Modeling of Bio-Fuelled Diesel Engine using ANN and Machine Learning

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Abstract- This research deals with the prediction of the exhaust emission characteristics of a diesel engine running on Karanja biodiesel and its blending with n-butanol using ANN modeling and Machine learning modeling. The experimental results indicated the decrease in the value of HC, Smoke and CO with increase in biodiesel percentage. On the other hand, with the increase in the blend of n- butanol in biodiesel or diesel showed an increase in the HC value, whereas the values of CO, and Smoke decreases. The comparison was made between the performance of ANN model using Feed Forward Back Propagation algorithm and Machine Learning model using Random Forest Regressor algorithm. The results showed the predicted values of ANN model for exhaust emission characteristics with the mean value of correlation coefficient (R) 0.99958 and mean value of the coefficient of determination (R^2) 0.99917 while these values for Machine Learning model were 0.99982 and 0.99965 respectively. This paper showed that Machine learning using Random Forest Regressor algorithm gave better accurate results. Thus, Machine Learning model can be considered as certain method and a better tool for prediction of diesel engine emission characteristic.

I. INTRODUCTION

Environmental problems caused by the diesel engine is mainly due to pollutants which are being emitted from the combustion of fuel, the effect on the human body can be seen, as the oxygen transporting effectiveness in blood veins get reduced when CO and NO_x combined with the hemoglobin present in the bloodstream [1].

Similarly, on the other hand, particulate matter like smoke and other carbonic products cause various health problems by affecting the human respiratory system by getting accumulated in the alveoli sacs and restricts the oxygen exchange, hence shortens the human life [2][3]. The usage of oil which is obtained from vegetables as a fuel seems to be less polluting than fuels obtained from petroleum sources [4].

Ambient air pollution is caused by inefficient energy production, usage and distribution, especially from the industrial, building sectors and transportation, and by poor waste management. In the case of transport systems, which are mainly based on individual power-driven transport that leads to further degradation in air quality [5].

During the 1980s up to 2000s, coal and oil were liable for approximately 40% of global CO_2 emissions and some considerable quantity of greenhouse gases. Emissions from oil are generally exceeding those from coal by a few percentage points [6]. Fossil fuels are identified as the main source of energy for various industrial applications. Fossil fuel reserves are rapidly falling, while the demand for energy is increasing worldwide. Production of petroleum product from the crude oil was 231.924 MMT in the year 2015-16 whereas the production was 221.136 MMT in 2014-15.This data shows 4.88% increment. During 2015-16, consumption of petroleum products in India was 184.674 MMT and compared to consumption of petroleum product of 165.520 MMT during 2014-15 shows an increment of 11.57% [7]. Some substitutes for oil which is used as a fuel for vehicles and planes, and as the raw material for the chemicals industry these sectors are responsible for the growth of oil consumption [8].

To overcome such problems related to the energy and environmental issue. First, we need to understand the scope of biodiesel blended fuel by evaluating their performance and the emissions after the combustion process. Biomass sources like biofuels have attracted much attention as an alternative energy source because of its availability, renewability and have proved to be a cleaner fuel and more environment friendly than other fossil fuels.

The result showed that BSFC and NO_X increase, whereas the CO, HC and PM emissions reduced, predominantly at high engine loads. Biodiesel produced from used palm oil was blended with diesel by different volume proportions and smoke density produced is lower than diesel fuel [9].

The effect of using biodiesel and ultra-low sulfur diesel with their blends concentration on BSFC shows the significant increment and decrement in the case of BTE. The exhaust emissions mainly HC and CO decreases but on the other hand NOx and NO_2 emissions increases. The smoke concentrations diminish significantly at high loads [10].

ANN modeling is capable of providing a high degree of preciseness and accuracy when it is used to simplify the previous unobserved data sets, which are not required in the 'training' process of the base problem. Knowledge and information can be stored in the trained network which can be readily accessed by the user[11]. To calculate the multiple output parameters it analyzes and predicts the multiple input parameters. For the same process in engineering, ANN can be used as an alternative method [12]. A well-trained artificial neural network is more acceptable and faster than established obsolete method to predict the result because it does not need to solve mathematical problems which are lengthy and much more complex than they seem [13].

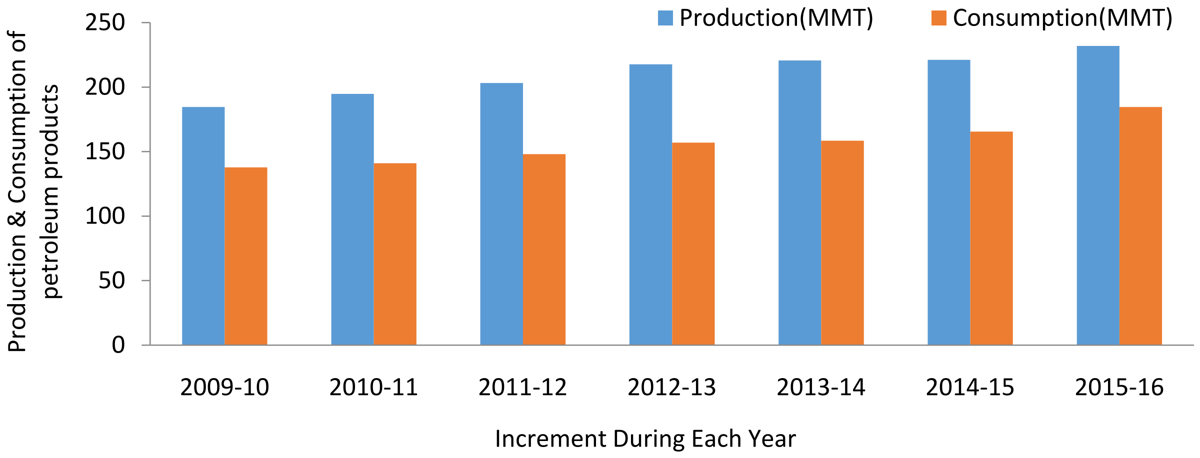

Figure 1.1 Consumption and Production of Petroleum Products [7]

Machine learning is introduced to overcome most of the ANN problems. It is a semi-automated machine which extracts knowledge from the data, in this process question can be answerable using the existing sample data. Machine learning is not a fully automated process. The primary goal of machine learning is that it generalizes the sample data and accurately predicts the futuristic outcomes of the existing data and further helps in predicting the new data set of which the user don't know the true outcome. According to Ka In Wong, Pak Kin Wong, Chun Shun Cheung, and Chi Man Vong in this study the emission characteristic of diesel blended engine with various bio-oils is constructed by the help of ELM and LS-SVM models [14]. In this research paper, the Machine Learning algorithms and its comparison with the traditional ANN algorithms are introduced for the modeling of biodiesel engine, in order to determine the performance and emission characteristic using biofuels blended with n-butanol. ANN and Machine Learning both require data for model training and verification purpose by comparing the predicted and the experimental values.

II. EXPERIMENTAL SETUP FOR SAMPLE DATA COLLECTION

2.1. Fuel Preparation

Biodiesel composed of long chains of methyl or ethyl fatty acids under ester family group and shows similar characteristics and properties to that of diesel obtained from petroleum. Therefore a biodiesel is considered as a better substitute for petroleum diesel. The biodiesel used for this experimentation is Karanja Biodiesel which can be obtained from of Karanja tree seed. A biodiesel fuel can be produced through transesterification process of vegetable oil or fat by processing them with the help of alcohols under the influence of different catalysts. The Karanja biodiesel is separated from the Karanja Oil through transesterification process which reduces the viscosity of triglyceride. On heating the Karanja oil at 60^{o}C in a reactor which has the capacity of 10 Liters. The two separate layers of Karanja oil methyl ester and glycerol is formed when oil is treated with 40% methanol under the action of 0.75% KOH as a catalyst. Glycerol is then separated from the valve of the reactor which got accumulated at the bottom most part. After the separation of glycerol from the biodiesel, the excess alcohol is then removed by the distillation process. The properties of Karanja biodiesel obtained are shown in Table 2.1 along with neat diesel and n-butanol.

Table 2.1 Properties of Fuels

Fuel Property	Neat Diesel	n-butanol	Karanja Biodiesel
Density (kg/m^3)	837	810	891.8
Cetane Number	50	25	46
Lower Calorific value (MJ/kg)	43	33.1	37.58
Kinematic Viscosity (mm^2/s)	2.6	3.6	5.02
Latent Heat of Evaporation (kJ/kg)	250	585	-

2.2. Experimental Setup

Machine learning and ANN methods uses experimental data, for fulfilling the purpose of testing and validation of collected sample data, to predict the new unknown inputs which lie in between the sample data limits. A naturally aspirated water cooled 4-cylinder, 4-stroke with direct fuel injection diesel engine is employed for experimentation. The detailed Specifications of the engine are shown in Table 2.2.

TABLE 2.2 Engine Specifications

Engine Model	Force Motors
Engine type	4-cylinder,In-line, vertical, water cooled diesel engine
Combustion System	4-stroke, Direct fuel injection
Bore (mm)	77
Stroke (mm)	95
Compression ratio	18.65:1
Engine rpm	2200
Rated Power (HP)	27
Capacity (cc)	1797

To measure the exhaust emission and smoke emission level AVL437C meter and AVL444N made gas analyzer with electrochemical sensor had been employed. The schematic block diagram of setup is shown in Figure 2.1 which mainly comprises of analyzing equipment namely smoke meter and Exhaust gas analyzer. The specification of equipment is shown in Table 2.3.

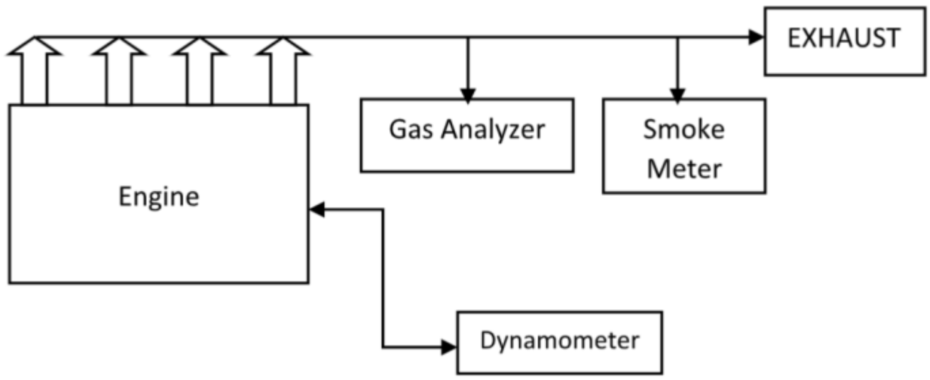

Figure 2.1 Schematic block diagram of experimental setup

Table 2.3 Equipment Specification

S. N.	Name of equipment	Measurement	Range	Resolution	Accuracy
1	Exhaust Gas analyzer	CO	0-15% Volume	0.01% Volume	±3%
		HC	0-30000 ppm	1 ppm vol.	±8 ppm
2	Smoke meter	Smoke density	Opacity 0–100%	0.10%	±1 %

2.3 Characteristics of Sample Data

The experiment had been conducted at five BMEPs of 0.1 bar, 0.2 bar, 0.3 bar, 0.4 bar, and 0.5 bar with different percentage of Biodiesel (0, 20, 50, 80, 85, 90, 95, 100%) and n-butanol blends (0, 5, 10, 15, 20%) combined with normal diesel. Since the collection of data is very time consuming and expensive, therefore, only 100 sets of experimental data is collected at different combinations of inputs. The following formulae were used to evaluate the statistical error i.e. R, R^2, MSE, RMSE.

$$R = \sqrt{1 - \left\{\frac{\sum_{i=1}^{n}(t_i - o_i)^2}{\sum_{i=1}^{n} o^2}\right\}} \quad \text{.... (1)}$$

$$R^2 = 1 - \left\{\frac{\sum_{i=1}^{n}(t_i - o_i)^2}{\sum_{i=1}^{n} o^2}\right\} \quad \text{.... (2)}$$

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

$$RMSE = \sqrt{MSE} \quad \text{.... (4)}$$

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\left(\left|\frac{ti - oi}{ti}\right|\right) \times 100 \quad \text{.... (5)}$$

Here, in these equations 't_i' and 'o_i' represents the experimental and predicted values, where 'n' represents the total numbers of outcomes. Terms like 'T', 'ω', 'HA/sec', '$\dot{m}$f' signifies 'torque', 'angular velocity', 'heat added per second', and 'injected mass of fuel' respectively.

2.3.1 Characteristics of CO

The emission of CO decreases with the percentage increase in the n-butanol blends with normal diesel and biodiesel. This situation arose because of the presence higher O_2 content in the n-butanol compound. The higher O_2 content promotes the further oxidation of CO which improves the combustion efficiency hence, results in lower CO emissions [15]. The decrement in the CO emission at BMEP 0.5 bar is about 48.87% at BD80nB20 compared to pure diesel. The emission characteristic of CO data is depicted in and Figure 2.10 to 2.13. The lowest CO emissions can be seen at BD80nB20 and BD50nB20 at BMEP 0.5 bar.

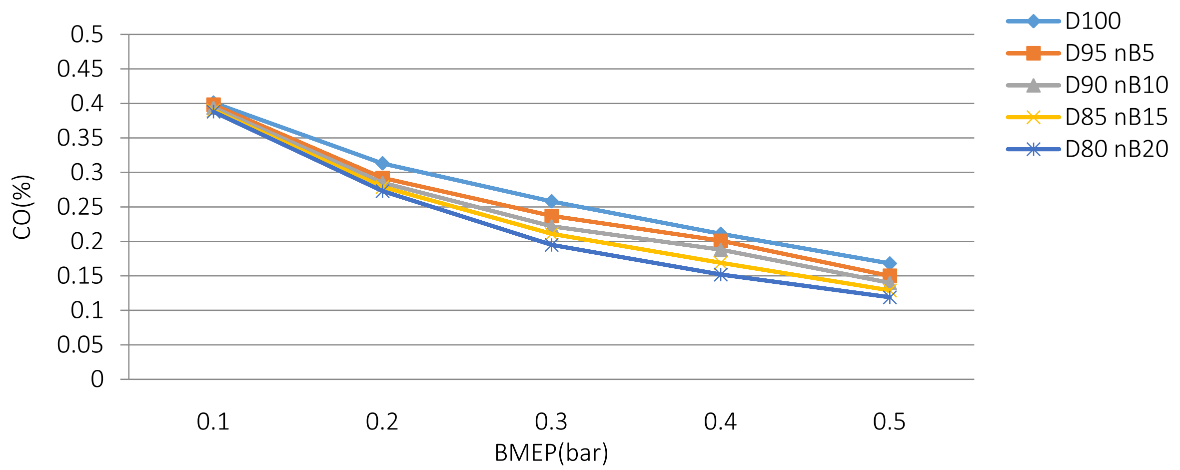

Figure 2.10 CO Vs BMEP for 100% diesel

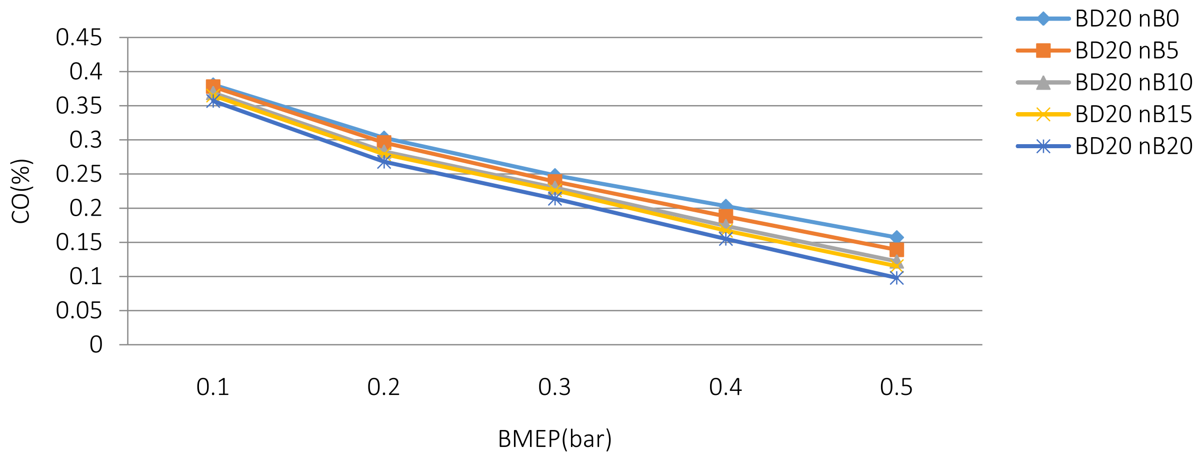

Figure 2.11 CO Vs BMEP for 20% biodiesel

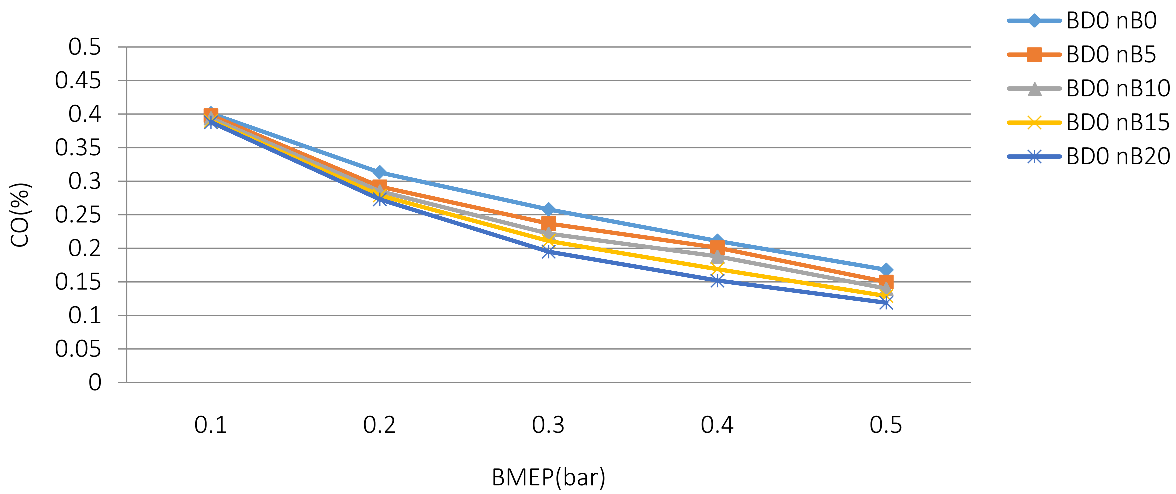

Figure 2.12 CO Vs BMEP for 50% biodiesel

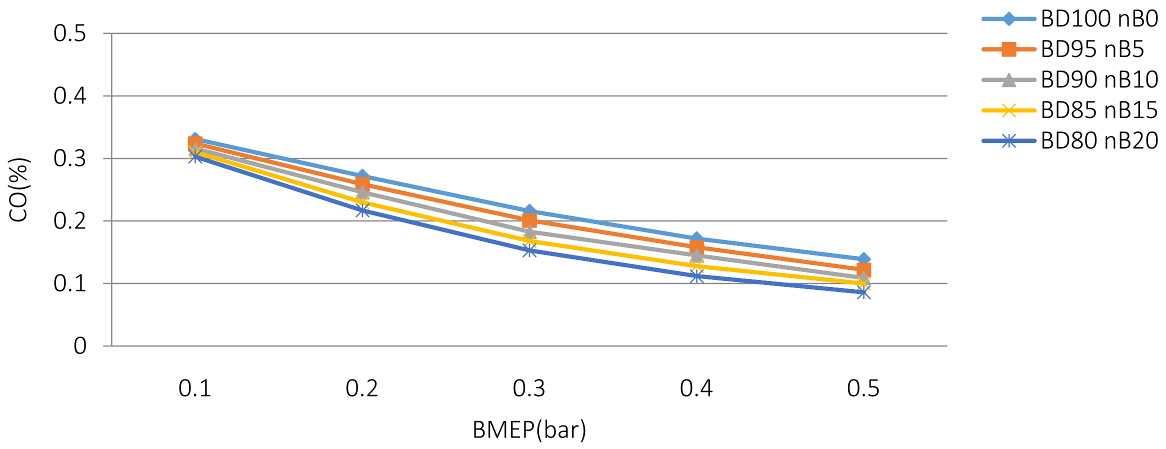

Figure 2.13 CO Vs BMEP for 100% biodiesel

2.3.2 Characteristics of HC

The emission of HC in an IC engine is mainly due to inaccurate air induction system and lack of oxygen inside the combustion chamber. The emission of HC decreases with the use of biodiesel due to complete combustion of fuel and increases when blending is done by n-butanol[91]. The increment in the HC value for BD80nB20 as compared to the value of neat biodiesel and neat diesel at BMEP 0.5 bar is found to be 33.31% and 19.72% and can be seen in Figure 2.14 and Figure 2.17 respectively. The emission characteristics of HC data are depicted in and Figure 2.14 to 2.17 the maximum emission of HC is at BMEP 0.5 bar and BD50nB20, on the other hand, the minimum emission is at BMEP 0.1 bar and BD100nB0.

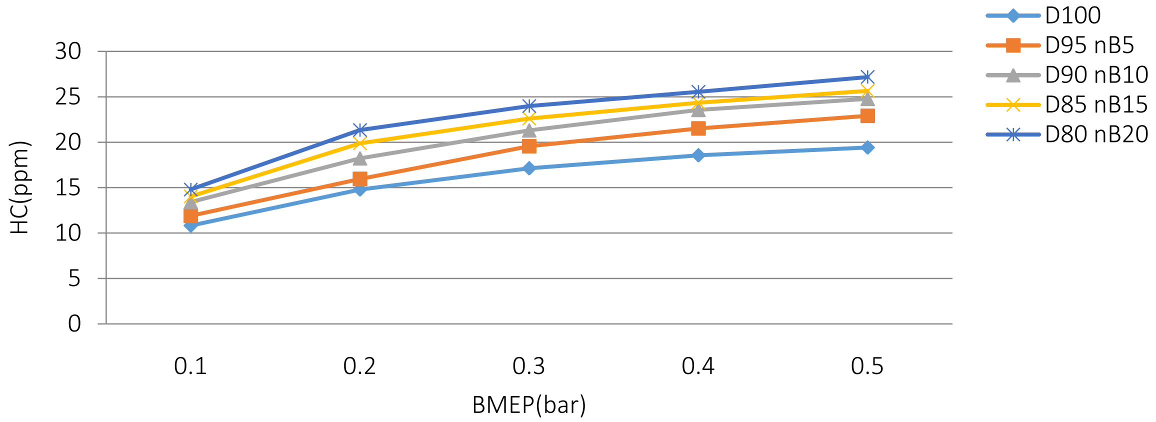

Figure 2.14 HC Vs BMEP for 100% diesel

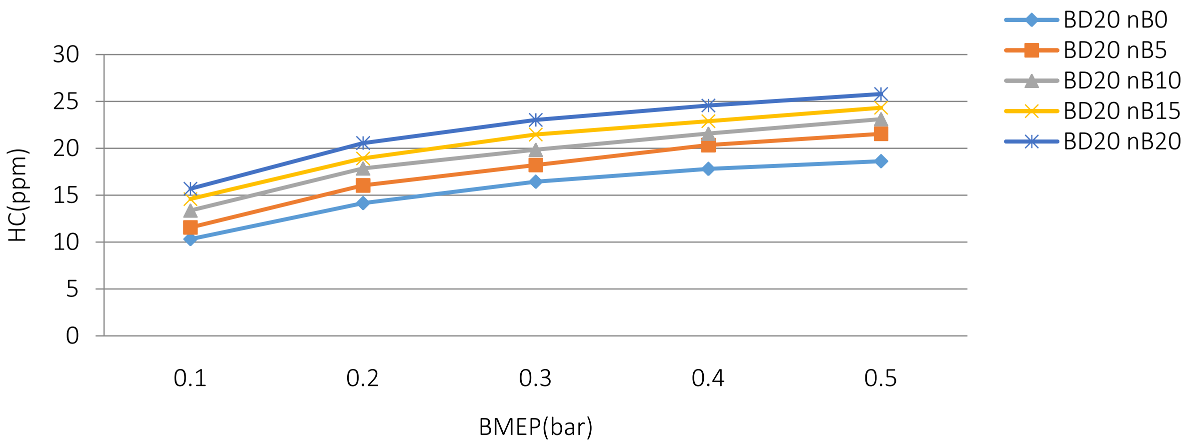

Figure 2.15 HC Vs BMEP for 20% biodiesel

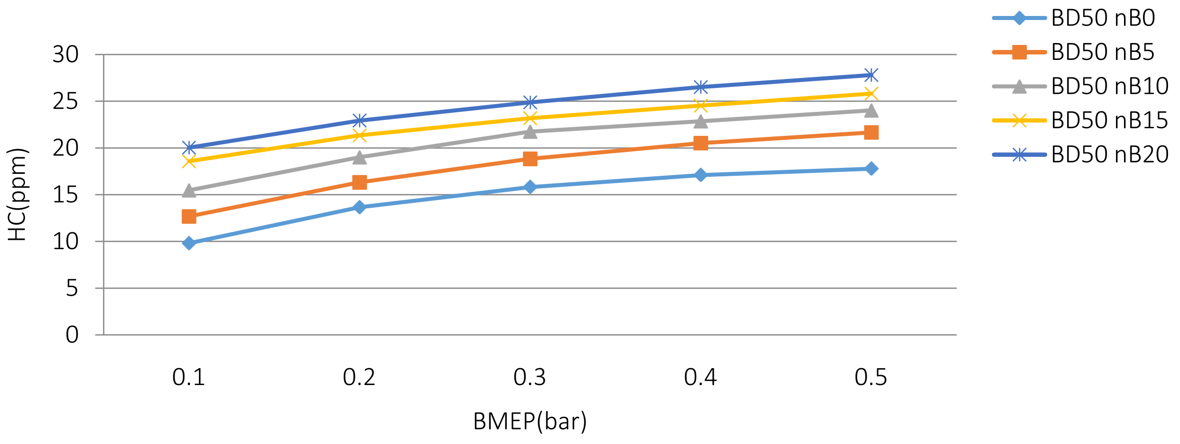

Figure 2.16 HC Vs BMEP for 50% biodiesel

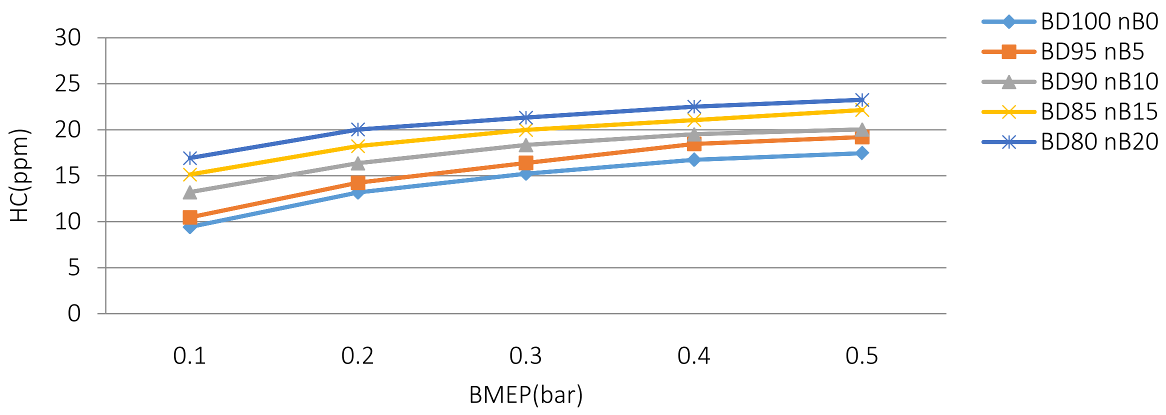

Figure 2.17 HC Vs BMEP for 100% biodiesel

2.3.3 Characteristics of Smoke

The level of smoke emission rises when O_2 content is less in the fuel and high carbon content. The emission of smoke decreased by the addition of 20% n-butanol to neat biodiesel at BMEP 0.1 bar is 6.54% and at BMEP 0.5 bar is 34.35%, this is because of the less carbon content and high O_2 content in the fuel when blended with n-butanol. The decrement of the smoke emission at BMEP 0.1 bar for BD50nB20 is 16.53% when compared to BD20nB20. The smoke emissions can be seen decreasing at all BMEP conditions for all 50% and 20% biodiesel combinations. Emission characteristics of Smoke data are depicted in and Figure 2.18 to 2.21.

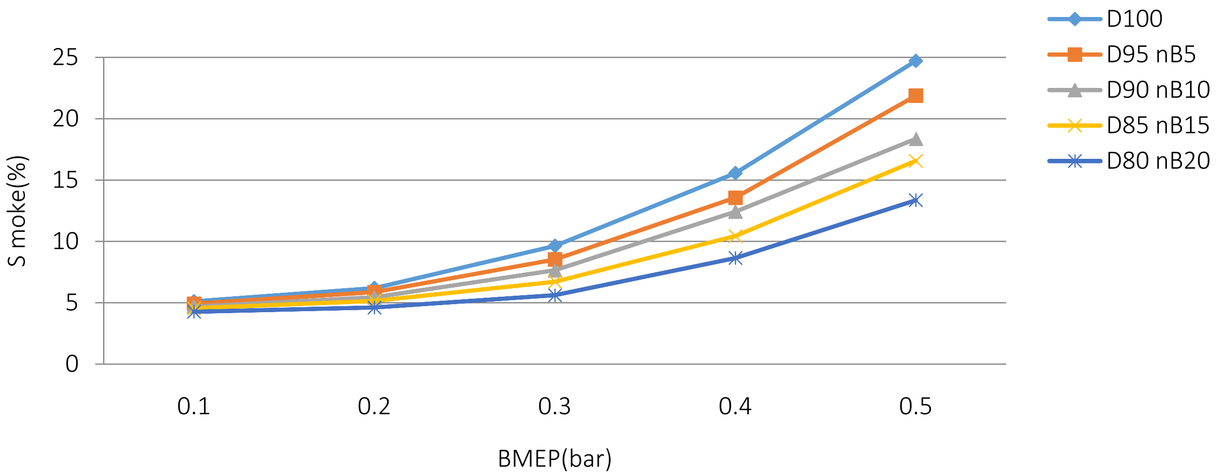

Figure 2.18 Smoke Vs BMEP for 100% diesel

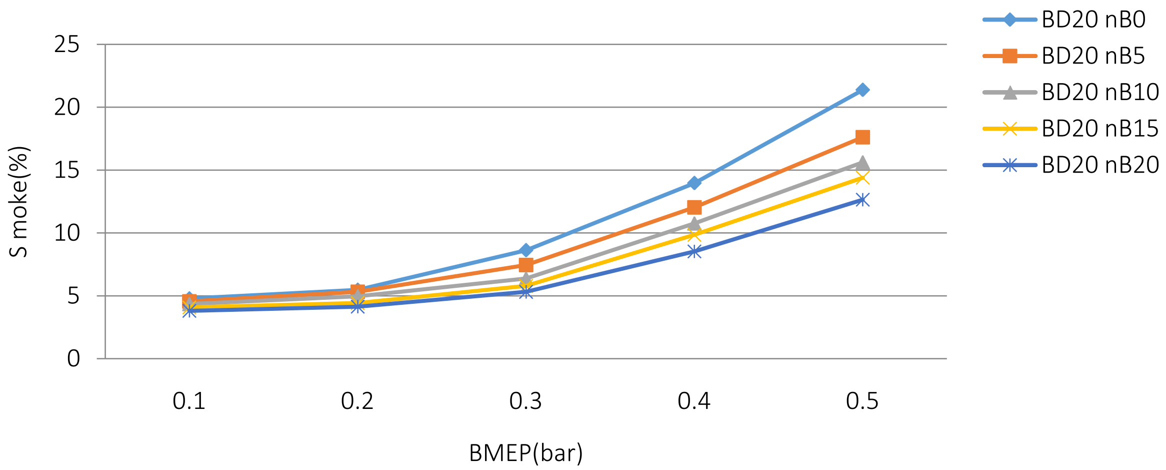

Figure 2.19 Smoke Vs BMEP for 20% biodiesel

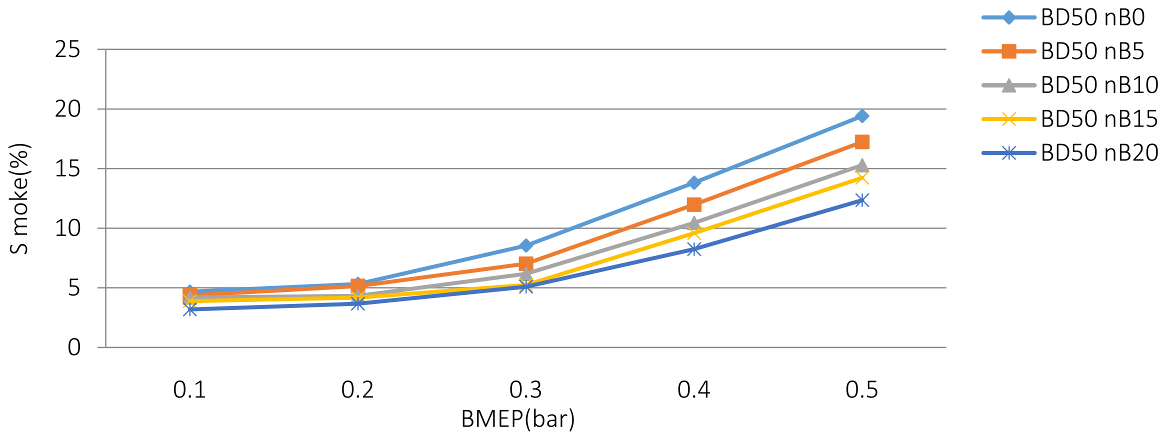

Figure 2.20 Smoke Vs BMEP for 50% biodiesel

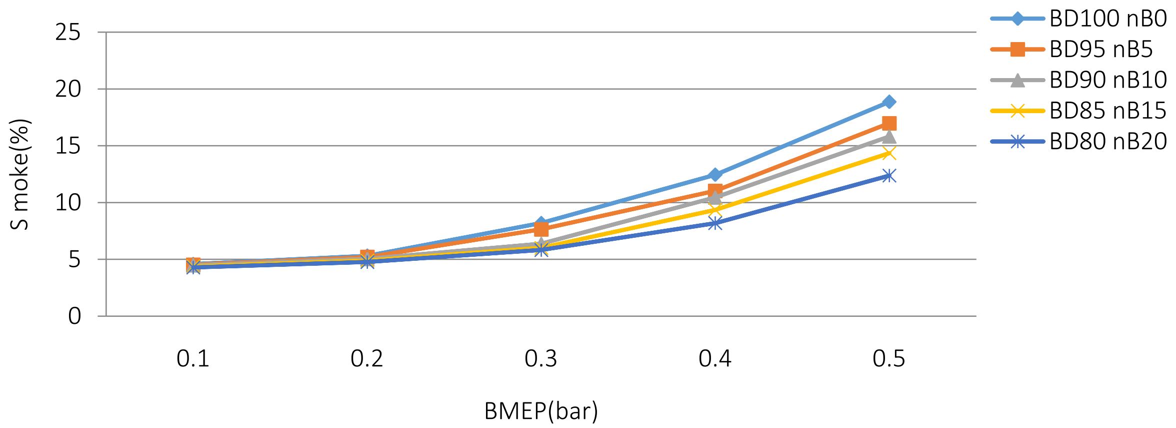

Figure 2.21 Smoke Vs BMEP for 100% biodiesel

III. ANN MODELLING

The input parameters were %BD, %nB and engine BMEP and output parameters were CO, HC, and Smoke. Apart from the input parameters, each model has its own parameter which has to be tuned. Therefore, the modeling algorithm of ANN was implemented using MATLAB R2015b which runs in Windows 10 on a computer with Intel Core i5 processor (2.50 GHz) with 4 GB RAM onboard. The value of R and R^2 should be close to 1 in order to get better accuracy. LM training function and LOGSIG and TANSIG as transfer function is used in the modeling with a different number of hidden neurons. An Artificial Neural Network is an interlinked group of nodes, similar to the humongous network of neurons in a brain. Here, each spherical node represents an artificial neuron and an arrow represents a connection from the output of one neuron to the input of another. Figure 3.1 shows the network of an ANN model. Feed forward back propagation algorithm is introduced in this model.

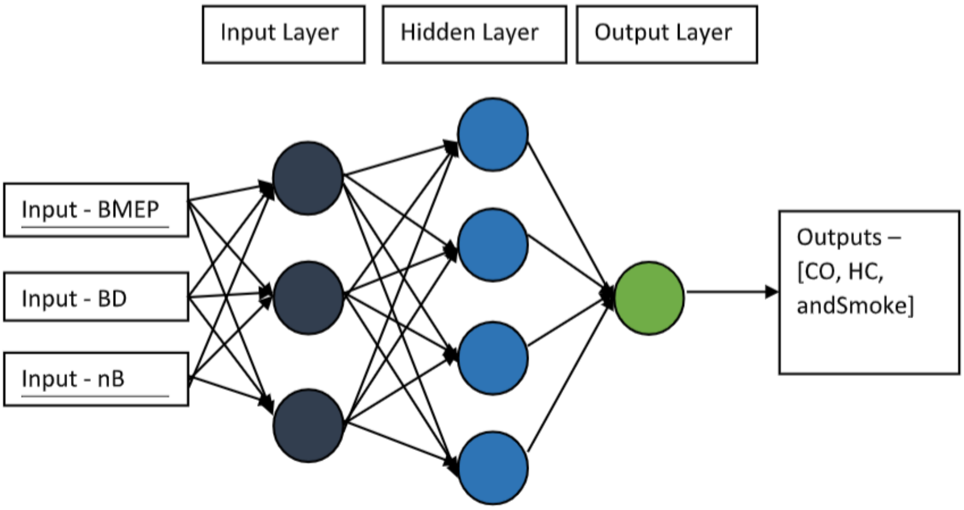

Figure 3.1 Network of ANN

ANN is training and validating method which tries to establish the mapping between input and output data and then generates the prediction results from the set of input-output data. The structure of ANN model id depicted in Figure 4.2 in which W and b are the membership functions of the input and output hidden layer respectively. It consists of two layers for tuning process of the ANN model, the function signal proceeds forward until and unless the hidden layer and MSE calculate the consequent parameters. The flow chart for model training and prediction is shown in Figure 3.2

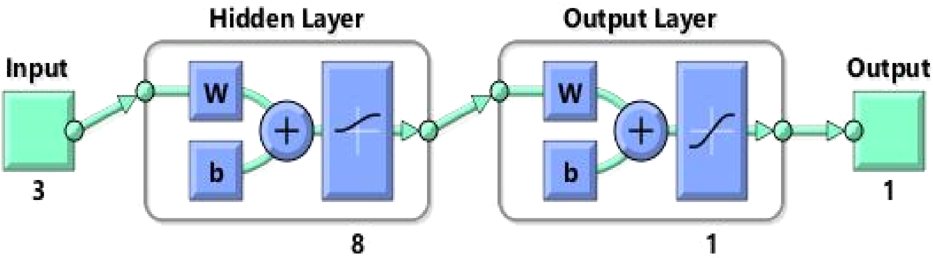

Figure 3.2 ANN Structure

The procedure used in an ANN modeling approach to represent the data, which implements artificial intelligence in opposition to the modeling principles is shown in Figure 3.3. ANN is described as a data-driven method which carries the structure of an adaptive neural network. ANN uses different training algorithms which create an input/output mapping which established on the input and output parameters, which were gathered by the experimentation of diesel engine using different biodiesel blends for the training of created neural network.

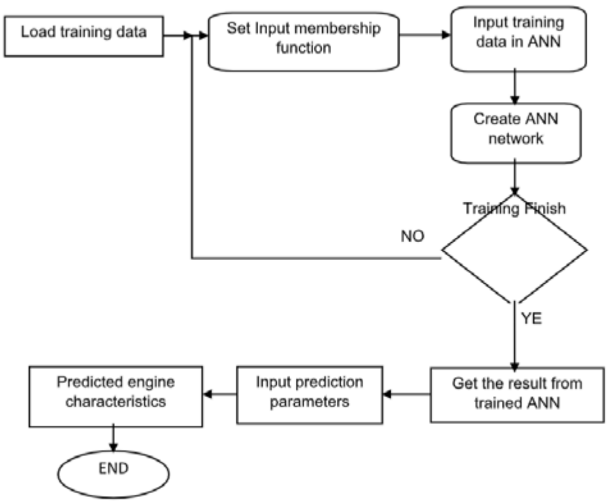

Figure 3.3 Flowchart of ANN modeling procedure

IV. MACHINE LEARNING MODELLING of DIESEL ENGINE

This section presents the modeling of a diesel engine using Python's (version 3.6) Scikit Learn library which executed under Windows 10 on a computer with Intel Core i5 processor (2.50 GHz) and 4 GB RAM onboard. The Random Forest Regressor algorithm (Supervised Machine Learning) is chosen for the modeling since it is a regression problem. The Model produced good results in regression fitting than others during the testing of the data. A Random Forest Regressor is a Meta estimator and falls under the ensemble classifier category which fits a number of data on various sub-samples of the overall dataset and uses averaging of the data which is loaded into the model to improve the predictive accuracy and to control over-fitting. The modeling procedure is shown in Figure 4.1. The modeling is done by loading the three input parameters namely BMEP, BD, nB for which the exhaust emissions were selected as the output parameters. Command has been given in the model to detect the input values which are BMEP, BD, nB and output value which is CO, HC, and Smoke in the machine learning model. MinMaxScaler is used to perform scaling over numerical variables. This allowed us to have each value between 0 and 1 in order to detect the minimum and maximum value of the array. The cross validation function is then used to split the sample data into training and testing sets. After fitting the model the predicted regression target of the input parameters is computed as mean predicted regression target of the data in the entire dataset.

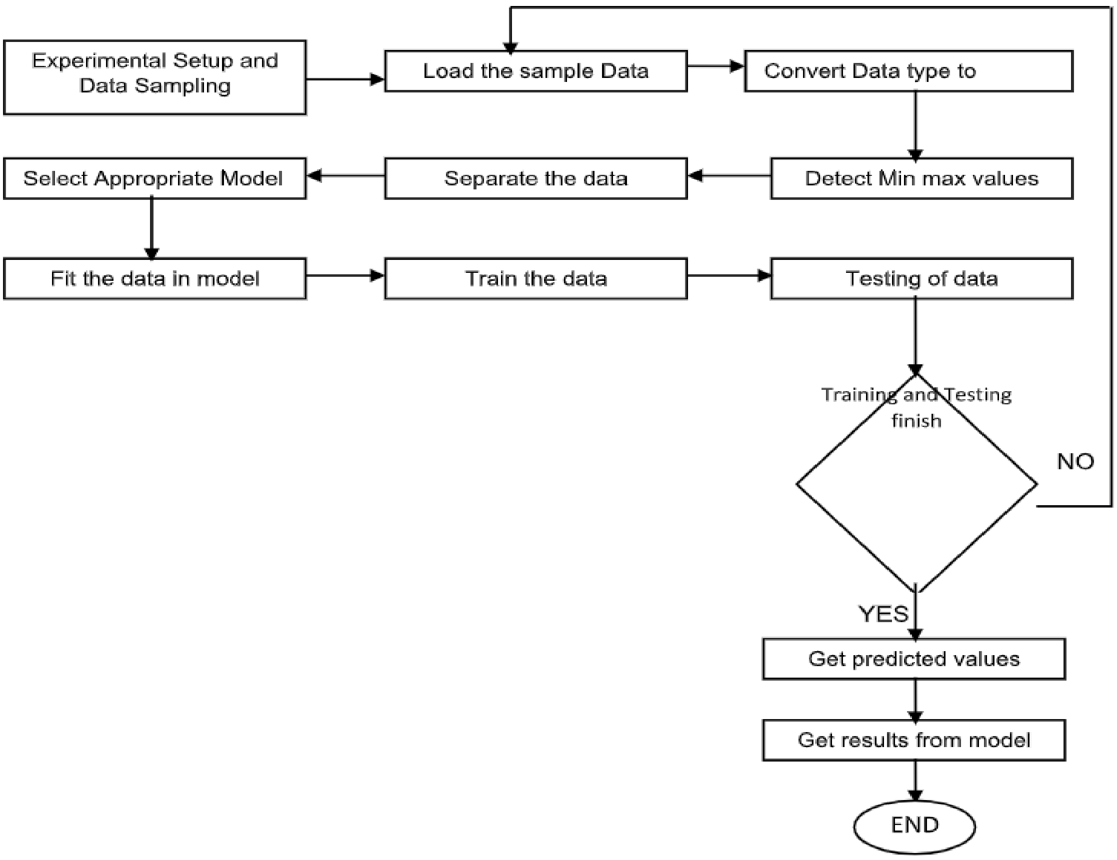

Figure 4.1 Modelling procedures for machine learning

V. RESULTS AND DISCUSSION

5.1 ANN Modelling Results:

The experiment was performed on a multi-cylinder engine with the input parameters are five BMEPs of 0.1 bar, 0.2 bar, 0.3 bar, 0.4 bar, and 0.5 bar with different percentage of Biodiesel (0, 20, 50, 80, 85, 90, 95, 100%) and n-butanol blends (0, 5, 10, 15, 20%) combined with normal diesel. The CO, HC and smoke are the various emission parameters which have been evaluated during the experimentation. Training and prediction of the data have been done on the ANN model. In the FFBP network of ANN model with the Levenberg Marquardt training function is utilized under LOGSIG and TANSIG transfer function using different numbers of hidden neurons (8, 10, 12, and 14) with the default number of 2 layers has been adapted. MSE as the performance function with LEARNGD and LEARNGDM as the adaptation learning function. Values of MSE and R for training, testing and prediction were obtained from the different ANN networks are shown in Table 5.1.

Table 5.1 Values of MSE and R for different ANN networks

S.No.	Outputs	Training Function	Transfer Function	Adaptation Learning Function	Number of Neurons	MSE	R (Training)	R (Validating)	R (Testing)
3	CO	LM	LOGSIG	LEARNGD	14	0.00002	0.9994	0.9979	0.9957
4	HC		TANSIG	LEARNGDM	10	0.11918	0.9957	0.9987	0.9947
5	Smoke		TANSIG	LEARNGDM	10	0.00002	0.9987	0.9983	0.9972

5.1.1 CO

The results of CO for different BMEP conditions varying from 0.1-0.5 bar were predicted by using LM training function with LOGSIG transfer function. The graph between experimental and predicted values is shown in Figure 5.5 indicated that the values are very close to each other. Hence, this signifies that the developed model is highly effective for the prediction of CO. The plots between training, validation, and testing of experimental values are shown in Figure 5.6.

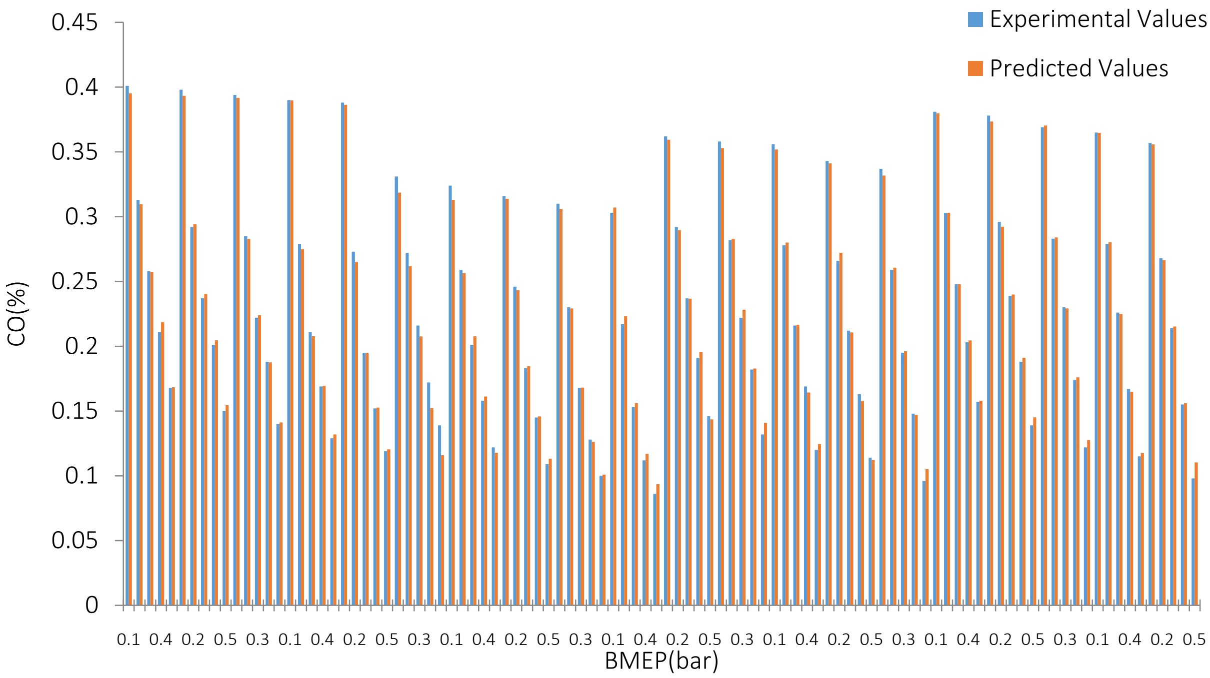

Figure 5.5 CO experimental and predicted values

5.1.2 HC

The results of HC for different BMEP conditions ranging from 0.1 to 0.5 bar were predicted by using LM training function with TANSIG transfer function. The graph between experimental and predicted values is shown in Figure 5.7 indicated that the values are very close to each other. Hence, this signifies that the developed model is highly effective for the prediction of HC. The plots between training, validation, and testing of experimental values are shown in Figure 5.8.

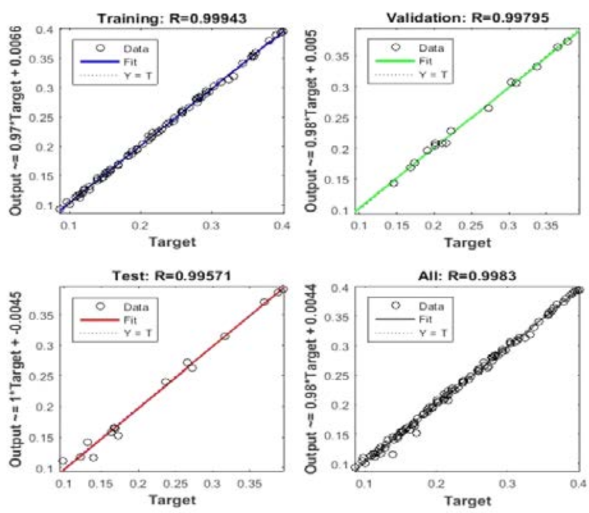

Figure 5.6 ANN CO regression plots

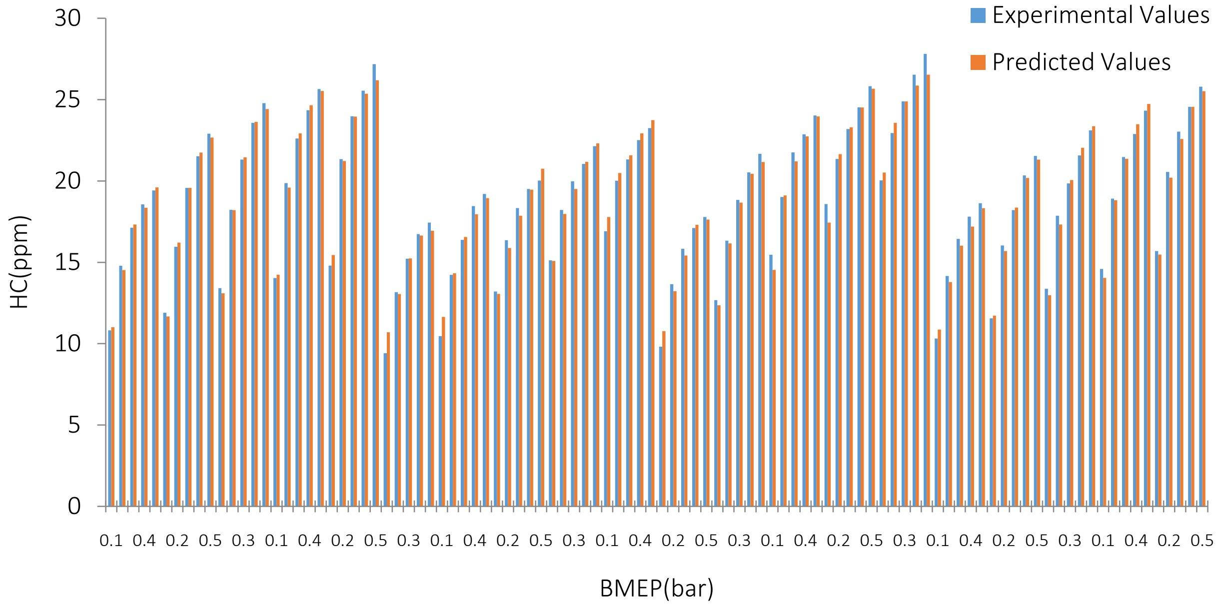

Figure 5.7 HC experimental and predicted values

5.1.3 Smoke

The results of smoke for different BMEP (0.1, 0.2, 0.3, 0.4, 0.5 bar) conditions were predicted by using LM training function with TANSIG transfer function. The graph between experimental and predicted values is shown in Figure 5.9 indicated that the values are very close to each other. Hence, this signifies that the developed model is highly effective for the prediction of smoke. The plots between training, validation, and testing of experimental values are shown in Figure 5.10.

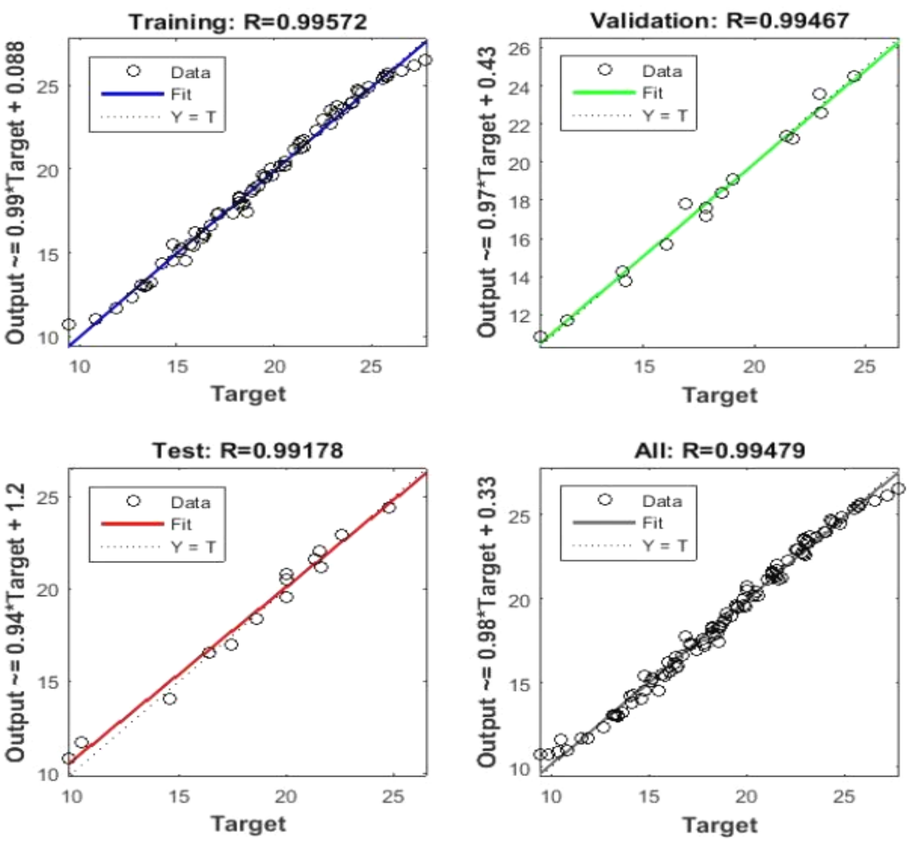

Figure 5.8 ANN HC regression plots

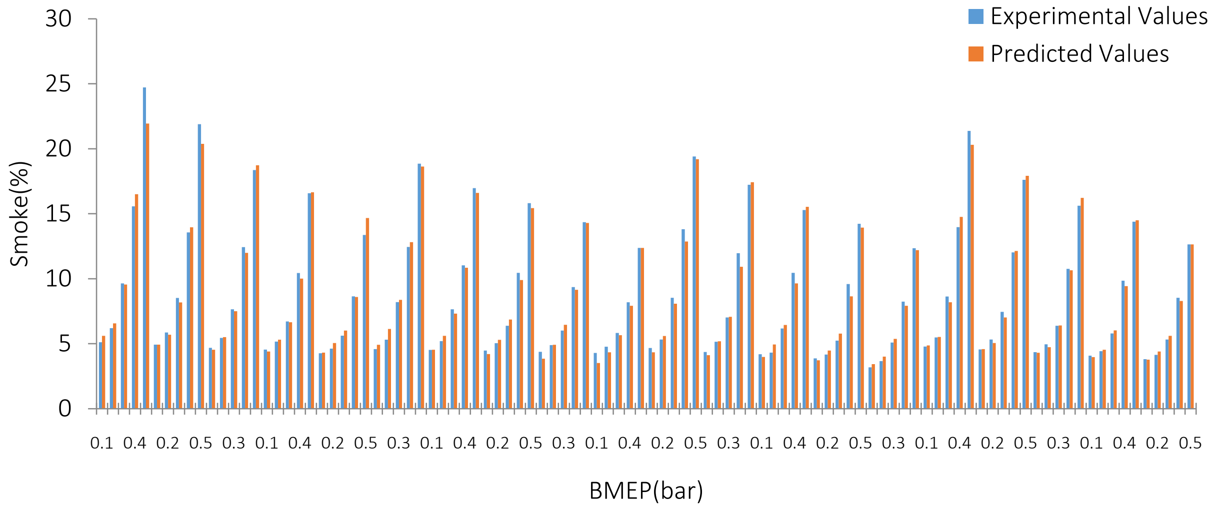

Figure 5.9 Smoke experimental and predicted values

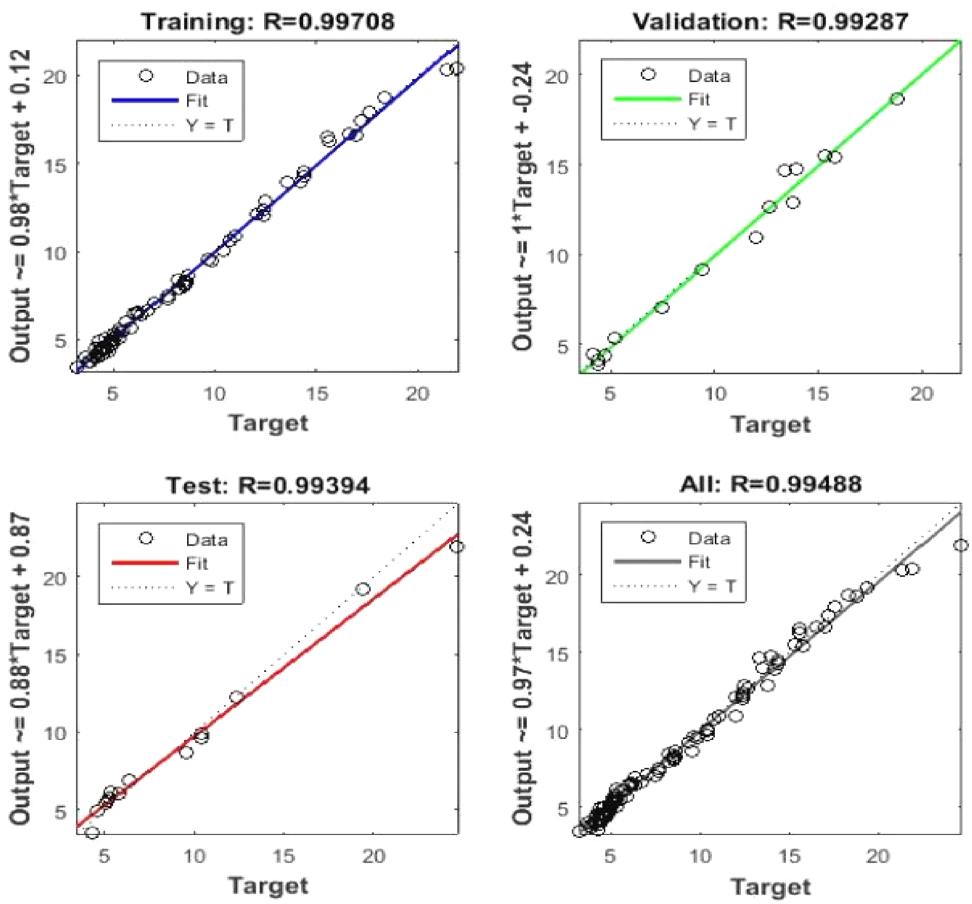

Figure 5.10 ANN Smoke regression plots

5.2 Machine Learning Results

Training and prediction of the experimental data have also been done on the Machine learning model. The Random Forest Regressor algorithm is chosen for the modeling because it produced good results in regression fitting than others during testing of the data. Commands have been given in the model to detect the input values which are BMEP, BD, nB and output value which is CO, HC, and Smoke in the machine learning model which further predicts the resulted outcome. Values of MAPE, MSE, RMSE, R^2 and R for training, testing and prediction were obtained from Machine Learning models are shown in Table 5.2.

Table 5.2 Machine Learning Model results

S. No.	Output	Model	R	R^2	MSE	RMSE	MAE
3	CO	RandomForest Regressor	0.99891	0.99782	0.000015	0.003873	0.0031
4	HC	RandomForest Regressor	0.99489	0.98982	0.187164	0.432624	0.3269
5	Smoke	RandomForest Regressor	0.99819	0.99638	0.088368	0.297267	0.1941

5.2.1 CO

The results of CO at different BMEP, biodiesel and diesel conditions were predicted by using Machine Learning modeling with RandomForest Regressor algorithm. The modeling result signifies that the developed model is highly effective for the prediction of CO. The graph between experimental and predicted model values is shown in Figure 5.13.

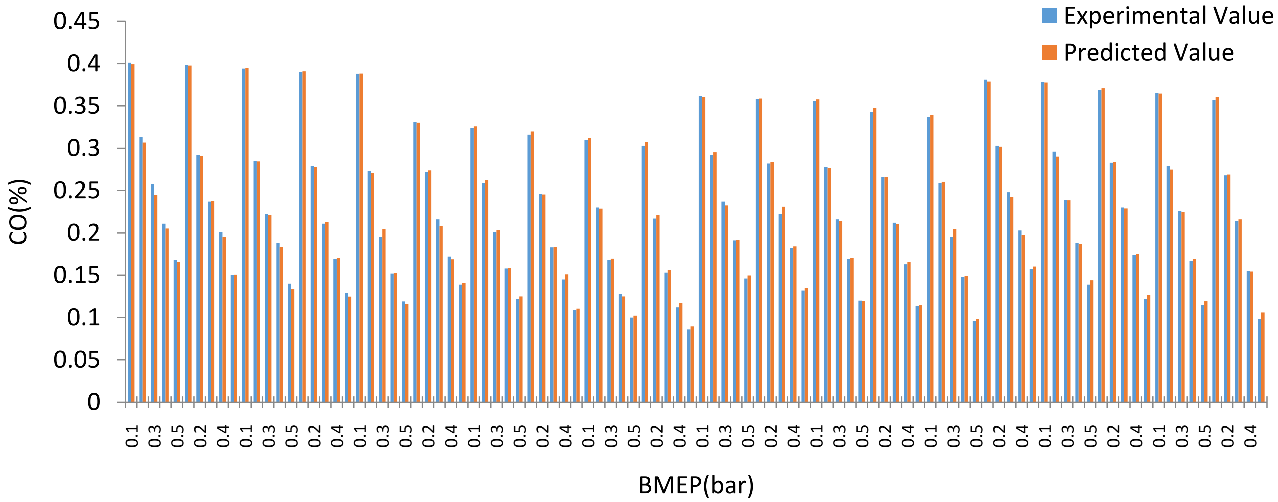

Figure 5.13 CO experimental and predicted values

5.2.2 HC

The results of HC at different BMEP, biodiesel and diesel conditions were predicted by using Machine Learning modeling with RandomForest Regressor algorithm. The results shown signify that the developed model is highly effective for the prediction of HC. The graph between experimental and predicted values is shown in Figure 5.14.

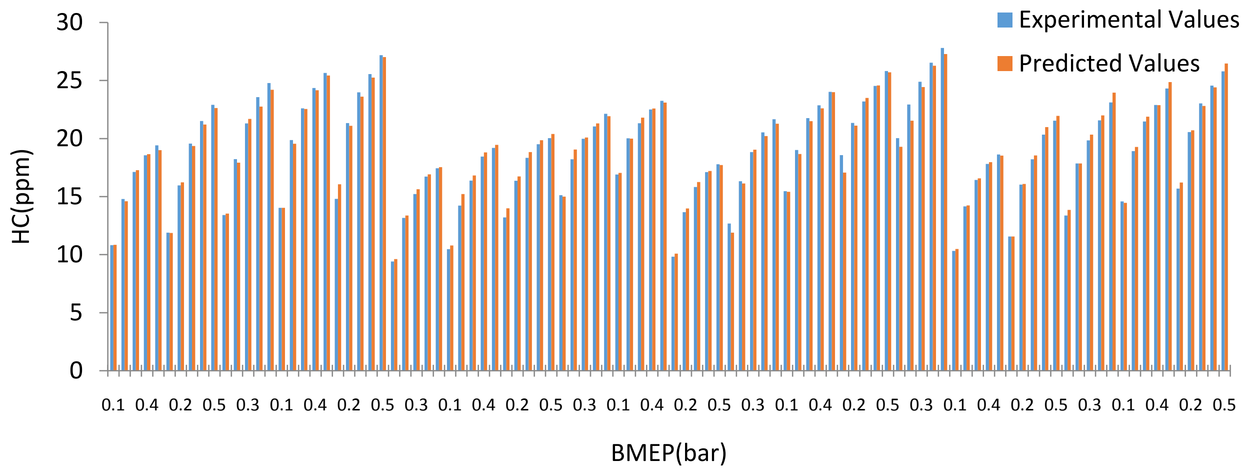

Figure 5.14 HC experimental and predicted values

5.2.3 Smoke

The results of Smoke at different BMEP, biodiesel and diesel conditions were predicted by using Machine Learning modeling with RandomForest Regressor algorithm. The modeling result signifies that the developed model is highly effective for the prediction of Smoke. The graph between experimental and predicted values is shown in Figure 5.15.

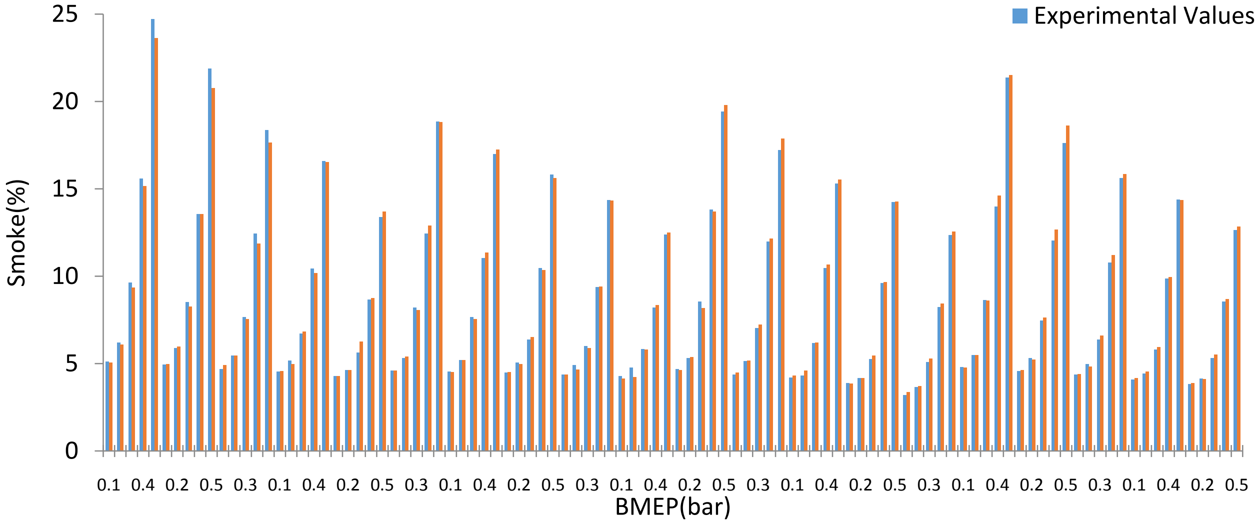

Figure 5.15 Smoke experimental and predicted values

5.3 Comparison between ANN and Machine learning modeling results:

The modeling of ANN and Machine learning is done simultaneously with their best-preferred training functions. ANN modeling is done with the help Feed Forward Back Propagation algorithm with LM as training function, on the other hand, Machine Learning modeling used Random Forest Regressor algorithm for the prediction of exhaust emission characteristics. The manually calculated results (R, R^2, MAPE, MSE, and RMSE) from predicted outcomes (CO, HC, and Smoke) are shown in Table 5.3 for ANN results and Table 5.4 for Machine Learning model.

Table 5.3 ANN Calculated results

S.No.	Outputs	Training Function	Transfer Function	Adaptation Learning Function	Number of Neurons	R	R^2	MSE	RMSE	MAPE
1	CO	LM	LOGSIG	LEARNGD	14	0.99977	0.99954	0.00002	0.00518	1.9656
2	HC		TANSIG	LEARNGDM	10	0.99974	0.99948	0.19471	0.44126	1.9925
3	Smoke		TANSIG	LEARNGDM	10	0.99865	0.99731	0.26667	0.51640	4.3977

Table 5.4 Machine Learning Calculated results

S. No.	Output	Algorithm	R	R^2	MSE	RMSE	MAPE
1	CO	RandomForest Regressor	0.99986	0.99973	0.00001	0.00398	1.5754
2	HC		0.99975	0.99951	0.18716	0.43262	1.7806
3	Smoke		0.99956	0.99913	0.08836	0.29726	2.1611

CO Comparative Results:

The results of CO at different BMEP conditions were predicted by using LM training function with LOGSIG transfer function under 14 neurons. The validation of ANN model used for the prediction of CO yields the best correlation coefficient (R) of 0.999771 and the coefficient of determination (R^2) was 0.999542. The value of MSE, RMSE, and MAPE are 0.0000269, 0.005187, and 1.9656 respectively. On the other hand, the validation results of

Machine Learning model using RandomForest Regressor algorithm for the prediction of CO yields the best correlation coefficient (R) of 0.99987 and the coefficient of determination (R^2) was 0.99973. The value of MSE, RMSE, and MAPE are 0.000015, 0.00398, and 1.5754 respectively. The regression plots between ANN model and Machine Learning model for CO are shown in Figure 5.16(a) and 5.16(b) respectively.

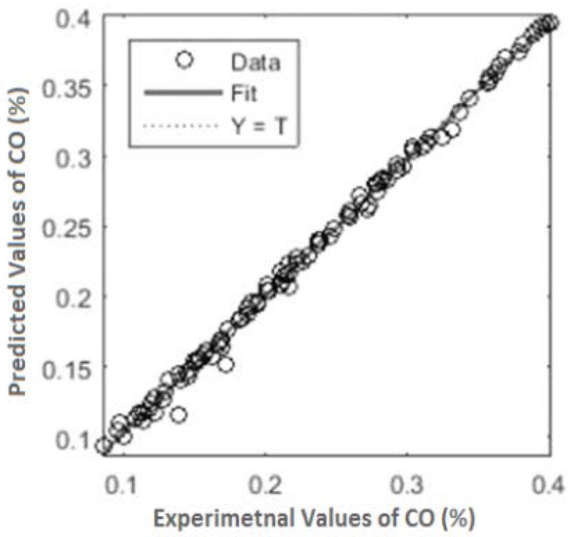

Figure 5.16(a)

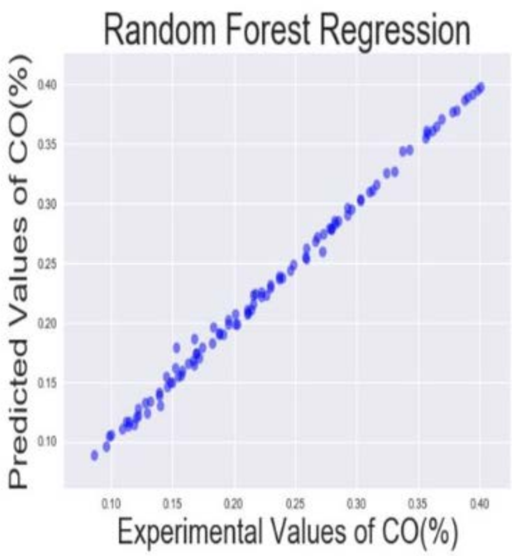

Figure 5.16(b)

HC Comparative Results:

The results of HC for different BMEP conditions were predicted by using LM training function with TANSIG transfer function under 14 neurons. The validation of ANN model used for the prediction of HC yields the best correlation coefficient (R) of 0.999744 and the coefficient of determination (R2) was 0.999488. The value of MSE, RMSE, and MAPE are 0.194716, 0.441266, and 1.9925 respectively. On the other hand, the validation of this Machine Learning model using RandomForest Regressor algorithm for the prediction of HC yields the best correlation coefficient (R) of 0.99976 and the coefficient of determination (R2) was 0.99951. The value of MSE, RMSE, and MAPE are 0.187164, 0.432625, and 1.7806 respectively. The regression plots between ANN model and Machine Learning model for CO are shown in Figure 5.16(c) and 5.16(d) respectively.

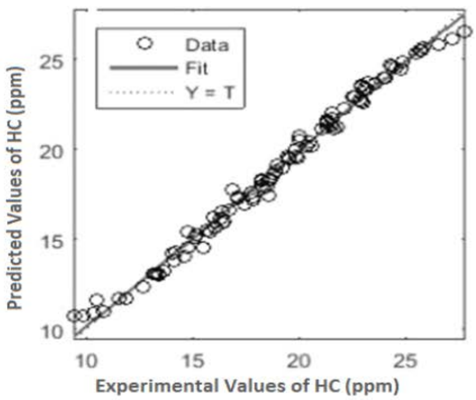

Figure 5.16(c)

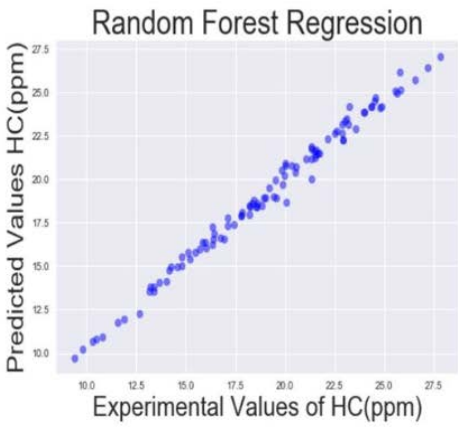

Figure 5.16(d)

Smoke Comparative Results:

The results of smoke for different BMEP conditions were predicted by using LM training function with TANSIG transfer function under 10 neurons. The validation of ANN model used for the prediction of smoke yields the best correlation coefficient (R) of 0.998658 and the coefficient of determination (R^2) was 0.997318. The value of MSE, RMSE, and MAPE are 0.26667, 0.516401, and 4.3977 respectively. On the other hand, at.

different BMEP, biodiesel% and diesel% conditions the validation of Machine Learning model using Random Forest Regressor algorithm for the prediction of Smoke yields the best correlation coefficient (R) of 0.99957 and the coefficient of determination (R^2) was 0.99914. The value of MSE, RMSE, and MAPE are 0.088368, 0.297268, and 2.1611 respectively. The regression plots between ANN model and Machine Learning model for CO are shown in Figure 5.16(e) and 5.16(f) respectively.

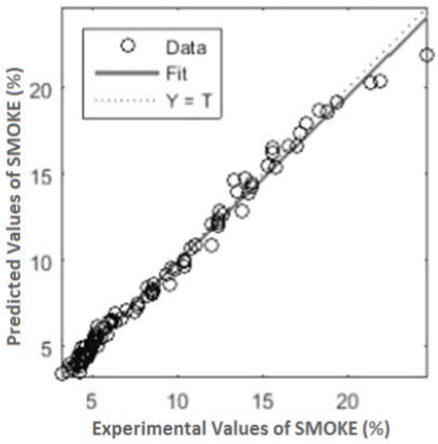

Figure 5.16(e)

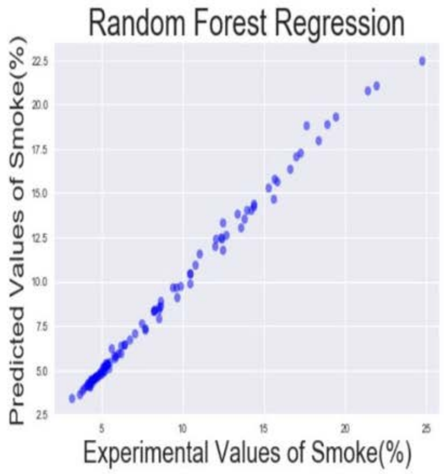

Figure 5.16(f)

VI. CONCLUSION

This paper deals with the prediction of exhaust emission characteristics of a diesel engine fuelled with Karanja biodiesel and its blending with different percentages of n-butanol using ANN and Machine learning models. The experimental results showed the decrease in the value of HC, Smoke and CO with increasing biodiesel content. On the other hand, with the increase in the percentage blend of n- butanol in biodiesel or diesel showed an increase in the HC values, whereas the values of CO, and Smoke decreases. In this research work, the comparison was made between the performances of ANN model using Feed Forward Back Propagation algorithm with LM as training function and Machine Learning model using Random Forest Regressor algorithm. The results showed the predicted values of ANN model for exhaust emission characteristics with the mean value of correlation coefficient (R) was 0.99958 and mean value of the coefficient of determination (R^2) was 0.99917 while these values for Machine Learning model were 0.99982 and 0.99965 respectively. In exhaust emission characteristics as CO, HC, and Smoke, the values of MSE values predicted by ANN model were 0.00002, 0.19471, and 0.26667 respectively, the RMSE values were 0.00518, 0.44126, and 0.51640 respectively, along with MAPE values which were 1.9656, 1.9925, and 4.3977. Whereas, the Machine Learning modeling results showed the MSE values for exhaust emission characteristics as CO, HC, and Smoke were 0.00001, 0.18716, and 0.08836 respectively, the RMSE values which were 0.00398, 0.43262, and 0.29726 respectively, along with MAPE values which were 1.5754, 1.7806, and 2.1611 respectively.

It is well observed that Machine learning modeling with Random Forest Regressor algorithm gave the better performance and accuracy than ANN model. Thus, Machine Learning model can be considered as a promising method and a better tool for prediction of diesel engine emission characteristics.

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