27.59197	-0.03815	0.27466	18.25848	-5.54902
8	0.03378	0.07207	-0.00700	21.03447	-2.47785
9	0.00336	-0.00278	0.14753	-35.59790	0.92134
10	-0.32745	0.09911	0.07932	-12.65669	0.17750
11	0.06035	-0.26686	-0.10013	12.48774	-0.79994
12	-0.49760	13.87262	-2.20122	-6.53331	-4.27400
13	-0.06191	0.18445	0.09272	-12.07641	0.66094
14	28.99197	-0.03118	0.29243	18.70664	-5.79685
15	-0.21668	0.24002	0.02438	-1.01150	0.70035
16	-0.01288	0.52007	-0.00113	3.43850	-0.34383

The performance curve of the prediction model is as illustrated in Fig. 9. The model had successfully trained the input data, as indicated by train curve. The validation and the test curves that appear similar to the end of alteration dismiss the occurrence of data overfitting. In fact, the best validation performance was attained at epoch 563 with a minimum mean square error value of 0.0000546. Meanwhile, the error distribution of the training, the validation, and the test are presented in Fig. 10. Bars that appear blue, green, and red represent training, validation, and testing data, respectively. The training errors occurred within the range between −0.028 and

+0.025, while errors for validation and test ranged from −0.016 to +0.013. Most of the prediction errors occurred within a relatively small range of values.

The regression plot that displays the correlations between the model outputs and the corresponding targets for training, validation, test, and overall datasets are shown in Fig. 11. The dashed line in each plot represents the perfect result between output and target. Meanwhile, the solid line reflects the best fit of the linear regression line between output and target datasets. The prediction results exhibited a good agreement with the experimental data, as indicated by the R-value that is close to unity. Indeed, the values of R for training, validation, test, and overall are 0.99972, 0.99973, 0.99968 and 0.99972, respectively. Based on these values, the developed ANN model is able to generate 99% of prediction accuracy.

The combustion pressure prediction formula generated from the ANN model is given in Eq. (7). The F_1 to F_{16} parameters can be calculated based on sigmoid-tangent transfer function, as specified in Eq. (5). This equation can be used to calculate the engine combustion pressure by incorporating related input data. The validation of ANN predicted results against the experimental data are portrayed in Fig. 12. The curve of the ANN prediction appears to be almost identical to the experimental data as indicate by the blue colour line. Besides, the ANN model offers the best fit to the experimental data points, apart from generating the best prediction for the combustion pressure exerted by the diesel engine

$$\begin{aligned} Combustion\ Pressure = \ & -(0.01048 \times F_1) + (10.00582 \times F_2) - \\ & (4.39712 \times F_3) - (7.85022 \times F_4) + (7.27446 \times \\ & F_5) - (0.00212 \times F_6) - (3.19503 \times F_7) + \\ & (0.12672 \times F_8) - (7.57291 \times F_9) + (4.41841 \times \\ & F_{10}) + (5.19709 \times F_{11}) + (0.00374 \times F_{12}) + \\ & (10.66395 \times F_{13}) + (3.19013 \times F_{14}) - \\ & (0.006474 \times F_{15}) - (2.87810 \times F_{16}) - 0.94756 \end{aligned} \quad (7)$$

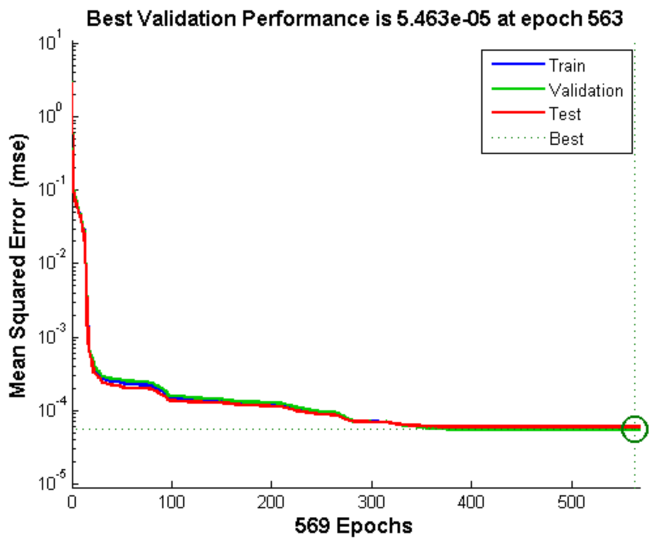

Fig. 9. Artificial neural network model performance curve.

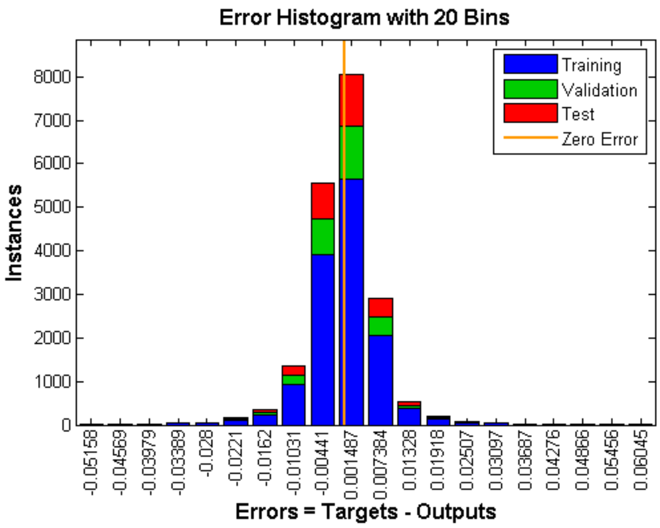

Fig. 10. Error distribution histogram.

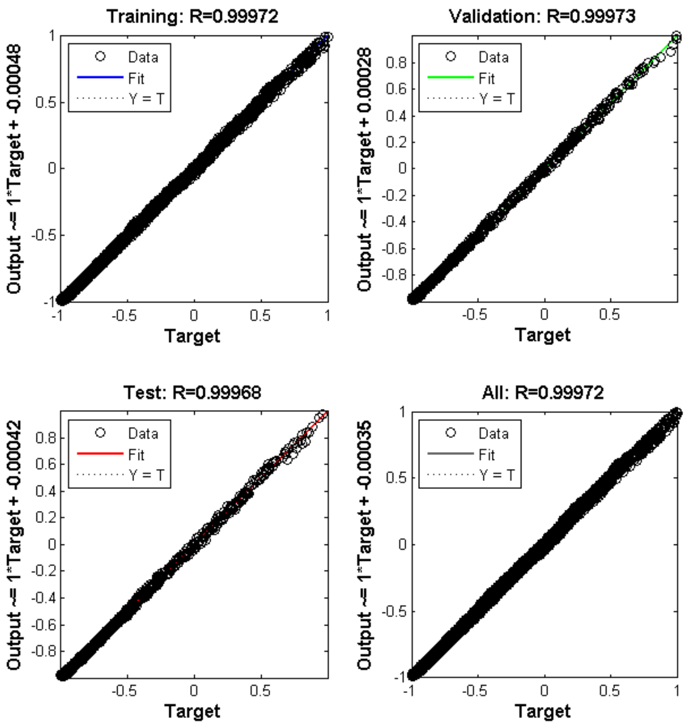

Fig. 11. Regression plot between model output and target data.

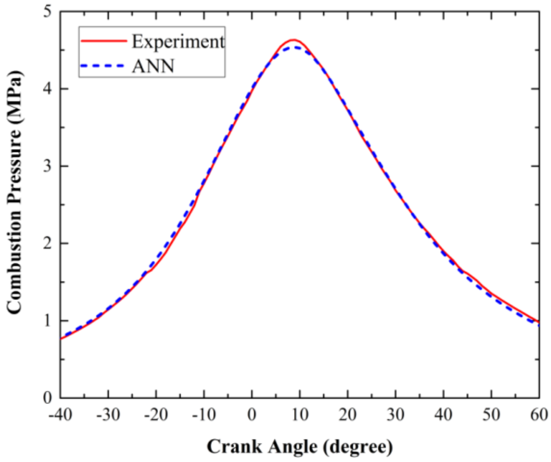

Fig. 12. Validation of artificial neural network results against the experimental data.

5. Conclusions

The diesel engine combustion pressure model was successfully developed by using the ANN-based method. The data from engine testing fuelled by different palm biodiesel blends was used as the model input. The Levenberg-Marquardt was adopted as a training algorithm, while tangent-sigmoid and pure-linear were applied as a transfer function. Several concluding observations from the investigation are given below.

- ANN architecture with 16 neurons in the hidden layer appears to be the best setup for the prediction in this study.
- The prediction results of ANN model provides a close agreement to the experimental data as indicated by higher R-value, between 0.99968-0.99973.
- ANN model is a powerful prediction tool and suitable to be applied in non-linear scenarios with high accuracy.

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Nomenclatures

b	Bias value
N	Number of inputs value
o	Output value
R	Correlation coefficient

R^2	Coefficient of determination
t	Target value
w	Weight value
x	Input value
Y	Output signal

Greek Symbols

Σ	Summation of input parameters
φ	Activation function

Abbreviations

ACO	Ant Colony Optimization
ANN	Artificial Neural Network
BFGS	Broyden-Fletcher-Goldfarb-Shanno
BP	Back-propagation
CP	Cylinder Pressure
DI	Direct Injection
FFNN	Feed-Forward Neural Network
MAPE	Mean Absolute Percentage Error
MSE	Mean Square Error
RMSE	Root Mean Square Error

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