Artificial Intelligence for Prediction of Performance and Emission Parameters of CI Engine using Bio-Fuel

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Abstract. The objective of this work is to find the performance and emission parameter of different blends of Karanja biodiesel with diesel and compare these parameters with pure diesel. This study investigates the potential of Karanja oil as a source of biodiesel. The objective of this work is to find the performance and emission parameters of 10 %, 20 %, 30 %, 40 %, and 50 % of blends with biodiesel and compared various parameters with diesel. The results showed that Brake Thermal Efficiency (BTE) decreases with an increase in the percent of biodiesel and Brake Specific Fuel Consumption (BSFC) decreases with an increase in the percent of biodiesel. Hydrocarbon (HC) and carbon monoxide (CO) emission reduces with an increase in blend percent whereas Nitrous oxide (NOx) emission increases with an increase in blend percent. Neural networks obviate the need to use complex mathematically explicit formulas, computer models, and impractical and costly physical models. In this work we use Neurosolution software for prediction of performance and emission parameters, separate models were developed for performance parameters as well as emission parameters. To train network, load, blend percentage, calorific value, the viscosity of fuel & air-fuel ratio was used as input value whereas engine performance parameters like brake thermal efficiency, brake specific fuel consumption & exhaust gas temperature were used as output value for performance model and engine exhaust emission such as NOx, CO, and HC values were used as the output parameters for emission model. Artificial Neural Network (ANN) results showed that there is a good correlation between the ANN predicted values and the experimental values for various engine performance and exhaust emission parameters. It is observed that the ANN model can predict the engine BTE, BSFC with a correlation coefficient of about 0.998435668, 0.990616392, and 0.993346689 respectively for performance model and emission model CO, HC and NOx predict with a correlation coefficient of 0.986098699, 0.991243454 & 0.9855593.

NOMENCLATURE

<table>
<thead>
<tr>
<th>Acronym</th>
<th>Definition</th>
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<tbody>
<tr>
<td>BTE</td>
<td>Brake Thermal Efficiency</td>
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<tr>
<td>IP</td>
<td>Indicated Power, kW</td>
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<tr>
<td>HC</td>
<td>Hydrocarbon</td>
</tr>
<tr>
<td>CO</td>
<td>Carbon monoxide</td>
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<tr>
<td>NOx</td>
<td>Oxides of Nitrogen, ppm</td>
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<td>ANN</td>
<td>Artificial Neural Network</td>
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<tr>
<td>CI</td>
<td>Compression-Ignition</td>
</tr>
<tr>
<td>CP</td>
<td>Specific heat at constant pressure</td>
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<tr>
<td>CV</td>
<td>Specific heat at constant volume</td>
</tr>
<tr>
<td>MPS</td>
<td>Mean Square Error</td>
</tr>
<tr>
<td>N</td>
<td>Speed (RPM)</td>
</tr>
<tr>
<td>PME</td>
<td>Pongamia Methyl Ester</td>
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<tr>
<td>GA</td>
<td>Genetic Algorithms</td>
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<tr>
<td>R</td>
<td>Coefficient of Correlation</td>
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</table>
INTRODUCTION

Energy is an essential and vital input for economic activity. Building a strong base of energy resources is a pre-requisite for the sustainable economic and social development of a country. During the last decade, India has maintained a high growth rate in accepting the improved technological challenges in the global scenario. Also due to the gradual depletion of the world petroleum reserve, rising petroleum prices, increasing threat to the environment from exhaust emission, and global warming have generated intense international interest in developing alternative non-petroleum fuels. In 1950, the British mathematician and computer pioneer Alan Turing declared that one day there would be a machine that could duplicate human intelligence in every way. ANN is one type of artificial Intelligence which is derived from the human brain. S. Kalogirou (2003) illustrates how AI techniques might play an important role in modelling and predicting the performance and control of the combustion process. one can see that AI techniques have been applied in a wide range of fields for modelling, prediction, and control in combustion processes. The performance of the selected models is tested with the data of the history of the real system [1-14]. Shivakumar et al. (2010) investigate the influence of injection timing on the performance and emissions of a single-cylinder, four-stroke stationery, variable compression ratio, the diesel engine was studied using waste cooking oil as the biodiesel blended with diesel. There is a good correlation between the ANN predicted values and the experimental values for various engine performance parameters and exhaust emission characteristics and the relative mean error values (MRE) were within 8%, which is acceptable [9,15]. Najafi et al. (2007) combustion analysis has been conducted to evaluate the performance of a commercial DI engine, water-cooled two cylinders, in-line, naturally aspirated, RD270 diesel engine using waste vegetable cooking oil as an alternative fuel. The developed model can be used as a diagnostic tool for estimating the emissions of biodiesels and their blends under varying operating conditions [17]. Sarala et al. (2012) used some of the experimental data for training; an ANN model was developed based on the standard Back-Propagation algorithm for the engine. ANN results showed a good correlation between the ANN predicted and the desired values for various engine exhaust emissions [5,6,18]. As an alternative to classical modelling techniques, the ANN approach can be used to predict the performance and emissions of internal combustion engines [10,19]. In recent years, ANNs are increasingly being used to solve engineering problems that deal with highly nonlinear functional approximations. Predictive models on emissions with the various engines and fuel parameters have been successfully developed. We use Neurosolution software for ANN modelling. To train the network, we develop a separate model for performance as well as emission parameters.

Preparation of Various Blends

The mixture of Karanja oil and diesel used in different proportions (by volume) at room temperature as follows:

- PME 10: It contains 10% Karanja oil and 90% Diesel by volume
- PME 20: It contains 20% Karanja oil and 80% Diesel by volume
- PME 30: It contains 30% Karanja oil and 70% Diesel by volume
- PME 40: It contains 40% Karanja oil and 60% Diesel by volume
- PME 50: It contains 50% Karanja oil and 50% Diesel by volume

Properties of Various Blends

The measured properties are density, calorific value, viscosity, flash point & cloud point shown in Table 1.

<table>
<thead>
<tr>
<th>Fuels and Blends</th>
<th>Density (kg/m³)</th>
<th>Calorific Value (kJ/kg)</th>
<th>Viscosity at 40 °C (Cst)</th>
<th>Flash Point (°C)</th>
<th>Cloud Point (°C)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Diesel</td>
<td>850</td>
<td>44000</td>
<td>2.87</td>
<td>56</td>
<td>-16.5</td>
</tr>
<tr>
<td>PME 10</td>
<td>860</td>
<td>43850</td>
<td>3.05</td>
<td>65</td>
<td>4.8</td>
</tr>
<tr>
<td>PME 20</td>
<td>868</td>
<td>43756</td>
<td>3.39</td>
<td>73</td>
<td>5.3</td>
</tr>
<tr>
<td>PME 30</td>
<td>870</td>
<td>42360</td>
<td>4.21</td>
<td>81</td>
<td>5.8</td>
</tr>
<tr>
<td>PME 40</td>
<td>871</td>
<td>41810</td>
<td>4.63</td>
<td>88</td>
<td>6.0</td>
</tr>
<tr>
<td>PME 50</td>
<td>873</td>
<td>41608</td>
<td>5.12</td>
<td>99</td>
<td>6.2</td>
</tr>
<tr>
<td>Testing Procedure</td>
<td></td>
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<tr>
<td>ASTM D4052</td>
<td></td>
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<td>ASTM D240</td>
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<td>ASTM D445</td>
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<td>ASTM D93</td>
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<td>ASTM D2500</td>
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**XPERIMENTAL SETUP**

The schematic diagram of the experimental setup is shown in Fig. 1. The engine is a single-cylinder four-stroke direct-injection water-cooled diesel engine. The engine has a rated output of 5.2 kW at speed of 1500 RPM with a compression ratio of 17.5, injection pressure 180 kg/cm$^3$, and coupled with rope brake dynamometer. The performance test is carried out on a compression ignition engine using various blends of biodiesel and diesel.

![Schematic Diagram of Experimental Setup](image)

**FIGURE 1.** The schematic diagram of the experimental setup

**RESULT AND DISCUSSIONS**

This section is subdivided into two parts, namely, performance parameter and exhaust gas emission. In each of the parts mentioned, the variation of load with BTE, BSFC, exhaust gas temperature is presented and discussed accordingly.

**Performance Parameter**

The brake thermal efficiency tends to increase with an increase in load. From Fig. 2 it is evident that diesel fuel has a higher brake thermal efficiency compared to biodiesel and its blends. Due to its higher calorific value, the amount of heat produced in the combustion chamber is more, further, the combustion is complete and produced higher temperatures.

![Load vs Brake Thermal Efficiency](image)

**FIGURE 2.** The variation of brake thermal efficiency with load
It is the quantity of fuel consumed per unit of brake power per unit of time. The BSFC reduced with the load for all fuel blends. Figure 3 shows BSFC for the Karanja biodiesel blends is higher than diesel fuel due to low calorific value. The oxygenated biodiesels may lead to better combustion resulting but higher BSFC.

The exhaust gas temperature in the combustion chamber depends on the calorific value, latent heat, and viscosity of the fuel injected. Figure 4 shows that exhaust gas temperature increases with the load for all fuel samples. Due to the low calorific value of biodiesel, it requires more fuel to generate some power.

**Engine Exhaust Emission**

The emissions of carbon monoxide are toxic and its presence in the exhaust is due to incomplete combustion. Oxygen presents in biodiesel act as a combustion promoter, which results in better combustion and compensates for the increase in the emissions. Figure 5 shows that with an increase in blend percent, CO emission reduces.
It is observed that NOx increases with increasing load for all the blends of Karanja methyl esters. Figure 6 shows that if the percentage of blends of Karanja methyl esters increases, NOx increases. The NOx increase for PME may be associated with the oxygen content of the PME, since the fuel oxygen may augment in supplying additional oxygen for NOx formation.

![Graph of Load Vs NOx Emission(ppm)](image)

FIGURE 6. The variation of oxides of nitrides (NOx) with load

From Fig. 7, it is observed that HC increases with increasing load for all the blends of Karanja methyl esters. If the percentage of blends of Karanja methyl esters increases, HC reduces. The hydrocarbon emissions are inversely proportional to the percentage of PME in the fuel blend. The diesel oil operation showed the highest concentrations of HC in the exhaust at all loads. Since PME is an oxygenated fuel, it improves the combustion efficiency and hence reduces the concentration of HC in the engine exhaust.

![Graph of Load Vs HC Emission(ppm)](image)

FIGURE 7. The variation of hydrocarbon emission (HC) with load

**NEUROSOLUTION SOFTWARE MODELING**

This section deals with the modelling of the engine using Neuro-Solution software. It is followed by the ANN model for emission parameters along with training results for the same. In this step, a network is created by providing 2 hidden layers. With an increase in the number of hidden layers, the complexity of the network increases. In our network, 2, no of hidden layers shows better result compared to 1 no of the hidden layer. Axon works as a transmitting unit, it is the connection between two neurons as shown in Fig. 8. In our network, Linear TanhAxon is a transfer function for input and output variables. 300 epochs are required to create a network.
FIGURE 8. Snapshot creates network – new custom network

Neurosolution Software Modeling

For developing the ANN model for performance parameter load, blend percentage, calorific value, viscosity for all the fuel samples & air-fuel ratio is used as input value and brake thermal efficiency, brake specific fuel consumption & exhaust gas temperature are used as an output value.

ANN Model for Emission Parameters

For developing the ANN model for emission parameter load, blend percentage, calorific value & air-fuel ratio are used as an input value, and HC, CO & NOx emissions are used as the output value. For developing the ANN model, the same steps were followed as followed for developing the performance parameter. The steps are:

• Step 1: Normalize the original data and feed into an excel sheet
• Step 2: Randomize the normalized data in Neurosolution
• Step 3: Tag the column: (i) Take input column as input
(ii) Take output column as desired
• Step 4: Tag the rows by percentage as shown in Fig. 9.
  For training – 60 % data
  For cross-validation – 15 % data
  For testing – 25 % data
Here also we use 60 % data for training, 15 % for cross-validation, and 25 % for testing.
• Step 5: Create Network – New Custom Network
  (i) No of hidden layers -2
  (ii) Input Transfer Function- Linear TanhAxon
  (iii) Output Transfer Function - Linear TanhAxon
  (iv) No. of Epochs-200
For creating a network of emission model 2 No hidden layers are used. Here also Liner TanhAxon uses for connecting neurons. 200 no of Epochs is used for creating a network.
• Step 6 – Train Network - After creating a network, train the network by providing 200 No of Epochs.
Training Result

Training report as shown in Fig. 10 shows that for training at 183 No of Epochs it shows minimum MSE i.e. 0.003941991 and for cross-validation, at 6 No of Epochs it gives minimum MSE i.e. 0.00792484. The final MSE for the Training set is 0.005898229 and the cross-validation set is 0.027346413.

![MSE versus Epoch](image)

FIGURE 10. The variation of training result

The training report as tabulated in Table 2 shows the best networks parameter against the training and cross-validation for the same. The parameters considered are epoch, minimum MSE, and the final MSE.

<table>
<thead>
<tr>
<th>Best Networks</th>
<th>Training</th>
<th>Cross-Validation</th>
</tr>
</thead>
<tbody>
<tr>
<td>Epoch #</td>
<td>183</td>
<td>6</td>
</tr>
<tr>
<td>Minimum MSE</td>
<td>0.003941991</td>
<td>0.00792484</td>
</tr>
<tr>
<td>Final MSE</td>
<td>0.0058982</td>
<td>0.027346413</td>
</tr>
</tbody>
</table>

**TABLE 2** Training result
CONCLUSIONS

The summary/outcome of the paper is explained as follows:

• Karanja blends can be conveniently used in CI engines as blends with diesel without any engine modifications. 10 % and 20 % of blend showed the highest BTE among all blend samples. With an increase in blend percentage, the BTE decreases.

• BSFC for the biodiesel operations was found to be relatively higher than that for neat diesel operation for all the blends. 10 % and 20 % blend shows close results with diesel. CO and HC emissions were reduced for Karanja biodiesel blends.

• Neurosolution software modelling was applied to predict the performance and emission parameters. For the performance parameters, the MSE of BTE, BSFC, exhaust gas temperature is 0.001172318, 0.002423626, and 0.00147545 respectively. For emission parameters, the MRE of HC, CO, and NOx are 0.006781231, 0.007796799, and 0.001928225 respectively, which are found to be within the acceptable limits.

• For the combined model based on both the parameters, MRE was slightly more than the individual parameters and the accuracy of prediction slightly reduced. Hence it is preferable to have individual models for, rather than a combined model.

• It is observed that the ANN model in Neurosolution Software can predict the engine BTE, BSFC, and exhaust gas temperature quite well with a correlation coefficient of about 0.998435668, 0.990616392, and 0.993346689 respectively. It can be concluded that R values are very close to one for all the performance and emission parameters.

• Neurosolution software results showed that there is a good correlation between the ANN predicted values and the experimental values for various engine performance parameters and exhaust emission parameters. This reduces the experimental efforts and hence conserve as an effective tool for predicting the performance of the engine and emission characteristics under various operating conditions with different biodiesel blends.

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REFERENCES