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Full Length Research Paper

Influence of injection timings on performance and emissions of a biodiesel engine operated on blends of Honge methyl ester and prediction using artificial neural network

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In the present work, biodiesel prepared from Honge oil (Pongamia) was used as a fuel in C. I engine. Performance studies were conducted on a single cylinder four-stroke water-cooled compression ignition engine connected to an eddy current dynamometer. Experiments were conducted for different percentage of blends of Honge methyl ester with diesel at various compression ratios and at different injection timings. Experimental investigation on the Performance parameters and Exhaust emissions from the engine were done. Artificial neural networks (ANNs) were used to predict the engine performance and emission characteristics of the engine. Separate models were developed for performance parameters as well as emission characteristics. To train the network compression ratio, blend percentage, percentage load and injection timings were used as the input variables whereas engine performance parameters and engine exhaust emissions were used as the output variables. Experimental results were used to train ANN. Results showed good correlation between the ANN predicted values and the desired values for various engine performance values and the exhaust emissions. Mean relative error values were less than 10 percent which is acceptable.

Key words: Honge methyl ester, transesterification, emissions, epochs, artificial neural network.

INTRODUCTION

Agricultural sector of India is completely dependent on diesel for its motive power and to some extent for stationary applications. Increased farm mechanization in agriculture thus further increased the requirement of diesel. Nowadays due to the limited resources of fossil fuels, rising crude oil prices and the increasing concerns for the environment, there has been renewed focus on the vegetable oils and animal fats as an alternative fuel sources. The attractive features of the biodiesel are (i) since it is a plant derived fuel, its combustion does not increase the current net atmospheric levels of CO_2, a greenhouse gas (ii) it can be domestically produced offering the possibility of reducing petroleum imports and (iii) it is biodegradable. Ramdas et al. (2004), Hossain and Davies (2010), Raheman et al. (2004), Kumar et al. (2006) and Suryawanshi and Deshpande (2004) observed that the use of vegetable oils have reduced the levels of particulate matter, HC, and CO compared with the diesel combustion. Various vegetable oils both edible and non-edible can be considered as alternative sources for diesel engines. In most of the developed countries sunflower, peanut, palm and several other feed stocks are used as alternative sources which are edible in the Indian context. Therefore in the developing countries like India, it is desirable to produce biodiesel from non-edible oils which can be extensively grown in the waste lands of

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the country. It has been reported that non edible oils available in India are Pongamia, Jathropa rubber seed etc. However the major disadvantage of vegetable oils is their high viscosity which leads to poor atomization, which in turn may lead to poor combustion, ring sticking, injector coking, injector deposits, injector pump failure and lubricating oil dilution by crank case polymerization. Deepak et al. (2008), Baiju et al. (2009) and Surendra et al. (2010) observed that converting vegetable oils into simple esters is an effective way to overcome all the problems associated with the vegetable oils.

For a diesel engine, fuel injection timing is a major parameter that affects combustion and exhaust emissions. Proper ignition delay is necessary for ensuring proper pressure rise and peak pressure and hence maximum thermal efficiency, which in turn depends on the type of fuel also. Cenk et al. (2008) conducted experiments in a dual fuel CI (Compression ignition) engine to study the effect of injection timings on the exhaust emissions. They used ethanol blends with diesel and conducted experiments at five different injection timings. They observed that NO_x and CO_2 emissions increased and HC and CO emissions reduced for advanced injection timing. Nwafor (2007) carried out experiments on a single cylinder diesel engine with natural gas as the fuel. On advancing injection timing by 5.5° the engine showed erratic performance and when it was reduced to 3.5° he observed a smooth performance especially at low load conditions. Fuel consumption was slightly increased whereas CO and CO_2 emissions were reduced.

Manufacturers and engine application engineers usually want to know the performance of a C. I engine for various proportions of blends, for various compression ratios and at different injection timings. This requirement can be met either by conducting comprehensive tests or by modeling the engine operation. Testing the engine under all possible operating conditions and fuel cases are both time consuming and expensive. On the other hand, developing an accurate model for the operation of a C. I engine fuelled with blends of biodiesel is too difficult due to the complex nature of the processes involved. As an alternative, engine performance and exhaust emissions can be modeled by using artificial neural networks (ANNs). This modeling technique can be applied to estimate the desired output parameters when enough experimental data is provided.

In the present work, experimental investigations of the performance and emissions of the diesel engine were conducted for different proportions of blends of Honge oil methyl ester with diesel at different injection timing and for different compression ratios. In the later part of the work, ANN models have been developed for predicting the performance parameters and emissions characteristics using those experimental results.

Pongamia pinnata (Honge) is one of the forest based tree borne non-edible oil with a production potential of 135,000 metric tons per year in India. It is capable of growing in all types of lands (sandy and Rocky). It grows even in salt water and can withstand extreme weather conditions with a temperature range of 0 to 50°C. The oil content is around 30 to 40%. It is a fast growing medium sized tree which grows to a height of around 40 ft and its flowers are pink, light purple, or white. Pods are elliptical, 3 to 6 cm long and 2 to 3 cm wide thick walled and usually contains a single seed. Seeds are 10 to 15 mm long, oblong and light brown in color. A thick yellow–orange to brown non edible oil is extracted from the seeds. The comparison of properties of Pongamia oil with diesel is presented in Table 1. Since the high viscosity of Pongamia oil poses problems in pumping, atomization etc, it is very essential to reduce the viscosity by transesterification. After transesterification process, the viscosity of the Pongamia oil was found to be reduced to 5.6 mm^2/s from 41.06 mm^2/s which is nearer to the diesel value. Prepared Pongamia ester was then blended with diesel in various proportions (10, 15, 20 and 25%) by volume and used as fuel for running the engine. By blending operation it was observed that there was not an appreciable change in the properties except the calorific value. By measurement calorific values of the blends were found to be 40.78, 40.06, 39.76 and 39.12 MJ for 10, 15, 20 and 25% blends respectively.

EXPERIMENTAL SETUP

The performance test was conducted in a single cylinder four stroke diesel engine. Figure 1 shows the photograph of the experimental setup used for conducting experiments. It consists of a single cylinder four stroke water cooled compression ignition engine connected to an eddy current dynamometer. The compression ratio can be varied from 12:1 to 18:1. An AVL flue gas analyzer is used to measure NOx, UBHC and CO in the engine exhaust. A smoke meter is used to measure the smoke intensity in the engine exhaust. The specifications of the engine are shown in Table 2.

Experiments were conducted initially by using neat diesel at various loads and then using Honge methyl ester blends. Experiments were repeated by changing the compression ratios and injection timings. Matrix of the experiments conducted is as shown in Table 3.

RESULTS AND DISCUSSION

Engine performance

Brake thermal efficiency (BTE)

Figures 2 and 3 indicate the variation of BTE with compression ratios and injection timings respectively. Results indicated 20% blend of Honge methyl ester in diesel has maximum efficiency. Efficiency was found to be decreasing for higher blend proportions. This may be due to the decrease in the calorific value of the blend for increased blend proportions. On increasing the compression ratios, BTE was found to be increased for Honge ester blends. In the existing variable compression

Figure 1. Experimental set up.

Table 1. Properties of Pongamia oil and neat diesel.

S/No.	Properties	Pongamia oil	Diesel
1.	Flash point (°C)	263	49
2.	Specific gravity	0.912	0.83
3.	Acid value(mg/KOH)	1.52	-
4.	Kinematic viscosity(mm^2/s)	41.06	2.4
5.	Kinematic viscosity after transesterification	5.6	-
6.	Calorific value (MJ/kg)	34	41.86

Table 2. Specifications of the engine.

Engine	Four stroke, single cylinder, water cooled, constant speed diesel engine
Rated power	3.2 KW
Speed	1500 rpm
Bore	87.5 mm
Stroke	110 mm
Compression ratio	12 to 18: 1
Crank angle sensor	Resolution 1^o
Engine indicator	For data scanning & interfacing with Pentium III processor
swept volume	661cc

Table 3 . Experimental conditions using Honge methyl ester blends

S/No.	Operating parameter	Variations				
1	Engine Load (%)	0	25	50	75	100
2	Honge methyl ester blend (%)	10	15	20	25	
3	Compression ratio	16	17.5	18		
4	Injection timing (ºbTDC)	24	27	30		

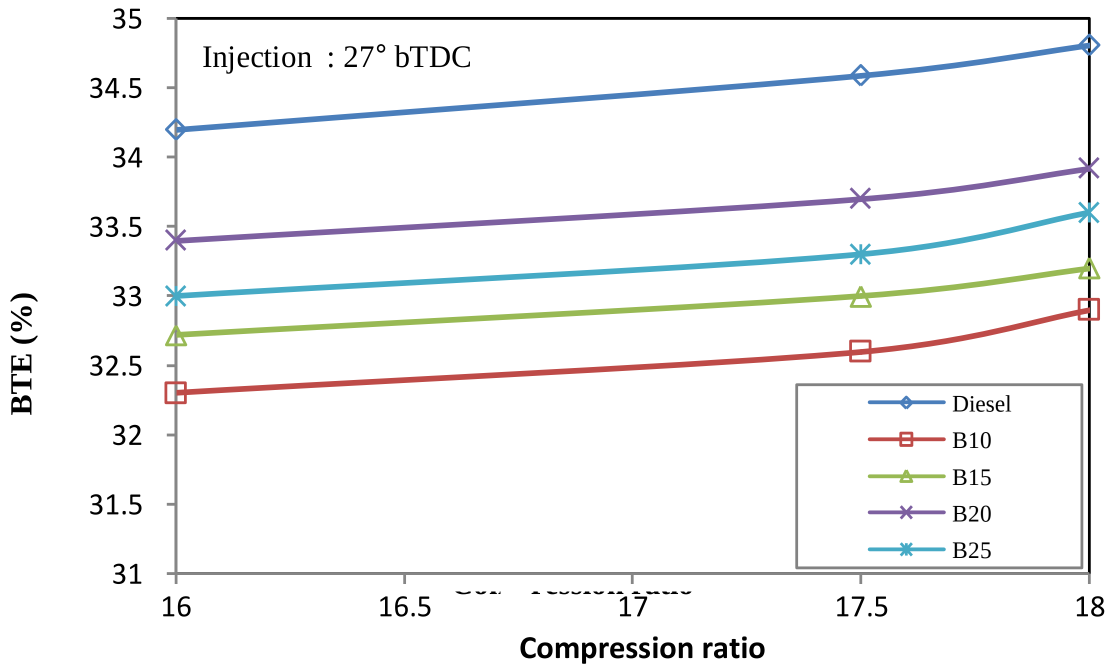

Figure 2. Variation of BTE with compression ratio at full load for diesel and Honge methyl ester blends.

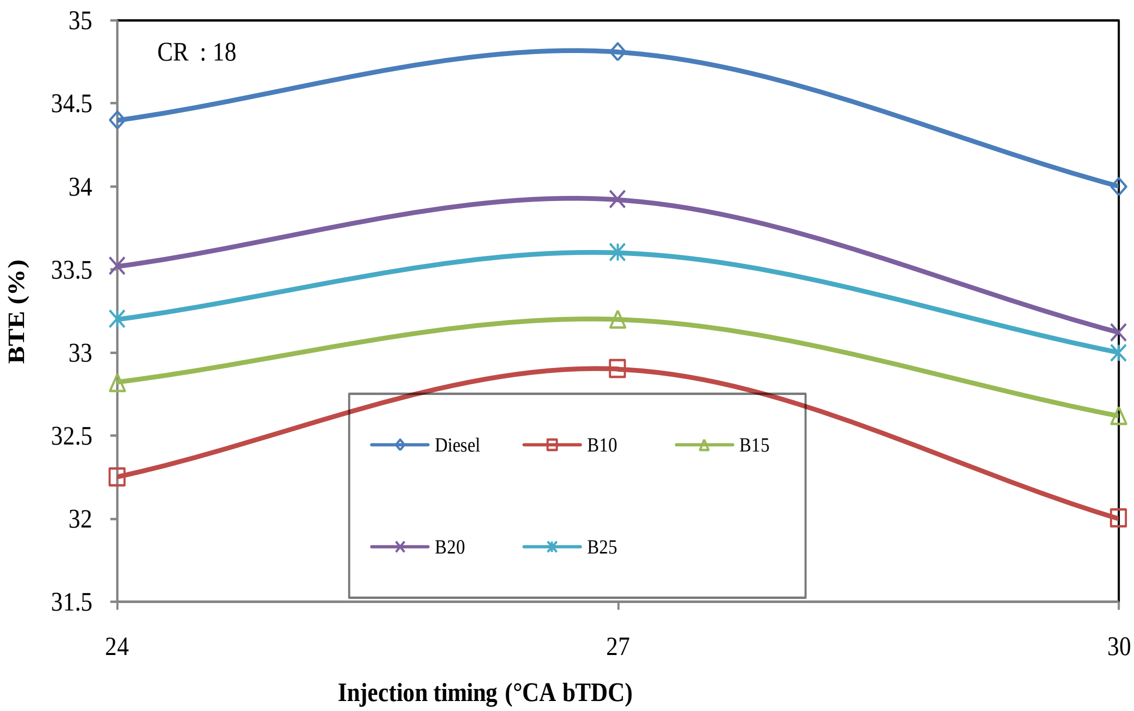

Figure 3. Variation of BTE with injection timing at full load for diesel and Honge methyl ester blends.

ratio engine set up, the maximum achievable compression ratio is 18. Efficiency was found to be maximum when the compression ratio was 18 and is considered as best compression ratio for that experimental setup. Considering the variation with injection timings, for 27° bTDC, the BTE value was found

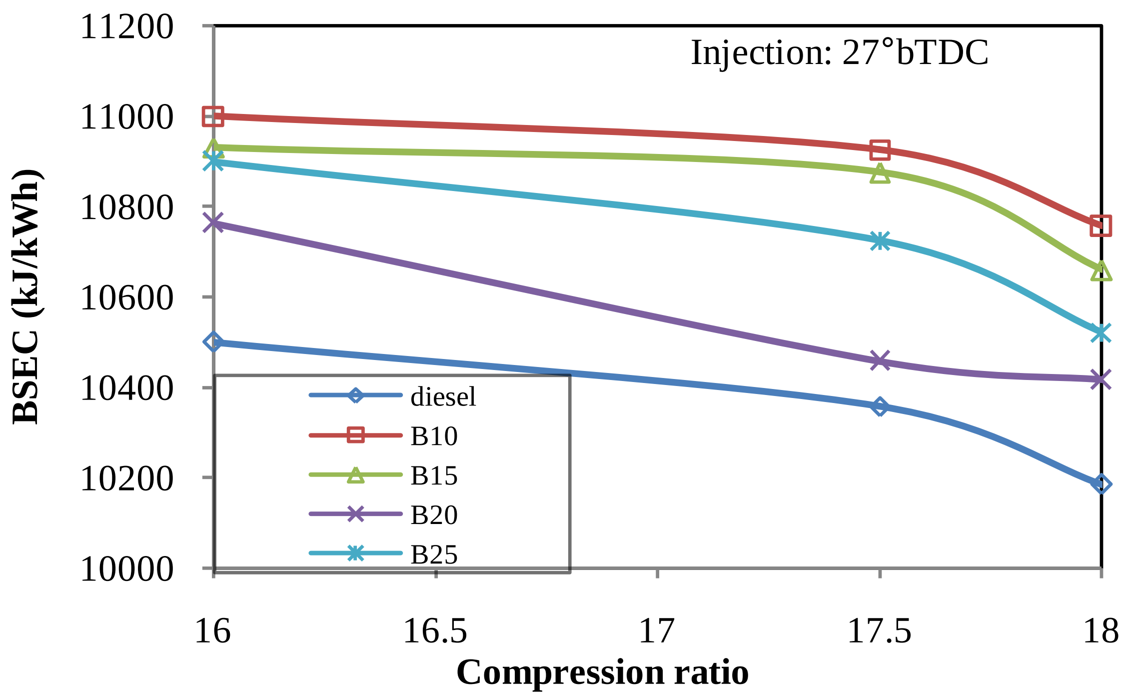

Figure 4. Variation of BSEC with compression ratio at full load for diesel and Honge methyl ester blends.

to be maximum for all the blends. Experimental results indicated a decrease in BTE by 1.15 and 2.1% for advanced and retarded injection timings from the normal value for B20 for the best compression ratio. On advancing the injection timing there is an increase in the delay period which reduced the thermal efficiency. At retarded injection timing the delay period decreases which reduces the power because larger amount of fuel burns during expansion.

Brake specific energy consumption (BSEC)

Figures 4 and 5 showed the variation of BSEC for different compression ratios and injection timings. BSEC decreased with load for diesel as well as Honge methyl ester blends. For 20% blend the BSEC value was minimum compared with other blends, but higher than that for neat diesel. Also on increasing the compression ratios, BSEC values reduced. For 27° bTDC, BSEC value was found to be minimum, when compared with values for 24° and 30° bTDC as is evident that thermal efficiency is maximum at this injection timing. Advancing the injection by 3° increased BSEC by 2.9 %, and retarding the injection by 3° increased BSEC by 5.2%.

Exhaust gas temperature

Figures 6 and 7 showed the variation in exhaust gas temperature with compression ratios and injection timings respectively. For higher compression ratios, T_{exh} increased and biodiesel blends showed higher values than that for neat diesel. In biodiesel operation the combustion is delayed due to higher physical delay period. As the combustion is delayed, injected Honge biodiesel fuel particles may not get enough time to burn completely before TDC, hence some fuel mixtures tends to burn during the early part of expansion, consequently after burning occurs and hence increase in the exhaust temperature.

With respect to the injection timings, advanced injection timing showed lowest T_{exh} showing efficient combustion. Advancing the injection timing has caused earlier start of combustion relative to TDC and hence complete combustion will take place and thus reducing the exhaust gas temperatures. Advancing the injection timing by 3° showed a reduction of T_{exh} by 2.6% for B20 for best compression ratio.

Emission characteristics

NOx emission

Figure 8 shows the variation of NOx with injection timings. NOx increased with the load for diesel as well as for biodiesel blends. NOx emission for biodiesel blends is higher than the neat diesel for all compression ratios since they contain inbuilt oxygen in their molecular structure. Also it increases with the increase in the blend

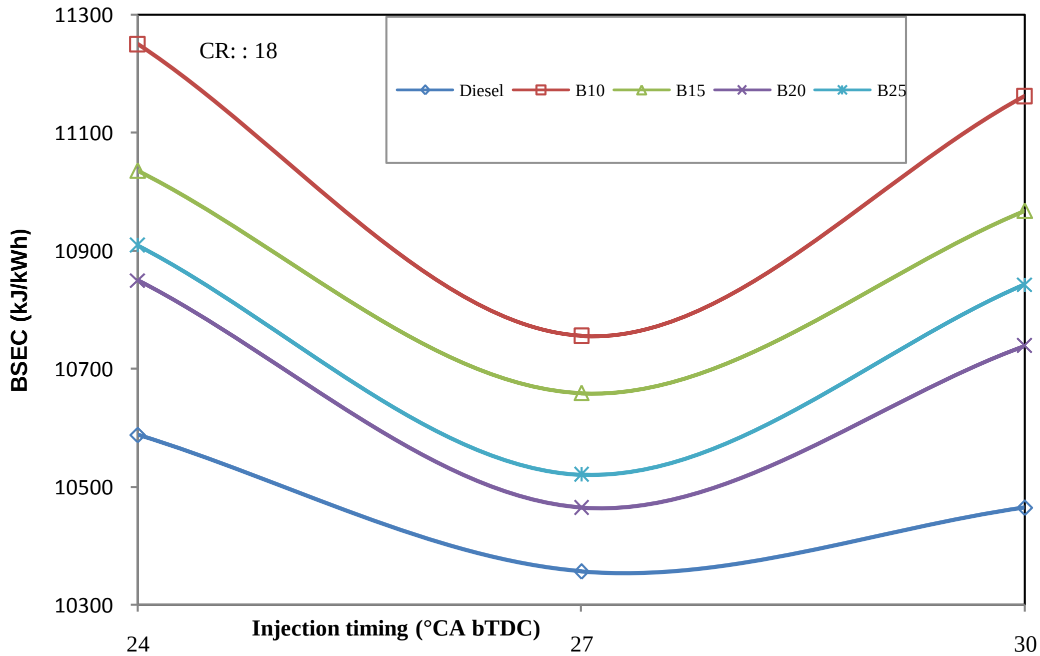

Figure 5. Variation of BSEC with injection timing at full load for diesel and Honge methyl ester blends.

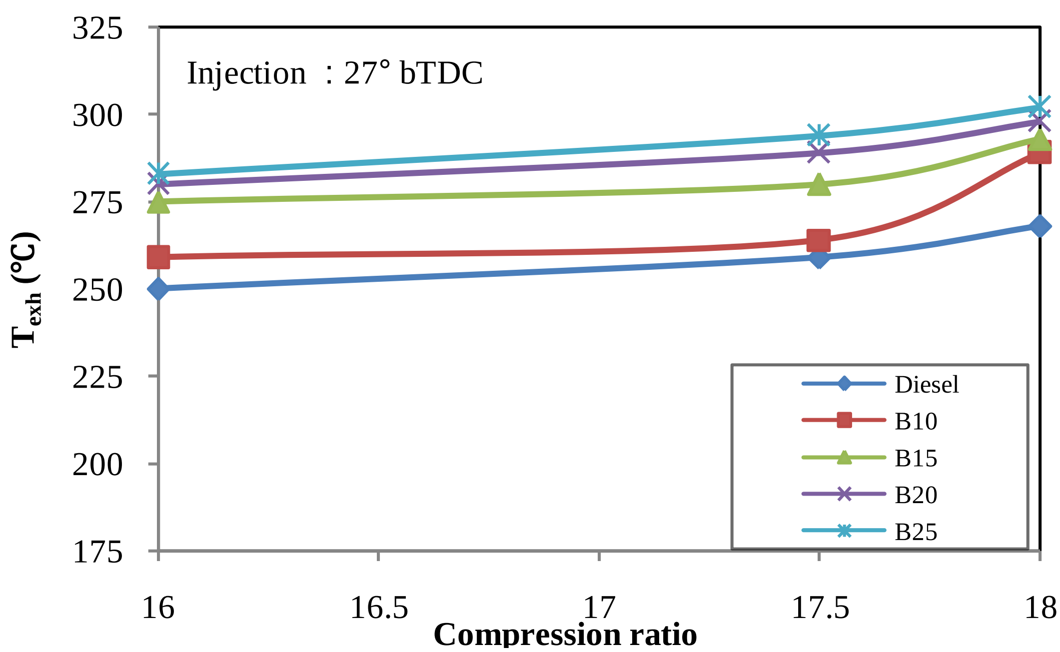

Figure 6. Variation of T_{exh} with compression ratios at full load for diesel and Honge methyl ester blends.

percentage because of increased oxygen content in higher percentage blends. Lower compression ratios with retarded injection timing showed lesser emissions. On retarding the injection timings cylinder pressure and temperature decreased, since more fuel burns after TDC and thus reducing NOx emissions. On retarding the injection by 3° from the normal value, NOx emission decreased by 4.8% for B20 at full load condition, which can be used as the combination for reducing the NOx emissions in a CI engine fuelled with Honge methyl ester

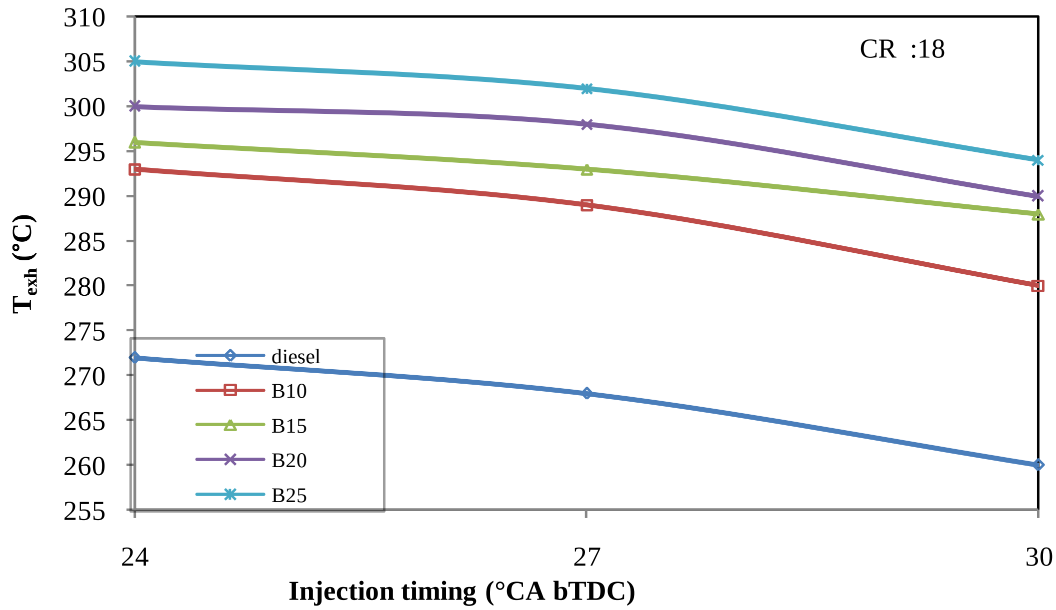

Figure 7. Variation of T_{exh} with injection timing at full load for diesel and Honge methyl ester blends.

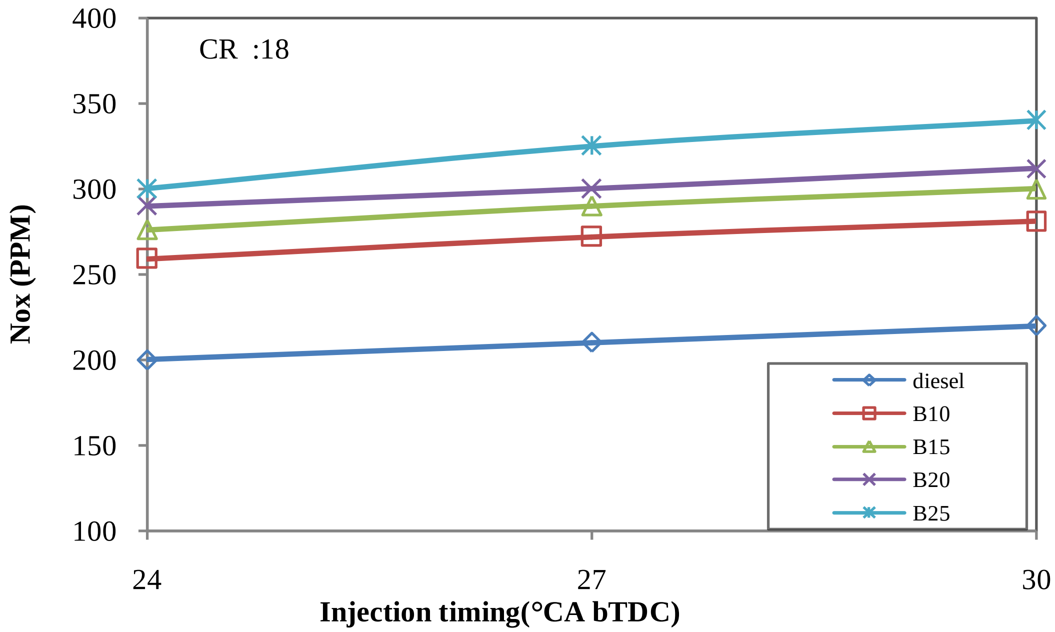

Figure 8. Variation of NO_X with injection timing for full load for diesel and Honge methyl ester blends.

blends.

Smoke, HC and CO emission

Figures 9 to 11 showed the variation of smoke opacity, HC and CO emissions with injection timings. It was observed that these emissions decreased with the increase in injection advance from the normal value. For advanced injection timings these emissions were reduced since cylinder operating temperature was higher and hence improved reaction between fuel and oxygen. On advancing the injection by 3° the smoke opacity, HC and CO emissions reduced by 4.2, 10 and 20% respectively for the best compression ratio. For higher compression ratios there was a further decrease in those emission

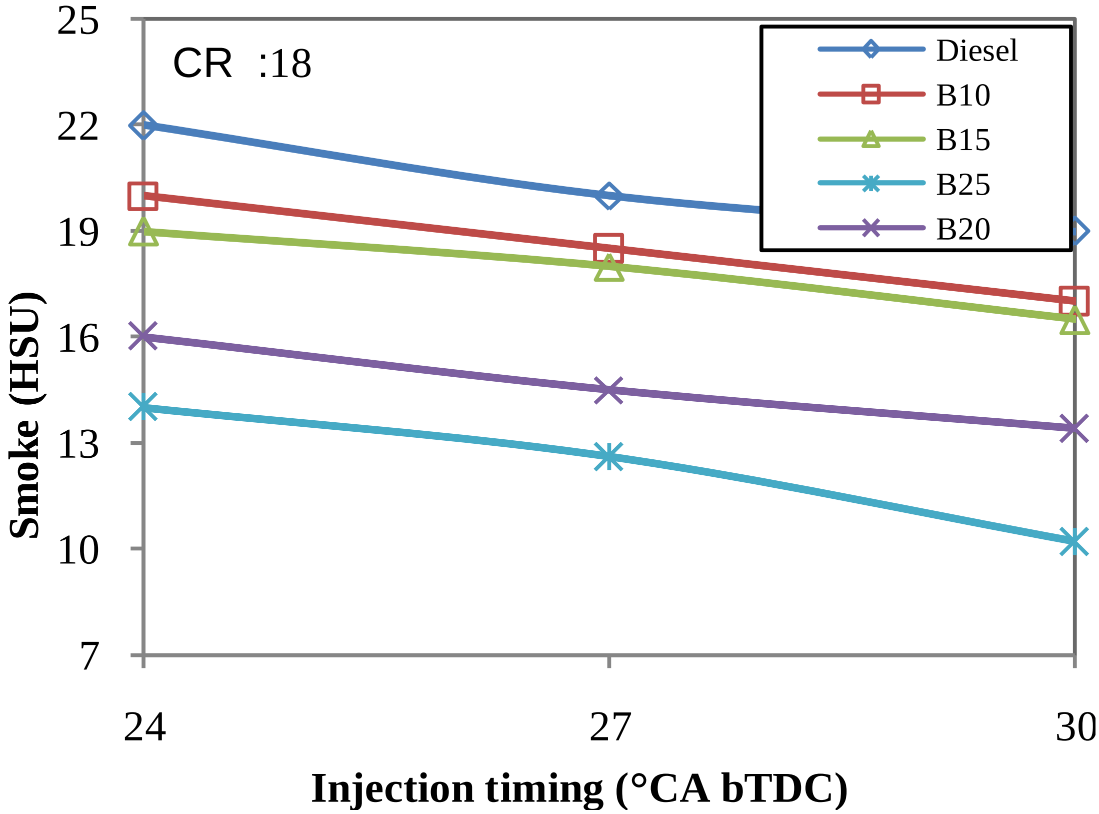

Figure 9. Variation of smoke with the injection timing at full for diesel and Honge methyl ester blends.

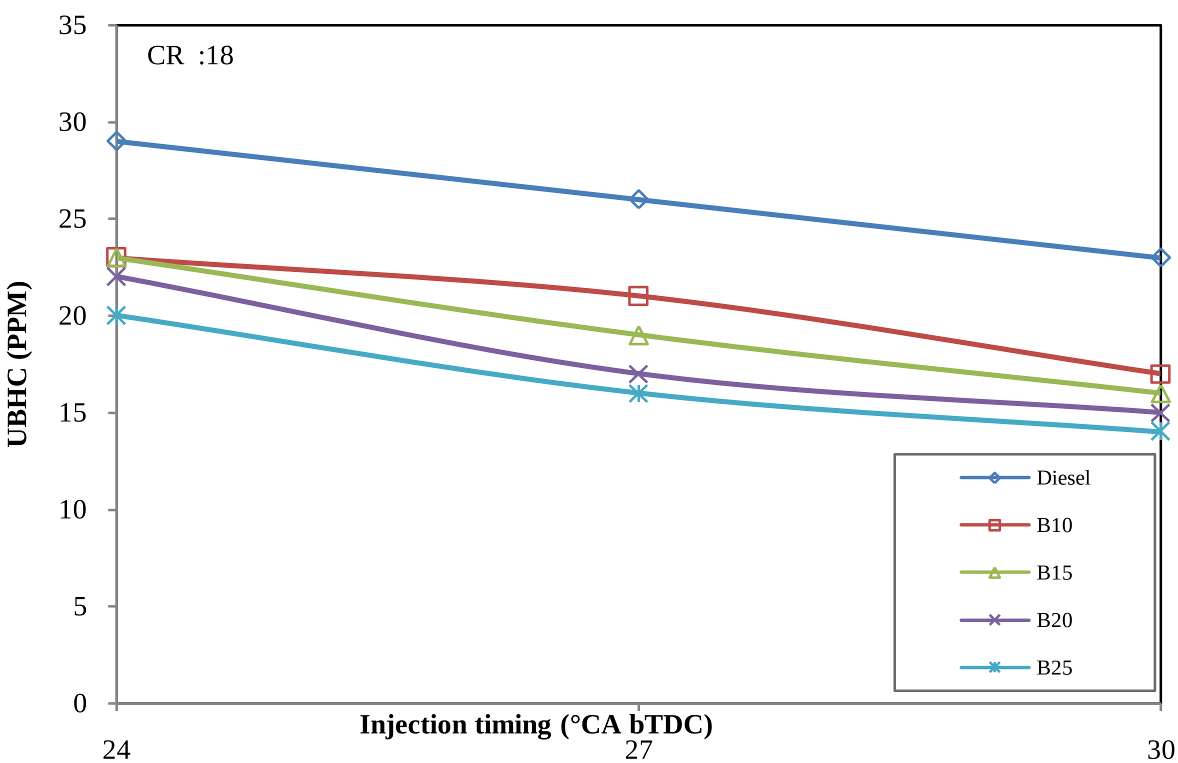

Figure 10. Variation of HC with injection timing at full load for diesel and Honge methyl ester blends.

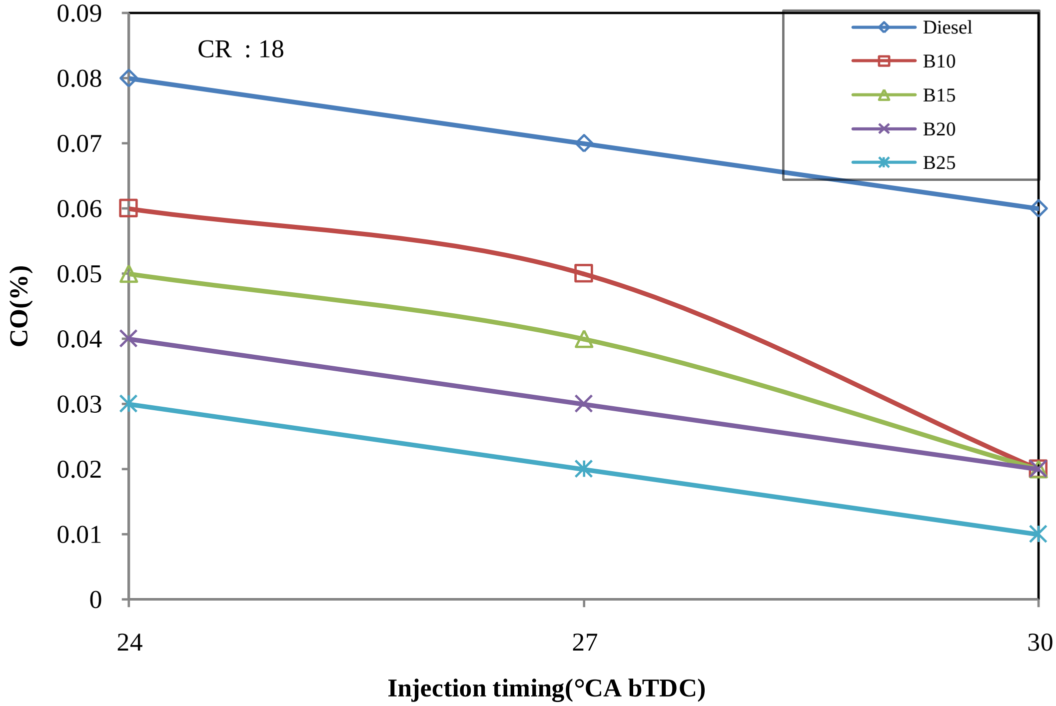

Figure 11. Variation of CO with injection timing at full load for diesel and Honge methyl ester blends.

values, indicating advanced injection timing together with increased compression ratio will reduce smoke, HC and CO emissions for CI engine fuelled with Honge methyl ester blends.

Artificial neural networks

Artificial intelligence systems are widely used as a technology offering an alternative way to tackle complex and ill-defined problems. Neural networks are a type of artificial intelligence systems that attempts to imitate the way the human brain works. They are nonlinear information processing devices, which are built from interconnected elementary processing devices called neurons. They are able to deal with nonlinear problems and once trained can perform prediction and generalization at high speeds. An ANN has the capability to relearn to improve its performance for the new available data. They differ from conventional modeling approaches in their ability to learn about the system that can be modeled without the prior knowledge of the process relationships. The prediction by a well-trained ANN is much faster than the conventional simulation programs or mathematical models as no lengthy iterative calculations are needed to solve differential equations using numerical methods.

They have been used in diverse applications in control systems, robotics, pattern recognition, forecasting, medicine, power systems, manufacturing, optimization, signal processing social and psychological sciences. This technology is even used in various thermal systems. Prieto et al. (2000) used ANN for forecasting the condenser performance. Bechter et al. (2001) used ANN for modeling vapor compression pumps. Application of ANN to the C. I engines is of more recent progress. This has been used for the prediction of emissions from Diesel engines and gasoline engines. Arcaklioglu (2005) used ANN to predict the performance and emissions from a diesel engine where they considered engine speed, injection pressure and throttle position as the input parameters and engine torque, power, specific fuel consumption together with emissions as the output parameters. They observed a good correlation between the experimental and test values. The overall mean relative errors were within 10%. Cenk et al. (2007) used ANN for the modeling of a gasoline engine to predict BSFC, BTE, exhaust gas temperature and exhaust emissions. They observed that mean relative errors for the whole of training data and the test data were within 2 to 7%. Mustafa et al. (2006) used ANN to model performance parameters and emissions of a biodiesel engine using Waste cooking oil as an alternate fuel.

An ANN consists of massively interconnected processing nodes known as neurons. It receives the input from the other sources combines them in some way, performs generally a nonlinear operation on the result and then outputs the final result. Network usually

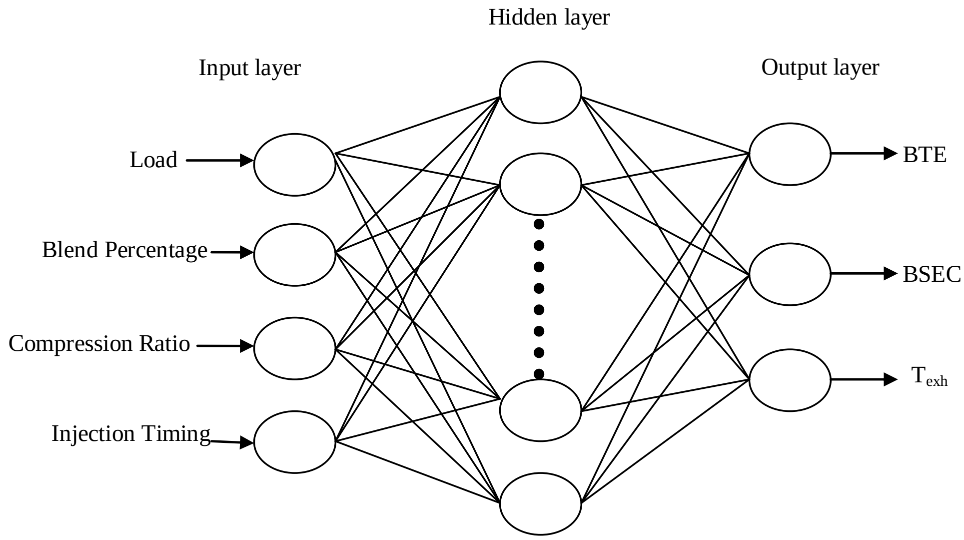

Figure 12. Schematic diagram showing the input and output variables for performance model.

contains an input layer, some hidden layers and an output layer. Each neuron in the network accepts a weighted set of inputs and responds with an output. Such a neuron first forms the sum of weighted inputs given by N=$\sum_{i=1}^{p} w_i \, x_i + b$, where p and w_i are the number of elements and the interconnection weight of the input vector X_i respectively and b is the bias for the neuron. The method of modifying the weights in the connections between network layers with the objective of achieving the expected output is called training a network. The internal process that takes place when a network is trained is called learning. The two types of training are supervised and unsupervised training. Supervised training is the process of providing the network with a series of sample of inputs and comparing the outputs with the expected responses. The training continues until the network is able to provide the expected responses. The weights will be adjusted according to learning algorithm till it reaches the actual outputs. Various training functions can be used to train the networks reach from a particular input to a specific target output. The error between the network output and the actual output, called as mean square error (MSE) is minimized by modifying the network weights and biases. When the error falls below a determined value or the maximum number of epochs have been reached the training process stops. Then this trained network can be used for simulating the system outputs for the inputs which have not been introduced before. Different algorithms are used for training the network. Of them most popular one is back propagation algorithm which has different variants. Back propagation algorithm with gradient descent and gradient descent with momentum are very slow for practical problems since they require a slow learning rate for stable learning. On the other hand conjugate gradient, Levenberg-Marquardt, Quasi–Newton are some of the fast learning algorithms. The performance of the network outputs is evaluated by mean relative error. Mean relative error which is the mean ratio between the error and the experimental values is given as mean relative error (MRE) = 1/N($\sum_{i=1}^{N} 100(\frac{ai-pi}{ai}$) Where N is the number of points in the data set, a_i is the actual or experimental value and p_i is the ANN predicted value.

Artificial neural network modeling

Steady state experimental data were used for ANN modeling. Independent models were developed for the performance parameters and the emission characteristics. For both the models around 70% of the data were used in the training set, 15% in the validation set and remaining 15% were employed for testing. Load percentage, blend percentage, compression ratio and injection timing were used as the input parameters and brake thermal efficiency (BTE), brake specific energy consumption (BSEC), and exhaust gas temperature (T_{exh}) were the output parameters for performance model. Similarly load percentage, blend percentage, compression ratio and injection timing were used as the input parameters and NOx, Smoke, UBHC and CO emissions were used as the output parameters for the emission model. Schematic representation of the both models is shown in Figures 12 and 13.

To ensure that each input provides an equal contribution in the ANN, inputs to the model were preprocessed and scaled into a common numeric range (-1, 1). Network with one hidden layer was used with the activation function in the hidden layer as tan sigmoid and linear in the case of output layer. Standard back-propagation algorithm, with *trainlm* training function has

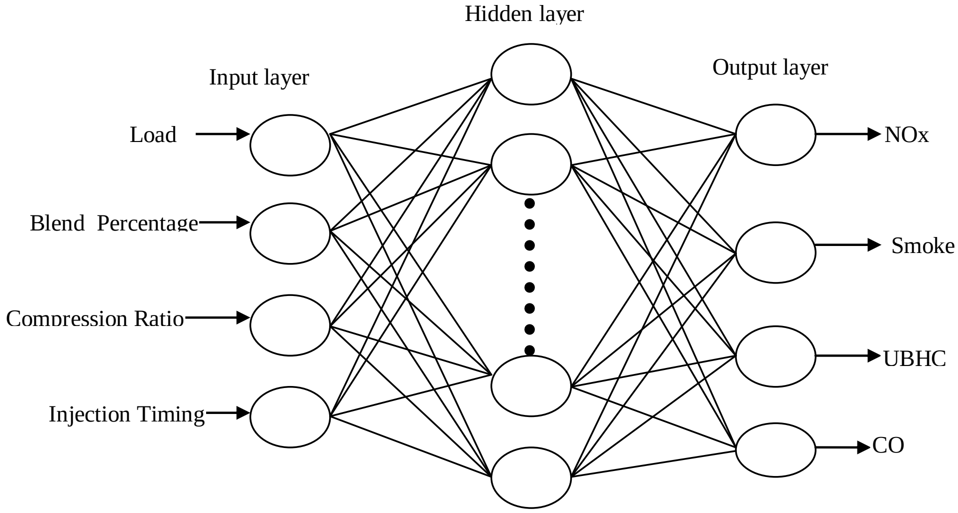

Figure 13. Schematic diagram showing the input and output variables for emission model.

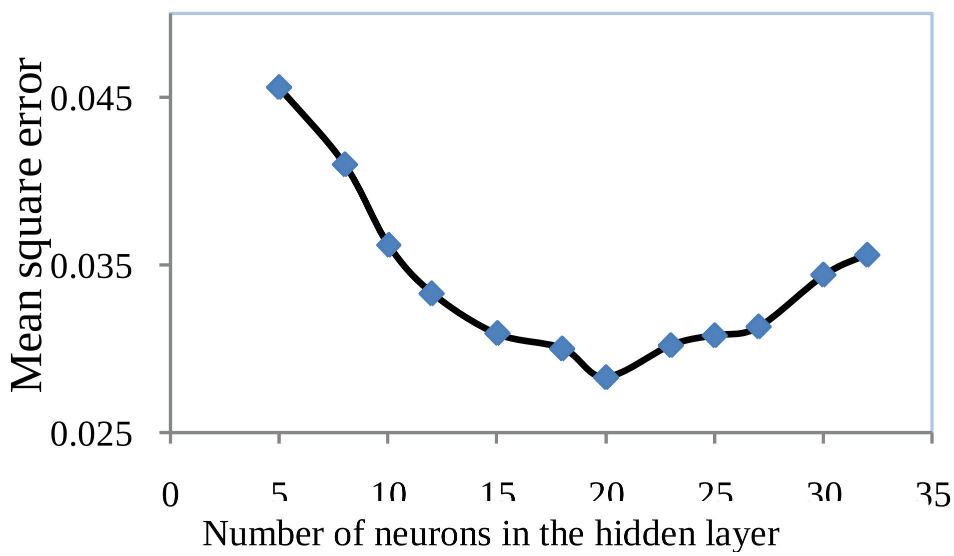

Figure 14. Variation of MSE with the number of neurons in the hidden layer for the performance model.

been used for training the network.

Initially network was trained by selecting randomly some number of neurons in the hidden layer. Then number of neurons were either increased or decreased so that MSE will be minimum. The number of neurons for which the MSE is minimum is selected as the optimum number of neurons in the hidden layer. In the case of performance model optimum number of neurons has been found to be 20 whereas as for the emission model it has been found to be 25. MATLAB 8 has been used for simulating the ANN model and the standard training functions defined in the neural network toolbox has been used in this work (Figures 14 and 15).

Trained network was tested for performance. For evaluating the testing performance of the developed ANN model, a MRE of 5% has been taken as a limit for the performance model and 10% for emission model. These figures have been arrived based on the literature related to this work. Table 4 shows the network performance for the performance model. MRE for the training data were 2.932, 2.681 and 2.192% for BTE, BSEC, T_{exh} respectively where as for the test data these values were 3.254, 2.723 and 2.558% respectively. Since the MRE values for the test data are well below the specified limit the developed model was found to be acceptable. Further the accuracy of the prediction for different parameters

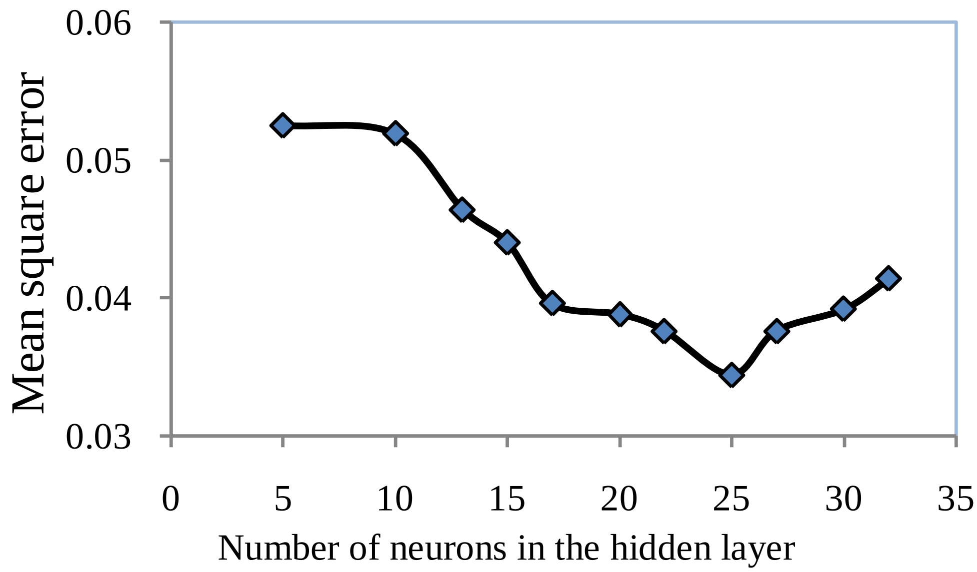

Figure 15. Variation of MSE with number of neurons in the hidden layer for emission model.

Table 4. Statistical values of the network for the performance model

Variable	MRE (Training)	% Accuracy (Training)	MRE (Test)	% Accuracy (Test)
BTE	2.932	91.3	3.254	87.5
BSEC	2.681	89.2	2.723	86.7
T_{exh}	2.192	92.7	2.558	92.3

has been listed in Table 4. The values are 91.3, 89.2, and 92.7% for BTE, BSEC and T_{exh} for the training data and 87.5, 86.7, 92.3% for test data. Figures 16, 17 and 18 showed the plot of the experimental values and ANN predicted values for BTE, BSEC, T_{exh}. These plots will indicate that there is a good correlation between the experimental and ANN predicted performance parameters.

Similarly for the emission model MRE for the training and testing data are given in Table 5. For the training data the values were 7.401, 6.053, 6.72 and 6.083% for the emissions of NOx, smoke, UBHC and CO respectively where as for the test data they were 8.281, 6.54, 6.83 and 9.29% respectively. The accuracy of the prediction for the various emissions is listed in the Table 5. For the test data they are 81.5, 78.9, 78.9, 74.8% respectively. These are comparatively lesser than those obtained for the performance model. The increase in MRE and decrease in accuracy could be attributed to error made during the measurement of different emission parameters. However MRE for the emissions are within 10% which is within the acceptable range. Figures 19, 20, 21 and 22 showed the plot of the experimental and ANN predicted values for NOx, smoke, UBHC and CO respectively. These figures will show that there is a good correlation between the experimental and ANN predicted values of emissions.

Conclusions

1. Brake thermal efficiencies of biodiesel engine run on Honge methyl ester blends are very close to diesel and 20% blend with diesel has shown maximum efficiency for biodiesel operation for all compression ratios. An improvement in BTE was observed for higher compression ratios. It was observed that higher BTE values were obtained at 27°bTDC injection timing, whereas retarding or advancing the injection timing lowered BTE values.
2. Brake specific energy consumption for biodiesel blends is more than that of diesel and decreased for higher compression ratios. With respect to the injection timings, advancing or retarding the injection timing from the normal value (27°bTDC) increased the BSEC values.
3. Exhaust emissions smoke, CO, HC were reduced for Honge methyl esters when compared with diesel values for increased compression ratios and for advanced injection timings as noted by the other researchers.
4. NOx emission increased for biodiesel blends

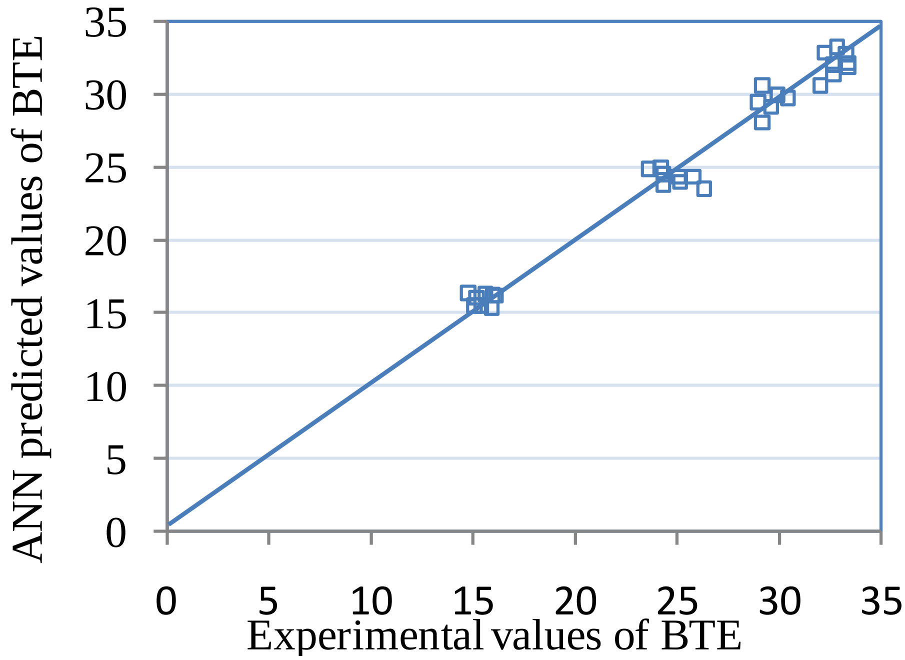

Figure 16. Experimental Vs ANN predicted values of BTE for the performance model.

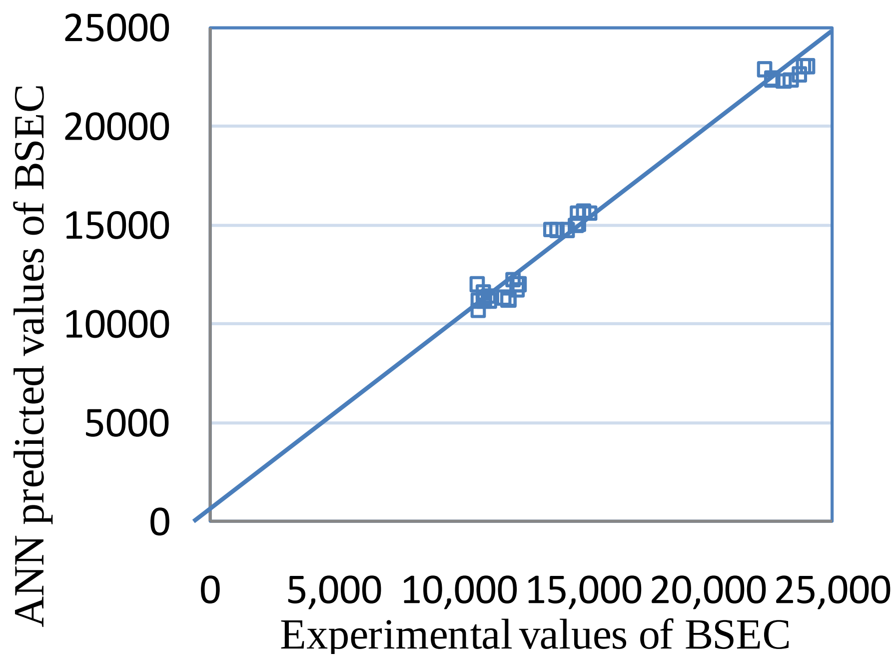

Figure 17. Experimental Vs ANN predicted values of BSEC for the performance model.

compared to that of diesel for all compression ratios. Further on retarding the injection timings from the normal value, a reduction in NOx emissions was observed which was similar to the observation of many researchers.

5. ANN modeling was applied to predict the performance and emission characteristics of a four stroke CI engine. It was observed that MRE of the test data for the performance and emission parameters were within 10%, which is acceptable.

6. The developed ANN model has been found to be

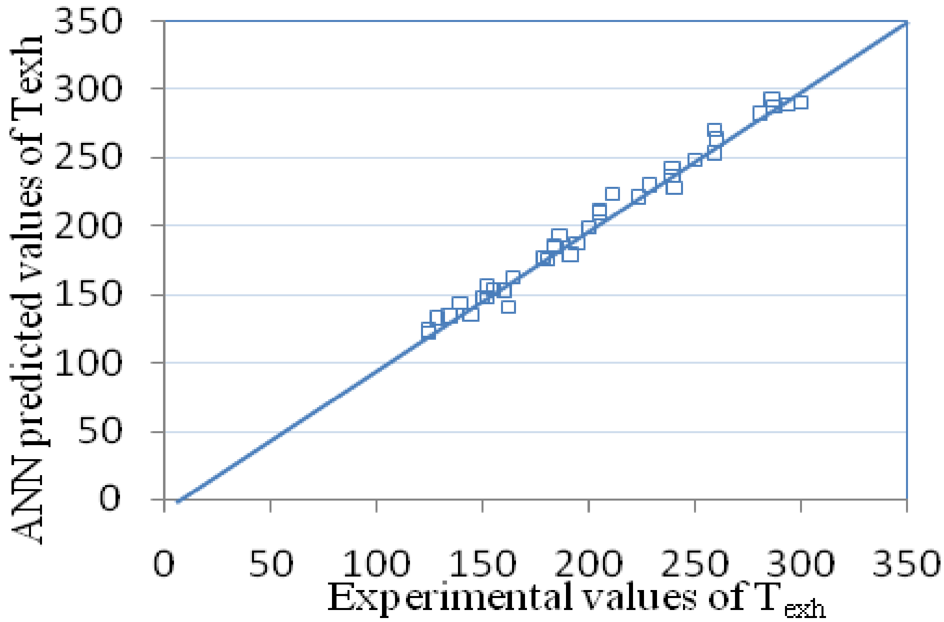

Figure 18. Experimental versus ANN predicted values of T_{exh} for the emission model.

Table 5. Statistical values of the network for emission model

Variable	MRE (Training)	% Accuracy (Training)	MRE (Test)	% Accuracy (Test)
NOx	7.401	88.3	8.28	81.5
Smoke	6.053	89.3	6.54	78.9
UBHC	6.72	88.6	6.83	78.9
CO	6.083	87.3	9.29	74.8

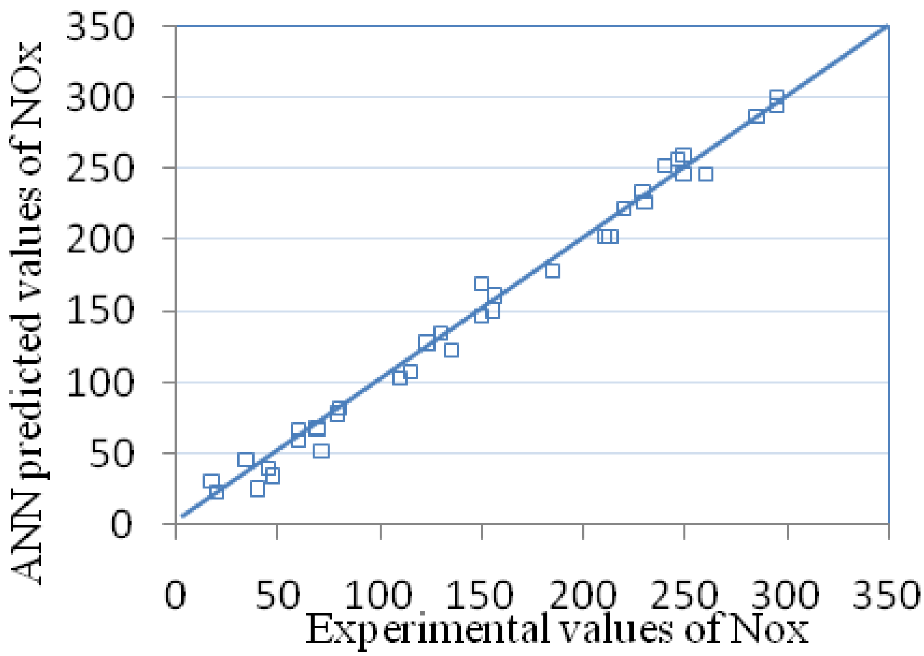

Figure 19. Experimental versus ANN predicted values of NO_X for the emission model.

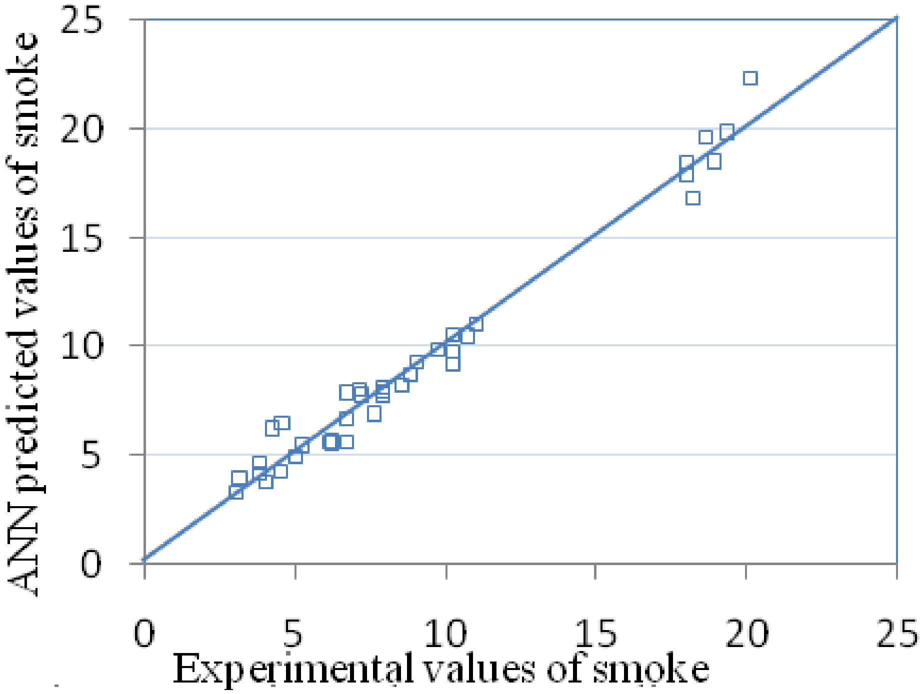

Figure 20. Experimental versus ANN predicted values of smoke for the emission model.

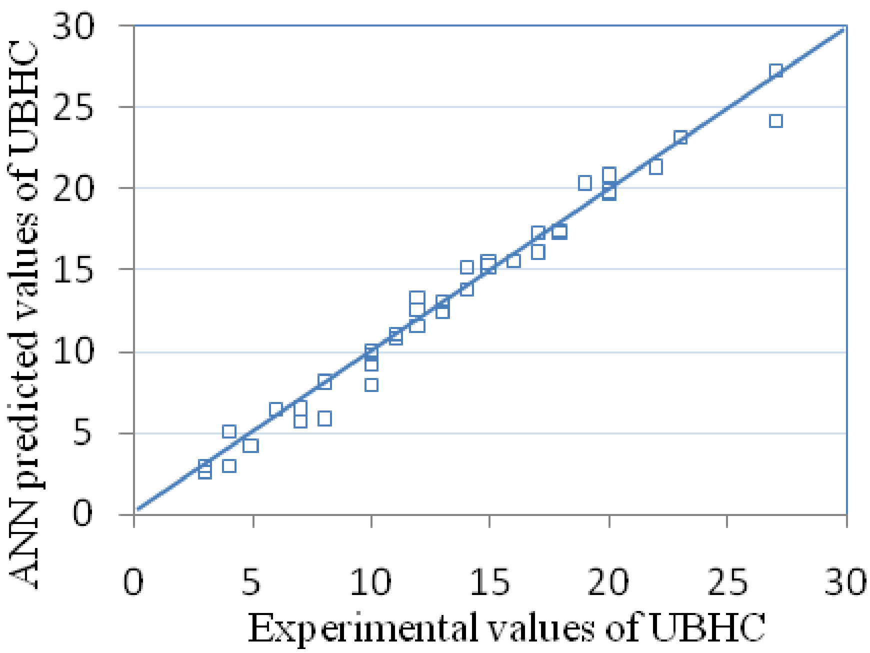

Figure 21. Experimental versus ANN predicted values of UBHC for the emission model.

useful for the prediction of engine performance and emission parameters. This reduces the experimental efforts and hence can serve as an effective tool for predicting the performance of the engine and emission characteristics under various operating conditions with different biodiesel blends.

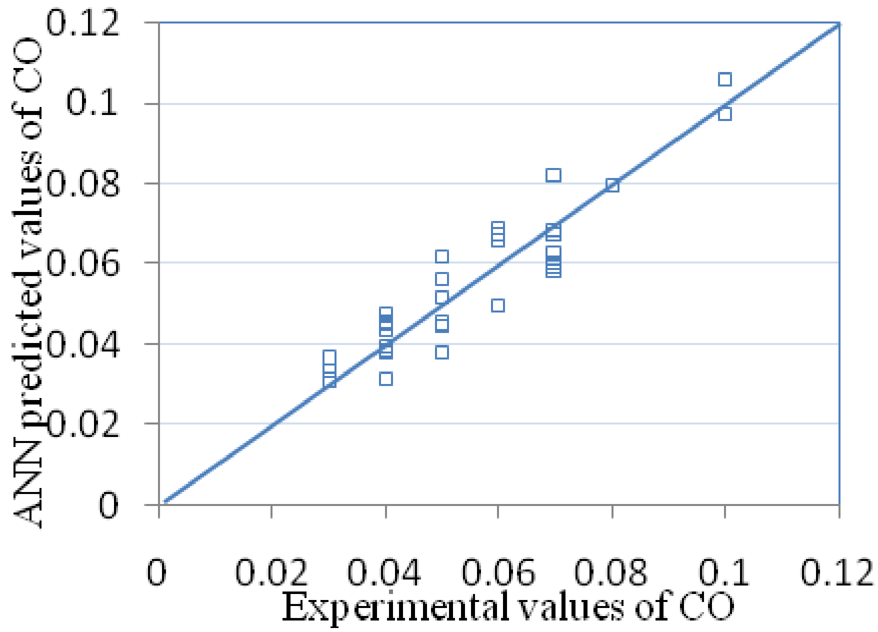

Figure 22. Experimental versus ANN predicted values of CO for the emission model.

Nomenclature

ANN, artificial neural network
BSEC, brake specific energy consumption (kJ/kWh)
BTE, brake thermal efficiency
bTDC, before top dead center
CA, Crank angle (˚)
MRE, mean relative error
T_{exh}, exhaust gas temperature (°C)
TDC, top dead center
HC, hydrocarbon
CO, carbon monoxide

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