

ANN Modeling of Emission and Performance Parameters of Polanga Biodiesel based CI Engine at Different Injection Pressures

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Abstract

The present work predicts the emission and performance parameters of a single cylinder 4-stroke CI engine at different fuel injection pressures using Polanga biodiesel by ANN. Experimental data for training and testing was obtained at a constant speed and full load condition. Standard Back-Propagation algorithm was used for the proposed ANN model and non-linear relation between the input and output parameters was obtained using Multi layer perception network (MLP). The proposed model predicted the parameters quite well. The correlation coefficient 0.99998, 0.9999, 0.99998, 0.9999, 0.9958, 0.9993, 0.9999 for the brake specific fuel consumption, brake thermal efficiency, exhaust gas temperature, NO_x, CO, smoke and UBH emissions, respectively.

Keywords – artificial neural network, performance, polanga, biodiesel, CI engine.

1. INTRODUCTION

Globalization and rapid economic growth has resulted in exhaustive use of energy resources worldwide. In this race, resurging India with rapid economic growth and large human population is putting huge pressure on global energy supply and environmental sustainability. India is growing at a faster rate and consuming more energy than it ever did in her long millennia old civilization. India needs an abundant and sustainable energy supply in the foreseeable future to maintain the economic growth momentum and progressive social transformation without jeopardizing

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environment. But unfortunately, it is not able to diversify its sources of energy whose sustainability as well as environmental effect are the factors of great concern. With respect to usage diesel engines are largely favored across a wide spectrum of activities like automotive application, small and decentralized power generation, prime mover for farm and agricultural machineries, small scale industrial prime mover and so on. Therefore, in Indian context, diesel consumption is always disproportionately higher than gasoline. The consumption of gasoline is increasing at a faster rate than the consumption of diesel, still diesel consumption in India is nearly four and half times higher than gasoline. The degradation of environment due to combustion of fossil fuel together with rise in crude oil prices has led to development of low emission alternate fuels for diesel engines. Biodiesel has become a potential alternate fuel due to: (i) combustion of biodiesel does not increase the greenhouse gas level as it is plant-derived (ii) it offers the possibility of reducing crude imports as it can be produced domestically (iii) its biodegradability; and (iv) low levels of CO and particulates in combustion products as compared to diesel [1]. The research on biodiesel has mostly been focussed on edible plants viz., sunflowers, soyabean, rapeseed and peanut [2]-[3]. Vegetable oils are the plant origin biofuels generally obtained from resins and plant seeds. Because of being a part of carbon cycle, the vegetable oils are carbon neutral. Moreover, these oils are extensively found all over the country with special penetration in rural areas. Certain characteristics like renewable background, higher lubricity, high cetane rating, low sulfur content, non-toxic nature, bio-degradability, superior anti-corrosion properties etc. make these fuels a promising alternative one for diesel engine application [4]. Polanga biodiesel has been identified as an alternative fuel for the existing compression ignition engines [2]. The emission and performance parameters of several non-edible based biodiesel has been studied. It was observed that bsfc for all the biodiesel blends increased with blends and decreased with speed. Injection timing, injection pressure, compression ratio and the blend are important parameters that influence engine performance [5,6].

Most of the literatures agreed on the common denominator that emissions of carbon monoxide and unburnt hydro carbons were reduced with biodiesel, whereas that of oxides of nitrogen increased. However, the same was not linear. In many cases even, reduction in oxides of nitrogen was reported. All most all of the literatures indicated increased in-cylinder pressure for lower volume fraction of biodiesel in the test fuels irrespective of the feedstocks. This led to shorter combustion duration, increased in-cylinder temperature and lower exhausts temperatures reported in many cases. However, at higher volume fractions of biodiesel some literatures indicated reduction in peak in-cylinder pressure where some indicated minimal change in the peak in-cylinder pressure. Therefore, the combustion phenomena using biodiesel is highly sensitive to the nature of the feedstock and transesterification process which actually determines the fuel properties. With increase in volume fraction of biodiesel, reduction in combustion heat release was reported in major cases. However, in some cases a marginal increase was reported at lower blends. Increased heat release in the diffusion phase, smoother engine operation etc. are some of the major conclusions in most of the literatures.

The performance of a CI engine for different operating parameters can be obtained either by conducting experiments or by modeling. It is both expensive and time consuming to test the engine under all possible conditions. Developing an accurate model, on the other hand, for the operation of a CI engine fuelled with biodiesel blends is too difficult due to the complex processes involved. An alternative is to model the engine using ANNs. The engine performance and emissions characteristics of biodiesels obtained from soybean oil and yellow grease using Artificial Neural Networks have been investigated [7]. The network obtained regression values of 0.98. An artificial neural network model with standard algorithm was proposed. The engine parameters were predicted quite well with regression values of 0.948, 0.99, 0.93 and 0.99 for the torque, BSFC, CO and UBH emissions, respectively [1]. ANN model for performance and emission of a biodiesel engine using WCO was investigated. The input variables were engine rpm and percentage blend and BP, torque, BSFC and emissions were the outputs [8]. ANN model to predict BP, torque, BSFC and emissions was developed [9, 10]. An artificial neural network model on methanol based engine was developed to predict BSFC, BP and MEP. The regression values were found to close to 1 [11].

In the present work, experiments were conducted for different Polanga blends at different fuel injection pressures at full load condition and ANN architecture has been proposed. In the model, Polanga blends, different fuel injection pressures are taken as input parameters. The output parameters are BSFC, BTE, EGT, CO, NO_x, smoke and UBH emissions.

2. EXPERIMENTAL INVESTIGATION

In the present work, single cylinder 4 stroke water cooled CI engine of Kirloskar make was used. The trial set up is shown in Figure 1.

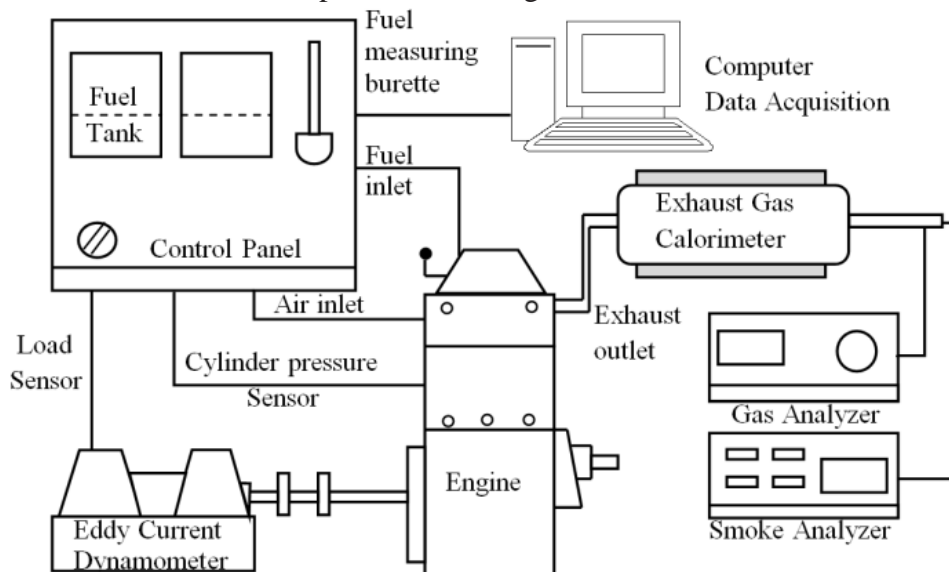


Fig. 1. Experimental Setup

Brake specific consumption of the engine was measured by a fuel consumption meter, DP transmitter. Cylinder gas pressure was determined by piezo-electric transducer that can measure up to 345 bars. Legion Brothers Labview based code was used for immediate data acquisition.

The emissions of HC, CO and NO_x were measured by emission analyser of AVL make. AVL smoke meter was used for measuring the smoke emission. The exhaust gas, water inlet and outlet temperatures were assessed by using K-type thermocouples. The percentage uncertainties of various instruments is given in Table 2.

Table 2. Percent uncertainties

Instrument	Range	Accuracy	Percent uncertainty
Gas Analyser			
Hydrocarbon	0-20000 ppm vol	<200: ±10	±0.3
		>200: ±5%	
Nitric oxide	0-5000 ppm vol	<500: ±50	±0.2
		>500: ±10%	
Smoke meter			
Opacity	0-100%	±1%	±1
EGT	0-1250°C	±1°C	±0.2
Burette fuel		±1cc	±1
Transducer	0-100 bar	±0.01bar	±0.1

Fuel consumption test was carried out by warming up of engine on zero loads, gradual loading up to 100 percent to stabilize its operation. The experiment was then replicated three times for each biodiesel blend and the mean value of parameters was calculated. Four Polanga blends were used viz., B10, B20, B30, B40. The fuel injection pressure was kept at 180 bars (manufacturer setting) and the fuel was then changed to biodiesel. Same procedure was replicated for other Polanga blends. To visualize the effect of fuel injection pressure, the procedure was carried out for injection pressure of 160 bar, 200 bar, 220 bar and 240 bar. The experimental data obtained has been summarized in Table 3.

Table 3 Experimental results under different injection pressures and biodiesel blends

IP (bar)	B (%)	BSFC (kg/kWh)	BTE (%)	CO (%vol)	UBHC (ppm)	NO _x (ppm)
160	10	0.24	38	0.077	41	777
160	20	0.247	36.21	0.07	40	790
160	30	0.258	35.1	0.058	38	826
160	40	0.267	34.02	0.0466	37	866

180	10	0.2268	40.23	0.0712	40	785
180	20	0.24	38.45	0.062	38	800
180	30	0.25	37.25	0.052	36	836
180	40	0.2614	36.66	0.039	35	878
200	10	0.2268	40.6	0.0637	36	797
200	20	0.238	39.31	0.05	34	811
200	30	0.243	38.27	0.043	34	842
200	40	0.2522	37.9	0.0254	31	888
220	10	0.2535	35.77	0.0502	33	807
220	20	0.247	36.63	0.04	32	814
220	30	0.241	37.84	0.029	31	846
220	40	0.2394	38.7	0.019	29	898
240	10	0.262	34.56	0.0366	32	784
240	20	0.2495	37.18	0.027	30	801
240	30	0.238	39.34	0.022	29	835
240	40	0.23	40.18	0.016	28	868

3. NEURAL NETWORK DESIGN

3.1 ANN networks

ANNs are programming technique having important features, such as learning, handling large number of variables, generalization etc. The ANN cells consist of five elements as shown in Figure 2.

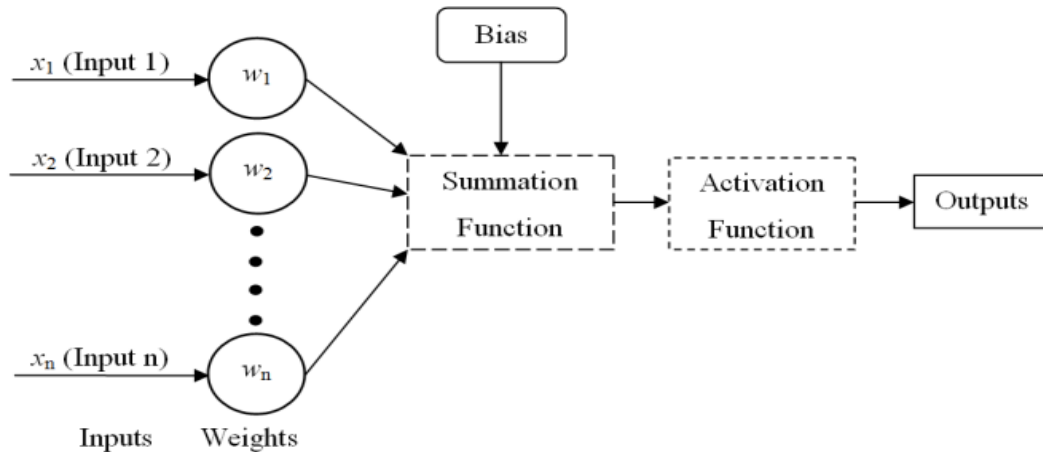


Fig. 2. ANN cell structure

The general ANN architecture has three main layers; input layer consist the data from the outside source, data processing (hidden) layer and output layers. The processing elements in the input layer transfers data to the hidden layer. Output is obtained using data from neurons in the input and hidden layers. The data is further

processed from the hidden layer and then network output is obtained. The summation function, Eq. (1), computes the net input.

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

The output of the cell is determined by the activation function by processing input to the neurons. The network performance is significantly affected by selection of an appropriate activation function. Some of the activation functions used in ANN are: threshold, hyperbolic tangent, step activation, and sigmoid function. A sigmoid function is used as the transfer function. The transfer function used in this study is given in Eq. (2).

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

The most important feature which determines the accuracy of ANN is the learning method. The output closest to the numerical values can be obtained by a combination of suitable learning method and the number of hidden layer neurons.

The BP algorithm along with different variants is the most widely applied algorithm. It uses standard numerical optimization techniques. To get the optimum outputs by the network, various network architectures were trained using the trial data. The number of neurons in the hidden layer was increased from 1 to 20 to obtain precise output. Levenberge Marquardt algorithm obtained best results for most of the parameters. The best artificial neural architecture obtained for prediction of UBH is shown in Figure 3.

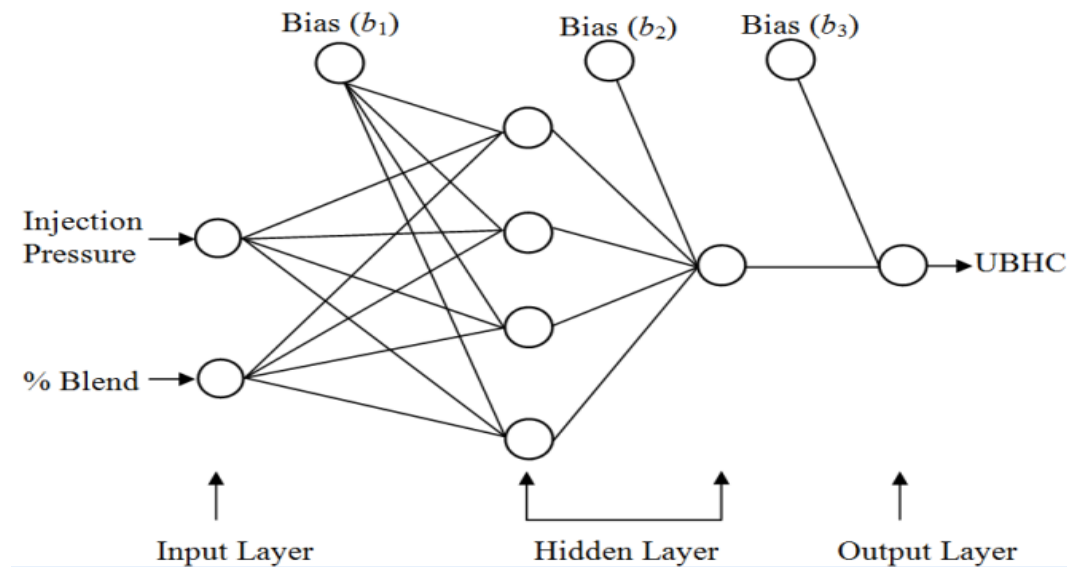


Fig. 3. ANN predicted best architecture for UBH

The correlation coefficients of performance parameters viz., BTE, BSFC and Tex, and emission parameters viz., Smoke, NO_x, CO, and UBH are shown in Table 4.

In this study, for the training and testing of the ANN, 20 data sets were prepared. The ratio for testing and training data was selected as 30%:70%.

In Back propagation model, ANN performance is affected by the scaling of parameters. Since the log-sigmoid function was used in this study, a value between 0 and 1 can be produced. The parameters were therefore normalized in the range of 0.1 – 0.9. For the output layer, linear transfer function was selected. The mean square error was taken as 0.00001. Finally, the network response was investigated by regression analysis. The computer program was developed in MATLAB 2010a.

Table 4. Network architecture and correlation coefficients

Parameter	Transfer function	No. of cells	Correlation coefficient	
			Train.	Test.
BTE	Sig/ lin/lin	3/1	0.9986	0.9617
	Sig/lin/lin	4/1	0.9999	0.9884
	Sig/lin/lin	8/1	0.9999	0.9448
BSFC	Sig/Sig/lin	10/10	0.9998	0.9988
	Sig/lin/lin	5/1	0.9999	0.9959
	Sig/lin/lin	8/1	0.99998	0.99992
	Tan/lin/lin	12/1	0.999	0.996
Tex	Sig/ lin/lin	2/1	0.9968	0.99996
	Sig/lin/lin	4/1	0.9999	0.9982
	Sig/lin/lin	6/1	0.99998	0.9996
CO	Sig/ lin/lin	2/1	0.9941	0.9981
	Sig/lin/lin	4/1	0.9934	0.9998
	Sig/lin/lin	6/1	0.99998	0.9958
NO _x	Sig/ lin/lin	2/1	0.9951	0.9977
	Sig/lin/lin	4/1	0.9991	0.9984
	Sig/lin/lin	6/1	0.9999	0.9994
Smoke	Sig/ lin/lin	2/1	0.9975	0.9912
	Sig/lin/lin	4/1	0.9993	0.9987
	Sig/lin/lin	6/1	0.9989	0.9974
UBHC	Sig/ lin/lin	1/1	0.9974	0.9983
	Sig/lin/lin	2/1	0.9976	0.9996
	Sig/lin/lin	4/1	0.9999	0.9896

4. RESULTS AND DISCUSSION

4.1 Biodiesel fuel characteristics and properties

There are several methods like dilution, pyrolysis, transesterification and engine hardware modification in which vegetable oil can be used in diesel engines. Amongst these methods, transesterification has been established as the best method to use

vegetable oils in diesel engines. Transesterification is a chemical process in which the triglycerides of the vegetable oil are converted in to monoalkyl esters and glycerol in presence of a catalyst. The vegetable oil alkyl esters are popularly known as biodiesel and have properties very similar to mineral diesel.

The energy consumption in two stage transesterification is higher. Therefore, optimization of process parameters is must in high FFA non-edible oil seeds for commercial scale production. Response surface methodology using central composite design method was followed by many researchers as an effective process optimization technique in biodiesel production from a wide range of feedstocks. However, most of the process optimization was confined to the final stage only with % yield as the response and not both the stages of transesterification. In many reported cases the final biodiesel sample produced did not comply with the designated standards of ASTM/EN/ISO etc. resulting in further addition of additives and post-processing.

Polanga biodiesel blends properties are mentioned in Table 5.

Table 5. Polanga biodiesel blends properties

Fuel	CV	Viscosity	Density	Flash point
Diesel	43996.3	2.91	0.830	77
10%B	40094.2	3.1	0.839	82
20%B	39193.7	3.2	0.847	88
30%B	38393.3	3.32	0.855	94
40%B	37792.9	3.6	0.863	99

4.2 Performance parameters

4.2.1 Brake specific fuel consumption (BSFC)

Table 3 shows BSFC results for various polanga blends and fuel injection pressures at full load condition. A decrease in fuel injection pressure enhanced the BSFC values for all the blends. The reason is that due to falling injection pressure, particle diameter will expand and ignition delay time will enhance. This condition causes an extend in the Brake specific fuel consumption. On the another side, rising injection pressure from the original pressure decreases the BSFC values for B20, B30 and B40. For blends B10 an increase in injection pressure increases the BSFC values due to a shorter ignition delay period. From Figure 4, minimum BSFC for B10 is 0.226 kg/kW-hr at 180 and 200 bar and increase in injection pressure from 200 to 240 bar, the BSFC is increased to 0.36 kg/kW-hr. It is noticed that the BSFC is reduced with raise in fuel injection pressure up to 200 bar. This may possibly be due to that, as fuel injection pressure increases the diffusion length and spray funnel angle increase. It is also notice that with increasing percentage of polanga biodiesel BSFC decline at elevated injection pressure, from experiments that is find that B40 shows 0.23 kg/kW-hr fuel consumption at 240 bar injection pressure, that is due to high viscosity of fuel.

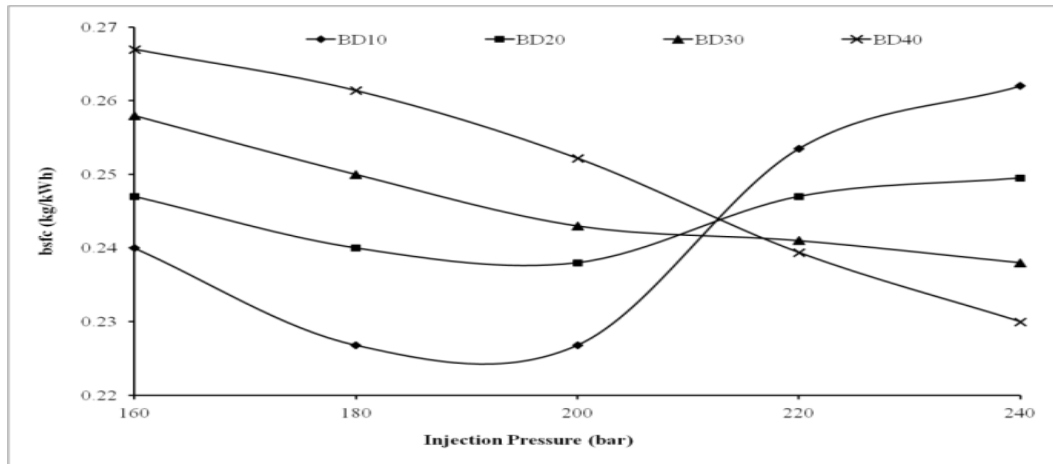


Fig.4. BSFC variation with injection pressure

4.2.2 Brake thermal efficiency (BTE)

As can be seen from Figure 5, an increase in polanga blend at the given injection pressure, BSFC increases due to the less calorific value of the blend. An increase in injection pressure improves the BTE due to the superior atomization and good combustion. BTE is highest at 200 bars for B10 is 40.6% this is due to healthy spray produced during injection and enhanced atomization as given in Figure 5.

Further the Brake thermal efficiency tends to decline, this could be due to that at elevated injection pressure the dimension of fuel particles reduce and very fine biodiesel fuel spray will be inject, due to this, diffusion of biodiesel fuel spray less and thrust of biodiesel fuel droplets will be lessen. Therefore, the Brake thermal efficiency usually dropped as the polanga biodiesel volume increased in the diesel for all injection pressures. As verified in Figure 5, the highest BTE was obtained as 40.18% for B40 at 240 bar fuel injection pressure.

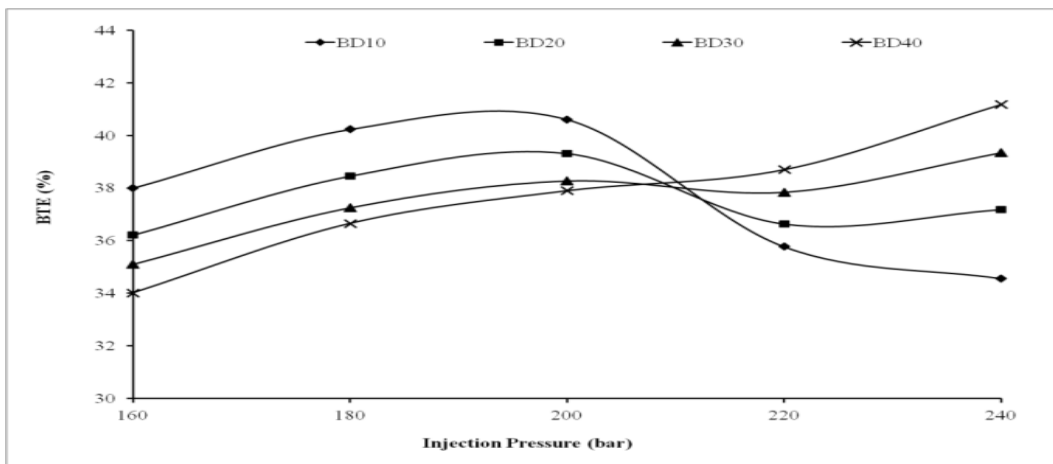


Fig. 5. BTE variation with injection pressure

4.2.3 Exhaust gas temperature (EGT)

The deviation of EGT with the injection pressure at constant full load for polanga blends is given in Figure 6. In broad-spectrum EGT increase with load, at elevated injection pressure the EGT is higher due to the operating temperature is high at elevated injection pressure. It is noticed that the EGT is raised by increasing the percentage blend. The EGT is minimum for 160 bar fuel injection pressure for all Polanga biodiesel blends, minimum 253°C for B10 polanga blends at 160 bar injection pressure. Increasing the fuel injection pressure increase in exhaust gas temperature (EGT) was shown in present study. Maximum exhaust gas temperature (Tex) 288°C for B40 this is due to high oxygen content with at 240 bars injection pressure occur in this study. Of all the polanga blends, B10 shows lesser values of EGT at the entire value of injection pressure, B40 shows elevated values of EGT at all the injection pressure due to increasing oxygen content with increasing blending.

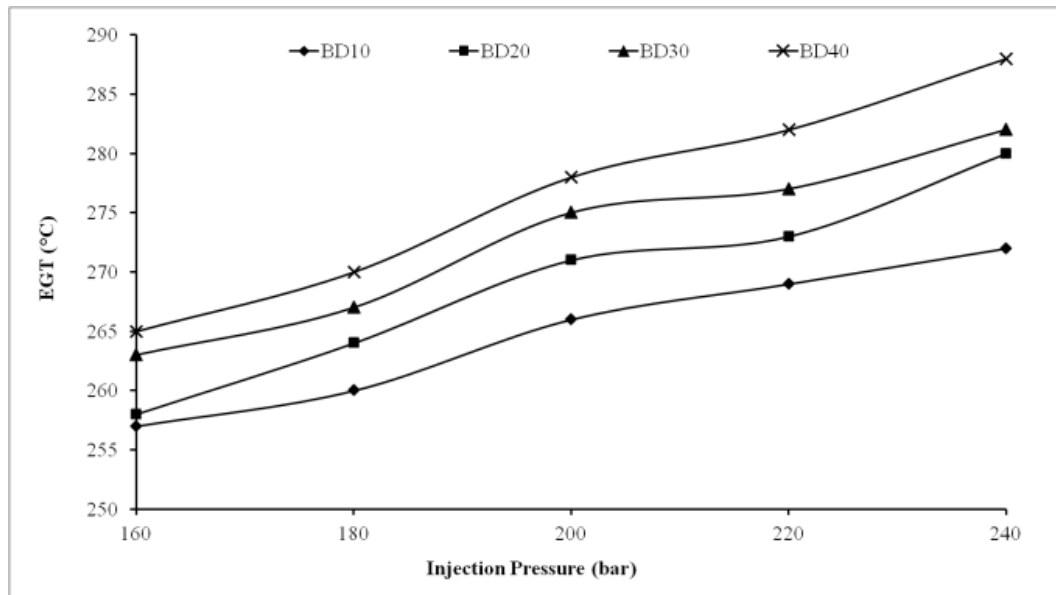


Fig. 6. EGT variation with injection pressure

4.3 Emission parameters

4.3.1 CO emissions

Table 3 shows carbon monoxide outcomes for diverse polanga biodiesel-blends fuels with injection pressures at constant full load condition. It is revealed from Figure 7 that carbon monoxide emission amount reduced with the more biodiesel proportion.

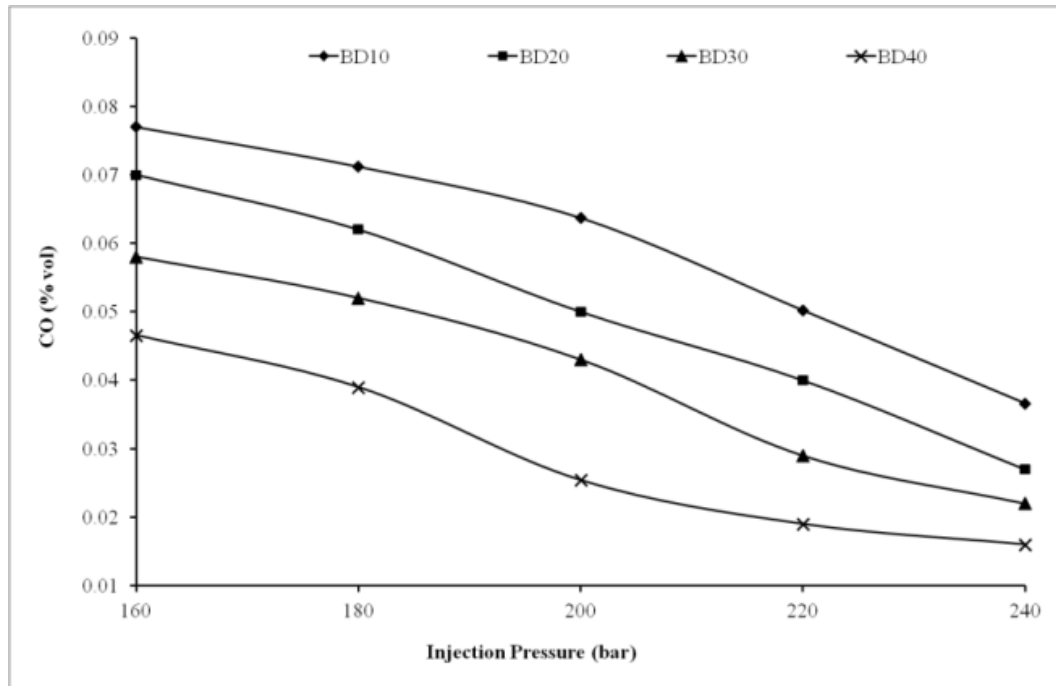


Fig. 7. Emission of carbon monoxide with injection pressure

As can be seen from Figure, it was accomplished that at elevated injection pressure narrowed the carbon monoxide emissions. The rising injection pressure enhance a better fuel–air integration, effortless and full combustion of the fine particle of fuel. These special effects escort to shrink CO emissions. However, B40 shows less emission of CO on all injection pressure. Reduction in CO was observed with increasing injection pressure for biodiesel. Minimum CO emission of 0.016% by vol. was observed at the injection pressure of 240 bar. This is due to the lower carbon content of biodiesel and also better combustion caused by the enhanced atomization, improved mixing process at elevated injection pressure of 240 bar and maximum carbon monoxide emission of 0.077% by vol. was recorded for B40 at the injection pressure of 240 bar.

4.3.2 UBH emission

As shown in Figure 8, UBH emission values reduced with the rising biodiesel proportion.

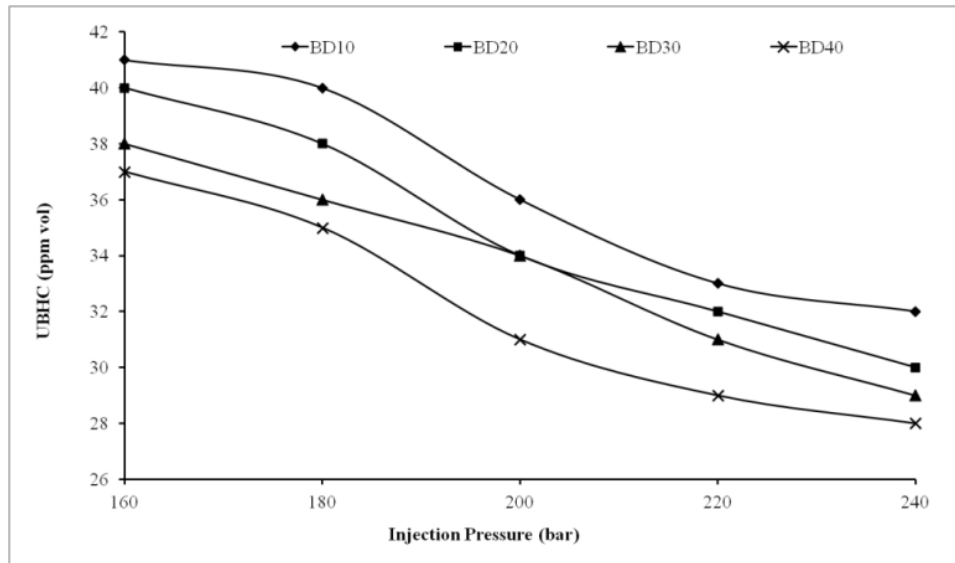


Fig. 8. UBH variation with injection pressure

The declined pattern of UBHC emissions of biodiesel blends may be occurrence of O_2 molecules in biodiesel facilitated for full combustion of fuel. Fig.8 also gives UBH emission results for different polanga biodiesel blends with fuel injection pressure at full load. The minimum UBH 28 ppm was find with B40 for 240 bar fuel injection pressure. A rise in fuel injection pressure develop better fuel air mixing in the combustion chamber resulting in less UBH emissions. Lowest UBH of 28 ppm was observed at 240 bar, which is 9 ppm lower than that of UBH emission at 160 bar for the same biodiesel blend B40. The reduction in UBH emission of biodiesel is mainly due to the better vaporization and proper atomization.

4.3.3 Oxides of nitrogen emissions

Figure 9 give NO_x values for various polanga biodiesel blends with different injection pressures at full load.

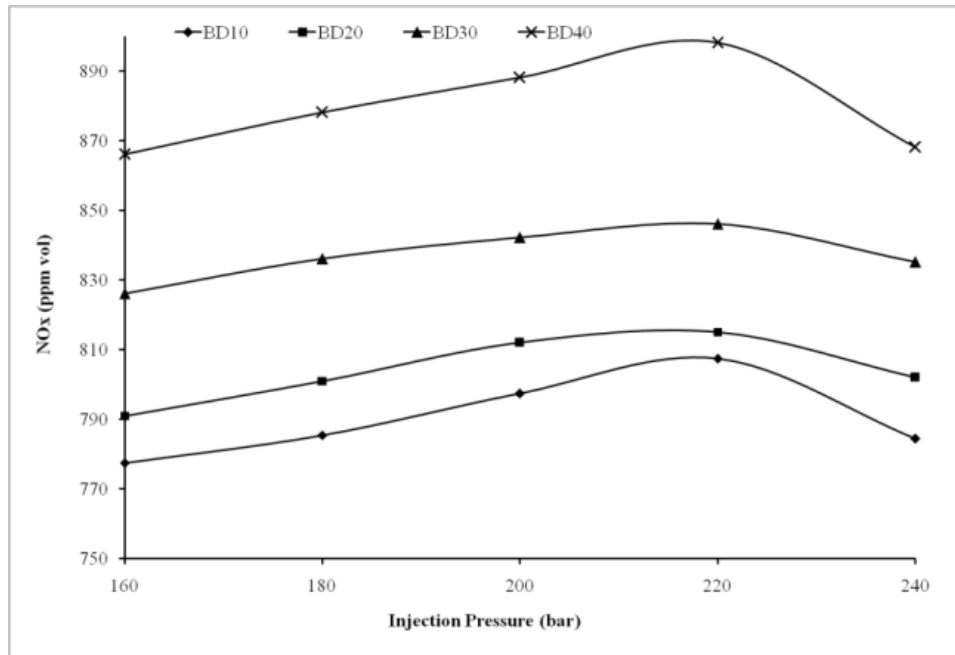


Fig. 9. Variation of NO_x with injection pressure

As seen from the figure, at elevated fuel injection pressure, NO_x emissions are higher. Maximum NO_x emissions was recorded to be 807.37 ppm vol, 814.98 ppm vol, 846.1 ppm vol, and 898.05 ppm vol for B10, B20, B30 and B40 at 220 bar injection pressure, correspondingly. The NO_x emission level increases rapidly with growing injection pressure, due to quicker combustion and high cylinder temperature. Maximum NO_x emission is 898.05 ppm vol at 220 bar of B40.

4.3.4 Smoke opacity

Formation of smoke occurs due to deficiency of air. Air or O₂ deficiency is nearby present within the engine. At the original injection pressure of 180 bar, smoke opacity was recorded to be 94% with B40 at full load. As illustrated in Figure 10, the smoke opacity drop off with increase polanga blend percentage. This can be due to the increase in oxygen content and reduction in carbon content in polanga blends. An increase in fuel injection pressure decreases the size of fuel particles. As seen in Figure 10, by increasing fuel injection pressure, smoke opacity reduced.

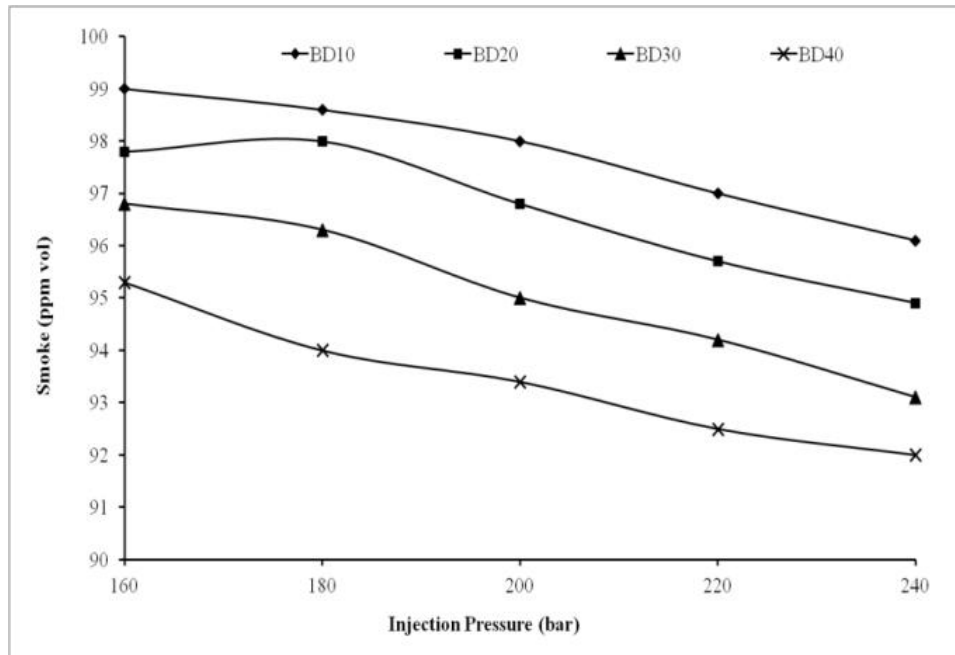


Fig.10 Smoke opacity with injection pressure

B40 polanga blend shows the less smoke opacity for all the fuel injection pressure. The opacity values are 95.3%, 94%, 93.4%, 92.5% and 92% at 160, 180, 200, 220 and 240 bar injection pressure respectively.

4.4 ANN Prediction of performance and emission

In this work, a computer code has been developed in MATLAB platform to predict BSFC, BTE, EGT, CO, NO_x, Smoke and UBH emissions of the engine. The input parameters are %blends and fuel injection pressures. The output parameters are BSFC, BTE, EGT, CO, NO_x, Smoke and UBH emissions. It was evident from Table 4 that all the network architectures provided acceptable accuracy. The regression values were more than 0.98. LM learning algorithm provided the best results. Figure 11(a) and (b) shows the comparison of ANN predicted values and trial results. It was observed that the prediction results are extremely close to the trial results.

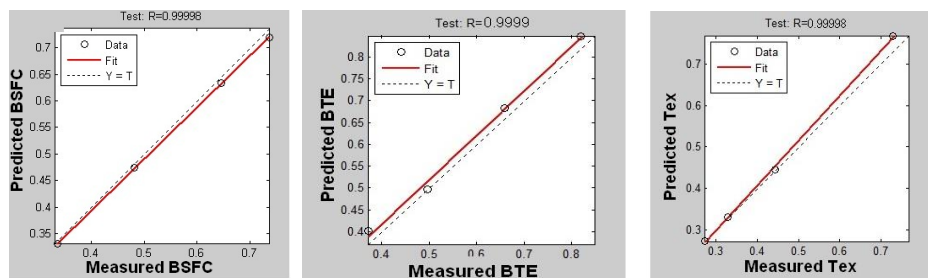


Fig.11. (a) ANN Predicted and test results of performance parameters

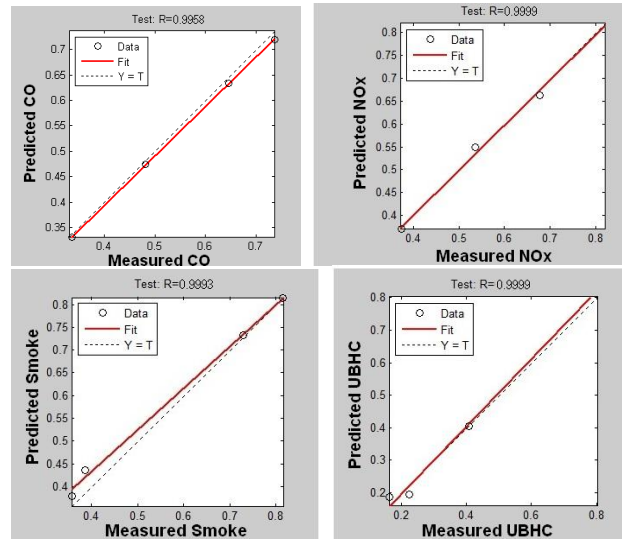


Fig.11. (b) ANN Predicted and test results of emission parameters

As shown in Figure11, the predictive capability of the network for performance and exhaust emissions parameters was found to be acceptable. Thus the choice of percentage blend and fuel injection pressure as influencing parameters provides reasonable output. The equations of the BSFC, BTE, EGT, CO, NO_x, Smoke and UBH emissions are given in Eqs. (3) to (9).

$$BSFC = \frac{1}{1 + e^{-(\sum_{i=1}^8 w_{2i}F_i + 0.34313)}} \quad (3)$$

$$BTE = \frac{1}{1 + e^{-(\sum_{i=1}^3 w_{2i}F_i + 27.144)}} \quad (4)$$

$$T_{ex} = \frac{1}{1 + e^{-(\sum_{i=1}^6 w_{2i}F_i + 0.35893)}} \quad (5)$$

$$CO = \frac{1}{1 + e^{-(\sum_{i=1}^6 w_{2i}F_i + 0.21331)}} \quad (6)$$

$$NOx = \frac{1}{1 + e^{-(\sum_{i=1}^4 w_{2i}F_i + 0.55572)}} \quad (7)$$

$$Smoke = \frac{1}{1 + e^{-(\sum_{i=1}^4 w_{2i}F_i - 5.2244)}} \quad (8)$$

$$UBHC = \frac{1}{1 + e^{-(\sum_{i=1}^4 w_{2i}F_i - 1.40738)}} \quad (9)$$

The weighted sum is given by

$$NT_i = (w_{11} \times IP + w_{12} \times BD + b_1) i \quad (10)$$

The weights appearing in equation (3) to (9) are given in Tables 6 and 7.

Table 6. Weights for performance parameters

	i	w_{11}	w_{12}	b_1	w_2
BTE	1	-1.606	-0.33597	0.69548	-3.5387
	2	1.9041	0.17425	0.089628	-6.3514
	3	2.3992	-0.04936	0.75344	3.2473
BSFC	1	-8.4865	-2.1788	7.6867	-2.3812
	2	3.9897	-7.4609	-4.8474	-0.03029
	3	6.8536	-3.178	-4.753	-4.4348
	4	5.3832	-5.2183	-2.5869	2.4336
	5	-5.7181	-5.1586	-1.6053	0.60699
	6	-1.7805	-7.7431	-3.2877	-0.40463
	7	6.2135	-5.0013	4.6958	1.9296
	8	6.8669	-2.51	8.8412	1.8265
Tex	1	1.5451	-6.6139	-4.0683	-0.47135
	2	1.7902	1.8627	-2.3114	2.1142
	3	-6.7453	-0.53401	-1.2285	-1.9449
	4	-7.0123	0.59678	-0.16528	0.86299
	5	-5.9686	-1.4068	-3.2659	-0.26475
	6	5.3103	-2.0479	8.4219	-0.52849

Table 7. Weights for emission parameters

	i	w_{11}	w_{12}	b_1	w_2
CO	1	-4.9444	-5.166	6.6262	-2.2294
	2	4.3453	3.5113	-1.2051	2.4863
	3	1.5648	6.6333	-0.5072	-0.2532
	4	2.744	-5.7003	2.3061	-0.1959
	5	3.8648	2.9246	3.0417	2.8129
	6	-6.641	-1.0035	-6.6432	-0.1159
NO _x	1	-7.8727	0.39004	3.466	1.1739
	2	0.19278	-1.5302	0.62291	-2.1956
	3	5.2309	1.0656	3.7598	1.1605
	4	-0.82161	5.7447	3.1143	0.56433
Smoke	1	2.1236	1.567	-5.9787	-2.1376
	2	21.6831	-16.1722	-3.6952	-1.7645
	3	-1.129	0.7635	-0.3215	-3.2821
	4	-0.0311	-2.783	-11.776	0.06438
UBHC	1	-4.0605	6.5114	11.7625	1.0639
	2	-4.5533	0.14418	-1.355	1.0155
	3	-1.675	-1.5619	-0.1434	2.1475
	4	3.142	-6.8655	7.6305	-0.3846

5. CONCLUSION

The different biodiesel blends in the present study can be used in 4 stroke single cylinder CI engines without any major engine modification. Experimental examination showed that the injection pressure of 240 bars was found to be the optimum condition for engine with B40 biodiesel. A drop in BSFC and upgrading in brake thermal efficiency was also observed. Biodiesel blends resulted in the fall in CO, UBH and smoke emission at elevated injection pressures. However NOx emission slightly increased with increasing injection pressures. Among the a range of injection pressure, 240 bars exhibited shorter ignition delay with slightly longer combustion. Multilayer feed forward network with back propagation training algorithm was used to predict the emission and performance features of CI engine at various injection pressures. The predicted R values were found to be very close to unity while the MSE error was less than 0.0004 for BSFC, BTE, Tex, CO, NOx, smoke and UBH.

REFERENCES

- [1] Ghobadian, B., Rahimi, H., Nikbakht, A. M., Najafi, G., and Yusaf, T. F., 2009. Diesel engine performance and exhaust emission analysis using waste cooking biodiesel fuel with an artificial neural network. *Renewable Energy* 34 (4):976–982.
- [2] Sahoo, P. K, Das, L. M, Babu, M. K. G., Naik, S. N., 2007. Biodiesel development from high acid value polanga seed oil and performance evaluation in a CI engine. *Fuel* 86:448–454.
- [3] Baiju, B., Naik, M. K., Das, L. M. 2009. A comparative evaluation of compression ignition engine characteristics using methyl and ethyl esters of Karanja oil. *Renewable Energy* 34:1616–1621.
- [4] Ramadhas, A. S., Jayaraj, S., Muraleedharan, C., 2005. Biodiesel production from high FFA rubber seed oil. *Fuel* 84:335–340.
- [5] Sahoo, P. K, Das, L. M, Babu, M. K. G., Arora, P., Singh, V. P., Kumar, N. R., Varyani, T. S., 2009. Comparative evaluation of performance and emission characteristics of jatropha, karanja and polanga based biodiesel as fuel in a tractor engine. *Fuel* 88:1698–1707.
- [6] Shivakumar, Srinivasa, P., Shrinivasa, B. R., 2011. Artificial Neural Network based prediction of performance and emission characteristics of a variable compression ratio CI engine using WCO as a biodiesel at different injection timings. *Applied Energy* 88:2344–2354.
- [7] Canakci, M., Gerpen, J. V., 2003. Comparison of engine performance and emissions for petroleum diesel fuel, yellow-grease biodiesel and soybean-oil biodiesel. *Transactions of the ASAE* 46(4):937–944.
- [8] Canakci, M., Ozsezen, A., N., Arcaklioglu, E., Erdil, A., 2009. Prediction of performance and exhaust emissions of a diesel engine fuelled with biodiesel produced from waste frying palm oil, *Expert Systems with Applications* 36:9268–9280.

- [9] Yusaf, T. F., Buttsworth, D. R., Saleh, K. H., Yousif, B. F., 2010. CNG-diesel engine performance and exhaust emission analysis with the aid of artificial neural network. *Applied Energy* 87:1661–1669.
- [10] Ismail, H. M., Kiat, N. H., Queck C. W., Gan S., 2012. Artificial neural networks modelling of engine-out responses for a light-duty diesel engine fuelled with biodiesel blends. *Applied Energy* 92:769–777.
- [11] Çay, Y., Korkmaz, I., Çiçek, A., Kara, F., 2013. Prediction of engine performance and exhaust emissions for gasoline and methanol using artificial neural network. *Energy* 50:177–186.