ISSN No: 2348-4845
International Journal & Magazine of Engineering, Technology, Management and Research
A Peer Reviewed Open Access International Journal

Performance and Emissions Characteristics of Cotton Seed Oil Biodiesel Blend In CI Engine Using Artificial Neural Network

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Abstract:

The rise in price and consumption of petroleum products and their effects on the industrialization and modernization of the world have been one of the key issues of the researchers. CI (Diesel) engine, one of the sectors based on the fossil fuel, is a prime issue for environmentalists and economists. To overcome this problem and as a substitute for diesel, biofuel is a better option to conserve the limited reserve of fossil fuels such as petroleum, coal and natural gas. Biodiesel, which is produced from variety of vegetable oils and animal fat through transesterification, has a lot of technical advantages over fossil fuels such as lower overall exhaust emission and toxicity, biodegradability, derivation from a renewable and domestic feedstock and negligible sulphur content. This paper deals with artificial neural network (ANN) modelling of a diesel engine using variable Karanja oil blends to predict the engine performance. To acquire data for training and testing the proposed ANN, a Single cylinder, four-stroke diesel engine was fuelled with blended diesel and operated at different engine speeds and loads. The experimental results exposed that blends of Karanja oil with diesel fuel provide better engine performance. Using some of the experimental data for training, an ANN model was developed based on standard Back-Propagation algorithm for the engine. Analysis of the experimental data by the ANN showing that there is a good correlation between the predicted data resulted from the ANN and with the measured ones. Therefore, the ANN proved to be a desirable prediction method in the evaluation of the tested diesel engine parameters.

Keywords- ***Artificial Neural Network; bp - Brake Power; bsfc - Brake Specific Fuel Consumption; mse - Mean square Error; KO- Karanja Oil; BTE – Brake thermal efficiency; Emissions – CO, HC, NOx, SMOKE, EGT.***

I. INTRODUCTION

The world is moving towards a sustainable energy era with major emphasis on energy efficiency and use of renewable energy sources. Liquid bio-origin fuels are renewable fuels coming from biological raw material and have been proved to be good substitutes for oil in transportation and agriculture sector. These fuels are gaining worldwide acceptance as solution for the problem of environmental degradation, energy security, restricting import, rural employment and agricultural economy. The most promising available biofuels market sans subsidy is ethanol, methanol, and vegetable oil based fuel. Researchers are also striving to develop second generation biofuels from cellulosic materials using different conversion processes [1].

The world is getting modernized and industrialized day by day. As a result vehicles and engines are increasing, but energy sources used in these engines are limited and decreasing gradually. This situation leads to seek an alternative fuel for diesel engine. Biodiesel is an alternative fuel for the diesel engine. The esters produced from vegetables oil and animal fats are known as Biodiesel. This paper investigates the prospect of making of biodiesel from karanja oil. Karanja curcas is a renewable non-edible plant [2].
Artificial neural networks (ANN) are used to solve a wide variety of problems in science and engineering,

particularly for some areas where the conventional modelling methods fail. A well trained ANN can be used as a predictive model for a specific application, which is a data-processing system inspired by biological neural system. The predictive ability of an ANN results from the training on experimental data and then validation by independent data. An ANN has the ability to re-learn to improve its performance of new available data [3].

An ANN model can accommodate multiple input variables to predict multiple output variables. It differs from conventional modelling approaches in its ability to learn about the system that can be modelled without prior knowledge of the process relationships. The prediction by a well-trained ANN is normally much faster than the conventional simulation programs or mathematical models as no lengthy iterative calculations are needed to solve differential equations using numerical methods but the selection of an appropriate neural network topology is important in terms of model accuracy and model simplicity. In addition, it is possible to add or remove input and output variables in the ANN if it is needed.

The objective of this study was to develop a neural network model for predicting engine parameters like brake power, fuel consumption and torque in relation to input variables such as engine speed and bio fuel blends.

This model is of a great importance due to its ability to predict engine performance under varying conditions [4].

AK Aggrawal etal have analyzed the performance and emission characteristics of a compression ignition engine fuelled with Karanja oil and its blends (10%, 20%, 50% and 75%) vis-a-vis mineral diesel. The effect of temperature on the viscosity of Karanja oil has also been investigated. Fuel preheating in the experiments – for reducing viscosity of Karanja oil and blends has been done by a specially designed heat exchanger, which utilizes waste heat from exhaust gases. A series of engine tests, with and without preheating/pre-conditioning have been conducted using each of the above fuel blends for comparative performance evaluation. The performance parameters evaluated include thermal efficiency, brake specific fuel consumption (BSFC), brake specific energy consumption (BSEC), and exhaust gas temperature. Karanja oil blends with diesel (up to 50%v/v) without preheating as well as with preheating can replace diesel for operating the CI engines giving lower emissions and improved engine performance [5].

T.K. Gogoi etal have developed that a cycle simulation model in corporating a thermodynamic based single zone combustion model to predict the performance of diesel engine. The effect of engine speed and compression ratio on brake power and brake thermal efficiency is analysed through the model. The fuel considered for the analysis are diesel, 20%,40%, 60% blending of diesel and biodiesel derived from Karanja oil (Pongamia Glabra). The model predicts similar performance with diesel, 20% and40% blending. However, with 60% blending, it reveals better performance in terms of brake power and brake thermal efficiency [6].

Mustafa Canakci et al have discussed that the prediction of the engine performance and exhaust emissions is carried out for five different neural networks to define how the inputs affect the outputs using the biodiesel blends produced from waste frying palm oil. PBDF, BI00, and biodiesel blends with PBDF, which are 50 % (B50), 20 % (B20) and 5% (B5), were used to measure the engine performance and exhaust emissions for different engine speeds at full load conditions. Using the artificial neural network (ANN) model, the performance and exhaust emissions of a diesel engine have been predicted for biodiesel blends [7].

B Ghobdian et al deals with artificial neural network (ANN) modelling of a diesel engine using waste cooking biodiesel fuel to predict the brake power, torque, and specific fuel consumption and exhaust

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International Journal & Magazine of Engineering, Technology, Management and Research
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emissions of the engine. To acquire data for training and testing the proposed ANN, a two cylinder, four-stroke diesel engine was fuelled with waste vegetable cooking biodiesel and diesel fuel blends and operated at different engine speeds. It was observed that the ANN model can predict the engine performance and exhaust emissions quite well with correlation coefficient (R) 0.9487, 0.999, 0.929 and 0.999 for the engine torque, SFC, CO and HC emissions, respectively. The prediction MSE (Mean Square Error) error was between the desired outputs as measured values and the simulated values were obtained as0.0004 by the model [8].

II. EXPERIMENTAL SETUP

The study was carried out in the IC engines laboratory on an experimental engine test rig consisting of a single cylinder, water cooled, four strokes, vertical, stationary and constant speed diesel engine connected to eddy current type dynamometer for loading. It also contains the fuel supply system for supplying fuel, water cooling system for engine cooling, lubrication system and various sensors and instruments integrated with data acquisition system for online measurement of load, air and fuel flow rate, exhaust gas temperature, cooling water temperature.

The setup enables the evaluation of thermal performance and emission constituents of the engine. The thermal performance parameters include brake power, brake thermal efficiency, brake specific fuel consumption, and exhaust gas temperature. Thermocouples are provided at appropriate positions and are read by a digital temperature indicator with channel selector to select position. The setup also includes the necessary measuring instruments for the measurement of smoke density and exhaust gas emissions. The exhaust emissions of the engine are analyzed by using an exhaust gas analyser. The constituents of the exhaust gas like CO, HC and NOx are measured with exhaust gas analyzer. The simple line diagram and photographic view of the experimental setup are shown in Fig 3.1 and 3.2 respectively.

The test engine used in the present work is a single cylinder, naturally aspirated, direct injection compression ignition engine of Kirloskar make. This diesel engine has a bore of 80mm and stroke of 110mm.The specification of the engine is shown appendix -A. The engine has a rated output of 5HP at a speed of 1500rpm. The engine was coupled to an eddy current type dynamometer to apply the load on the engine with an electrical panel. The engine is mounted on a stationary frame with a suitable cooling system. The lubricating system is inbuilt in the engine.

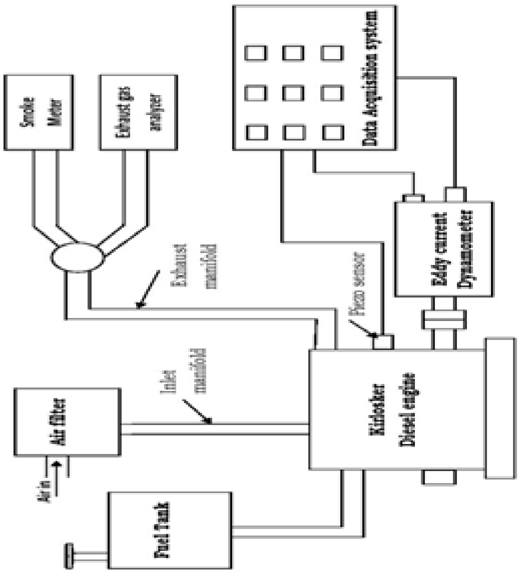

Fig.1. Experimental Setup

Fig.2. Photographic view of the experimental setu

The engine is connected to a swinging – field electrical generator meter with Ward – Leonard control that allowed the engine to be started and motored likewise. The load is controlled by dynamic changing the field sector current. The reading of load (voltage and current) is noted from the data acquisition panel board fixed to engine test setup by the manufacturer and the power absorbed is calculated.

The experimental study is conducted at various loads and hence an accurate and reliable load measuring system is a must. The load measuring system of this experimental test rig consists of a dynamometer of eddy current type, a load cell of strain gauge type and a loading unit. The load is applied by supplying current to the dynamometer using a loading unit. The load applied to the engine is measured by a load cell.

A dynamometer is a device which is used for measuring force, torque or power produced by an engine. It can also be used to apply load or torque on the engine. The dynamometer used in this study is an eddy current type with a water cooling system. The eddy current dynamometers provide an advantage of quicker rate of load change for rapid load setting.

The speed of the engine is measured by using an electro-magnetic pickup in conjunction with a digital indicator fixed to data acquisition panel board. A magnetic pickup is fitted near the fly wheel of the engine with pins mounted on the periphery. The signals generated are fed to the show unit that is graduated to point the speed directly in range of revolutions per minute (rpm).

Fuel is provided to the engine from the fuel tank through the measuring instrument fixed to data acquisition panel board. The rate of fuel flow is found by measuring the time required for the consumption of a known amount of fuel i.e. 10 cc from the measuring instrument.

A Nickel-Nickel chromium thermocouple fixed to the exhaust manifold of the engine exhaust valve is employed for measure of exhaust gas temperature. The reading of Exhaust gas temperature is noted from the data acquisition panel board fixed to engine test setup by the manufacturer.

The emission measurement system is used to measure the constituents of exhaust gas and its opacity (smoke number). This system consists of an exhaust gas analyzer and a smoke meter. The exhaust gas analyzer measures the exhaust gas constituents of Carbon monoxide (CO), Oxides of nitrogen (NOx) and Unburnt Hydrocarbons (HC). The smoke meter is used to measure the intensity of exhaust smoke

Bosch smoke meter is used to measure the smoke density. The exhaust monitor consists of a smoke chamber which contains the smoke column through which the smoke from exhaust pipe of the engine is passed and smoke density is measured. The gas to be measured is fed into the smoke chamber. The gas enters the smoke column at its center. The smoke column is a tube, which has a light source and a detector placed at one end. The opacity of smoke is directly proportional to the attenuation of light between a light source and a detector.

The brake power of the engine at different operating conditions was determined using the following equation:

$BP = (V * I)/1000$ ---- kW.

Where,

BP = Brake power in kW.
V = Voltmeter reading in Volts.
I = Ammeter reading in Amps.

Mass of fuel consumption

$Mf = Xcc * \text{Specific gravity of fuel}/1000 * t$ ----- kg/sec

Where,

Xcc is the volume of the fuel consumed = 10ml
T is the time taken in seconds

The brake specific fuel consumption of the engine at different operating conditions was determined using the equation as given below:

BSFC = mf * 3600/B.P ---- kg/kW – hr.

Where,

mf is mass of fuel consumed in kg/sec.

B.P is brake power in kW.

The brake thermal efficiency of the engine at different operating conditions was determined using the following equation:

BTE = 3600 / (CV × BSFC)

Where,

BTE = Brake thermal efficiency, %

CV = Calorific value of fuel used, kJ/kg

BSFC = Brake specific fuel consumption, g/kW – hr

III. EXPERIMENTAL PROCEDURE

In the 1st stage of investigation experiments were conducted at rated engine speed of 1500 revolutions per minute with the blends of above mentioned biodiesels.

Performance and emission characteristics of Cotton seed biodiesel blends with diesel as fuel in CI engine tests are conducted at 75% load with diesel and Cotton seed biodiesel blends [B5, B10, B15, B20, B25 and B30] for analyzing varied parameters like brake thermal efficiency, brake specific fuel consumption (BSFC), exhaust gas temperature, emissions of CO, HC, NOx and smoke density.

The thermal potency of diesel is 27.82%, where as for Cotton seed biodiesel blends B5, B10, B15, B20, B25 and B30 are 27.58%, 27.35%, 27.06%, 26.8%, 26.2% and 22.5% respectively.

The BSFC of diesel is 0.305 kg/kW-hr, where as for Cotton seed biodiesel blends B5, B10, B15, B20, B25 and B30 are 0.304 kg/kW-hr, 0.308 kg/kW-hr, 0.312 kg/kW-hr, 0.316 kg/kW-hr, 0.324 kg/kW-hr and 0.379 kg/kW-hr respectively.

The exhaust gas temperature for the diesel is 2850C, where as for Cotton seed biodiesel blends B5, B10, B15, B20, B25 and B30 are 2870C, 2900C, 2920C, 2960C, 3050C and 3200C respectively.

The smoke density for the diesel is 0.62 Bosch, where as for Cotton seed biodiesel blends B5, B10, B15, B20, B25 and B30 are 0.625 Bosch, 0.63 Bosch, 0.64 Bosch, 0.65 Bosch, 0.67 Bosch and 0.67 Bosch respectively.

The HC emission for diesel oil is 72 ppm and for Cotton seed biodiesel blends B5, B10, B15, B20, B25 and B30 are 71 ppm, 69 ppm, 67 ppm, 65 ppm, 64 ppm and 62 ppm respectively.

The CO emission for diesel oil is 0.63% volume and for Cotton seed biodiesel blends B5, B10, B15, B20, B25 and B30 are 0.63% volume, 0.62%, 0.61% volume, 0.6% volume, 0.58% volume and 0.56% volume.

The NOx emission for diesel oil is 680ppm and for Cotton seed biodiesel blends B5, B10, B15, B20, B25 and B30 are 685ppm, 690ppm, 695ppm, 700ppm, 710ppm and 715ppm respectively.

IV.ANN MODEL FOR SINGLE CYLINDER FOUR STROKE DIESEL ENGINE

The use of ANNs for modelling the operation of internal combustion engines is a more recent progress. This approach was used to predict the performance and emissions of diesel engine. Basically, a biological neuron receives inputs from other sources, combines them in some way, performs generally anon-linear operation on the result, and then outputs the final result.

The network usually consists of an input layer, some hidden layers, and an output layer. A popular algorithm is the back-propagation algorithm, which has different variants. Back-propagation training algorithms gradient descent and gradient descent with momentum are often too slow for practical problems

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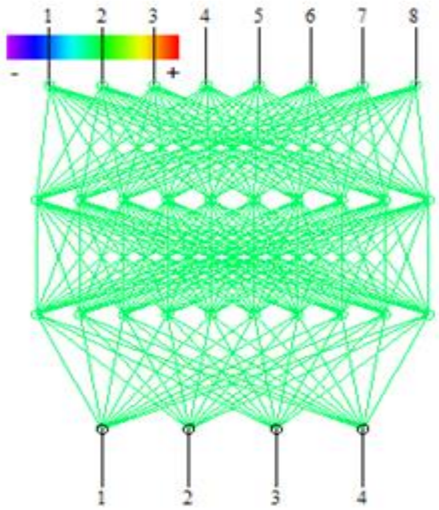
because they require small learning rates for stable learning. In addition, success in the algorithms depends on the user dependent parameters learning rate and momentum constant. Faster algorithms such as conjugate gradient, quasi-Newton, and Levenberg-Marquardt (LM) use standard numerical optimization techniques.

These algorithms eliminate some of the disadvantages mentioned above. ANN with back-propagation algorithm learns by changing the weights, these changes are stored as knowledge. LM method is in fact an approximation of the Newton's method. The algorithm uses the second-order derivatives of the cost function so that better convergence behaviour can be obtained.

In the ordinary gradient descent search, only the first order derivatives are evaluated and the parameter change information contains solely the direction along which the cost is minimized, whereas the Levenberg-Marquardt technique extracts more significant parameter change vector. Suppose that we have a function E(X) which needs to be minimized with respect to the parameter vector x. The error during the learning is called as root-mean squared (RMS)[II].

OUTPUT



INPUT

Fig.3. ANN model of the Diesel Engine

To get the best prediction by the network, several architectures were evaluated and trained using the experimental data. The back-propagation algorithm was utilized in training of all ANN models. This algorithm uses the supervised training technique where the network weights and biases are initialized randomly at the beginning of the training phase. The error minimization process is achieved using a gradient descent rule. There were four input and eight output parameters in the experimental tests. The four input variables are fuel, the percentage of biodiesel blending, load in amps and calorific value in KJ/Kg. The eight outputs for evaluating engine performance and emissions are Brake power in KW, Brake thermal efficiency, Specific fuel consumption in Kg/Kw-hr, CO in percentage of volume, HC in ppm, NOx in ppm, Smoke density in Bosch and EGT in 0C. Therefore, the input layer consisted of 4 neurons and the output layer had 8 neurons. The number of hidden layers and neurons within each layer can be designed by the complexity of the problem and data set. Arrangement of the model is shown in figure 6.

In this study, the number of hidden layers varied from one to two. To ensure that each input variable provides an equal contribution in the ANN, the inputs of the model were pre-processed and scaled into a common numeric range. The activation function for the hidden layer was selected to be logsig linear function suited best for the output layer.

This arrangement of functions in function approximation problems or modelling is common and yields better results. However, many other networks with several functions and topologies were examined. Three criteria were selected to evaluate the networks and as a result to find the optimum one among them. The training and testing performance (MSE) was chosen to be 0.00001 for all ANNs. The complexity and size of the network was also important, so the smaller ANNs had the priority to be selected.

Finally, a regression analysis between the network response and the corresponding targets was performed

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to investigate the network response in more detail. Different training algorithms were also tested and finally Levenberg-Marquardt (trainlm) was selected. The computer program MATLAB, neural network toolbox was used for ANN design.

In this study, for all the networks, the learning algorithm called back-propagation was applied for the single hidden layer. Scaled conjugate gradient (SCG) and Levenberg-Marquardt (LM) have been used for the variants of the algorithm. These normalized both for the inputs and outputs are realized between the values of 0 and 1. Neurons in the input layer have no transfer function. Logistic sigmoid (logsig) transfer function has been used.

ANN was trained and tested by means of the MATLAB software on a usual Pc. In order to identify the output precisely for training stage increased number of neurons (5-8) in the hidden layer was tried. Firstly, the network was trained successfully, and then the test data were used to test the network. By means of the results deduced by the network, a comparison was carried out using the statistical methods. Errors that happened at the learning and testing stages are described as the RMS and R', mean error percentage values, which are defined as follows, respectively.

$$R^2 = 1 - \frac{\sum_j (t_j - o_j)^2}{\sum_j (o_j)^2} \quad \text{------------1}$$

$$RMS = \left(\left(\frac{1}{P}\right) \sum_j (t_j - o_j)^2 \right)^{1/2} \quad \text{-------2}$$

$$\text{Mean \% Error} = \frac{1}{P} \sum_j \left(\frac{t_j - o_j}{t_j} \times 100 \right) \quad \text{----3}$$

Where t is the target value, o is the output value, and p is the pattern. Experimental results for different fuels and biodiesel blends are used as the training and test data for the ANN. The RMS, R2 and the mean error percentage values were used for comparing all of them.

V. RESULT AND DISCUSSION

The test samples in the range of 0% to 30% blends were tested in the laboratory and show the following differences, while comparing with standard diesel.

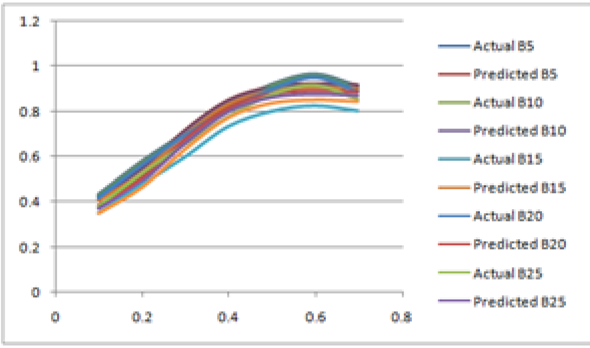

Fig.4. Load vs. BTE

In Figure 4, shows at constant speed of 1500 rpm it is observed that the brake thermal efficiency (B.T.E.) decreases with the increase in Cotton seed oil content in diesel. This decrease in efficiency is less; compared to the ability of the combustion system to accept the Cotton seed oil blends as fuel. This may be due to the high viscosity of Cotton seed oil content in the blends, and this may degrade fuel spray characteristics and lead to improper combustion.

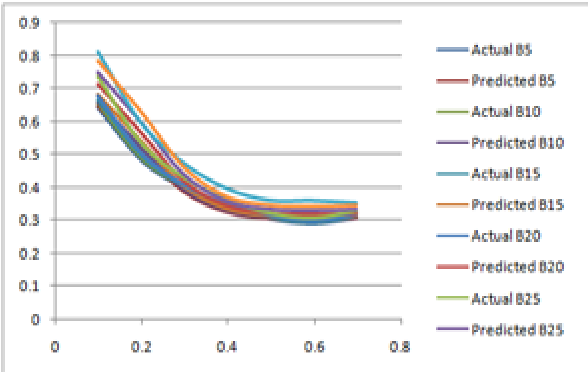

Fig.5. Load vs. BSFC

Figure 5 shows variation of BSFC with respect to engine load. The larger amount of biodiesel is supplied to the engine compared to that of diesel. Therefore, BSFC is higher for biodiesel than diesel. Brake specific energy consumption (BSEC) is an ideal variable because it is independent of the fuel.

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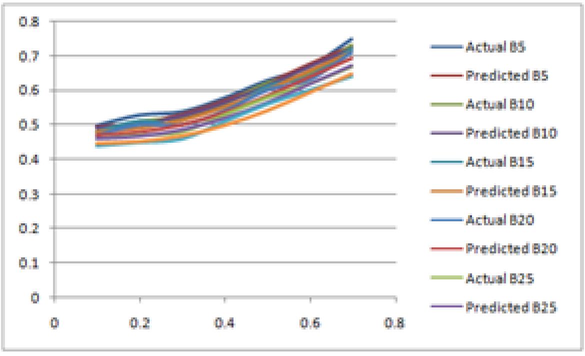

Fig.6. Load vs. CO

Figure 6 shows variation of CO with respect to engine load. The CO emissions are inflated with increase in engine load and reduce with the rise in amount of biodiesel within the blends. The lower CO emission of biodiesel blends compared to diesel oil is due to the presence of oxygen in biodiesel that helps in complete oxidization of fuel. The increase in the quantity biodiesel will increases the oxygen presence in the fuel, further this rich oxygen causes to reduce CO emission.

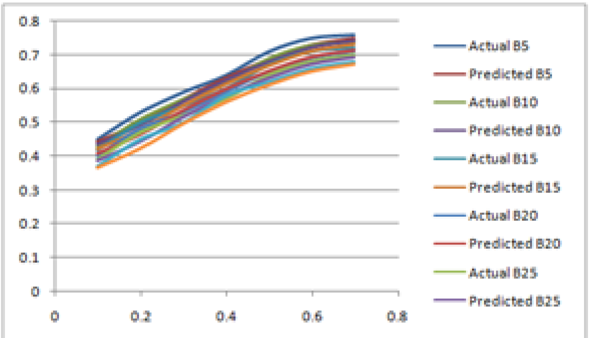

Fig.7. Load vs. HC

Figure 7 shows variation of HC with respect to engine load. The HC emissions rely on mixture strength i.e. amount of oxygen available. The HC emissions increases with increasing the load on the engine and reduce with increase in quantity of bio diesel in the mix. Lower heating worth of biodiesel leads to inject more quantities of fuel for a similar load condition. Compared to diesel, the oxygen content with in the bio diesel is additional. More amount of biodiesel leads to more oxygen either inherent in fuel or present within the charge. This excess oxygen helps for better combustion fuel. So that the HC emissions of Cotton seed biodiesel blends are less than the diesel oil.

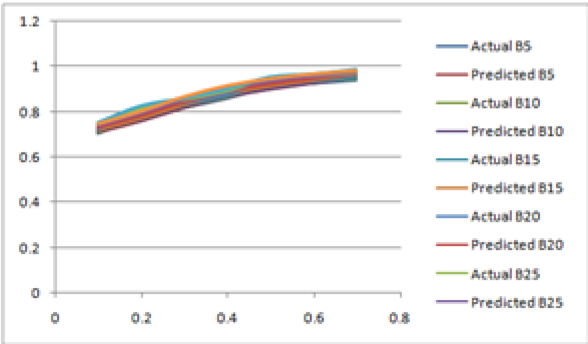

Fig.8. Load vs. NOx

Figure 7 shows variation of NOx with respect to engine load. The NOx emission will increase with increase in load on the engine for each diesel and Cotton seed biodiesel blends. These higher NOx emissions could be due to the higher temperature within the combustion chamber at higher loads. The NOx emissions are slightly higher for Cottonseed biodiesel blends as compared with pure diesel.

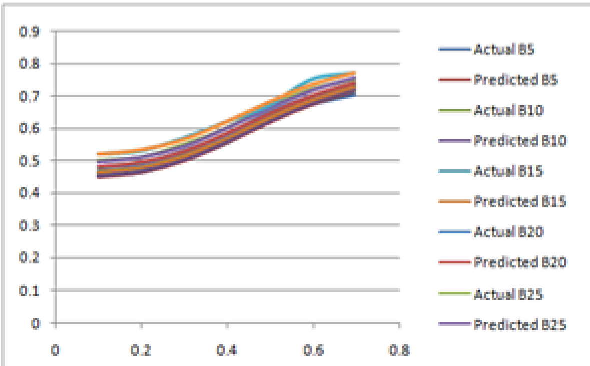

Fig.9. Load vs. SMOKE

Figure 9 shows variation of Smoke with respect to engine load. The smoke density will increase with the rise of engine load. For all loads the smoke density of the biodiesel blends was invariably on top of that of diesel oil. The smoke density will increase due to lean combustion and high ignition delay. The biodiesel mix has high viscousness, larger fuel droplet formation and reduces in fuel air combining rate. These are the factors concerned to extend the smoke density of biodiesel blends. The smoke density of the engine

ISSN No: 2348-4845
International Journal & Magazine of Engineering, Technology, Management and Research
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with diesel fuel is lower as compared with the Cottonseed biodiesel blends.

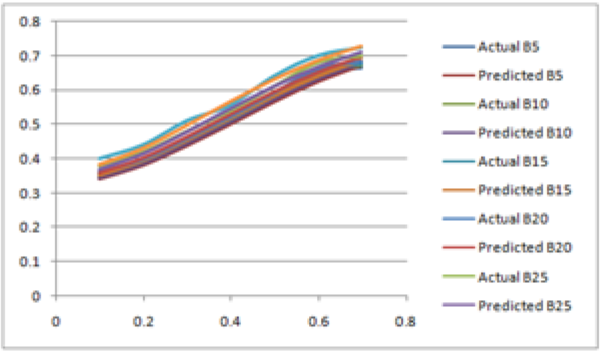

Fig.10. Load vs. EGT

The exhaust gas temperature was found to extend with increase in both the concentration of biodiesel within the mix and engine load. The rise in EGT with engine load is due to the actual fact that a more quantity of fuel is needed within the engine to get additional power required to take up conditional loading. Exhaust gas temperature for B-25 is highest. For the diesel oil the exhaust gas temperature is lowest as compared with the biodiesel blends.

VI. CONCLUSIONS

An experimental investigation was conducted to explore the performance of Cotton seed oil and its fuel blends with diesel in a direct-injection single-cylinder diesel engine and the results obtained suggest the following conclusions:

• Pure Diesel and blends of Cotton seed oil and diesel oil exhibited similar performance and broadly similar emission levels under comparable operating conditions.

• An artificial neural network (ANN) was developed and trained with the collected data of this research work. The results showed that the training algorithm of Back-Propagation was sufficient enough in predicting specific fuel consumption, Brake thermal efficiency, Emissions CO, HC, NOx, Smoke density and EGT for different engine speeds and different fuel blends ratios.

• An analysis of the experimental data by the ANN exposed that there is a good correlation between the predicted data resulted from the ANN and the measured ones. Therefore, the ANN proved to be a desirable prediction method in the evaluation of the tested diesel engine parameters. There is also a priority in using artificial neural networks, since other mathematical and numerical algorithms might fail due to the complexity and multivariate nature of the problem. Generally speaking, ANN provided accuracy and simplicity in the analysis of the diesel engine performance and emissions under test.

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