Performance Characteristics of Biodiesel Blend in CI Engine using Artificial Neural Network (Karanja Oil)

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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; b p- Brake Power; bsfc- Brake Specific Fuel Consumption; mse- Mean square Error; KO- Karanja Oil**

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, 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 modeling 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 modeling approaches in its ability to learn about the system that can be modeled 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 biofuel blends. This model is of a great importance due to its ability to predict engine performance under varying conditions [4].

A K Aggrawal et al 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 et al have developed that a cycle simulation model incorporating 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% and 40% 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, B100, 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) modeling of a diesel engine using waste cooking biodiesel fuel to predict the brake power, torque, specific fuel consumption and exhaust 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 as 0.0004 by the model [8].

II. EXPERIMENTAL SET UP

The experimentation was carried out on single cylinder four stroke direct injection medium speed naturally aspirated water cooled diesel engine.

A computerized automatic testing and acquisition system was installed so that the speed, fuel feed, air consumption and output torque could be controlled and the combustion process, different points pressure measurement, speed (rpm) measurement and cooling water flow measurement transported to this acquisition system could be measured as well.

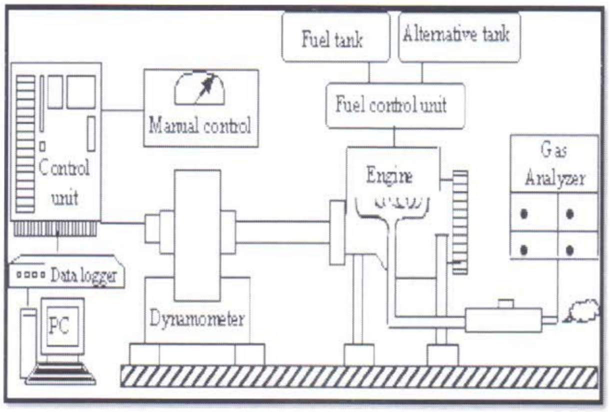

Fig.1 Experimental Setup

The data were displayed promptly on the monitor as well as stored by the computer. The schematic layout of complete experimental set up is shown in figure- 1. The basic data of the engine are given in table no. 1.

TABLE I
SPECIFICATION OF THE ENGINE

S.No.	Parameter	Specification
1	Make	Kirloskar Oil Engines Limited
2	Model	AV1
3	Type	1 Cylinder 4 Stroke
4	Bore	0.08 m
5	Engine No	10.1012/0600106
6	Stroke	0.11 m
7	Displacement	500 cc
8	Fuel	H.S.Diesel
9	Lubricating oil	SAE 30 / SAE 40
10	Rated Power	3.7 kW (5 hp)
11	Injector operating Pressure	15 MPa
12	Injector Timing	220 BTDC(Static)
13	Compression Ratio	17:1
14	Engine Speed	(1400-1600)rev/min
15	IVC	370 ABDC or (217 deg)
16	EVO	300 BBDC or (510 deg)

An engine dynamometer is used to measure the performance of the Single Cylinder Four Stroke Diesel engines. The engine is clamped on test bed and a shaft is connected to the dynamometer rotor. An electric brake dynamometer or electric generator is a device that converts mechanical energy to electrical energy. The specifications of the dynamometer are given in table no. 2.

Dynamometer was used to apply the load on the engine. The applied load causes the engine to produce a reaction torque (Newton's third law of action and reaction).

The product of the torque with the engine speed gives the output power. Figure 2 illustrates the operating principle of a dynamometer.

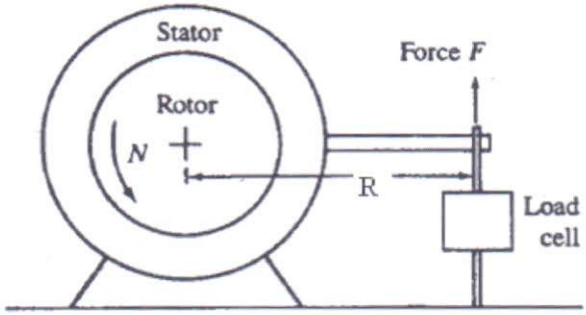

Fig. 2 Schematic diagram of Dynamometer

The rotor is coupled electromagnetically to a stator, which is supported in low friction bearings. [9]

The stator is balanced with the rotor stationary. The torque is exerted on the stator with weights. Using the notation in figure 2, if the torque exerted by the engine is T:

$$\tau = F \times R \quad \ldots\ldots\ldots\ldots\ldots\ldots \quad 1$$

The brake power (bp) delivered by the engine and absorbed by the dynamometer is the product of torque and angular speed:

$$\text{Brake Power} = 2\pi N\tau \quad \ldots\ldots\ldots\ldots\ldots\ldots \quad 2.$$

TABLE II
THE MAIN SPECIFICATION OF THE DYNAMOMETER

S.No.	PARAMETER	SPECIFICATION
1	Make	Kirloskar Brothers Limited
2	S. No.	07WKJD0015
3	Model	KBM-104
4	Type	Electric Brake air cooled
5	Output	4 KVA
6	Rated Speed	1500 rpm
7	Volt	250 V
8	Ampere	17.4 A
9	P.F.	1
10	Frequency	50 Hz
11	Arm Length	215 mm

A. Data acquisition computer set up

All computation is performed by a personal computer and a LABVIEW software customized by K.C. Engineers is shown in figure 3. A computational thread performs cycle analysis on full 720' cycles of pressure data, and makes the data available to a control thread through a status object.

Fig. 3 Data acquisition computer set up

A Lab View data acquisition system is used to condition and log signals from all of the sensors. Analog signals are amplified and low-pass filtered using a National Instruments SCXI 1327 instrumentation amplifier. Thermocouple signals are amplified using a National Instruments SCXI 1112 thermocouple amplifier. Analog to digital conversions are performed using an eight channel, 16 bit card resident in a PC. Pulses from the flow meter are counted using a TDS 3034B digital oscilloscope and converted into flow rate using the sensor's calibration factor. Acquisition of data from the oscilloscope is also controlled through the Lab View software. Figure 4 of the LABVIEW user interface was used to set user inputs and record engine data. Data from the dynamometer is recorded in one of two modes. In the default strip chart mode, the channels are scanned once per second and the data are written in a file which provides a record of everything that happened in the course of an experiment. These data are also written on virtual indicators and strip charts displayed on a software panel to provide real-time graphical indications of the state of the experiment.

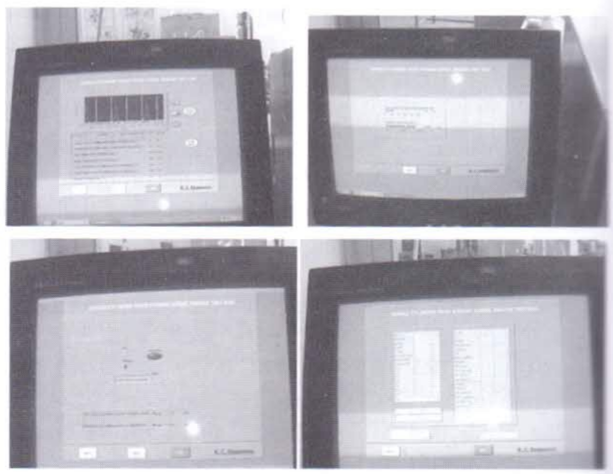

Fig. 4 LabView custom graphical user interface (GUI)

Figure 5 shows arrangement of all input cords in control panel. The interface displays the engine's speed (RPM) on a tachometer, a streaming torque chart, calculated horsepower, throttle and load settings, amount of fuel left, thermocouple temperatures, and ambient room conditions among other items.

The interface also allows the operator to control the engine's speed and torque by varying the load applied by the dynamometer. The data acquisition system also operates in the LabView environment and is integrated with the dynamometer control system. Analog signals from the torque sensor, speed sensor, and thermocouples are polled using the National Instruments 6036E data acquisition board.

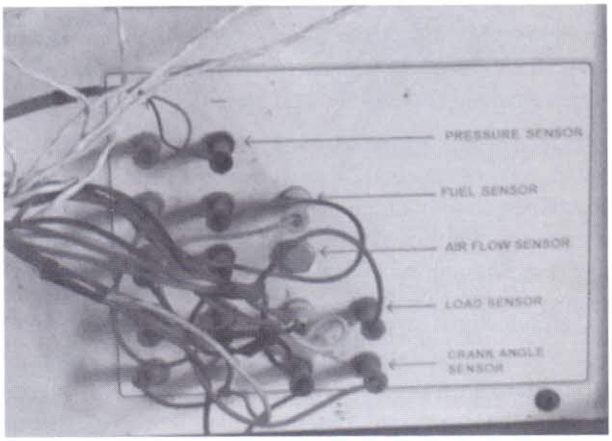

Fig. 5 Control Panel

Digital RS232 signals from the fuel scale are sent and received through the host PC's RS232 port using the LabView software. Data collection at a particular operating point is initiated by clicking a button on the user interface. Two files are created and saved to the user specified directory.

III. Experimental Procedure

The experimental installation used in the work presented here, consists of a Kirloskar model single-cylinder engine. This is a water-cooled, direct-injection, four stroke diesel engine. A dynamometer was used to load the engine at increments of 1 kg to a maximum load of 15 kg. The reaction force and the torque were measured by means of a load cell attached to the dynamometer arrangement. The fuel supply system was modified by solenoid valve which allowed rapid switching between the diesel oil used as a standard and the test plant fuels. At each loading, the speed of the shaft was measured using a rpm sensor. The fuel was fed to the injector pump under measuring arrangement. Volumetric flow rate was measured by noting the time taken for 40 ml of fuel to flow through a graduated measuring device. The relative humidity and ambient temperature were monitored. Experimental procedure is given below step-wise [10];

- At the very outset, the essential parameters and connections are checked before starting the engine for example, cooling water supply, diesel fuel in the tank and pressure measurement etc.
- Before cranking the engine, the flow of cooling water is adjusted, level of fuel tank is checked and then tank outlet is opened. Cranking handle of engine is adjusted with the extended shaft of the crank and the lock of decompression valve is raised. Now crank the engine.
- During the cranking, after a few rotations, the lock of decompression valve is lowered, and then the engine starts functioning. This is the process to start the machine.
- Flow of water outlet and flow of exhaust outlet are checked so as to identify whether the flow is proper or not.
- If all the parameters are in appropriate condition, then the computer is switched on so that Engine software can be used for the acquisition of data from the engine setup.
- As soon as, both, the engine and the computer are connected, constant data (for engine setup) appears on the screen of the computer with two buttons (BACK and NEXT).
- Click on the NEXT button of the software, then it will show the next window of the software. Other devices like control panel, pressure transducer and loading control unit are switched on. It is also kept in mind that no key of loading control unit is switched on. This software window shows the rpm and load on the engine.
- If the data are shown properly, then we start the further process. If everything is up to the mark, then real time graph appears between pressure and crank angle.
- On the very page, all the switches of temperature displays as well as different graph displays appear. When everything is the same as stated, then NEXT button is clicked. Fuel sensor is displayed and the flow of cooling water is displayed on the page.
- The temperature displayed on engine setup is checked according to position of temperature sensor. If it is right, NEXT is clicked. Otherwise, it requires troubleshooting in temperature sensor.
- After clicking on NEXT, a new page opens and solenoid valve starts functioning with a sound. Now, the direct fuel supply of Diesel Engine is closed. This page shows fuel sensor display as well as cooling water display.
- In addition to this, cooling water flow can be edited manually according to the actual flow of rota-meters.
- Next fuel start button is clicked, and with the effect of it the solenoid valve closes.

- Two levels, TOP and BOTTOM, are seen on the page. The top level appears to be ON, whereas the bottom level is in OFF position. The fuel consumption continues from the small fuel cylinder. When the top level empties of the fuel, instantly stopwatch starts and fuel measurement process takes place from top to bottom of the fuel cylinder. As soon as the bottom empties of the fuel, then the watch stops automatically.
- NEXT button is clicked and this reveals the observation table and the calculation. Altogether the Log Reading and Next Reading switches appear.
- Clicking on the Log reading switch, reading is logged automatically for the Run No.1. Simultaneously the data are shown in the calculation table. The data (Run No.1) are saved in scroll window.
- The Detail Calculation button is clicked to get the detailed calculation step by step. Clicking on the 'Next Reading' button, it comes to the initial stage of the experiment (the experimental cycle completes at this point).
- For further runs, load is applied with Rheostat loading unit.

IV. ANN Model For Single Cylinder Four Stroke Diesel Engine

The use of ANNs for modeling the operation of internal combustion engines is a more recent progress. This approach was used to predict the performance of diesel engines and the specific fuel consumption and fuel air equivalence ratio of a diesel engine. Basically, a biological neuron receives inputs from other sources, combines them in some way, performs generally a non-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 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 a better convergence behavior 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)[11].

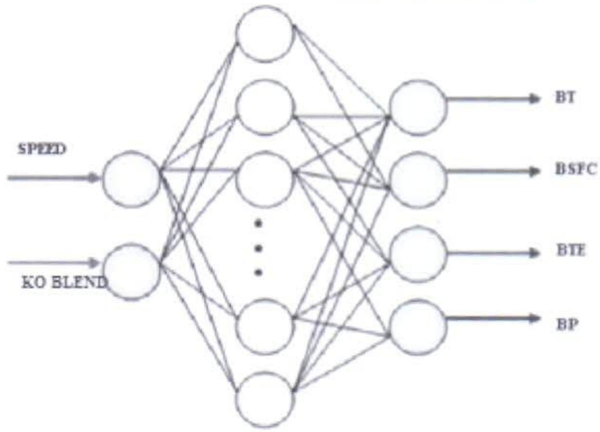

Fig. 6 Simple ANN model of the Diesel Engine

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 two input and four output parameters in the experimental tests. The two input variables are engine speed in rpm and the percentage of biodiesel blending with the conventional diesel fuel. The four outputs for evaluating engine performance are engine torque in Nm, Specific Fuel Consumption (SFC) in l/kWh. Therefore, the input layer consisted of 2 neurons which corresponded to engine speed and levels of KO blends and the output layer had 4 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 modeling 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 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 7.9, 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^2, mean error percentage values, which are defined as follows, respectively

$$R^2 = 1 - \frac{\sum_j (t_j - o_j)^2}{\sum_j (o_j)^2} \quad \ldots\ldots\ldots\ldots 3$$

$$RMS = \left(\left(\frac{1}{P}\right) \sum_j (t_j - o_j)^2 \right)^{1/2} \quad \ldots\ldots\ldots\ldots 4$$

$$\text{Mean \% Error} = \frac{1}{P} \sum_j \left(\frac{t_j - o_j}{t_j} \times 100 \right) \quad \ldots\ldots\ldots 5$$

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 experimentally tested fuels are PBDF, B0, and biodiesel blends with PBDF, which are 50% (B50), 20% (B20) and 10% (B10). The RMS, R^2 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 50% blends were tested in the laboratory and show the following differences, while comparing with standard diesel.

- Figure 7 shows fuel flow rate with respect to brake power, in that the lower energy content/ unit mass of blend compared to diesel fuel resulted in increased mass flow rate. A possible explanation is that the more viscous fuel blends reduce normal injection pump leakage enough to make a significant change in the volume discharged per stroke.

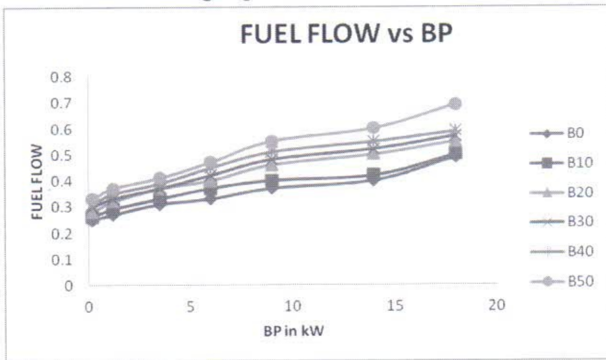

Fig. 7 Variation in fuel flow rate with Brake Power for different Blends

- Although the heating value relationship tends to reduce the specific energy input rate as blend fraction increases, the net effect is an increase in fuel heat supplied. Engine performance and emissions were influenced by basic difference between diesel fuel and (KO + DO) blends such as heating values, viscosity, density etc.
- In Figure 8, at constant speed of 1500 rpm it is observed that the brake thermal efficiency (B.T.E.) decreases with the increase in KO content in diesel. This decrease in efficiency is less, compared to the ability of the combustion system to accept the KO blends as fuel. This may be due to the high viscosity of KO content in the blends, and this may degrade fuel spray characteristics and lead to improper combustion, which result in a minor decrease in efficiency. B.T.E. decreases slightly with respect to BP at the maximum load; this may be due to a lower heat content of KO, which leads to non-uniform combustion of the fuel.

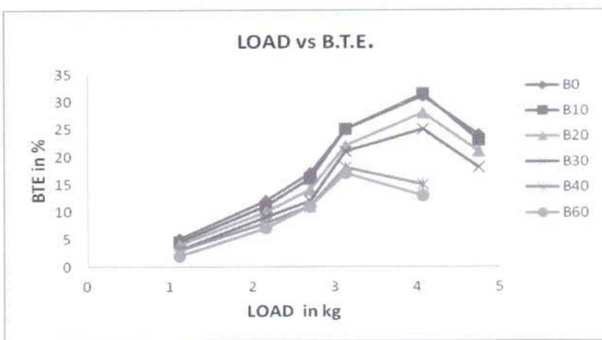

Fig. 8 BTE with Brake Power for different Blends

Considering the error values obtained from the network, we used the network to make predictions for different biodiesel blends (i.e. 50% (B50), 40% (B40), 30% (B30), 20% (B20), and 10% (B10)), other input values (i.e. humidity, dry bulb temperature, and pressure), which are measured again, and engine speed values used for training. So, mixing ratio has been generalized. The results obtained from ANN are given in Figure 9 to Figure 12. Fuel properties, such as heating value, density and viscosity, have influences on the engine performance and emissions. Therefore, the engine brake torques, BSFC and thermal efficiencies were predicted for different biodiesel blends.

- Figure 9 and Figure 10 show variation of BSFC with respect to engine speed at full load. Due to the above reasons, it is observed that a 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. This energy consumption is the energy input required to develop unit power which can be seen from equation 6.

$$BSFC(or\ SFC) = \frac{Q_f}{BP} \qquad \text{............ 6}$$

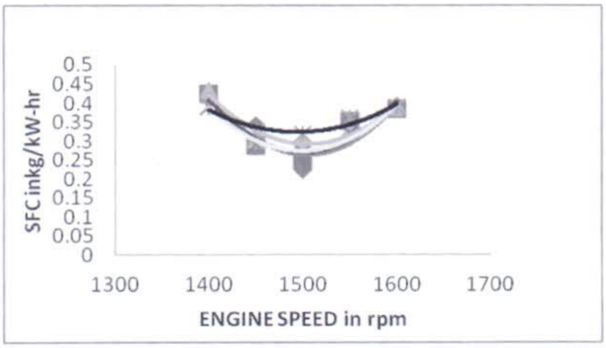

Fig. 9 Actual Performance of the BSFC with respect to engine speed for different fuel blends

Figure 9 and Figure 10 show the BSEC for biodiesel and diesel. Under almost all engine speed range, the BSEC for biodiesel is closer to that of diesel. At 1500 rpm engine speed, BSEC of biodiesel is lower than that of diesel. This small variation may be due to the combined effect of lower heating value and high density of biodiesel.

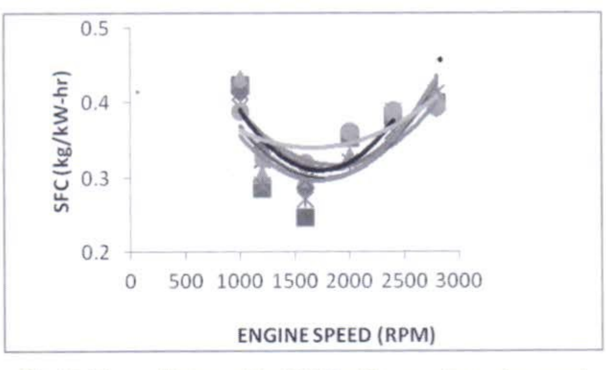

Fig. 10 The predictions of the BSFC with respect to engine speed for different fuel blends.

Figure 11 and Figure 12 also indicate the predicted brake thermal efficiencies for the different biodiesel blends if the engine was operated at different engine speeds at full load condition. Brake thermal efficiency is defined as actual brake work divided by the amount of fuel chemical energy as indicated by the fuel's lower heating value. As the figure shows, the thermal efficiency decreases with increasing ratio of the biodiesel in the fuel blend. The trends of the thermal efficiencies look similar for the brake torques for each fuel.

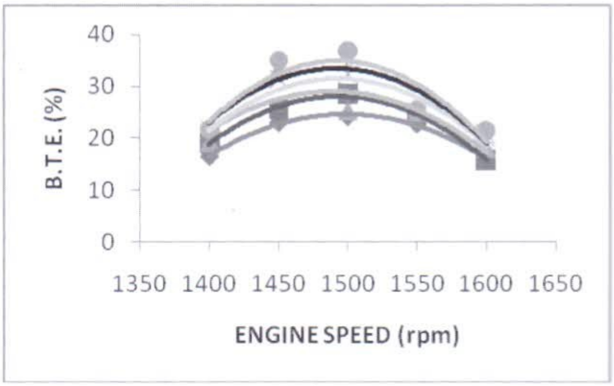

Fig. 11 The Actual Brake Thermal Efficiency with respect to engine speed for different fuel blends.

Fig. 12 The predictions of the Thermal Efficiency with respect to engine speed for different fuel blends

The predicted values for BSFC are shown also in Fig. 10. The BSFC increased with the increase of biodiesel percentage in the fuel blend. Therefore, if the engine was fuelled with biodiesel or its blends, the BSFC will increase due to the produced lower brake power caused by the lower energy content of the biodiesel. This result can be clearly seen at the higher biodiesel ratios. At the same time, for the same volume, more biodiesel fuel based on the mass flow was injected into the combustion chamber than pure diesel due to its higher density.

VI. CONCLUSIONS

An experimental investigation was conducted to explore the performance of karanja 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 karanja 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 and Brake thermal efficiency 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 under test.

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