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Application of Artificial Intelligence to Predict the Engine performance and emission paradigm fuelled with diesel-biodiesel blends

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ABSTRACT: Environmental pollution and fast depleting fossil fuels are the key factors leading to search for the alternative sources of energy. Unlike fossil fuels, bio-fuels are a renewable source of energy. A bio-fuel is defined as any fuel whose energy is obtained through a process of biological carbon fixation. Today, the use of bio-fuels has expanded throughout the globe. Some of the major producers and users of bio-fuels are Asia, Europe and America. Biodiesel is clean burning alternative fuel that is made from 100% renewable resources which is considered the fuel of the future. Many edible alternatives such as Palm oil, Sunflower, Soya Bean, and non-edible alternatives such as Neem, Mahua, Karanja, Jatropha, etc are tested successfully with or without engine modifications. The results are encouraging. Biodiesel does not contain petroleum, but can be mixed with petroleum to produce a biodiesel blend that can be used in a number of vehicles. 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 mat lab 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

KEY WORDS: Keywords: 2-EHN additive, NOx, UHC, ANN, FFNN, MAPE, MSE

I.INTRODUCTION

The rapid depletion of petroleum fuels and consequent price hikes have made a serious impact on the power and transport sectors as well as on the international economy. Vegetable oils might provide a viable alternative to diesel since they are renewable in nature and environmentally friendly. The use of raw vegetable oils in engines without any modification results in poor performance and leads to wear of engine components. The problems faced with raw vegetable oils as fuels are poor atomization due to their high viscosity and incomplete combustion leading to higher smoke density. In order to reduce the viscosity, a transesterification process is used to produce esters of vegetable oils. These esters are promising alternate fuels for CI (compression ignition) engines and are called 'biodiesel'. Several attempts have been made by many researchers to analyse the characteristics of a CI engine fuelled with biodiesel derived from different vegetable oils, which may be grouped as edible and non-edible oils [2]The investigations showed that esters of vegetable oils provide better performance and reduced emissions than that of raw vegetable oils. Since the biodiesels are derived from plant oils, they produce negligible net greenhouse gas emissions [3]. The use of edible vegetable oils such as like sunflower oil, rapeseed oil and soybean oil for fuel purposes may directly affect the economy, i.e., it may cause an increase in the prices of cooking oils. In order to avoid that consequence, it is essential to use non-edible oils for biodiesel production. Rubber seed oil, karanja oil, pongamia Pinnata oil and linseed oil are examples of non-edible oils. The government of India is promoting Pongamia Pinnata oil as a source of biofuel for the partial substitution of diesel [4]. Waste lands available in the country, like railway track sides and other non-food cultivation/dry lands, are proposed to be used for the plantation of Pongamia Pinnata trees. The Indian government has already taken initiatives to use the Pongamia Pinnata ester-diesel blend as fuel for railway engines. In addition, major

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automobile manufacturers are conducting fleet trial tests using biodiesel-diesel blends as fuel. The Pongamia Pinnata plant is easy to cultivate, grows fast and is drought tolerant [5]. The seeds of this plant cannot be used for nutritional purposes because they contain various poisonous compounds, but after treatment, the seeds or seed cake could be used as an animal feed. The seed of Pongamia Pinnata contains a viscous oil that can be used for soap making, in the cosmetics industry, and as a diesel/ kerosene substitute or extender[6]. The use of Pongamia Pinnata oil and its derivatives as fossil fuel substitutes to counter energy demand and greenhouse gas accumulation has received attention. The seed kernel contains 46.5% oil [7] The fatty acid composition of Pongamia Pinnata oil is palmiticacid (12.8%) stearic acid (7.3%) oleic acid (44.8%) linoleic acid (34.0%) and other acids (1.1%) [8].

A.MOTIVATION OF THE PRESENT STUDY

- To search for an alternative fuel which ultimately improves the engine performance parameters as well as reduces the engine exhaust emission parameters by using Pongamia Pinnata oil methyl ester (PME).
- A single cylinder four stroke direct injection diesel 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 Pongamia 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 Pongamia Pinnata. The biodiesel is the methyl ester of Pongamia 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. And the compression ratio can be varied from 18:1 to 11:1 as per requirement. The blends can also be varied from 0-100% 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% to100% with increment of 20%.

II.PONGAMIA PINNATA METHY ESTER

A. PRODUCTION OF PONGAMIA PINNATA METHYL ESTER:

Karanja oil is one of the potential oils with yearly production of 200 t (metric ton), out of which 6% is being presently utilized [6]. The main production area for the Karanja oil is in the village level and villagers use this oil in some of their daily activities. This paper highlights the efforts made to develop biodiesel from Karanja oil, which is available in rural India. Our experiment in the lab closely agrees with the reported literature that the presence of high FFA makes transesterification reaction difficult because of the formation of soap with alkaline catalyst. In the present set of experiments, the alternative route of using acid catalyst was adopted for biodiesel production from Karanja oil [7–9]. Typically Karanja oil, collected for the present investigation, was observed to contain 3.2% of free fatty acid (FFA).

B.TRANSESTERIFICATION PROCESS

Transesterification or alcoholysis is the displacement of alcohol from an ester by another in a process similar to hydrolysis, except then alcohol is used instead of water. This process has been widely used to reduce the high viscosity of triglycerides.
The transesterification reaction is represented by the general equation as:

$$RCOOR' + R''OH \leftrightarrow RCOOR'' + R'OH$$

If methane is used in this process it is called methanolysis. Methanolysis of glyceride is represented.
Transesterification is one of the reversible reactions. However, the presence of a catalyst (a strong acid or base) accelerates the conversion.

C.PHYSICO-CHEMICAL PROPERTIES:

The physicochemical properties of Pongamia Pinnata oil are shown in the table given below. :-

TABLE 1 Physico-chemical Properties of Pongamia Pinnata oil

Properties	Value
Water Content	0.05%
Specific Gravity	0.9366
Density	0.9358 gm/cc
Carbon Residue	0.80%
Ash Content	0.05%
Flash Point	212 C
Fire Point	224 C
Copper Strip Corrosion	No corrosion was observed
Acid Value	16.8
Iodine Value	86.5
Boiling Point	330 C
Sediments (insoluble in hexane)	0.006%
Cloud Point	2 C
Pour Point	-4 C
Calorific Value(Kcal/kg)	8742
Cetane Number	38
Saponification Value	85.7
Unsaponifiable matter	0.90%

III.Experimental Setup and Procedure.

A. Preparation of Modified Fuels: The fuel used for the current investigation is a bio diesel product, derived from Jatropha. The viscosity, density, and Calorific value of the bio diesel were measured using standard equipment and are 52 cSt at 32◦C, 906 kg/m3 and 34.5MJ/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%.

B. Determination of Fuel Properties: The viscosity, flash and fire points, and the pour and cloud points were measured using standard test methods**.** The viscosity was measured using the Redwood viscometer [15]. A Cleveland open cup flash and fire point apparatus [10] was used for measuring the flash point, and a standard cloud and pour point apparatus was used for measuring the cloud and pour points [11].

C. Description of the Test Engine: A four stroke, single cylinder, water-cooled compression ignition engine was used to conduct the performance and emission studies. Standard constant speed load tests were also performed on the engine. An electrical generator was used for loading the engine. Specifications of the engine used for the performance study are given in Table 1, and a schematic block diagram of the experimental test facility is illustrated in Figure 1.

D. Details of Testing Equipment

The performance test is carried out on a single cylinder variable compression ratio DI diesel engine using high speed diesel, methyl ester of Pongamia 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 Tables 4.1, 4.2 and 4.3 given below. The different compression ratio taken varies from 14:1 to 18:1. The load range taken is from 3kg to12 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 DIGAS 444 gas analyzer fitted with DIGAS SAMPLER at the exhaust. Table shows the engine details.

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Manufacturer	Kirloskar Oil Engines Ltd.
Model	TV 1
Type	Four stroke, Water Cooled
No. of cylinder	One
Rated Power	3.5 kW @ 1500 RPM
Compression Ratio	12:1 to 18:1
Bore	87.5 mm
Stroke	110 mm
Injection Timing	23° before TDC
Method of Loading	Eddy Current Dynamometer

The engine is directly coupled to an eddy current dynamometer using flexible Coupling and a stub shaft assembly; the output of the engine Current dynamometer is fixed to a strain gauge load cell of electronic data acquisition system for measuring load applied to the engine. Provisions are available to provide different load (3 kg, 6kg, 9Kg and 12kg) on the engine, leading to load ranging from 20% and ending up at 100%[13]. By knowing the dynamometer shaft length 0.185m, the applied torque on the engine can be calculated. A gas analyzer is used for the measurement of carbon monoxide (CO), nitric oxide (NO_X), unburnt hydrocarbon (HC), oxygen (O_2), particulate matter (PM). CO was measured as percentage volume and NO, HC was measured as n- hexane equivalent, ppm, which is fitted at the exhaust, by this arrangement we can get the emission characteristics. A glass burette is provided at the fuel tank assembly for diesel and bio-diesel fuel measurement separately. The fuel consumption is measured from the glass burette; by this we can measure the fuel consumption by volume per minute, for this purpose a stop watch is also used and then we can calculate the BSFC and BTE. The experiments are started at a rated speed of 1500 rpm but as the load increases the rpm decreases. No adjustment is made at the fuel injection timing; 23°c BTDC is used for diesel and Pongamia Pinnata Oil Methyl Ester (PME), respectively. The experiments are conducted by using diesel (D100), B20 (20% PME+80% diesel), B40 (40% PME+60% diesel), B60 (60% PME+40% diesel), and B100 (100% PME), at different load conditions on the engine from 0 to 100% in appropriate steps at different compression ratios (CR) of 14:1, 15:1, 16:1, 17:1 and 18:1[14]. The compression ratio can be changed by the arrangement provided to the cylinder head by decreasing or increasing the clearance volume. When the clearance volume is increased the compression ratio decreases and vice versa. For every fuel change, the fuel line is cleaned and the engine is left to operate for 30 min to stabilize at its new condition. In each experiment, engine parameters related to the thermal performance of the engine such as fuel consumption and applied load are measured.

E. 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 Pongamia Pinnata biodiesel with diesel. For this experiment we have used blends of diesel and biodiesel in following proportion. They are mentioned below:-

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.

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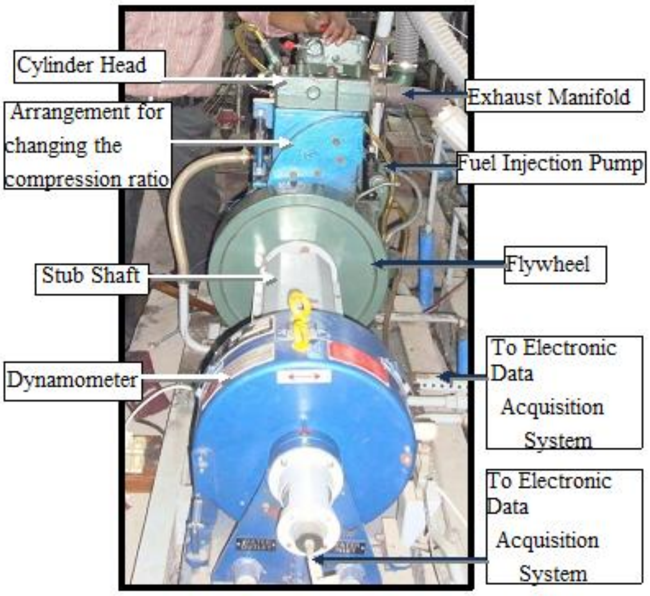

Fig 1: The Schematic Diagram of Experimental Setup

S.NO	Property	Pongamia Pinnata	B100	B10	B20	B30	Diesel	specification	Test methods
1	Density (kg/m3)	912	898	856	862	868	850	860–890	P16
2	Kinematic viscosity (cSt)	27.84	5.46	3.23	3.49	3.77	4.842	2.5–6.0	P 25/D 445
3	Calorific value (MJ/kg)	34	39.15	43.32	42.23	41.34	44.82		D5865
4	Flash Pt C	242	196	89	91	95	76	120	P 21/D93
5	Cloud Pt	14.6	10.2	7	7.1	8.2	6.5	–	D2500
6	Pour Pt C		4.2	3.5	3.6	3.7	3.1	–	D2500
7	Cetane no	46	57.9	48.2	47.9	47.6	49	51	P9/D613
8	Sulphur (mg/kg)	0.007	0.005	23	21	16	29	<50	P 83/D 5453
9	Carbon residue (% mass)	1.2	0.0035	0.0861	0.015	0.0083	0.1	<0.05	ASTM 4530
10	Sulphated ash (% mass)	0.014	0.002	0.001	0.001	0.001	0.001	<0.02	P 4/D874
11	Water content (mg/kg)	–	340	71	118		52	<500	P 40/D2709
12	Acid value (mg KOH/g)	5.06	0.42	0.15	0.15	0.2	0.1	<0.5	P 1/D 664
13	Methanol (% mass)	–	0.09	0.02	0.02	0.03	–	<0.20	EN 14110
14	Ester content (% mass)	–	98		–	–	–	>96.5	EN 14103
15	Free glycerol (% mass)	–	0.01	–	–	–	–	<0.02	ASTM D6584
16	Total glycerol (% mass)	–	0.19	–	–	–	–	<0.25	ASTM D6584
17	Phosphorous (mg/kg)	–	3.2	–	–	–	–	<10	ASTM D4951
18	Iodine value (g I_2/100 gm)	96	86.5	–	–	–	38.3	<120	EN 14104
19	Oxidation 110^0C (h)	–	11.6	–	–	–	–	>6	EN 14112

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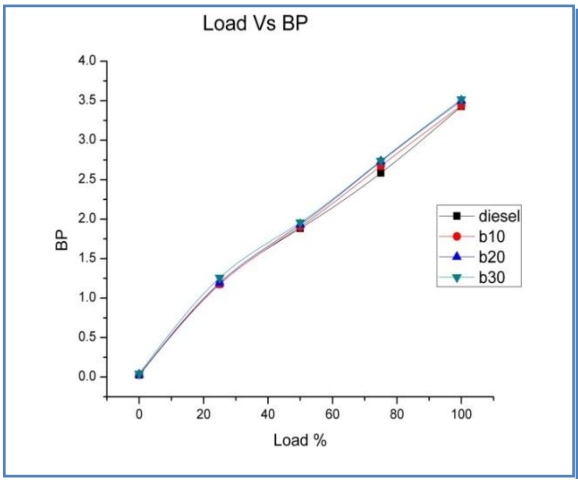
IV. Results and discussion.

A. LOAD vs BP graph:



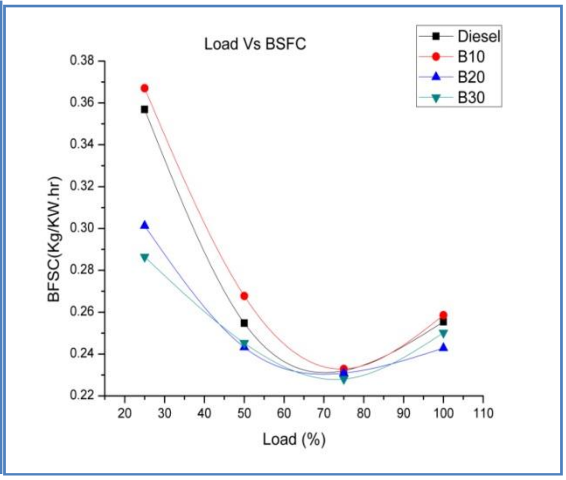


Figure 5.1 shows the variation of brake power with respect to load for diesel fuel and Pongamia Pinnata biodiesel and additives .it can be observed from the figure that shows that there is no significant change in brake power .All blends i.e B10,B20, B30 including diesel gave more or less same readings. In specific 6% loss in Brake power is observed, this is because of low energy content of Pongamia Pinnata blends.

B. LOAD vs BSFC graph:

Figure 5.2 shows the variation of brake specific fuel consumption with respect to load for diesel fuel and Pongamia Pinnata biodiesel and additives. It can be observed from the 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

C.LOAD vs BSEC graph:

Figure 5.3 shows the variation of brake specific energy consumption with respect to load for diesel fuel and Pongamia 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.

D. LOAD vs CO graph:

Figure 5.5 shows the variation of co with respect to load for diesel fuel and Pongamia 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 Pongamia 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 Pongamia Pinnata blends which resulted in complete combustion and formed carbon-dioxide instead of carbon-monoxide.

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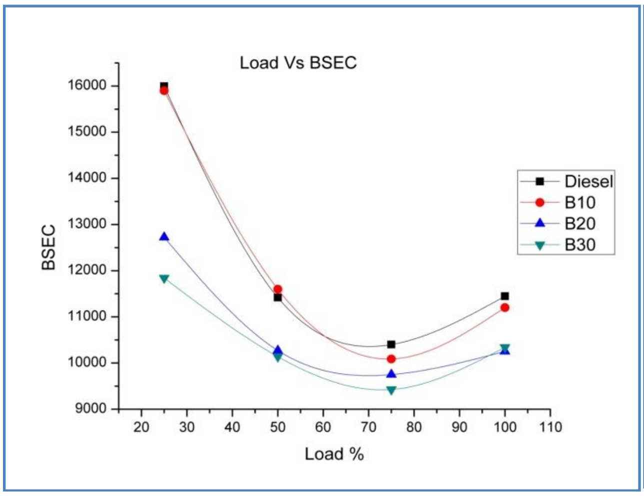
E. LOAD vs CARBONDIOXIDE graph:



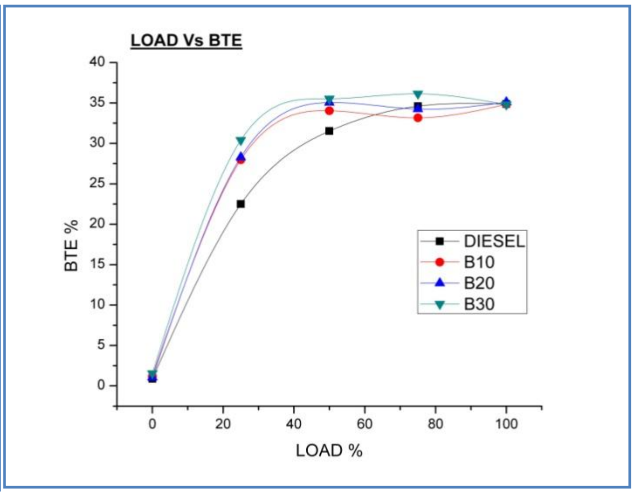
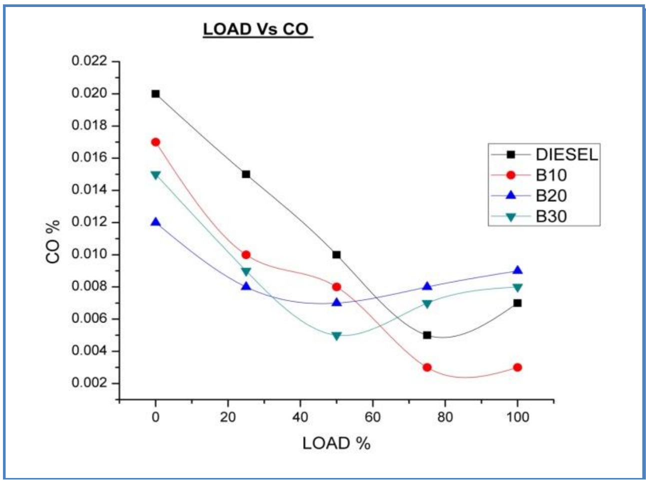


Figure 5.6 shows the variation carbondioxide with respect to load for diesel fuel and Pongamia Pinnata biodiesel and additives.it is clearly seen that from graph all the blend shows low emissions of carbondioxide at low loads and slightly increases at half loads which is negligible and again decreases at full loads when compared with conventional diesel

F. LOAD vs HYDRO CARBONS graph:



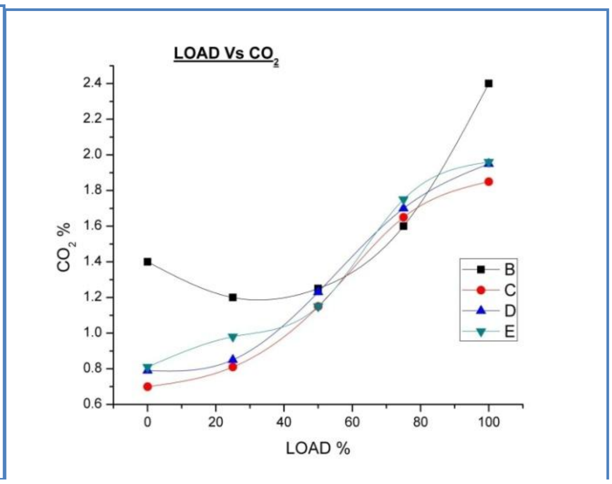


Figure 5.7 shows the variation hydrocarbons with respect to load for diesel fuel and Pongamia Pinnata biodiesel and additives .Due to the excess oxygen present in the biodiesel complete combustion took place and formation of HC gone down .from the graph it is clear that B30 showed least HC production.

G. LOAD vs EXHAUST GAS TEMPERATURE graph:

Figure 5.8 shows the variation exhaust gas temperature with respect to load for diesel fuel and Pongamia Pinnata biodiesel and additives. It is a measure of performance as higher exhaust gas temperatures results in higher heat release in combustion chamber there by giving probability to increase brake thermal efficiency. From the graph it is clearly seen that that EGT is high in all the blends when compared to conventional diesel**.**

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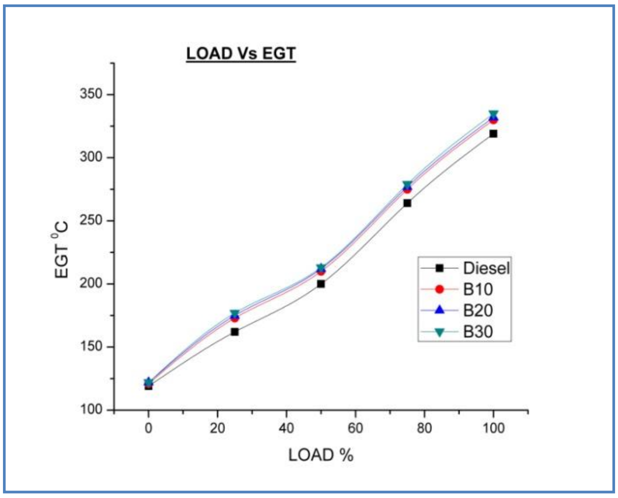
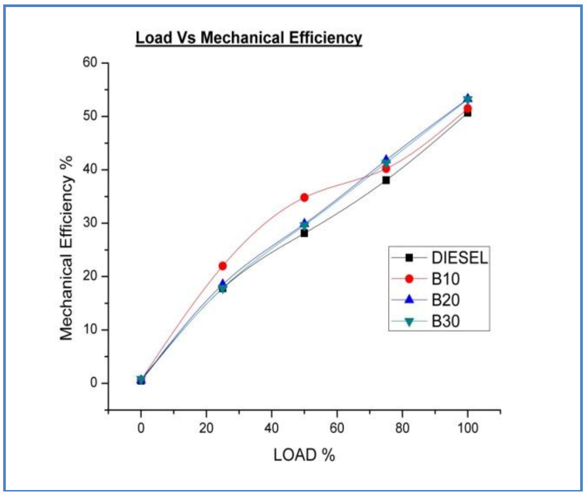
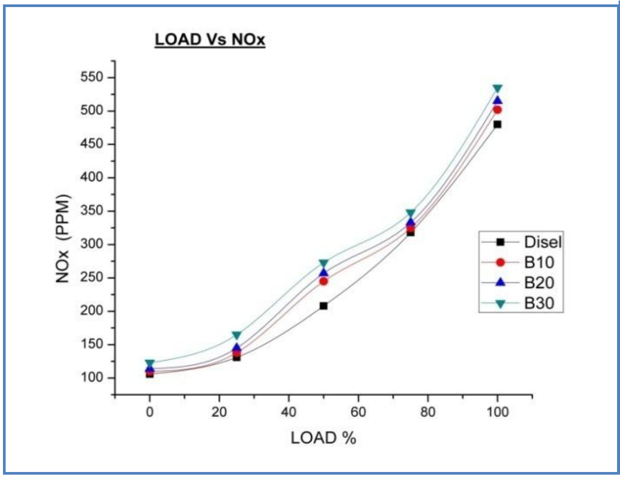
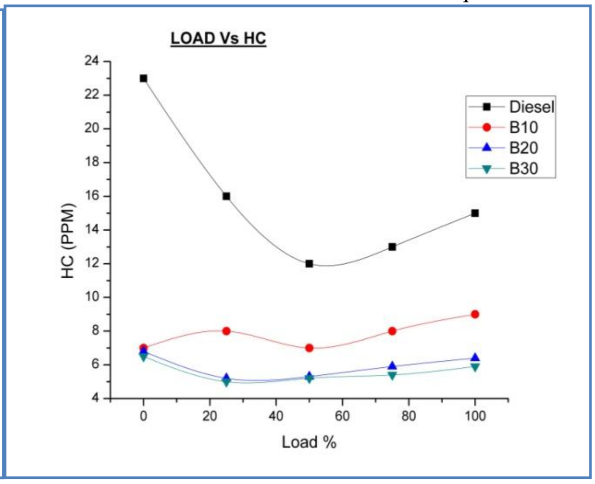




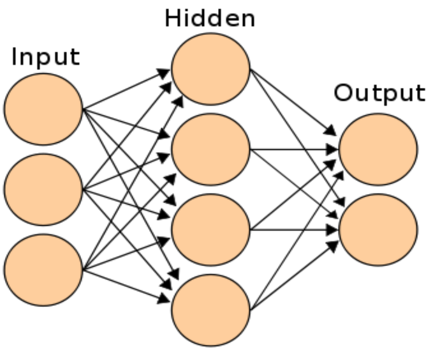
H. LOAD vs NOX graph :

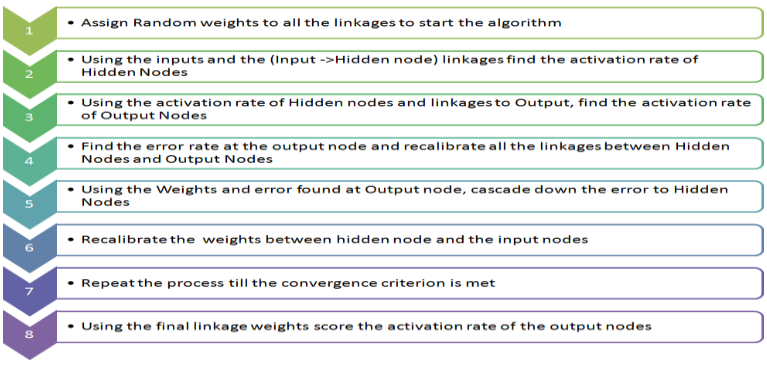
Figure 5.9 shows the variation of NOx with respect to load for diesel fuel and Pongamia Pinnata biodiesel and additives.Due to the excess oxygen present in the biodiesel complete combustion took place and temperature inside the combustion chamber increased thereby increasing the NOx emission. From the graph it is clear that B30 showed maximum NOx emissions. It cannot be completely stopped but it can be minimized like EGR techniques.





V. ARTIFICIAL NUERAL NETWORKS (ANN





ANN technique has been a useful mathematical tool that has been used to predict parameters required long (experimentally) time and sophisticated instruments such as internal combustion engines. Essentially, ANN refers to a

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computation configuration modelled on biological processes, predominantly on the execution of human brain, comprising number of interconnected processing elements called as neurons, which process information based on their dynamic state in respond to inputs. The processing of the data depends on the effectiveness between two attuned neurons called as weight which encloses the information gained through training, testing and validation. Learning has been gained by adjustment of weights with reference to input blueprints. Flexibility to new situations has been attainedthroughadjustmentsintheweights.ThegreatabilityofANNhasbeentoforecasttheoutput for an unknown input accessible to it. As forecasting has been executed via prediction of future from the knowledge achieved in the past, neural network has been used for decision support coordination. The neural network has been a good tool for simulation and prediction in engineering applications. The prediction by a well-trained ANN has been made much faster than the conventional simulation programs or mathematical models as no lengthy iterative calculations have been needed to solve differential equations using numerical methods. In the present investigation feed forward with back propagation neural network model has been employed.

Artificial intelligence based engine modeling offers a potential for a very fast multidimensional, adaptive model of a system understudy along with their inherent robustness to accommodate data with appreciable degrees of uncertainties of observation coupled with low computational cost neural network due to its inherent adaptive capabilities have been able to develop robust models simulating accurate engine behavior corresponding to the variables under study and as such are becoming an indispensable and inexpensive basis of a virtual sensing system for onboard measurements of measured or difficult to measure NOx, PM, HC emissions continuously in real time for a truly optimized control. With the advent of the era of dual fuel strategies to meet the ever changing emission standards, implementation of conventional multi-physics based simulation platforms have become more computationally demanding in the face degrees of freedom that are needed to be addressed in the modeling of the pollutants requiring increased model complexity and consequent high computational footprint. The versatility of artificial neural networks to simulate multiple nonlinear objectives simultaneously without the knowledge of the underlying physics of the problem provides an alternative platform to model and predict the performance and emission spectra of dual fueled diesel engines

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A. Development of ANN model

Normalization of data is done by using the following formula

$$\frac{\text{Actual value} - \text{Minimum}}{\text{Maximum} - \text{Minimum}} x(\text{High} - \text{Low}) + \text{Low}$$

In the present investigation feed-forward with back propagation neural network model has been employed. To obtain the optimum engine performance and exhaust gas emission prediction, ANN has been used considering various model configurations. The developed ANN models have been trained using the collected experimental data. Performance of ANN depends upon the data presented to it, hence scaling of input and output data is vital. In the present work, an ANN modeling has been used to predict the relationship of BSEC, BTE, NOx, FSN, UHC and CO2 with load and hydrogen injection durations as inputs. The correlation between the chosen input variables and desired outputs in the purview of the present study which has been reviewed in the correlation matrix bear testimony to the conflicting influences of the input variables on the desired emission and performance output variables. The correlation matrix signifies the relationship between the inputs and outputs (considered in the present experimental study) in terms of Pearson Product Moment correlation coefficient whose value varies between [-0.8, 0.8]. For example, a zero correlation coefficient between 'a' and 'b' input output pair signifies that the variation in the output 'b' is independent of any variations in the input 'a'. A positive correlation coefficient indicates the direct-proportionality between 'a' and 'b'. However, negative correlation coefficient indicates the inverse-proportionality between 'a' and 'b'. Experimental input and output data have been normalized using simple normalization method. The data have been normalized to the range 0.1e0.9. After normalization, the data have been randomized before training the network. From the data, approximately a total of 20 samples are used in this model, 60% of the data (12 samples) set has been randomly assigned as the training set, while the 20% of data (4 samples) are put aside for testing and the remaining 20% is used for prediction and validation. Simulations have been performed using MATLAB. A multi-layer perception network (MLP) has been used for non-linear mapping between the input and the output variable. To an extra second derivative of error information and automatic internal adjustments that are made to the learning parameters. In the current algorithm, the network weights and biases have been initialized randomly at the beginning of the training phase. Error minimization process has been achieved by using a gradient descent rule. There have been two input and seven output

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parameters in the experimental test. The two input variables have been considered to be as 'load' expressed in percentage and the 'Biodiesel percentage' in terms of percentage. The seven outputs have been outlined as BSEC, on MATLAB software, which has been also chosen as our iteration solver.Exhibits the network model details. The developed ANN model has been limited to the experimental dataset which have been obtained on the existing engine set-up that has been used in this experimental investigation as detailed. The ANN structure has developed with double hidden layer and 16 neurons proved to be the best ANN option in this simulation since the R^2 values have been observed generally close to unity. During the ever ANN model training, the minimum gradient of $10^{-7}$and 10,000epochs has been used as stopping criteria. Trained model has been simulated for all inputs to realize corresponding respective outputs of the model. Using targets and outputs of the model, regression coefficients, MAPE and MSE have been evaluated using the following expressions[16]

Where n is the total number of datasets, ei is the experimental value and pi is the network predicted value. The R-value was set to be limited to 15 neurons in the hidden layer. Thus, the network with 15 neurons in the hidden layer has been satisfactory. To achieve an accurate result, a regression analysis of outputs and desired targets has been performed and has been presented. The accuracy of the training process has been validated by the testing process.

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

The testing process involves in presenting a completely unique set of experimental data to test the accuracy of the trained network in predicting the specific variables. A general measure of the accuracy of the testing phase is the MSE shown in Eq. The mean square error (MSE) and correlation coefficient (R^2), showed in the table, have also been computed when compared with the predicted and experimental values. MSE provides information on the short-term performance of the model by allowing term-by-term comparison of actual deviation between the predicted and measured values .The MSE has been always positive and a zero value has been the ideal.MSE provides an indicator of the predictive error relative to the correct value. The lower the MSE shows a better correlation between the predicted and experimental results. The R2 value provides an alternative indicator between the predicted and experimental data, Where R2values closest to 1 represents the most accurate prediction.

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

B. Results and Discussions

ANN model training has been carried out for different training functions for 100 iterations. Levenberge Marquardt training algorithm with logarithmic sigmoid and hyperbolic tangent sigmoid transfer function for layer-1 and layer-2 respectively, yields best regression, MAPE and MSE compared to all other algorithms. It has been observed that MSE is higher for lesser number of neurons, restating the fact that the less number of neurons drive the decision making strenuous. Whereas, MSE is higher for higher number of neurons as adjustment of weights to reduce error is onerous. The optimal number of neurons for which MSE has been observed to be nominal is 15. In pursuance of parameters to access the proximity of actual and predicted values, MSE alone was not enough. As for the case of any training algorithm, although MSE has been in the acceptable range, MAPE and regressions have not been in the acceptable range. Therefore the proficient ANN model has been developed by captivating regression, MSE and MAPE as an assessment standard.

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

Levenberge Marquardt training algorithm with logarithmic sigmoid and hyperbolic tangent sigmoid transfer functioned ANN predictions for test cases. Displayed excellent overall agreement indices with the experimental observations wherein it has achieved a 98.7869%. Pearson Product Moment correlation coefficient (R) and the additional correlation metrics of MSE have been observed to be 0.8975, 0.8955, 0.7944, 0.6946, 0.6433 and 0.5943 respectively. Statistical analyses for Brake Specific Energy Consumption (BSEC) has revealed that the developed ANN model had a very low MSE content of 0.0141 with the U2 uncertainty of 0.06983 along with MSE of 0.02309 and MAPE of 3.423% across all the test points respectively[17]. The promise of the ANN predicted BTE has also been evident in the persistent concurrency with the experimental values for all cases of experimental observations as evident from a and b. It has been also observed inthat the ANN provides good level of accuracy in modeling the emission concentration of NOx, FSN, UHC and CO2. As shown in, the emission model shows that the R2 value of NOx, FSN, UHC and CO_2 values have been 0.9994, 0.9993, 0.9954 and 0.9976 respectively. An overall, the accuracy of the

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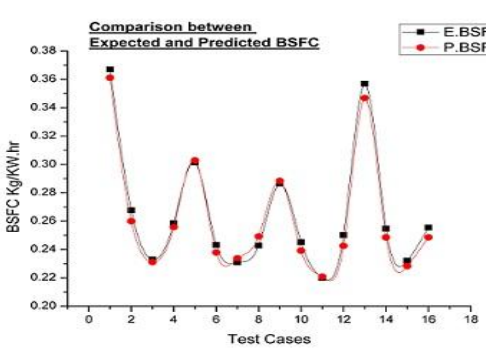
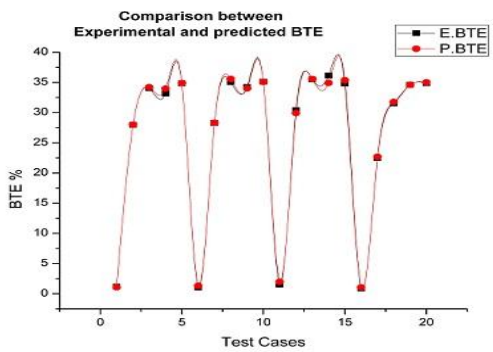
developed model has been determined based on the MSE (mean square error).The results showed that the average simulated values have been 0.0006 of MSE (Mean Square Error) error a and b illustrates the predicted versus experimental data for NOx emission. In predicting NOx emission, analysis showed that the ANN model scored extremely low MSE of 0.005633 with very low Theil U2 uncertainty of 0.023807 and MSE content of 0.01[18]. The MAPE observed was 4.73%. The correlation coefficient(R), NSE between the predicted and experimental NOx has been found to be 0.9973, 0.9984 and 0.991respectively. The MSE, Theil U2 and MSE of the ANN model in estimating the NOx emissions have been observed to be 0.023807, 0.001 and 0.001 respectively. This has been corroborated by the consistent concurrency of the ANN predicted values with the experimental observations for the entire range of observations. Similarly, for Soot (FSN) emissions have been predicted accurately as evident from the resemblance with the experimental values for all cases of experimental observations. From the experimental results we infer that there is a significant reduction in the CO, CO2 and HC emission levels due to better combustion characteristics exhibited by the test fuels. Table shows Regression values at various neurons and the maximum regression is achieved at a topology of 16 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





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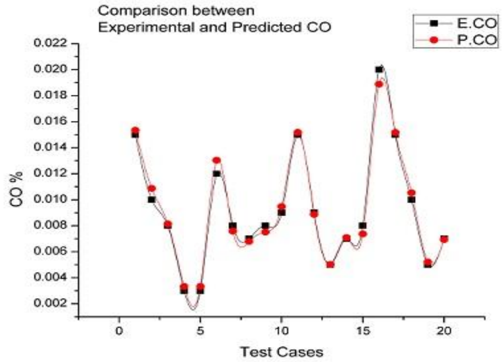

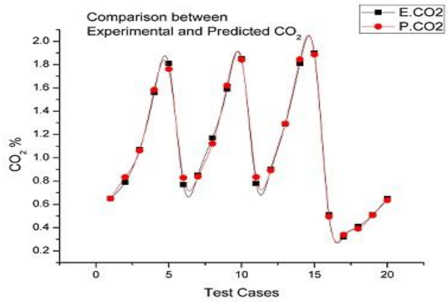

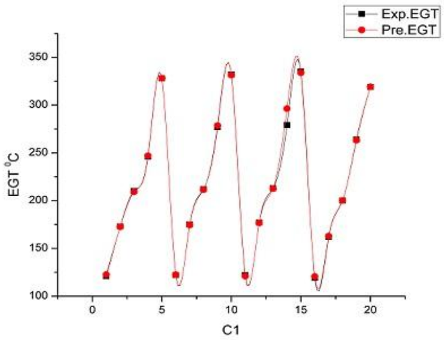

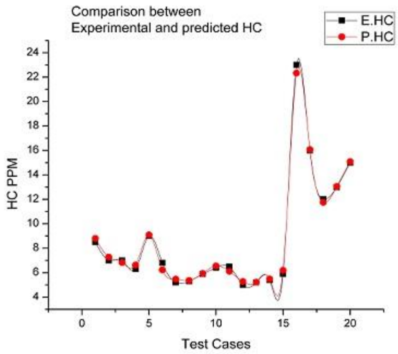

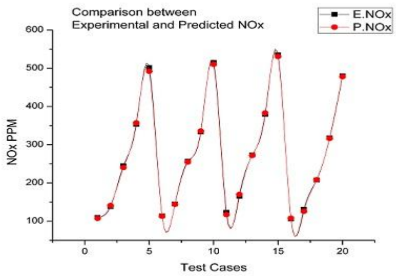

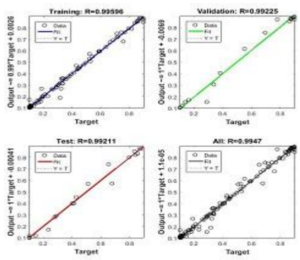

Best topology

VI.CONCLUSIONS

NOx level a considerable amount of increase due to excess oxygen present in the biodiesel. Here we can observe that the emissions values predicted by FFNN that follow a definite trend have a lower error percentage value than compared to those that doesn't follow a definite flow. Further the emissions that vary more or less in a linear fashion have a very minimal percentage of error than those that follow a quadratic or a cubic curve. Thus based on the nature and the trend of emission graph we can use FFNN to predict the emission levels depending upon the required level of accuracy and thus providing the necessary emission values without carrying out the actual experimental analysis.

Pongamia methyl ester seems to have a potential to use as alternative fuel in diesel engines without any modification in CI engine. Blending diesel decreases the viscosity considerably. The following results are made from the experimental study

1. It was founded that blends of PME and diesel could be successfully used with acceptable performance than pure diesel up to a certain limit.
2. From experiment it is concluded that B20 could replace the diesel for diesel engine for getting better performance.
3. The brake thermal efficiency was marginally better than pure diesel fuel.
4. Brake specific fuel consumption is lower for PME blends than diesel at all the load condition.

5. The exhaust gas temperature is found to increase with concentration of PME in fuel blends due to coarse spray formation and delayed combustion.
6. Volumetric efficiency is found to be better for PME blends than pure diesel fuel for all the load conditions.
7. It is also concluded from the experiment that use of 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

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