Artificial Intelligence Based Artificial Neural Network Model to Predict Performance and Emission Paradigm of a Compression Ignition Direct Injection Engine Under Diesel-Biodiesel Strategies

Kiran Kumar Billa, G. R. K. Sastry and Madhujit Deb

Abstract Environmental pollution as well as fast depleting fossil sources are key factors leading toward search for the alternative resources of energy. Unlike fossil fuels, biofuels are renewable source of energy. Biofuel is defined as any fuel whose vitality is obtained through a course of biological carbon change. Today, the use of biofuels has extended throughout the earth. Major producers include Asia, Europe and America and they consume too. Biodiesel is unpolluted burning alternative energy source from 100% renewable resources which can be termed as the fuel for the future. Many edible alternatives such as Palm oil, Sunflower, Soya Bean and, non-edible alternatives such as neem, canola, mahua, karanja, and jatropha are tested successfully with or without engine modifications. The results are encouraging. Biodiesel is a green fuel that can be mixed with petroleum diesel to produce biodiesel blends to run diesel machines. This action can reduce huge foreign exchange load on government, and helps in reducing harmful emissions. In the present study, *Pongamia pinnata* methyl ester with an oxygenative additive DEE is added with diesel. Further, with the help of artificial intelligence an attempt is made to find out the optimal blend. Artificial Neural Networks in MATLAB are used to serve the purpose. Furthermore, with the help of an ANN meta model an attempt is made to find out the optimal blend.

Keywords 2-EHN additive · NO_x · UHC · ANN · FFNN · MAPE · MSE

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1 Introduction

The swift depletion of petroleum energies and consistent price hikes of crude barrels have made a serious impact on the fuel and transport sectors and on the individual country's economy. Many alternatives were proposed by the researchers to analyze the characteristics of a diesel engines running on biodiesel derived from various vegetable oils, which may be congregated as edible and non-edible oils [1, 2] The investigations disclosed that vegetable oil esters provide improved performance and reduced emissions when compared to crude vegetable oils. Since the biodiesels are derived from plant and vegetable oils, they produce trifling greenhouse gas emissions [3]. The practice of using edible veggie oils such as like palm, sunflower, soya, rapeseed for fuel purposes may not be good idea as they are being used for cooking and can affect country's economy; i.e., it may fluctuate the cooking oil rates. Non edible variants should be used to avoid such an issue. Jatropha, rubber seed, *Pongamia pinnata* oil and linseed oil are examples of non-edible oils. *P. pinnata* is encouraged by the Indian government like a partial substitute to mineral diesel [4]. Proposed cultivation lands are side ways of railway tracks, dry lands of country side and government lands of hill sides to grow these shrubs. The Indian railways, one of the largest consumer of petroleum diesel started utilization of biodiesels to run some special engines. In addition, State governments also took initiative and they started using vehicles with bio fuels for transport and personal use. *P. pinnata* is easy to cultivate, grows faster and utilizes less water [5]. The by-products like seed crush can be used to feed cattle and even they can be used as a fertilizer in farm fields. The seed consists of viscous oil capable of having calorific value and is used to produce soap oil [6]. The practice of blending the *P. pinnata* methyl ester blends as fuels substitutions for diesel engines helps to minimize the energy demand and can minimize the huge foreign exchange to go out. The *P. pinnata* seed kernel has 46.5% viscous oil content [7]. The *P. pinnata* has palmitic (12.8%), stearic (7.3%), oleic (44.8%), linoleic (34.0%) acids in its chemistry [8].

1.1 Motivation of the Present Study

- To search an alternative fuel which ultimately improves the engine performance parameters as well as reduces the engine exhaust emission parameters by using *P. pinnata* oil methyl ester (PME).
- A single-cylinder four-stroke DICI engine with no engine modification is used to carry out the experiment with different blends of PME with fossil diesel.
- Proper blending with 2-EHN additive with the biodiesel-diesel fuel blends to enhance the performance of the biodiesel which in turn enhances the engine performance parameters and also reduces the engine exhaust emission parameters to make the fuel ideal.

- For optimization, Artificial Neutral Network approach is applied to predict the values of all required points within the ranges depending upon the values of input parameters coming out from experimental results.

At last, to establish the compatibility of *P. pinnata* oil biodiesel as a clean and environment friendly fuel for future use with distinguished effect in engine performance and exhaust emission.

In the present study, biodiesel is produced from non edible oil *P. pinnata*. The biodiesel is the methyl ester of *P. pinnata* oil. Its properties are similar to that of high-speed diesel. Before conducting the performance test of biodiesel in the Kirloskar made single-cylinder variable compression ratio engine, we need to design the experiment. In the present study, there are three input variables: load, compression ratio and blend of fuel. The blends can also be varied from 0 to 100% by any sort of variation as shown in the literature. As per the literature the load also can vary from no load to full load in any sort of variation. Moreover we choose the levels of these three input parameters or design factors as five as per the literature suggested. The load is varied from 20 to 100% with increment of 20%.

2 Pongamia Pinnata Methyl Ester

2.1 Production of Pongamia Pinnata Methyl Ester

It is estimated that *P. pinnata* oil has potential oils with a yearly production of 200 metric ton, from which only 6% is utilized commercially [6]. In most of the Asian villages these trees are visible and are the main production areas and village people make use of this tree products for various purposes. This investigation highlights the efforts to produce biodiesel from *P. pinnata* from rural Indian forests and the experiments in the laboratory meticulously approves with the testified literature that the attendance of high Free Fatty Acid marks transesterification reaction hard because of the development of soap with alkaline catalyst. In the present virtue of experiments, the another route of using acid catalyst was implemented for the biodiesel production from *P. pinnata* oil [7–9]. Typically *P. pinnata* oil, collected for the present study, was detected to comprise 3.2% of FFA.

2.2 Transesterification Process

Transesterification or sometimes alcoholysis is the dislocation of alcohol group from an ester by another in a manner similar to hydrolysis, with the exception of alcohol is utilized instead of water. This practice has been widely utilized to reduce the high viscous triglycerides.

The transesterification chemical reaction is epitomized by the following general equation:

$$\mathrm{RCOOR}' + \mathrm{R}''\mathrm{OH} \longleftrightarrow \mathrm{RCOOR}'' + \mathrm{R}'\mathrm{OH}$$

If methyl alcohol is used in this course it is termed as methanolysis and its glyceride is represented. Transesterification is a reversible reaction. However, the presence of a catalyst (a strong acid) accelerates the conversion.

3 Experimental Setup and Procedure

3.1 Preparation of Modified Fuels

The test fuels used for the present investigation are biodiesel blends, derived from *P. pinnata*. The kinematic viscosity, specific gravity, and Calorific value of the bio diesel were measured by means of standard equipment and are 5.2 cSt at 32 °C, 0.93660 and 34.5 MJ/kg, respectively. The fuel additive used in this investigation is Di Ethyl Ether (DEE), density of 7.13 g/mL. The dosing level of the DEE (by volume) in the base fuel was 2%.

3.2 Determination of Fuel Properties

The kinematic viscosity, flash point, fire point, pour point and cloud point were measured by means of standard test methods. The viscosity was gauged by means of the Redwood viscometer [10]. A Cleveland apparatus for flash point and fire point [11, 12].

3.3 Details of Testing Equipment

A single-cylinder, water-cooled four-stroke DICI engine was used to investigate the performance and emission profiles shown in Fig. 1. The performance test is carried out on a single cylinder variable compression ratio DI diesel engine using high-speed diesel, methyl ester of *P. pinnata* oil and their blends with diesel. The engine is assembled and coupled with an eddy current dynamometer. The arrangement of experimental setup used for carrying out the present study is shown in Table 1. The load range taken is from 3 to 12 kg.

During experiment, fuel consumption is measured by a burette and a stop watch, the engine exhaust (CO, HC, CO_2, O_2 and NO_X) is analyzed and calculated by AVL

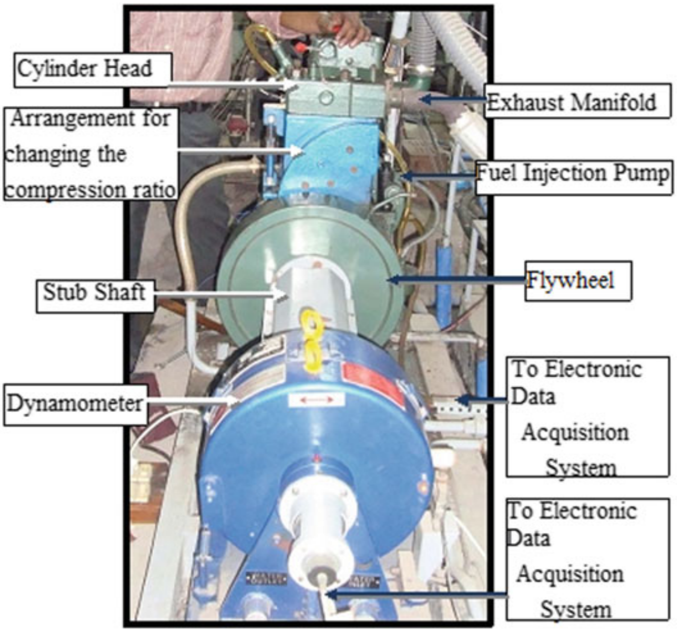


Fig. 1 Schematic diagram of experimental setup

Table 1 Test rig details

Make	Kirloskar
Model details	TV 1 (VCR)
Type	DI-type 4-stroke, water-cooled
Cylinder	One
Rated power	3.5 kW @ 1500 RPM
CR	12:1–18:1
Bore	87.50 mm
Stroke	110.0 mm
Injection timing	23° bTDC
Loading type	Eddy current dynamometer

DIGAS 444 gas analyzer fitted with DIGAS SAMPLER at the exhaust. Table 1 shows the engine details.

Table 2 Properties of the sample fuels

Property	*Pong. pinn.*	B100	B10	B20	B30	Diesel
Density (kg/m^3)	912	898	856	862	868	850
Pour point (°C)	−4	4	3.5	3.6	3.7	3.1
Cloud point (°C)	14.6	10.2	7	7.1	8.2	6.5
Fire point (°C)	244	199	91	93	96	78
Flash point (°C)	242	196	89	91	95	76
Cetane number	38.0	57.9	48.2	47.9	47.6	49
Calorific value (MJ/kg)	34.5	39.22	43.32	42.23	41.34	44.82
Kinematic viscosity (cSt)	27.79	5.46	3.23	3.49	3.77	4.842

3.4 Methodology

The fuels used in this study are standard diesel and PME (99.9% purity, Laboratory used). The blending was done on volume basis as we know that biodiesel is miscible diesel in all proportions. Hence there is no problem of miscibility of *P. pinnata* biodiesel with diesel. For this experiment we have used blends of diesel and biodiesel in following proportion. They are mentioned below (Table 2):

1. D100—sample containing 100% diesel fuel.
2. B10—Sample containing 10% biodiesel + 0.5% EHN + 89.5% diesel.
3. B20—Sample containing 20% biodiesel + 0.5%EHN + 79.5% diesel.
4. B30—Sample containing 30% biodiesel + 0.5% EHN + 69.5% diesel.

4 Results and Discussion

4.1 Load Versus BP Graph

Figure 2 shows the disparity of brake power with regard to load for diesel fuel and *P. pinnata* biodiesel and additives. It can be observed from the figure that there is no significant change in brake power. All blends, i.e., B10, B20, B30 including diesel gave more or less the same readings. In specific 6% loss in Brake power is observed, this is because of the low energy content of *P. pinnata* blends.

4.2 Load Versus BSFC Graph

Figure 3 shows the disparity of brake specific fuel consumption with respect to load for diesel fuel and *P. pinnata* biodiesel and additives. It can be observed from the

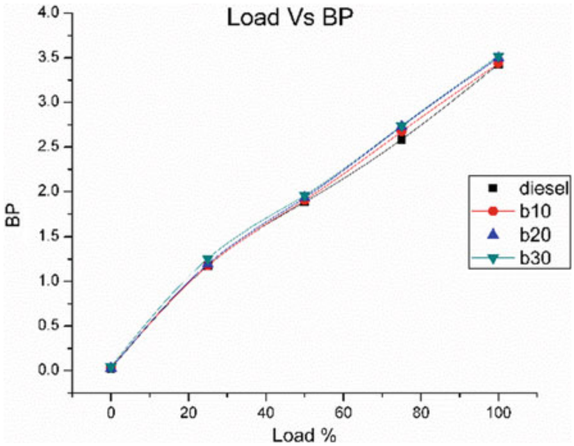


Fig. 2 Load versus BP graph

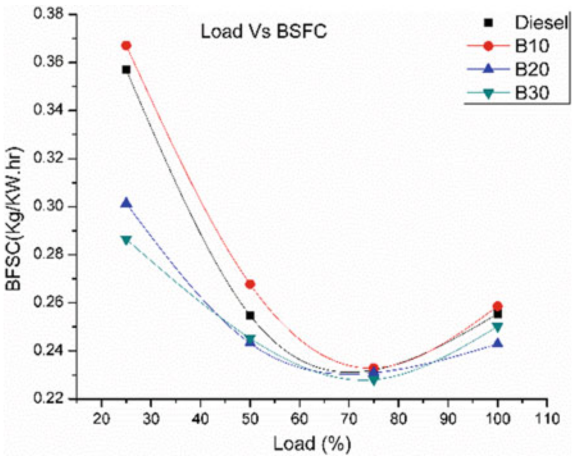


Fig. 3 Load versus BSFC graph

figure that shows b20 and b30 blends shows lower specific fuel consumption when compared to the conventional diesel But b10 biodiesel blend shows higher specific fuel consumption at any load. so should prefer b10 when for lower fuel consumption.

4.3 Load Versus BSEC Graph

Figure 4 shows the disparity of brake specific energy consumption with respect to load for diesel fuel and *P. pinnata* biodiesel and additives. It can be observed from the figure that shows B20 and B30 blends shows lower specific energy consumption when compared to the conventional diesel but B10 biodiesel blend shows higher specific energy consumption at low load. But after half load energy consumption decreases.

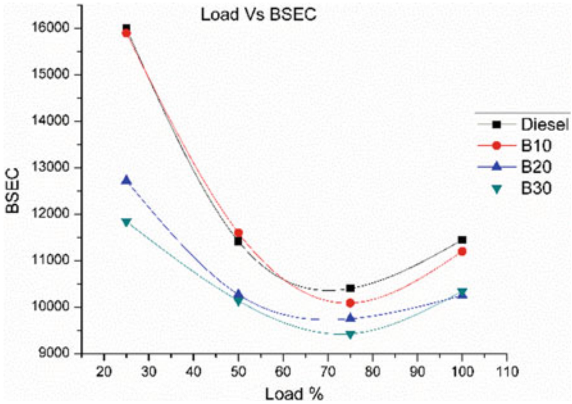


Fig. 4 Load versus BSEC graph

4.4 *Load Versus BTE Graph*

Figure 5 shows the disparity of CO with regard to load for diesel fuel and *P. pinnata* biodiesel and additives. It can be seen that the BTE of B20 is very close to diesel at higher loads. However all biodiesel samples were performing satisfactorily when compared to diesel. This is because of the excess oxygen portion in the biodiesel and the oxygenative additive helped in complete combustion and maximum utilization of the heat content in the biodiesel samples.

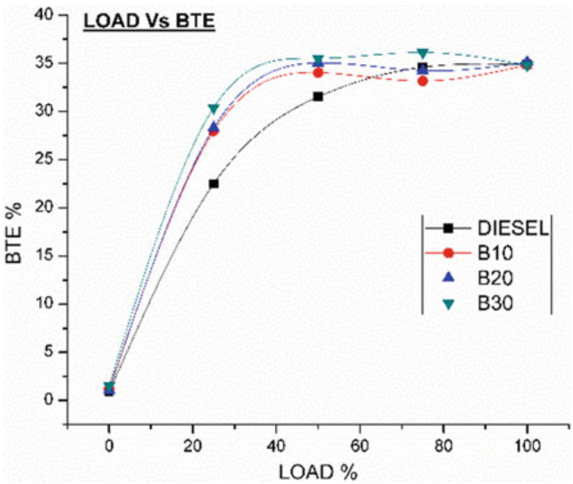
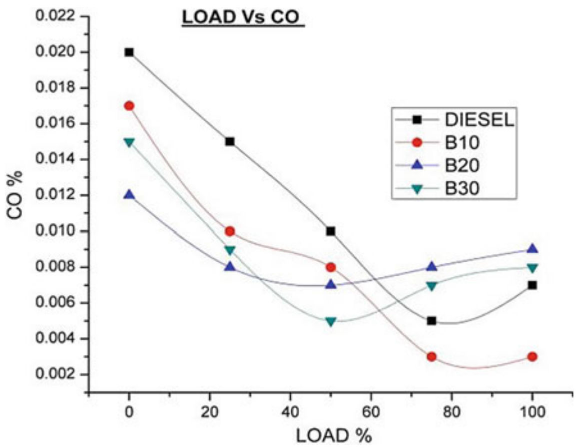


Fig. 5 Load versus BTE graph

Fig. 6 Load versus carbon monoxide graph



4.5 Load Versus CO Graph

Figure 6 shows the disparity of CO with regard to load for diesel fuel and *P. pinnata* biodiesel and additives. It is one of the prime objectives of the project. CO emissions are very less up to half load for any *P. pinnata* blend but after half load the CO emissions of B20 and B30 slowly creeped up. This is because of excess oxygen content in the *P. pinnata* blends which resulted in complete combustion and formed carbon dioxide instead of carbon monoxide.

4.6 Load Versus Carbon Dioxide Graph

Figure 7 shows the disparity carbon dioxide with regard to load for diesel fuel and *P. pinnata* biodiesel and additives. It is clearly seen that from graph all the blend shows low emissions of carbon dioxide at low loads and slightly increases at half loads which is negligible and again decreases at full loads when compared with conventional diesel.

4.7 Load Versus Hydro Carbons Graph

Figure 8 shows the disparity hydrocarbons with regard to load for diesel fuel and *P. pinnata* biodiesel and additives. Due to the excess oxygen present in the biodiesel and the oxygenative additive DEE complete combustion took place and formation of HC gone down. It is clear that B30 showed least HC production from the graph.

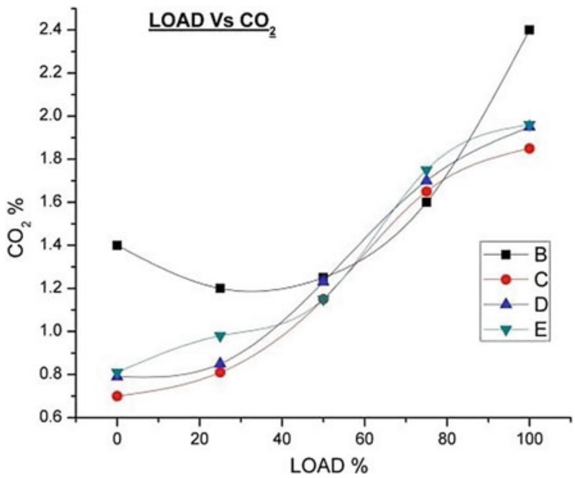


Fig. 7 Load versus carbon dioxide graph

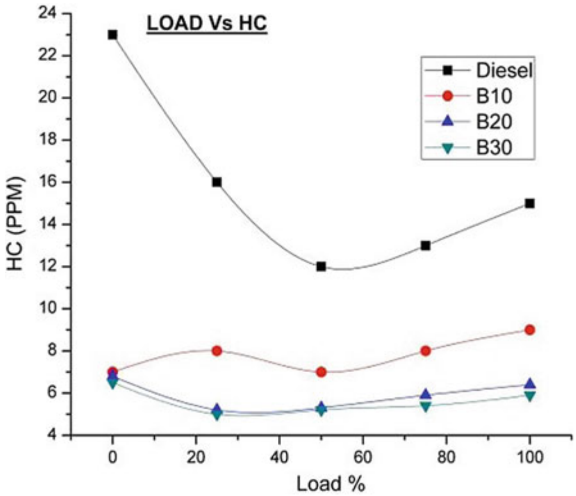
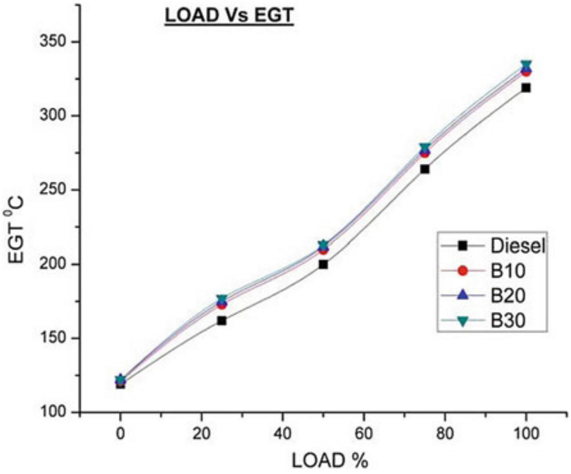


Fig. 8 Load versus HC graph

4.8 Load Versus Exhaust Gas Temperature Graph

Figure 9 shows the disparity of exhaust gas temperature with regard to load for diesel fuel and *P. pinnata* biodiesel and additives. It is a degree of performance as progressive exhaust gas temperatures results in greater heat release in combustion chamber and hence giving probability to rise brake thermal efficiency. From the graph it is clearly seen that that EGT is high in all the blends when compared to conventional diesel.

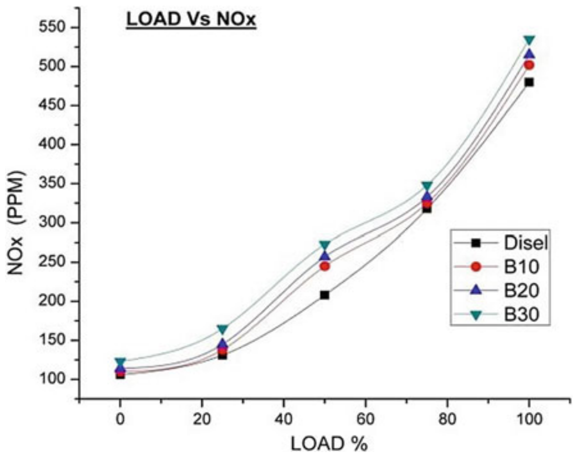
Fig. 9 Load versus EGT graph



4.9 Load Versus NO_x Graph

Figure 10 shows the variation of NO_x with respect to load for diesel fuel and *P. pinnata* biodiesel and additives. On the account of the excess oxygen present in the biodiesel complete combustion took place and temperature inside the combustion chamber increased thereby increasing the NO_x emission. From the graph it is clear that B30 showed maximum NO_x emissions. It cannot be completely stopped but it can be minimized like EGR techniques.

Fig. 10 Load versus NO_x graph



5 Artificial Nueral Networks (ANN)

ANN technique is a beneficial mathematical tool that has been adopted to predict responses required extended (experimentally) time and sophisticated devices such as internal combustion engines. Essentially, ANN denotes to a computation configuration method exhibited on biological processes, primarily on the implementation of human brain, involving number of interconnected meting out elements termed as neurons, which process data based on their active state with reference to inputs. Figures 11 and 12 demonstrates the typical architecture and the modelling tree of the proposed neural network model.

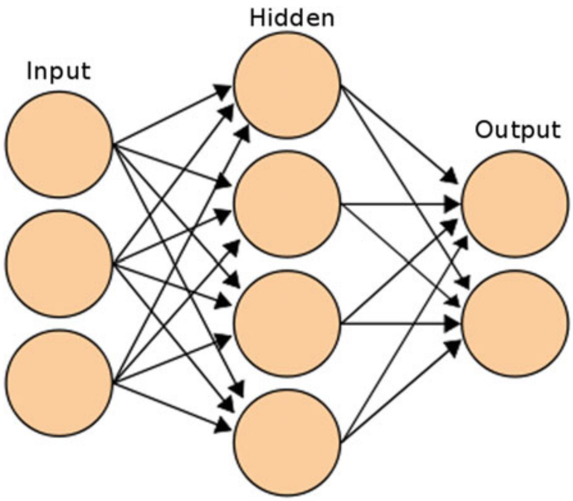


Fig. 11 Typical neural network model

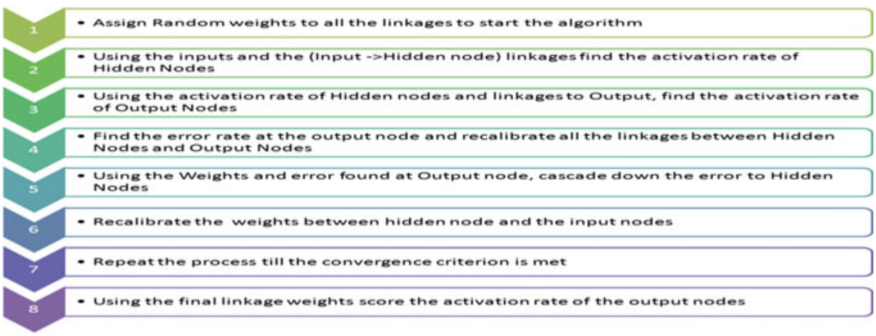


Fig. 12 ANN modeling tree

5.1 Development of ANN Model

Normalization of data which bring homogeneity among the engine responses is done by using the following formula

$$\frac{\text{Actual value}}{\text{Maximum} - \text{Minimun}} \times (\text{High} - \text{Low}) + \text{Low}$$

In the present research feed-forward neural network with back propagation technique is being employed. ANN has been cast-off considering innumerable model configurations to attain the optimum engine routine and exhaust gas discharge prediction. The developed ANN models is being trained using the collected experimental paradigm. Performance of ANN is subject to the data presented to it, hence mounting of input and output information is vital. In the current investigation, an ANN modeling is being used to predict the relationship of BSEC, BTE, NO_x, EGT, UHC and CO with load percent and percentage of biodiesel as input parameters. The relationship between the preferred input variables and anticipated outputs in the comprehension of the current study which has been studied in the association matrix bear proof to the inconsistent influences of the input parameters on the anticipated emission and performance responses. From the dataset, about a total of 20 samples are used in this model, 60% of the data (12 samples) dataset has been arbitrarily assigned as the training, while the 20% of dataset (4 samples) are utilized for testing and the residual 20% is used to estimate and validation. The developed Model is run using MATLAB toolbox. Multi-layer perception network (MLP) is used in nonlinear mapping among the inputs and the output paradigm. To an additional second derivative of error data and automatic internal alterations that are prepared to the learning constraints. In the present algorithm, the network weights as well as biases are initialized arbitrarily at the commencement of the training chapter. Error minimization method is achieved by means of a gradient descent rule. There are two input and six output parameters in the experimental test. The two input variables are considered to be as ‘load percent’ expressed in percentage and the ‘Biodiesel percentage’ also in terms of percentage. The six outputs have been outlined as BSEC, BTE, NO_x, EGT, UHC and CO on MATLAB toolbox, which was also selected by way of our iteration solver. The developed ANN model is limited to the tentative data which is obtained on the existing engine setup. The ANN edifice has established with double hidden layer and 16 neurons evidenced to be the best ANN selection in this replication subsequently the R^2 values are observed mostly closer to unity. During the constantly ANN model training, the minimum gradient of 10^{-5} and 1000 epochs are used as ending criteria. Trained model is simulated for all input parameters to comprehend corresponding individual output responses of the model. By means of targets as well as outputs of the model, regression coefficients, MAPE and MSE have been estimated using the following expressions [13]

$$\text{Regression Coefficient}(R) = \sqrt{1 - \left(\frac{\sum_{i=1}^{n}(e_i - p_i)^2}{\sum_{i=1}^{n} p_i^2}\right)}$$

where n is the total number of datasets, e_i is the experimental value and p_i is the network predicted value. The R-value was set to be limited to 25 neurons in the hidden layer. Thus, the network with 15 neurons in the hidden layer was found satisfactory. To attain an accurate outcome, a regression scrutiny of outputs and anticipated targets is performed and is presented. The precision of the training process is validated by means of the testing method.

The testing course involves in presenting a totally unique set of experimental dataset to test the precision of the trained network in forecasting the specific engine responses. A broad measure of the precision of the testing segment is the MSE shown in following equation.

$$\text{Mean Square Error} = \frac{1}{n}\left\{\sum_{i=1}^{n}(e_i - p_i)^2\right\}$$

The mean square error (MSE) and correlation coefficient (R^2), displayed in the table, are also computed when matched with the anticipated and investigational values. MSE provides data on the temporary performance of the model by authorizing term-by-term evaluation of actual deviation between the predicted and measured values. The MSE has been always positive and a zero value to be ideal. MSE delivers a pointer of the prognostic error relative to the precise value. Lower the MSE demonstrates a superior correlation among the prophesied and experimental outcomes. The R^2 value offers an another pointer between the prophesied and experimental information, Where R^2 values nearby to 1 signifies the most precise prediction.

5.2 *Results and Discussions*

ANN model training was utilized for number of times with 1000 iterations. Levenberg–Marquardt training procedure through logarithmic sigmoid transfer function employed for layer-1 as well as for layer-2 respectively, produced paramount regression, MAPE and MSE. It was observed that MSE is greater for smaller number of neurons, reaffirming the point that the smaller number of neurons determines decision-making vigorous. Although, MSE is greater for greater number of neurons as tuning of weights to diminish error is time-consuming. The optimum figure of neurons why ever MSE was perceived to be insignificant is 16. In acquirement of constraints to access the propinquity of actual and anticipated values, MSE alone was not adequate. Pursuant to the case of training algorithm, even though MSE is in the tolerable range, MAPE and regressions may not in the acceptable limits. Thus the skillful ANN model was developed by enchanting regression, MSE and MAPE in place of a valuation standard.

$$\text{Mean Absolute Percentage Error(MAPE)} = \left\{ \frac{100}{n} \sum_{i=1}^{n} \left| \frac{(e_i - p_i)}{(e)} \right| \right\} \%$$

Levenberg–Marquardt training function through logarithmic sigmoid transfer function, the ANN prophecies for proposed test cases demonstrated outstanding overall agreement catalogues with the experimental responses where it attained a 99.47% regression. Statistical studies for Brake Specific Energy Consumption (BSEC) has shown that the proposed ANN model gave least MSE content of 0.0141 [14]. The assurance of the ANN prophesied BTE is evident in the tenacious concurrency in association with the experimental data for all iterations of experimental data as evident from Fig. 13a–g. It is also witnessed that the ANN affords decent level of accuracy in demonstrating the engine responses. This has been supported by the reliable concurrency of the ANN anticipated values with the experimental dataset for the total series of observations. Likewise, NO_x emissions also anticipated precisely as obvious from the similarity with the observed data. From the tentative results we conclude that there is a substantial reduction in the CO, CO_2 and HC emission profiles because of superior combustion characteristics demonstrated by the pilot test fuels. Table 3 shows Regression values at various neurons and the maximum regression is achieved at a topology of 16 neurons as shown in Fig. 14.

6 Conclusions

NO_x levels were a bit higher than the petro diesel due to the reason that excess oxygen levels in the pilot fuel sample. We can witness that the emission profiles predicted with FFNN that track a certain trend have a poorer error percent than matched to those that doesn't track a certain flow. Additionally, the emissions that disagree approximately in a linear manner have a nominal percent of error than those that track a quadratic or a cubic equation. Therefore contingent to the nature as well as the tendency of emission profile we can practice FFNN to forecast the emission profiles depending upon the obligatory level of precision and thus providing the required emission profiles without resonant the actual experimental investigation. *P. pinnata* methyl ester seems to have a prospective to practice as alternative fuel in DICI engines deprived of any modification. Based on the above results the conclusions were drawn on whole as laid below.

1. Blending diesel declines the viscosity substantially.
2. It is also concluded from the experiment that practice of adding additives with diesel and biodiesel blends has increased the cetane number, lubricity, and stability of the testing fuel which resulted into improved performance with the PME blends.

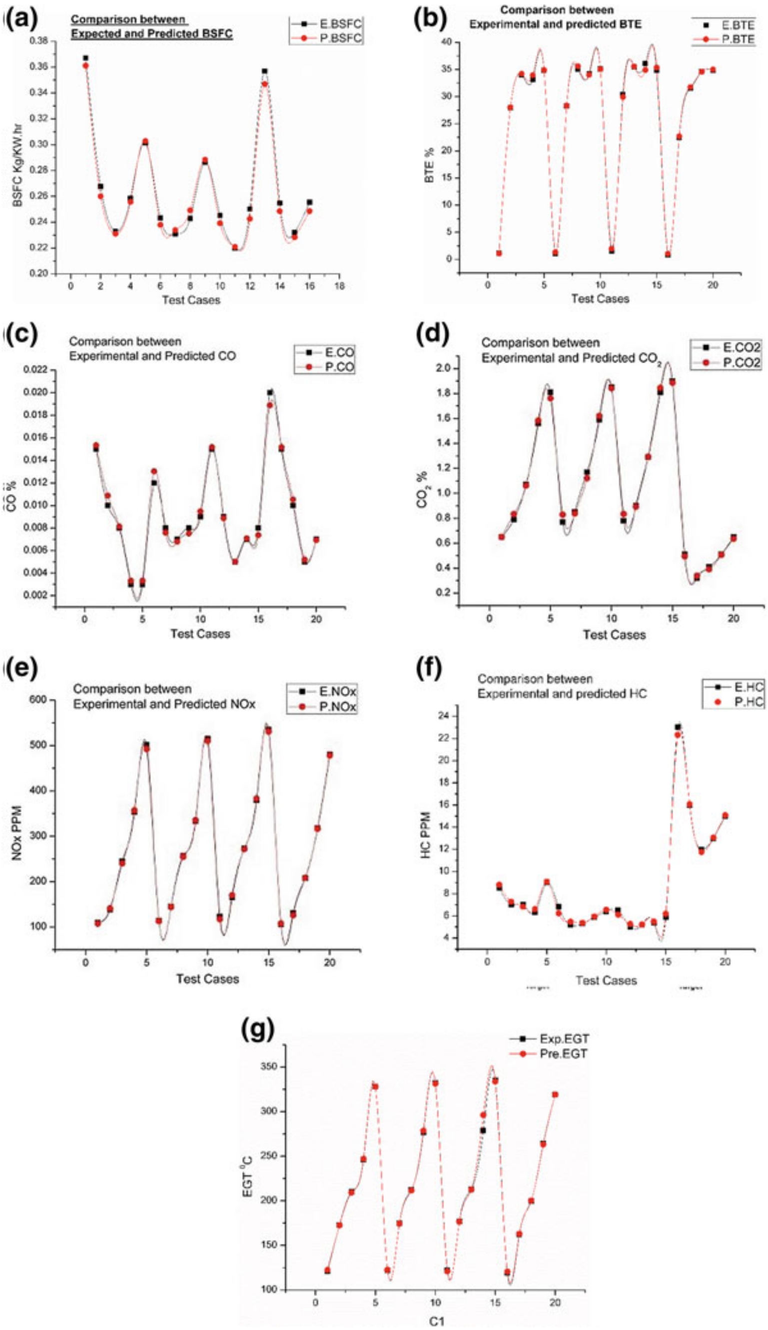


Fig. 13 **a**–**g** Comparison of experimental versus predicted properties

Table 3 Topology of various neurons

Neurons	Regression coefficient (r)			
	Training	Validation	Testing	Overall
10	0.96038	0.99807	0.99824	0.97078
11	0.98648	0.95858	0.99873	0.98466
12	0.98958	0.9592	0.8598	0.96496
13	0.97214	0.97223	0.97846	0.97329
14	0.99736	0.96716	0.97593	0.98805
15	0.97133	0.99875	0.99883	0.97799
16	**0.99596**	**0.99225**	**0.99211**	**0.9947**
17	0.96728	0.99077	0.99865	0.97372
18	0.98602	0.9679	0.84972	0.96468
19	0.9726	0.98899	0.99488	0.97844
20	0.92631	0.99713	0.99727	0.95181
21	0.97295	0.88313	0.99756	0.96326
22	0.95315	0.99412	0.99301	0.96728
23	0.94956	0.98571	0.99682	0.96064
24	0.94375	0.97692	0.97248	0.95204
25	0.97161	0.95927	0.94135	0.96417

3. It was instituted by the experiment that the blends of PME, DEE and diesel could be practiced successfully with satisfactory performance than pure diesel capable to a certain limit.
4. From experiment it is concluded that B20 could replace the diesel for diesel engine for attainment of better performance.
5. The brake thermal efficiency was slightly better than pure diesel fuel.
6. Brake specific fuel consumption is lesser for PME blends than diesel at all the load conditions.
7. The exhaust gas temperature is instituted to increase with percentage of PME in test fuels in accordance with coarse spray foundation and delayed combustion.
8. ANN is found to be capable of predicting the engine output responses with regression values close to the unity and MAPE and MSE values under acceptable threshold.

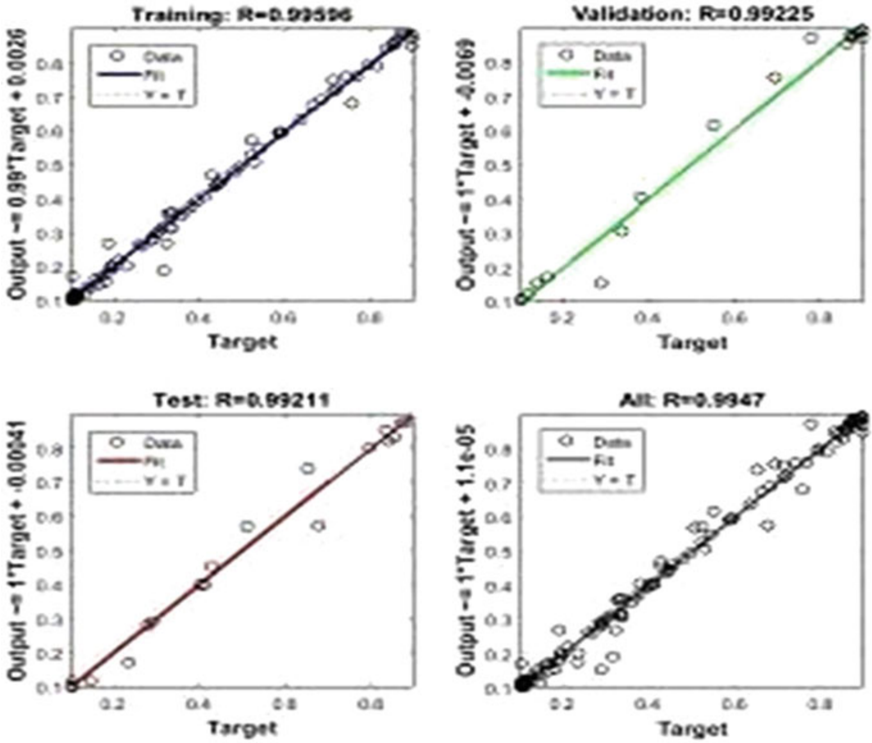


Fig. 14 Best topology

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