

Experimental and artificial neural network based prediction of performance and emission characteristics of DI diesel engine using *Calophyllum inophyllum* methyl ester at different nozzle opening pressure

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Abstract The present work investigates the effect of varying Nozzle Opening Pressures (NOP) from 220 bar to 250 bar on performance, emissions and combustion characteristics of *Calophyllum inophyllum* Methyl Ester (CIME) in a constant speed, Direct Injection (DI) diesel engine using Artificial Neural Network (ANN) approach. An ANN model has been developed to predict a correlation between specific fuel consumption (SFC), brake thermal efficiency (BTE), exhaust gas temperature (EGT), Unburnt hydrocarbon (UBHC), CO, CO₂, NO_x and smoke density using load, blend (B0 and B100) and NOP as input data. A standard Back-Propagation Algorithm (BPA) for the engine is used in this model. A Multi Layer Perceptron network (MLP) is used for nonlinear mapping between the input and the output parameters. An ANN model can predict the performance of diesel engine and the exhaust emissions with correlation coefficient (R^2) in the range of

0.98–1. Mean Relative Errors (MRE) values are in the range of 0.46–5.8%, while the Mean Square Errors (MSE) are found to be very low. It is evident that the ANN models are reliable tools for the prediction of DI diesel engine performance and emissions. The test results show that the optimum NOP is 250 bar with B100.

Keywords *Calophyllum inophyllum* Methyl ester · Diesel engine · Nozzle opening pressure · Performance · Emissions · Artificial neural network

Highlights

- Modification the Nozzle Opening Pressure (NOP) of the diesel engine for CIME fuel.
- Effects of NOP on the engine performance are investigated.
- An ANN model is developed for rapid prediction of engine performance and emissions.
- Prediction results of the ANN model are compared with the experimental results.
- NOP 250 bar gives optimum performance and low NO_x emissions.

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1 Introduction

Rising fuel costs and future emission regulations have sharpened the automotive industry's focus on efficiency. Moreover, the rapid depletion of fossil fuels due to extensive use has been forced to investigate the renewable fuel with low emission. In the search for alternative fuels, the good option is found to be renewable fuels like vegetable oils, alcohols, etc. Biodiesel is derived from vegetable oils such as jatropha, karanja, *Madhuca indica*, sunflower, cotton seed, neem, corn, and *calophyllum inophyllum* (punnai seed oil) by a process called transesterification [1, 2]. Out of these edible and non-edible vegetable oils are preferred for engine applications in India. This study focuses on *Calophyllum inophyllum* biodiesel. Some researchers [3, 4] investigated the testing of alternative diesel fuel from *Calophyllum inophyllum* biodiesel in a DI diesel engine. Engine performance, exhaust emissions and combustion analysis of each fuel blend are monitored and compared with those of diesel fuel.

Fuel injection pressure is one of the most important operating parameters affecting the performance and emissions in diesel engine. Some researchers [5–10] have found that viscosity is the main dominating effect, whereas density is the

lowest on mean fuel droplet size and consequently to improve fuel atomization viscosity should be the first choice of a biodiesel physical property to be reduced. The above mentioned problem can be solved by blending diesel with CIME which will reduce the viscosity. The another way to improve atomization is injecting biodiesel at higher NOP which in turn increase the atomization process by increasing dispersion of CIME fuel spray.

Artificial Neural Network (ANN) which is used to determine the engine performance map for different operating conditions and biodiesel blends. This is one of the soft computing techniques, which is used as a computational modeling tool to reduce the burden of experimental cost and time. ANN and biological neural network have important differences in terms of both architectures and capabilities. Recently, ANN has been a prominent and commonly used method for engine performance tests, cutting mechanics; signal processing, data decomposition and the image process [11]. Moreover, this modeling method is able to produce novel solutions for some problems. Ghobadian et al. developed an ANN model to estimate diesel engine performance and emission analysis using waste cooking biodiesel fuel [12]. In this study, it is observed that the ANN model can predict the engine exhaust emissions and performance quite well with correlation coefficient.

To the reader's knowledge, the effect of the NOP has not been clearly studied when using CIME in a diesel engine. Therefore, these topics need to be investigating the experiments and final results are validated by using ANN. The aim of this paper is twofold. One is to obtain better thermal efficiency by burning CIME injected at a higher NOP in a DI diesel engine. Higher NOP results in better atomization of CIME which may improve the combustion and thereby releasing more heat [13]. The other is to develop an ANN model to predict the performance of the engine and the exhaust emission. The changes NOP have been observed by using CIME as fuel without any modifications in a DI engine, and the fuel impact on engine performance has been examined. An ANN model is developed by considering the load, blend (B0 and B100) and NOP in the input layer. By this way, prediction of some parameters such as SFC, BTE, EGT, UBHC, CO, CO₂, NO_x and smoke density is aimed. Also, the mathematical models for output results are obtained using MATLAB 8.01 program.

2 Materials and methods

2.1 Biodiesel properties

The biodiesel chosen for the present investigation is *Calophyllum inophyllum* Methyl Ester (CIME). The properties of the CIME are experimentally evaluated. The properties of raw *Calophyllum inophyllum* oil, CIME (B100) are compared with the diesel (B0) in Table 1.

Table 1 Properties of *Calophyllum inophyllum* Methyl Ester compared with Diesel

S. No	Name of the Properties	ASTM Code	B0	B100
1	Kinematic Viscosity at 40 °C in cSt	D2217	2.83	5.34
2	Gross Calorific Value in kJ/kg	D4809	42,250	40,600
3	Flash Point in °C	D93	56	170
4	Fire Point in °C	D93	58	186
5	Specific Gravity	D445	0.82	0.91
6	Cetane Number	D975	46	52.4

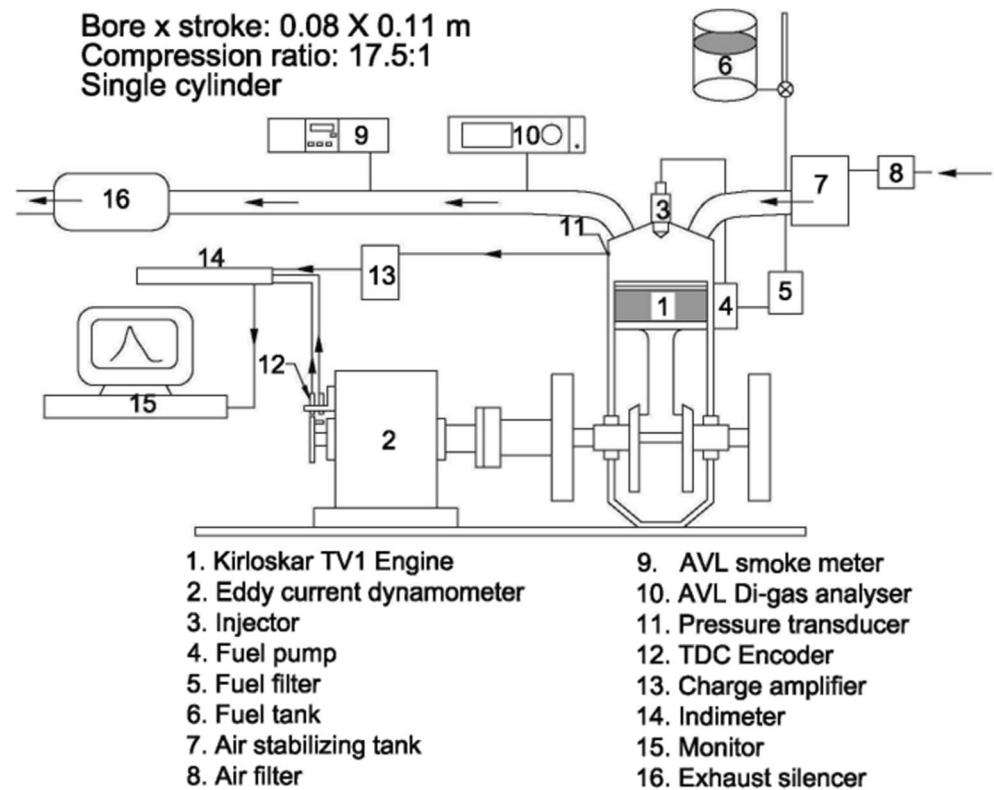
3 Experimental setup

Experiments have been conducted in an electronically controlled, 4 stroke, kirloskar, Tangentially Vertical (TV-1) single cylinder, Direct Injection (DI) diesel engine developing power output of 5.2 kW at 1500 rpm connected with water cooled eddy current dynamometer. The Fig. 1 shows the schematic diagram of experimental setup. The detailed specifications of the engine are presented in Table 2. The standard static injection timing of 23° bTDC and nozzle opening pressures of 220, 230, 240 and 250 bar are used for the entire experiments at different load condition of the engine. The photographic view of fuel injector nozzle is shown in Fig. 2. The fuel injector nozzle modeling is developed by using solid works is shown in Fig.3. AVL 444 di-gas analyzer is used for the measurement of exhaust emission of HC, CO and NO_x. Smoke level is measured by using standard AVL 437 smoke meter. The accuracy of measurement and their performance may vary depending on the operational conditions and experimental environment. For this reason, the uncertainty occurs due to fixed or random errors. The uncertainties in the measured parameters are estimated based on analytical progression. The uncertainties calculated for the measured quantities are given in Table 3. All the experimental readings are taken from 0% to 100% in a step of 20% load and steady state conditions of the engine. The performance and emission values are observed as test values. To train and test the ANN, the test results obtained in the experimental study are used.

4 Experimental results

4.1 Effect on performance parameters

The variation of SFC with respect to the brake power for different NOPs of 220, 230, 240 and 250 bar by using diesel (B0) and CIME (B100) are shown in Fig. 4. It can be observed that at all loads and NOPs; the fuel consumption is higher in the case of CIME compared to diesel. This may be due to higher density and lower heating value of CIME compared

Fig. 1 Schematic diagram of the diesel engine setup

to diesel. The variations of BTE with respect to the brake power for different NOPs by using diesel (B0) and CIME (B100) are shown in Fig. 5. High NOP means, the injection always takes place at high pressure and hence, fuel atomization is better and mixing with air is good. It leads to better

combustion and in turn, improves BTE. The results show that efficiency at full load is closer to diesel fuel for the reason that of improved atomization and better mixing process at higher NOPs. A smaller droplet will have lesser momentum and its relative velocity decreases in air which results in its partial suffocation by its own products of combustion. It can be seen that at NOP 250 bar, the efficiency is marginally higher than diesel fuel. This may be resulting to the better combustion of CIME. It is to be noted that the oxygen (12%) in the CIME

Table 2 Specification Details of the Engine

Name of the Description	Details / Value
Make	Kirloskar TV1
Type	Vertical diesel engine, 4stroke, Water cooled, single cylinder
Bore	87.5 mm
Stroke	110 mm
Compression Ratio	17.5:1
Swept Volume	661 cm ³
Rated Brake Power	5.2 kW(7 HP)
Speed	1500 rpm
Combustion Chamber	Hemispherical Combustion Chamber
Ignition System	Compression Ignition Engine
Static Injection Timing	23° bTDC
Nozzle Opening Pressure	220 bar
Fuel Injection Pump	MICO Inline, with Mechanical Governor and Flange Mounted
Nozzle Injector Holes with diameters	Hole 3 (0.28 mm)
Loading Device	Eddy Current Dynamometer
Dynamometer arm length	0.195 m

**Fig. 2** Photographic view of fuel injector nozzle

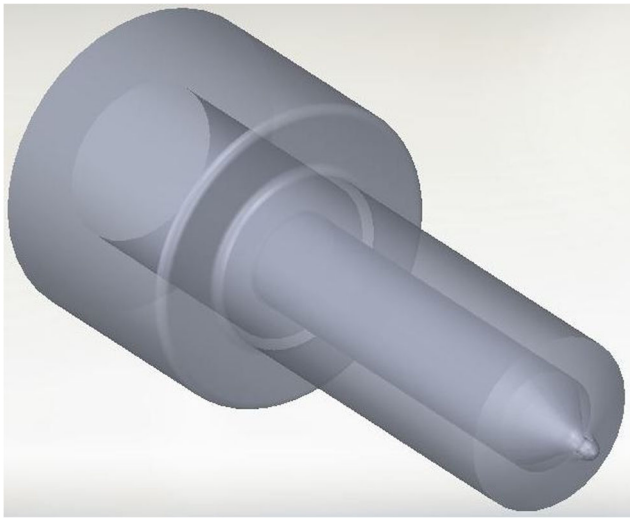


Fig. 3 Solid works modeling view of fuel injector nozzle

takes part in combustion which in turn, enhances the combustion process [13]. The variations of EGT with respect to the brake power for different NOPs by using diesel (B0) and CIME (B100) are shown in Fig. 6. It is seen that the EGT of CIME is increased because better combustion takes place compared to diesel when NOP is increased at full load. By increasing NOP, the EGT is increased and this could be due to lower heat transfer rate at high NOP which is apparent from the trends of BTE [14].

4.2 Effect on emission parameters

The UBHC and CO emissions of both fuels are lower in partial load. However, they increase at higher engine load as shown in Fig. 7 and Fig. 8 respectively. This happens due to relatively less oxygen available for the reaction, when more fuel is injected in to the engine cylinder at higher engine load. This claim has been validated in Fig. 9, and it shows the CO₂

variation. CO₂ emissions for CIME are comparatively higher than that of diesel fuel at full load condition of the engine. As the NOP increases the fuel droplet travel with a high velocity that may hit the combustion chamber wall, which may lead to higher UBHC emissions. It is observed that CO and HC emissions of CIME drop as, NOP is increases and reaches to a least at 250 bar. High NOP improves spray characteristics and they will lead to a lower physical delay period. This will improve the performance of CIME, which normally has a high ignition delay due to its high viscosity. The improved spray also leads to better combustion and brake thermal efficiency. The variations of oxides of nitrogen with respect to brake power for different NOPs are shown in Fig. 10. The formation of NO_x is lesser than diesel fuel, due to lower EGT. In addition, the higher oxygen content of CIME leads to more complete combustion, which result in greater combustion temperature peaks and they cause higher NO_x emissions when NOP is increased. However, the higher viscosity and density of biodiesel cause delayed combustion phase, which results in the slower combustion characteristics of *Calophyllum inophyllum* biodiesel. The variations of smoke emissions with respect to brake power for different NOPs are shown in Fig. 11. This may be due to heavier molecular structure, double bonds in the vegetable oil chemical structure and high viscosity of CIME. The number of double bonds present in the fatty acid is strongly related to emissions. These factors are responsible for higher smoke emissions which result in incomplete and lethargic combustion [14].

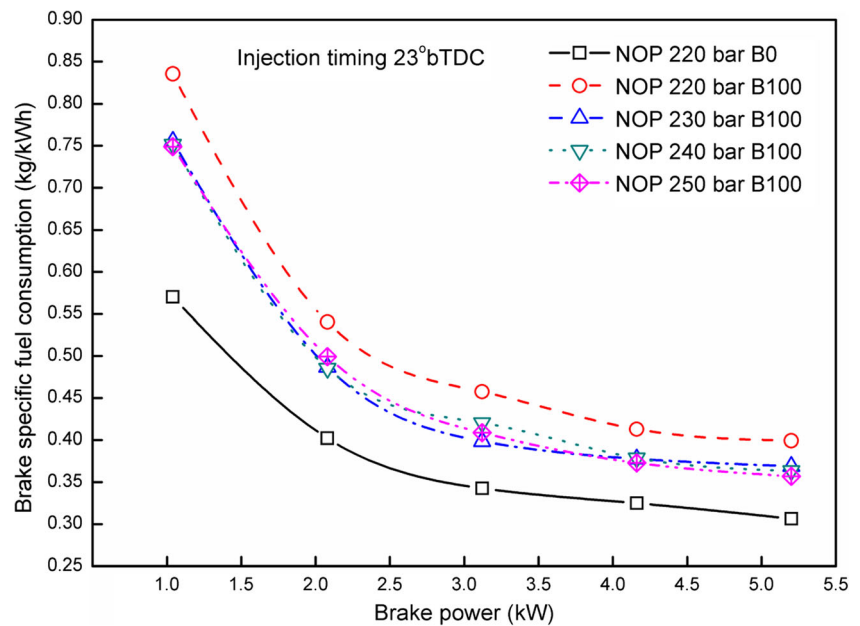
4.3 Effect on combustion characteristics

Cylinder pressure crank angle variation at full load with diesel (B0) and CIME (B100) at different NOPs are given in Fig. 12. The cylinder pressure runs for 100 cycles. The maximum cylinder pressure is recorded at 240 bar injection pressure for B100 and it may be due to the longer ignition delay period.

Table 3 Uncertainties and measurement methods of instruments used in engine experimentation

S. No	Measurement	% Uncertainty	Measurement Technique
1	Load	±0.2	Strain gauge type load cell
2	Speed	±0.1	Magnetic pickup principle
3	Temperature	±0.15	Thermocouple
4	Diesel fuel measurement	±1	Volumetric measurement
5	Biodiesel Measurement	±1	Volumetric measurement
6	Time	±0.2	Stop watch
7	Manometer	±1	Principle of balancing column of Liquid
8	Piezoelectric pressure transducer	±0.1	Magnetic pickup principle
9	Crank angle encoder	±0.2	Magnetic pickup principle
10	CO	±0.2	NDIR technique
11	HC	±0.1	NDIR technique
12	NO _x	±0.2	NDIR technique
13	Smoke Density	±1	Opacimeter

Fig. 4 Specific fuel consumption
 V_s brake power



As the ignition delay period increases, more fuels accumulate which results in increase in peak pressure. But, when the NOP increases, the ignition delay reduces. This is due to higher dispersion, shorter breakup length, lower sauter mean diameter and better atomization. The heat release rates at various crank angles are shown in Fig. 13.

The maximum heat release takes place during the premixed combustion phase. This is because of the higher NOP, which improves atomization and mixing leading to better combustion. The Cumulative Heat Release Rates (CHRR) at various crank angles are shown in Fig. 14.

The decrease in CHRR for NOP 250 bar is believed due to the high latent heat of vaporization of test fuel. Heat loss

occurs, due to combustion. Further, cylinder wall heat transfer and losses happen owing to friction on the test engine.

5 Modeling with ANN for optimum nozzle opening pressure

5.1 Network structure

ANN consists of artificial neural cells called neurons. The networks contain input, hidden, and output layers which are made of a number of nodes. Neurons (processing elements) at input layer transfer data from external world to hidden layer. The data

Fig. 5 Brake thermal efficiency
 V_s brake power

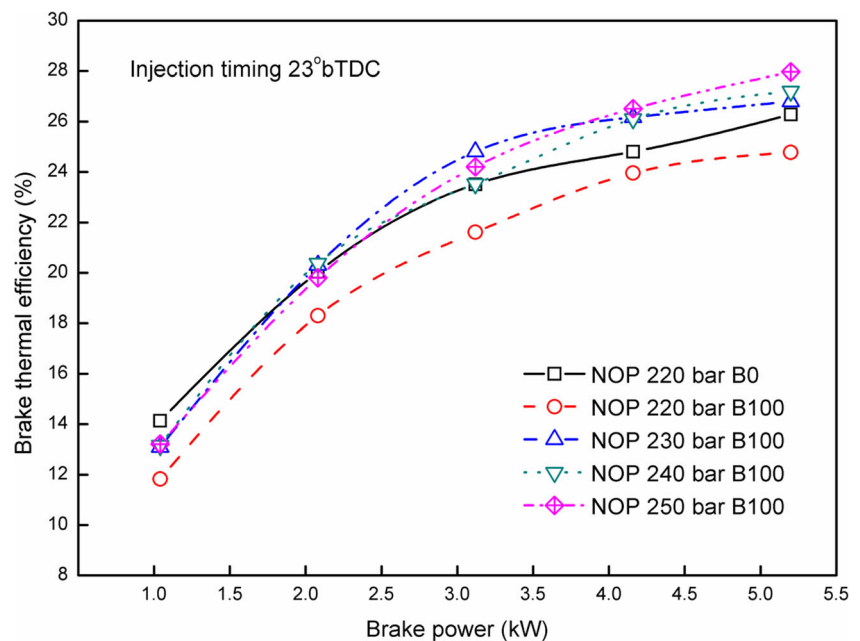
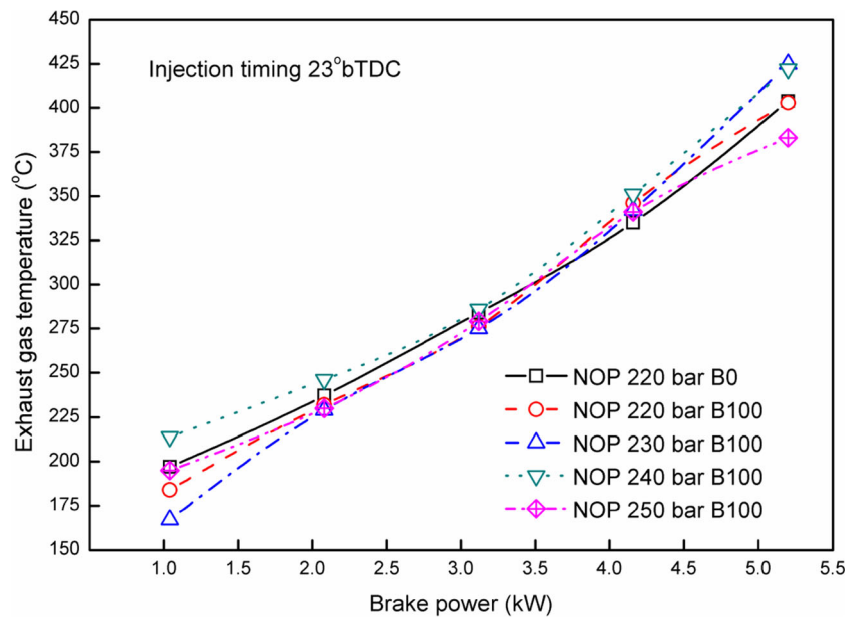


Fig. 6 Exhaust gas temperature V_s brake power



in the input layer do not process the data to the other layers. In the hidden layer, outputs are produced using data from neurons in the input layer. Then, summation and activation are performed. There can be more than one hidden layer. In this case, the single hidden layer sends outputs to the following output layer.

The output of the network is produced by processing data from the hidden layer and sent to external world through the output layer. The summation function calculates the net input coming to a cell. The most common one is to calculate the weighted sum. Inputs (Load, Blend and NOP) are the knowledge from other cells or external world to the input cells. These are determined by examples that the network wants to be trained. Weights (w_1, w_2, \dots, w_n) are the values which

determine the effect of input set or one more processing element in the preceding layer on the processing element. Every input value is multiplied by weight value which connects it to the processing element and subsequently, it is combined by summation function. Thus, net input of the network can be found. The summation function is given in Eq. (1).

$$NT_i = \sum_{j=1}^n (w_{ij}x_j + w_{bi}) \quad (1)$$

Activation function provides a curvilinear match between input and output layers. Also, it determines the output of the cell by processing net input to the cell. The constructed network performance significantly affects the selection of

Fig. 7 Unburnt hydrocarbon exhaust gas emissions V_s brake power

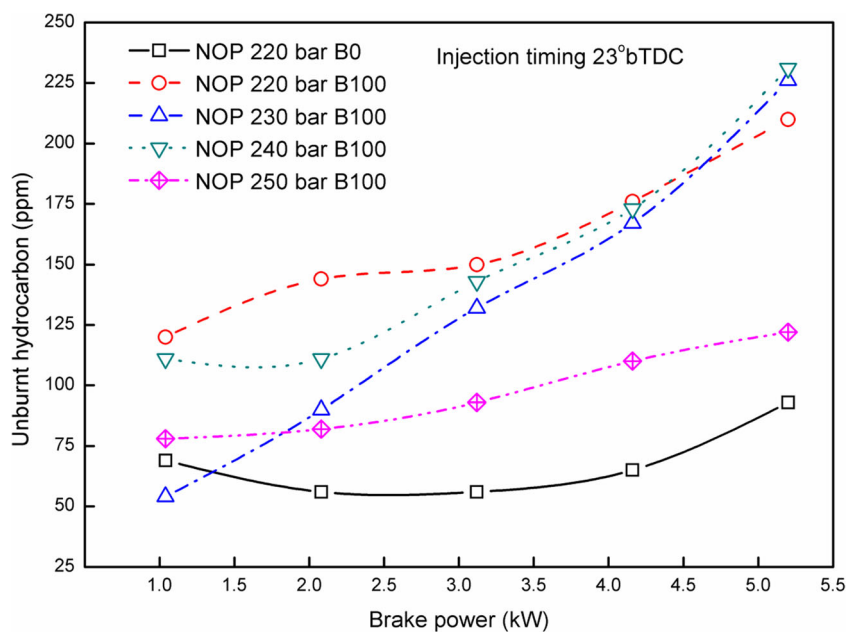
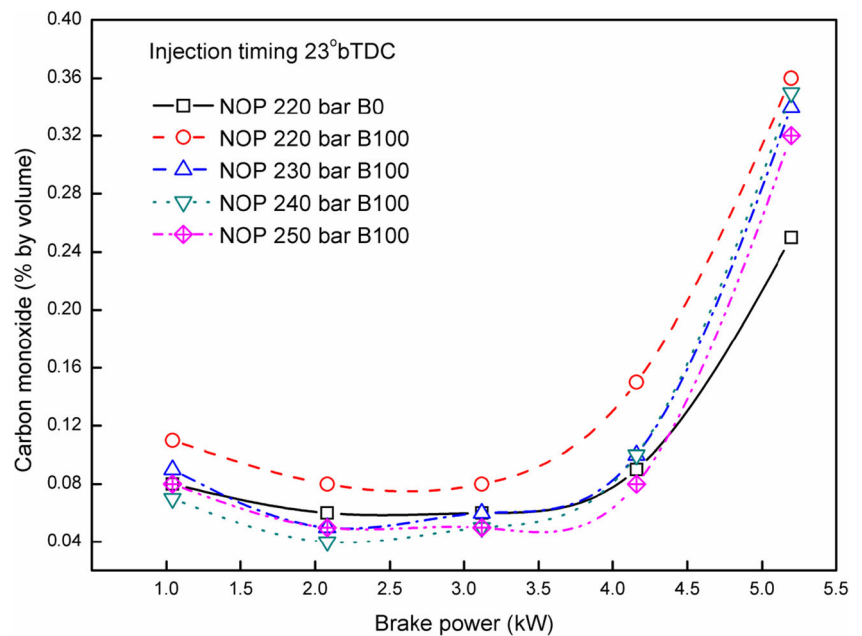


Fig. 8 Carbon monoxide exhaust gas emissions V_s brake power



appropriate activation function. Recently, logistic sigmoid transfer function has been generally used as an activation function in the MLP network model, because it is a differentiable, continuous and non-linear function. Hence, the logistic sigmoid (sigln) transfer function is used as the activation function in this analysis. This function produces a value between 0 and 1 for every one value of net input. The formula of the logistic sigmoid function is given in Eq. (2).

$$f(NT_i) = \frac{1}{1 + e^{-NT_i}} \quad (2)$$

According to the trial results, ANN architecture with three neurons in input layer, twenty-three neurons in hidden layers

and eight neurons in output layers obtains better predictions and is shown in Fig. 15.

5.2 Learning algorithm

There are many learning algorithms in order to determine the weights in ANN. The back propagation is one of the most common learning algorithms. This back propagation method updates the weights in accordance with the difference between available data and network output. Learning parameter employed in the method has a great importance to reach the optimum results. Learning parameter can be constant or

Fig. 9 Carbon dioxide exhaust gas emissions V_s brake power

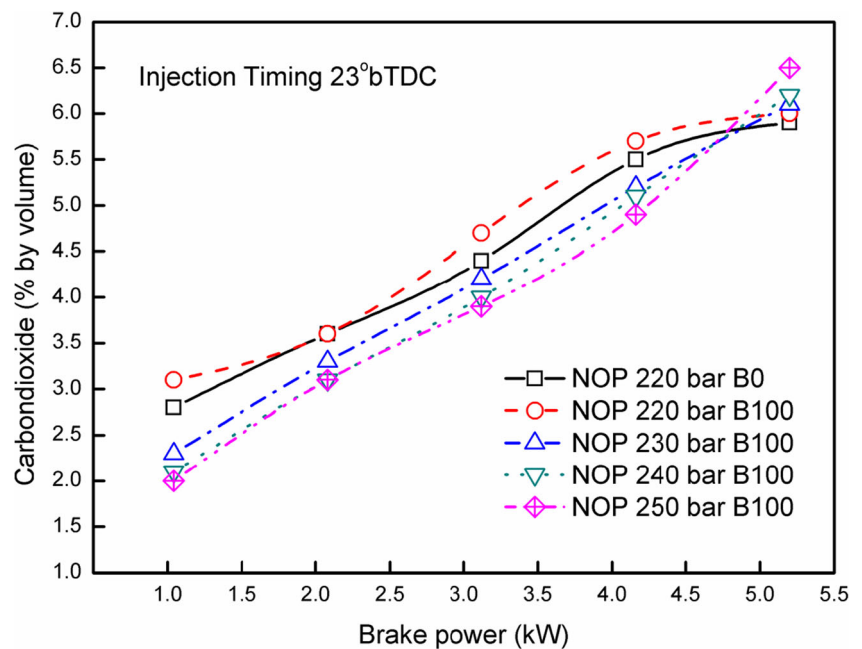
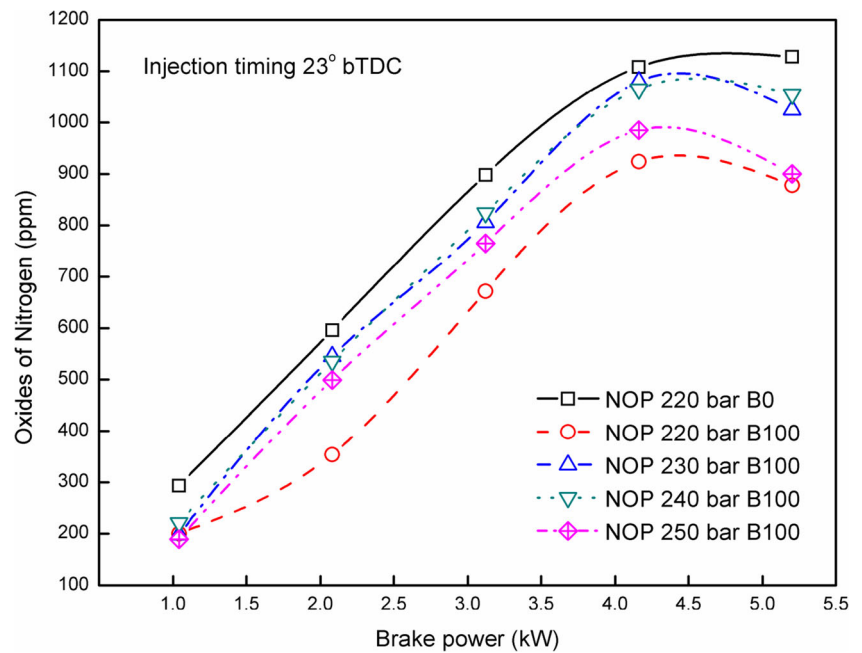


Fig. 10 Oxides of nitrogen exhaust gas emissions V_s brake power



dynamically restructured in the model. There are various training functions that have been applied by the previous studies such as gradient descent with adaptive learning rule, Levenberge-Marquardt, gradient descent with momentum and adaptive learning rule, scaled conjugate gradient and Bayesian regularization [15–21]. In order to obtain the closest output values to experimental results, the best learning algorithm with optimum number of neurons in hidden layer is determined. For this reason, both SCG and LM learning algorithms and different numbers (20–28) of neurons in hidden layer are used in the built network structure for effective power. In consequence of trials, the best learning algorithm and the

network architecture for the prediction of effective power become LM: 3–23–8 (Fig. 15). The Table 4 show the determination of the best learning algorithm and optimal number of neurons for effective power.

5.3 Training and testing data

A vital role for building an ANN architecture is the determination of percentages of training and testing data. When the studies in literature are analyzed, it is revealed that different ratios are used for training and testing the data. The percentages of training, testing and validating the data are

Fig. 11 Smoke density V_s brake power

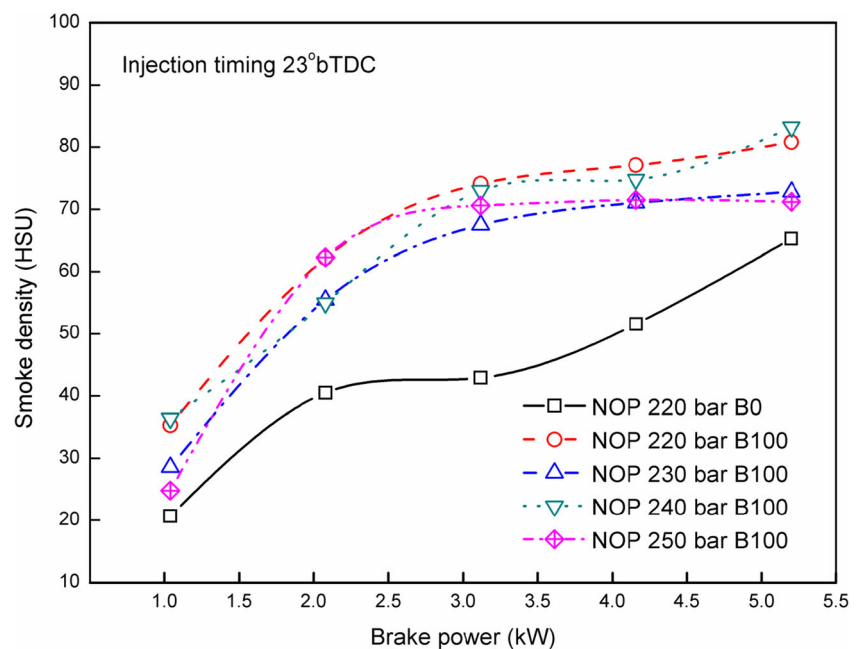
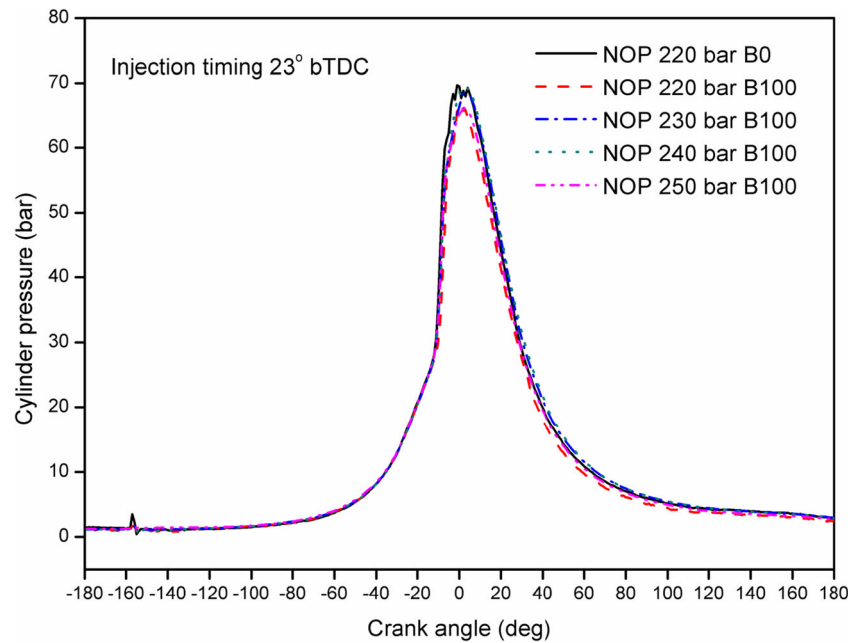


Fig. 12 Comparisons of cylinder pressure at full load



70%:15%:15% respectively. In this study, 17 experimental results have been prepared for training, validating and testing the data of ANN. The ratios for training, testing and validating the data are selected as 70%:15%:15%. In this context, 4 data for validating, 4 data for testing and 17 data for training are randomly selected.

5.4 Normalization of input and output data

The scaling of inputs and outputs significantly affects performance of ANN in back propagation model. The logistic sigmoid transfer function is used in this study as mentioned above. One of the features of this function is that only a value

between 0 and 1 can be produced. Input and output data sets are normalised before training, validating and testing process.

According to the studies in the literature, two formulas are used for the normalization. In this work, all the data sets (X_i) (from the training, validation and test sets) are scaled to a new value x_i using the formula in Eq. (3). The MSE value is given by Eq. (4).

$$x_i = \frac{x_i - X_{\min}}{X_{\max} - X_{\min}} \quad (3)$$

$$\text{MSE}(xy) = \frac{1}{n} \sum_{i=1}^n (x_i - y_i)^2 \quad (4)$$

Fig. 13 Comparisons of heat release at full load

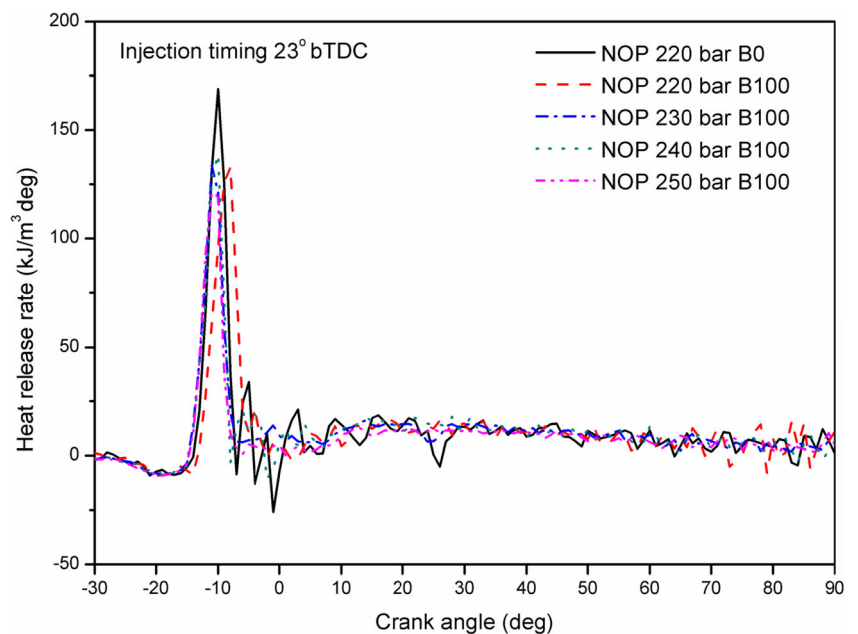
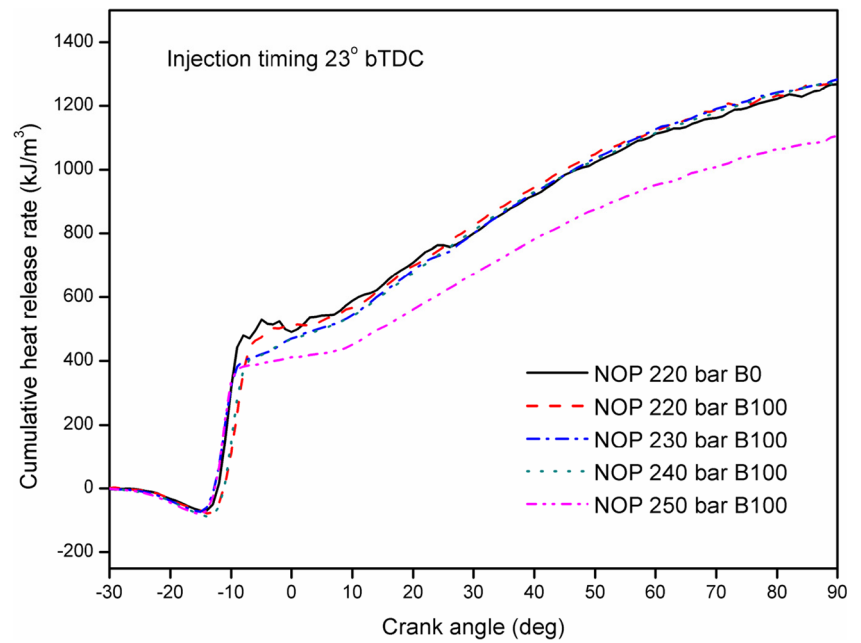


Fig. 14 Comparisons of cumulative heat release at full load



where n is the number of samples and x_i and y_i are the values of the i^{th} samples in x and y , respectively.

5.5 Statistical evaluation of outputs

Back-Propagation (BP) training algorithm is a ramp descent algorithm. The BP algorithm minimises total error by varying the weights through its ramp consequently tries to improve the

performance of the ANN network. The training of the network is stopped, the tested values stop and the ANN learning is completed. Then, the performance of the ANN predictions is measured by comparing the predictions with the experimental results which are not used in the training process. In order to understand whether an ANN makes good predictions, the testing data, that have never been accessible to the network, are used and the results are checked at this stage.

Fig. 15 Network configuration of ANN model

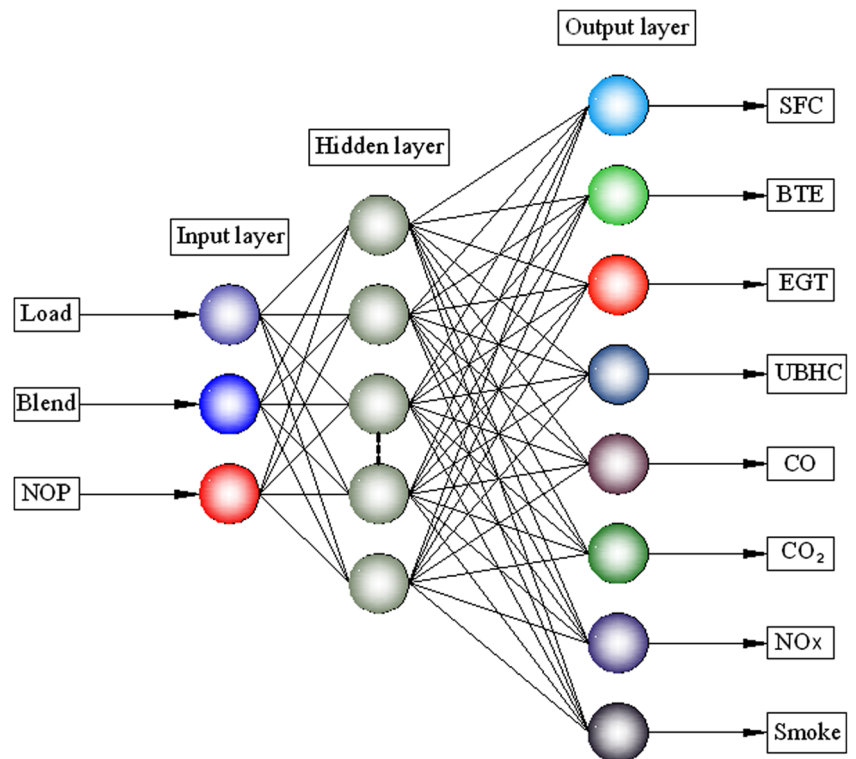


Table 4 Summary of different networks evaluated to yield the criteria of network performance for the ANN model

Activation function	Training rule	Neurons in hidden layer	Training error	Training R ²
sig/lin	trainlm	20	9.10315 X 10 ⁻⁴	0.9968
sig/lin	trainlm	21	6.51244 X 10 ⁻⁴	0.9934
sig/lin	trainlm	22	1.34686 X 10 ⁻⁴	0.9974
sig/lin	trainlm	23	1.16823 X 10 ⁻⁴	0.9989
tan/lin	trainlm	23	4.45431 X 10 ⁻³	0.5857
sig/lin	traingdm	23	5.4658 X 10 ⁻³	0.8465
sig/lin	trainscg	23	12.2554 X 10 ⁻³	0.8945
sig/lin	trainrp	23	18.5425 X 10 ⁻³	0.8421
sig/lin	trainlm	24	1.89311 X 10 ⁻³	0.9931
sig/lin	trainlm	25	3.71309 X 10 ⁻³	0.9847
sig/lin	trainlm	26	2.10119 X 10 ⁻³	0.9904
sig/lin	trainlm	27	3.57211 X 10 ⁻³	0.9925
sig/lin	trainlm	28	3.55556 X 10 ⁻³	0.9852

5.6 Prediction of engine performance using ANN

The aim of using the ANN modeling is considered as a practical approach to test the ability of predicting a correlation between specific fuel consumption, brake thermal efficiency, exhaust gas temperature, UBHC, CO, CO₂, NO_x and smoke density using load, blend (B0 and B100) and Nozzle opening pressure (NOP) as input data. The developed ANN is found to be successfully predicted the output parameters as shown in Figs. 16, 17, 18, 19, 20, 21, 22 and 23.

6 Conclusions

Based on the experimental work on a DI diesel engine fueled with diesel fuel (B0) and CIME (B100) the following conclusions are drawn. With B100, increasing the NOP from the standard value (220 bar) to 250 bar resulted in improvement

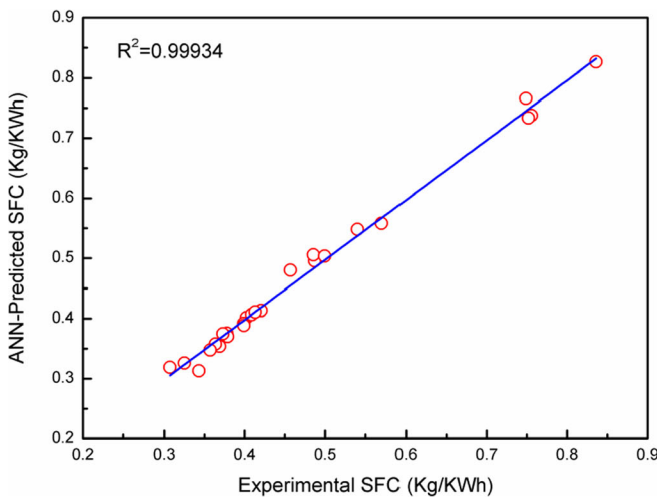


Fig. 16 Regression coefficient, Experimental and ANN- predicted SFC

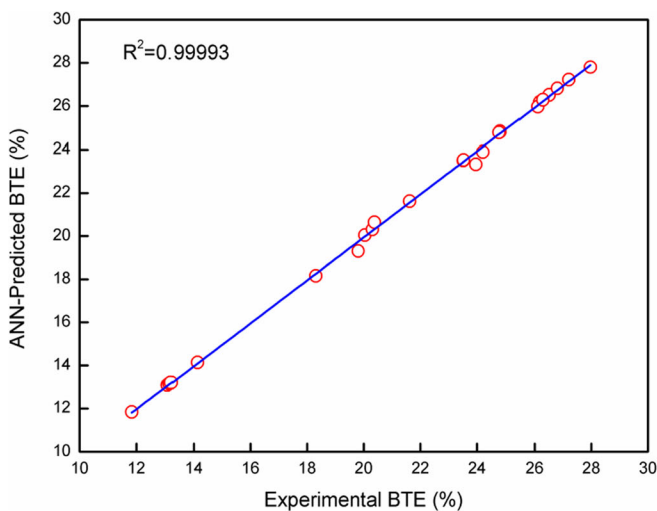
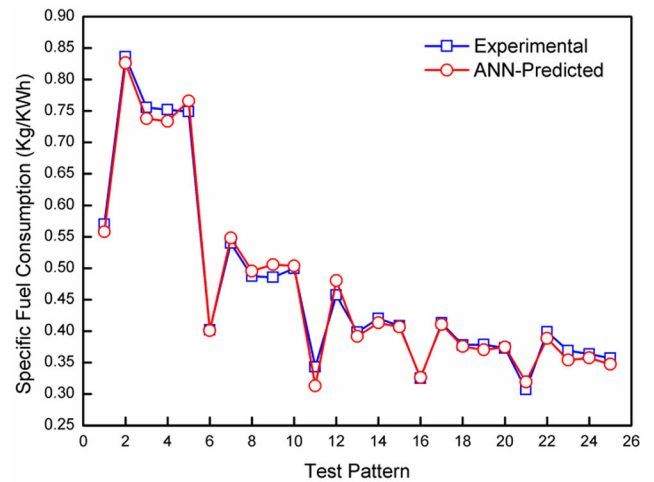
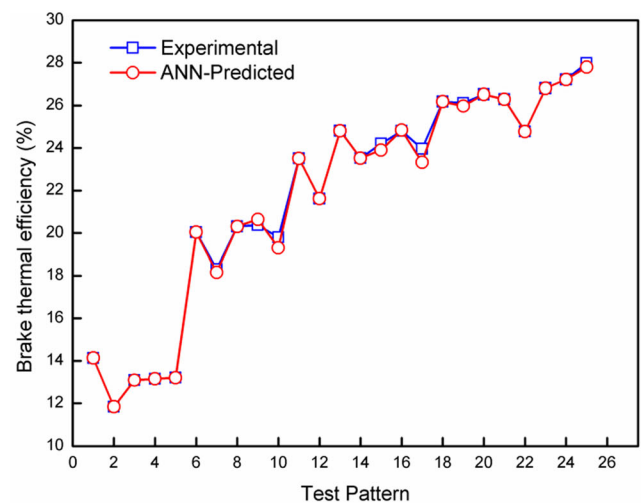


Fig. 17 Regression coefficient, Experimental and ANN- predicted BTE



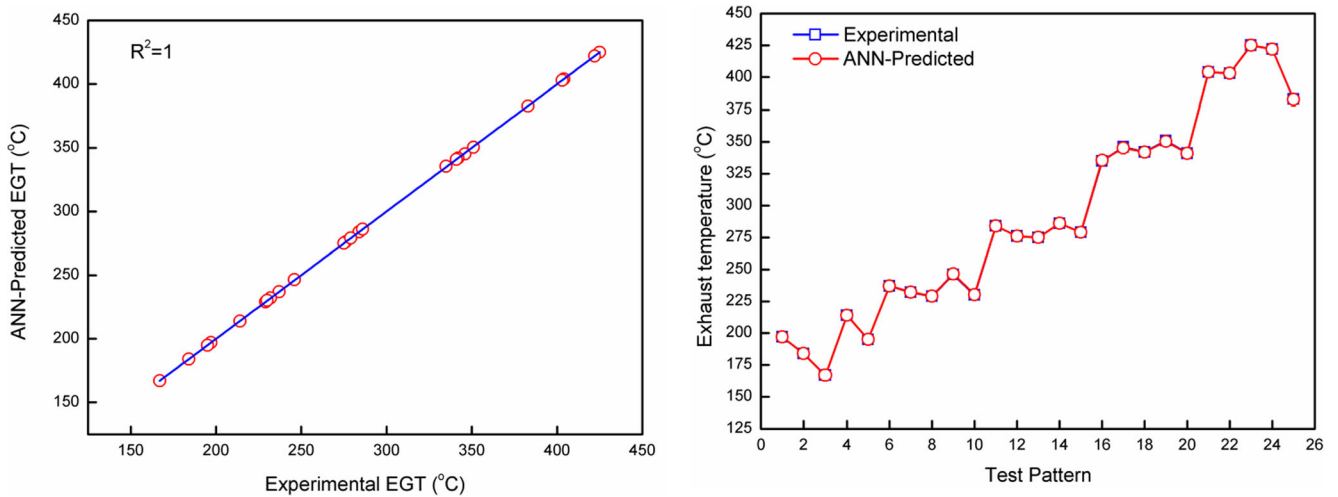


Fig. 18 Regression coefficient, Experimental and ANN- predicted EGT

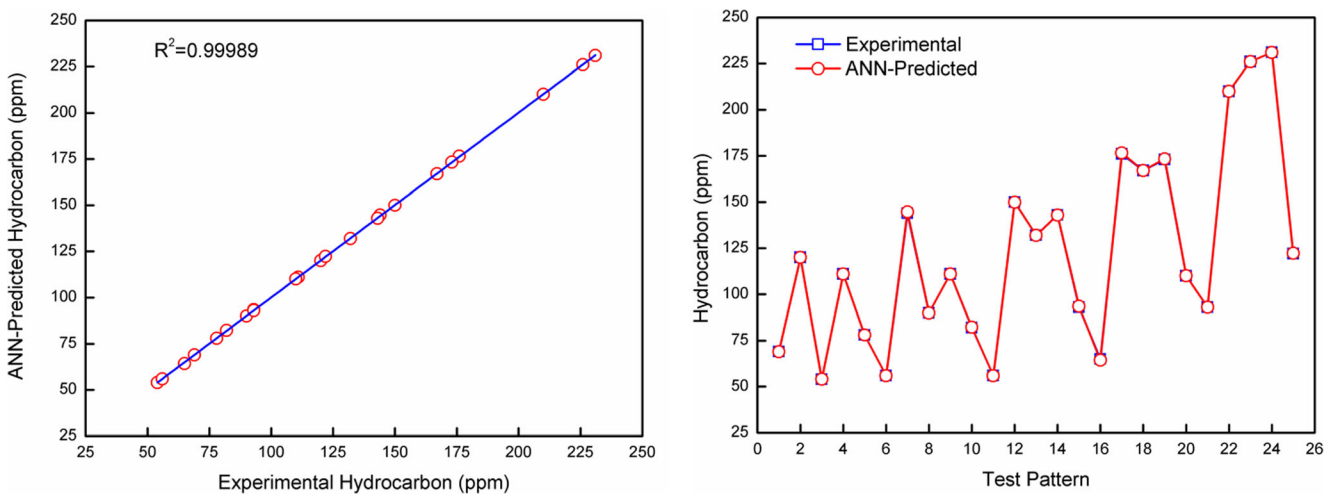


Fig. 19 Regression coefficient, Experimental and ANN- predicted UBHC emission

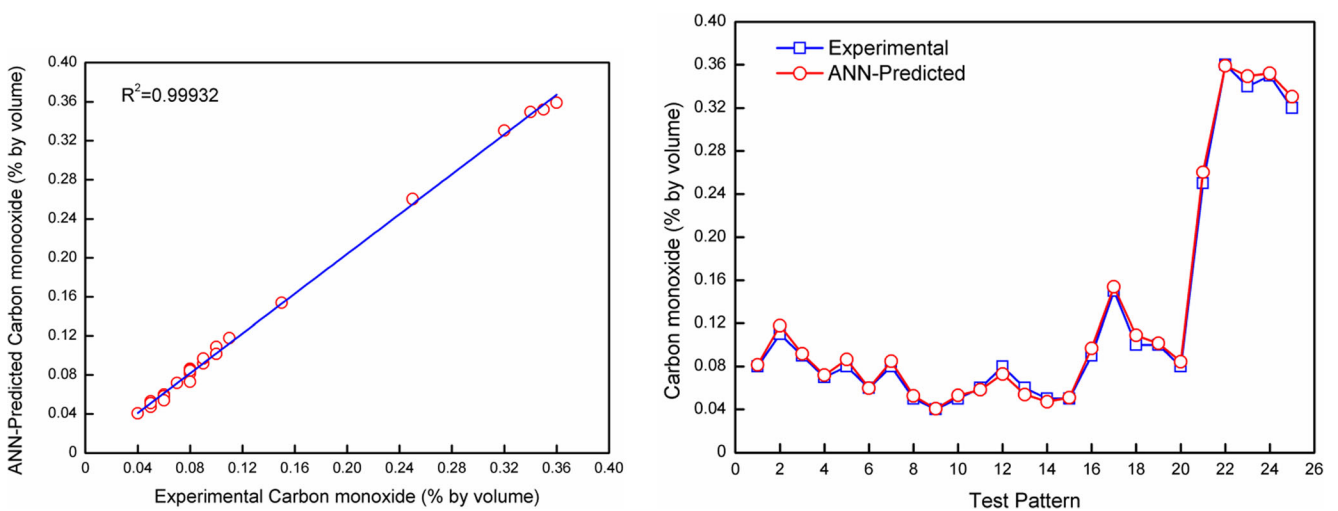


Fig. 20 Regression coefficient, Experimental and ANN- predicted CO emission

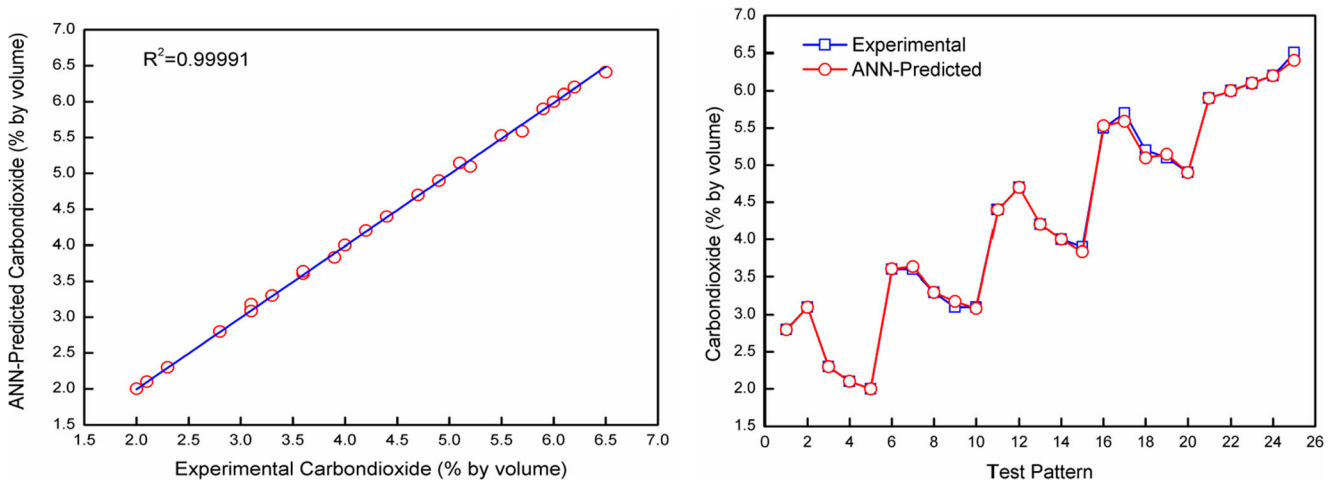


Fig. 21 Regression coefficient, Experimental and ANN- predicted CO₂ emission

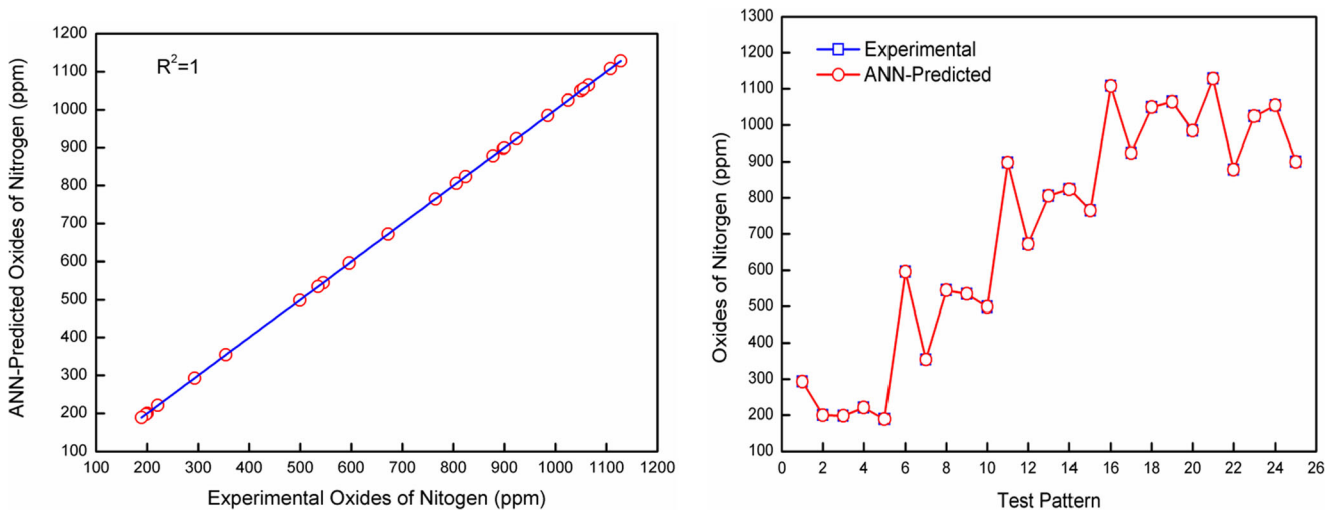


Fig. 22 Regression coefficient, Experimental and ANN- predicted NO_x emission

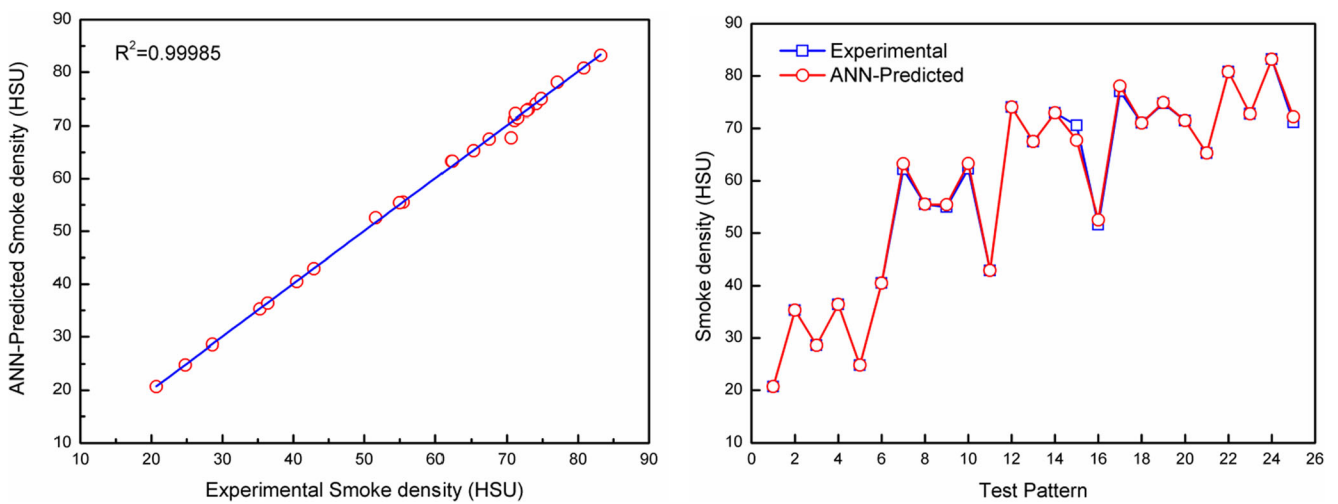


Fig. 23 Regression coefficient, Experimental and ANN- predicted Smoke emission

of performance and emissions due to better spray formation in turn combustion. The following changes are noticed at maximum load.

- By transesterification process the CIME properties are closer to diesel fuel.
- CIME, derived from non-edible oil, which is an oxygenated fuel, used in a diesel engine reduces NO_x at NOP 250 bar.
- At NOP 250 bar, the thermal efficiency improves with increased emissions.
- Brake thermal efficiency increases from 26.288% to 27.973%.
- The smoke density increases with decreasing NO_x content and is observed at NOP 250 bar.
- NO_x reduces from 1128 ppm to 900 ppm which may be due to the combined effect of operating fuel as well as high NOP.
- An improvement in the heat release rate noticed with increase in the NOP of 240 bar.
- The applicability of ANNs has been investigated for the performance and emissions of a DI engine.
- After investigating, it is found that the R^2 values are very closely 1 for the training and testing data. MSE is smaller than 3.8% for the testing data.
- MRE are found to be within acceptable limits. This shows good correlation between the experimental and ANN predicted values.

This ANN analysis shows that, as an alternative to conventional modelling technique and hence, this ANN approach can be used to accurately predict the problems of IC engines. Moreover, as an alternative to classical modelling technique the ANN approach can be highly recommended to predict the engine's emissions and the performance instead of undertaking complex and time-consuming experimental studies.

The optimum NOP can be identified based on the performance, emission and combustion characteristics by conducting the load test on the DI diesel engine. This may probably be due to the changes in the fuel spray structure which affects combustion. The changes in the spray may be higher dispersion, higher spray tip penetration, shorter break-up length and lower sauter mean diameter. Thermal efficiency at NOP 220 bar is comparatively lower than that of diesel. Finally, it is concluded that NOP 250 bar could improve the combustion, performance and emissions with CIME in a DI diesel engine.

B100, 100% CIME; ANN, Artificial Neural Networks; BP, Back-Propagation; bTDC, before Top Dead Center; BSFC, Brake Specific fuel consumption; BTE, Brake Thermal efficiency; CIME, *Calophyllum inophyllum* Methyl Ester; CO, Carbon monoxide; CO_2 , Carbondioxide; CI, Compression Ignition; R^2 , Correlation coefficient; $^\circ\text{CA}$, degree crank angle;

B0, Diesel; DI, Direct Injection; HSU, Hartridge Smoke Unit; HRR, Heat Release Rate; IC, Internal Combustion; KJ, Killo Joules; Kg, Killogram; kW, Kilowatt; TRAINLM, Levenberg–Marquardt; purelin, linear; logsig, log-sigmoid; MRE, Mean Relative Error; MSE, Mean-Squared Error; NN, Neural Networks; X_i , Normalised input/output; NOP, Nozzle Opening Pressure; NO_x , Oxides of Nitrogen; ppm, Parts Per Million; P, Pressure (bar); SD, Smoke Density; tansig, tangent-sigmoid; TDC, Top Dead Center; UBHC, Unburnt hydrocarbourn.

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