Analysis on Emissions and Performance of Ceramic Coated Diesel Engine Fueled with Novel Blends Using Artificial Intelligence

Tarun Kumar Kotteda,1 Rama Bhadri Raju Chekuri,1 B. Naga Raju,2 Prasada Raju Kantheti,1 and S. Balakumar3

1Department of Mechanical Engineering, Sagi Rama Krishnam Raju Engineering College, Bhimavaram, Andhra Pradesh, India
2Department of Mechanical Engineering, Anil Neerukonda Institute of Technology and Sciences, Visakhapatnam, Andhra Pradesh, India
3Arba Minch University, Arbaminch, Ethiopia

Correspondence should be addressed to S. Balakumar; sbk25dec@gmail.com

Received 1 June 2021; Revised 16 June 2021; Accepted 22 June 2021; Published 1 July 2021

Academic Editor: Samson Jerold Samuel Chelladurai

1. Introduction

The enormous outrush of overseas trade-off, on the one hand, and enlarging emissions forefront towards environmental depletion, on the other hand, have triggered attentiveness towards replacement for diesel oil and petrol. Fuel oils furnish energy about 90% of shipment and transportation, and the demand is gradually increasing, specifically in swiftly developing countries such as India and China. The domiciliary stock of petroleum oil in our country met quarter of the percentage out of the full demand, whereas the remaining needs are to be satisfied with the help of petroleum by-products imported from foreign countries. Hence, necessary steps have been followed to overcome the foreign dependency on imports of crude oil. Biodiesel blends are renewable, which are extracted by the chemical treatment of vegetable oils, animal fats, and biomass using transesterification process and are called fatty acid methyl esters [1]. Predominant research has been done on various engines fueled with biofuels blended in diesel and observed appreciable improvement in emissions and performance concern [2, 3]. Karmee and Chadha [4] identified fuel characterization of Pongamia pinnata methyl esters relevant to ASTM standards. Suresh Kumar et al. [5] stated that, supervising a single cylinder, diesel engine fueled with PPME blends, the heating value of biodiesel dropped down with an increment of volume % of PPME. In addition, an increase in BSFC and a decrease in NOx and HC were...
noticed at high loads. Significant improvement in CO and NOx was identified with 20% of Pongamia pinnata biodiesel while testing a water-cooled type, single cylinder CI engine, whereas BTE and volumetric efficiency also increase [6].

Rakopoulos et al. [7] triggered research on n-butanol blended with diesel and noticed the drop of emissions except HC emissions, and this reduction is higher in percentile increment of butyl alcohol. Nathagopala et al. [8] studied the effect of pentanol and butanol added with Calophyllum inophyllum biodiesel tested on the diesel engine and revealed that BTE was gradually decreased, whereas BSFC increased. On the other hand, CO, NOx, HC, and opacity emissions were rapidly decreased. This reduction rate is increased with higher % of alcohol content in the blend. Moreover, nitrogen oxides were significantly decreasing due to the cooling effect of alcohol in the blend and high latent heat of vaporization. Ramakrishnan et al. [9] assessed the influence of n-pentanol added (10, 15, and 20%) with Calophyllum inophyllum diesel blend of 20% on VCR engine and suggested that 20% n-pentanol added blend is the feasible one for better performance and combustion, whereas NO and CO emissions are slightly increasing due to effective combustion. Imtenan et al. [10] done their studies on a high speed, four-cylinder diesel engine tested with Calophyllum inophyllum blends added with n-butanol additive and revealed that the blends with high concentration of additive give promising BSFC and BTE, whereas, on the other hand, nitric oxides and CO emissions are dropped with respect to diesel outcomes.

In recent times, researchers used various optimization techniques, like ANN and RSM; thereby, they can easily predict performance, combustion, and emission parameters relevant to their work. As per their assessment, it is easy to understand the influence of blends thoroughly; thereby, R&D cost may reduce [11–13]. However, so many complications may arise while doing the experimental work on IC engine to analyze its performance and emissions. It is not surprisingly effective in the view of economic and time factors. By considering all these consequences, predicting the performance, combustion, and exhaust gas emissions of an engine using various optimization techniques has received notable recognition recently. In this study, various parameters like load acts on an engine, speed of the engine, blend ratio, injection advance, etc. [14]. The computer-interface training techniques are among the precious methods to estimate the engine performance and emission characteristics [15]. ANN and RSM have been selected by innumerable investigators to reduce the number of trails. Because of the accuracy and the potentiality to examine indiscriminate problems that will not have a chance of being solved by statistical and traditional techniques, ANN has become desirable for estimating various engine outcomes [16].

Safeddin Ardebili et al. [17] studied various engine parameters using RSM as an optimization strategy. In this approach, gasoline and fuel fuel have been tested at various ratios ranging from 25 to 75% with an interval of 25% in terms of volume basis. Prediction responses showed 4% of maximum evaluated error compared with that of experimental outcomes. Subsequently, it can be proved that the RSM models are fitted suitably for predicting performance and emissions of the test rig. In another study, Safeddin Ardebili et al. [18] employed a study of multi-objective optimization with RSM technique. Feasible operating conditions have been examined for various blends of fusel oil mixed with nanobiochar additive. In this investigation, speed of the engine varies from 1800 to 2600 rpm with an interval of 200 rpm, whereas the fusel oil blended with diesel fuel ranges from 5 to 20% with an interval of 5%, and the additive is added at various rates (25, 50, 75, 100, and 125 ppm). Speed of the engine, concentration of fuel oil, and additive have been considered as input responses for prediction analysis, whereas power, BSFC, torque, and various emissions were examined as output responses. At last, comparative analysis has been made in between prediction responses and experimental outcomes. The results depict that the feasible operating conditions for the additive (nanobiochar) were found at 2300 rpm speed and the engine fueled with 10% of fusel oil blended in 90% of diesel and 100 ppm biochar. Prediction analysis using RSM reveals the estimated error below 5%. Despite the fact that various approaches have been progressed to escalate the prediction accuracy of ANN model, the algorithm named feed forward back propagation is the notable one in this area [19]. Mainly, it consists of 3 layers (minimum) as input, hidden, and output layers. Each and every individual layer may include various nodes. Among all, both input and output layers require the particulars from the experimental statistics to create the network architecture and simulation of the system. Levenberg–Marquardt (Trainlm) training function has been practiced for error-free evaluation, in which mean square error decides the dereliction consequence of the network [20]. Most of the experimental investigations have been carried out on various engines with the application of ANN for optimizing the outcomes [21–25]. As time passes on, researchers may use various ceramic coatings to the combustion chamber, piston, etc., in order to improve the performance and reduce the emission with the enhancement of heat transfer rate in combustion reaction [26–30].

There have been innumerable investigations on internal combustion engines powered with Pongamia pinnata/Calophyllum inophyllum diesel blends. Moreover, no significant studies have been found from the literature related to predicting the engine outcomes using optimization techniques. Therefore, in the present study, ANN and regression models have been employed for optimizing and predicting the emission characteristics of a CI engine fueled with Pongamia pinnata and Calophyllum inophyllum oils. The originality of the current study is to compare the performance and emission parameters of CI engine with ceramic coated piston tested with novel blends with respect to the diesel outcomes. In addition, comparative analysis has been made in between two optimization models to predict the feasible (emission) responses with best working conditions of a CI engine; thereby, the % of average accuracy has been estimated.
2. Materials and Methods

In this study, Transesterification has been adopted as a filtration technique to prepare the pure biodiesel that has to be followed by esterification technique, as *Pongamia pinnata* and *Calophyllum inophyllum* oils are having high content of free fatty acids. Here, transesterification has been done by heating, followed by stirring of crude sample with an addition of NaOH as base catalyst and methanol. Gravitational technique has followed traditionally, in order to estrange glycerol content from biodiesel using distilled water after the chemical reaction and water wash isolation. Then, the methyl esters of *Pongamia pinnata* and *Calophyllum inophyllum* have been prepared as depicted in Figure 1.

These methyl esters have been blended with neat diesel under various proportions in terms of volume (P10, P20, C10, and C20) with magnetic stirrer setup. Again, these samples are added with an additive (butyl alcohol) in different probabilities varying from 6 to 12% in terms of volume with an interval of 6%. In the current study, n-butanol has been used as an additive (oxygenated), and it can easily react with diesel due to its high burning velocities. So, it seems to support the combustion possessed with sufficient amount of oxygen [7, 8, 10]. The nomenclature of the fuels was tested for analyzing the performance and emissions of engine expressed in Table 1. Initially, the properties of all blends are measured with various equipments before testing on an engine and are mentioned in Table 2.

3. Steady State Thermal Analysis

In the current study, statistical analysis has been done on a single cylinder, water cooled type, four-stroke, Kirloskar-TV1, and eddy current dynamometer CI engine with its piston made up of aluminum alloy using ANSYS workbench. This engine has power of 5.2kW at a configured speed of 1500 rpm. Here, the geometric compression ratio is 17.5:1. FEA approach has been implemented on traditional, ceramic glazed piston coated with a thickness of 200 µm topcoat. The particulars to the geometry configuration have been specified at modal section of the segment. The configuration has levant affix contiguity connecting topcoat-bond coats, piston rings-rings groove, and bond coat-membrane. In this manner, geometric modeling of piston has been done, followed by generating a fine meshing with default features considered in workbench settings as shown in Figure 2. The configured model consists of around 45,227 nodes with 27,174 elements.

The study of heat transfer in compression ignition engines is consistently treated as a prejudiced research domain because of complexity. In this study, convective heat transfer has been chosen as the main mechanism for examining the engine performance. Because of the following factors, it is difficult to study the heat transfer in CI engines:

1. Uninterrupted variation of gaseous temperatures has been found inside the cylinder
2. It is extremely difficult to identify the precise temperature levels and heat transfer coefficient

3.1. Uncoated Piston. Temperature distribution has been found for both coated and uncoated pistons using the FEA approach, as depicted in Figures 3 and 4.

3.2. Coated Piston. To simulate the model for temperature distribution, ANSYS, a mechanical finite element analysis computer software, has been chosen for thermal analysis at steady state. The range of temperatures found for an uncoated piston (without modification) has been found to be of a maximum of 350°C and minimum of 313.96°C, respectively. For a modified piston (ceramic coated at top surface), the temperatures were found to be of a maximum of 355°C and minimum of 323.85°C. Similarly, heat flux of uncoated and coated pistons is disclosed in Figures 5, and 6, respectively.

From the above steady state thermal analysis, plasma spray method has been chosen as a thermal spray coating method to apply the ceramic coating on piston with a thickness of 200 µm topcoat. The coated medium has been transformed into molten phase by means of heat, affects the membrane surface, and swiftly cools down to form coating [26–30]. For decreasing the vital aggregate of gas contamination discharged from engine, this study implies a piston coated with ceramic material for testing the biodiesels.

4. Experimental Engine Test Setup

In this study, the investigations are carried out on a single cylinder, water cooled type, four-stroke, direct injection CI engine with a ceramic coated piston equipped with a dynamometer of eddy current type to apply the load. Alumina has been used as a ceramic material for coating the piston with 200 µm thickness of top coat. A Compression Ignition (CI) engine with its piston coated with any ceramic material attains less heat loss, and it can be named as low heat rejection engine. In view of fuel price hikes and environmental depletion, this modified engine has gaining massive significance in the contemporary world, as it releases fewer emissions [26–30]. It was very well equipped, including combustion pressure and crank angle measurement. There is a provision to measure the flow of air and fuel, temperatures, etc. Here, calorimeter water flow and cooling water are measured by using Rotameters equipped. The engine test rig allows the elucidation of performance characteristics. The schematic representation of engine test bed is depicted in Figure 7. Engine soft package has been attached to assess the computerized performance. There is a provision for measuring injection pressure of fuel at the nozzle with computerized mode. The detailed specifications of engine test bed are described in Table 3. The gaseous emissions are recorded by AVL DI GAS 444N analyzer, and smoke density has been measured with AVL 437C Smoke Meter.
All the blends have been tested by varying the load (0%, 50%, and 100%) at a fixed speed of 1500 rpm with a rated compression ratio (17.5:1). Emissions and performance analysis are carried out on an engine once achieving the stable state. Prediction analysis has been done by considering the experimental data using mathematical modeling and ANN. Finally, a comparative analysis has been done in between the experimental outcomes and soft computing responses.

5. Results and Discussion

5.1. Exhaust Emission Parameters. The ever-increasing demand of petroleum refined products and the unpredictability in their availability may be a reason for the matter of global concern [1–3]. At present, global transformation from ignition engines to electric propulsion mainly depends on emissions. Emissions of diesel engines are inferior to gasoline; however, decreasing the emissions is essential, and the green initiative is necessary.

5.1.1. Nitrogen Oxides (NO\textsubscript{x}) Emission. NO\textsubscript{x} emission is considered as a major pollutant that requires rigorous diminution. These emissions may depend on in-cylinder temperature, air/fuel ratio, and reaction rate of oxygen in the blend. Generally, oxygenated additives produce high range of NO\textsubscript{x} emissions; it is happened only due to the fact that the amount of nitrogen in the air/fuel mixture reacted with the surplus amount of oxygen in the combustion chamber. Thereby, NO\textsubscript{x} emissions are developed in subsequent mechanism called Zeldovich mechanism [9]. But, here, as per the trend statistics of our study, it was clear that the blends of PPME and CIME were added with $n$-butanol additive forms comparatively lower than NO\textsubscript{x} with respect to conventional diesel. Irrespective of loads deployed, P10B12, C10B12, and C20B12 blends give lower emissions as illustrated in Figures 8(a) and 8(b). The researchers [7, 8, 10] revealed that this phenomenal reduction was possible with higher amount of $n$-butanol in the blend. It has occurred due to the consequence of lowering the temperature of $n$-butanol. Moreover, the aspects such as rise of dissipated heat and low heating value impact this nature and are superior at odds with their incompatible effects laid due to their lower cetane number compared with diesel [9].

5.1.2. Carbon Monoxide (CO) Emission. In general, CO emissions are developed if adequate quantity of oxygen is not intricate in an enzymatic reaction of combustion process, which may be due to low temperature and lack of oxygen. This resembles what was considered as a byproduct

| Sample  | Composition                                      |
|---------|-------------------------------------------------|
| D100    | 100% diesel                                      |
| P10B6   | 94% (10% PPME + 90% diesel) + 6% $n$-butanol     |
| P10B12  | 88% (10% PPME + 90% diesel) + 12% $n$-butanol    |
| P20B6   | 94% (20% PPME + 80% diesel) + 6% $n$-butanol     |
| P20B12  | 88% (20% PPME + 80% diesel) + 12% $n$-butanol    |
| C10B6   | 94% (10% CIME + 90% diesel) + 6% $n$-butanol     |
| C10B12  | 88% (10% CIME + 90% diesel) + 12% $n$-butanol    |
| C20B6   | 94% (20% CIME + 80% diesel) + 6% $n$-butanol     |
| C20B12  | 88% (20% CIME + 80% diesel) + 12% $n$-butanol    |
of deficient combustion of carbon. As depicted in Figures 9(a) and 9(b), the PPME and CIME related n-butanol blends exhibit lower CO emissions compared with diesel. Irrespective of loads applied, this reduction of CO emissions has been identified as an increase in the ratio of n-butanol in the blend [7, 8, 10]. The density of n-butanol is lesser than that of conventional diesel, which evaporates inside the cylinder; thereby, the length of spray atomization is decreased [9]. It results in reduction of CO emissions for n-butanol added blends. Moreover, the samples P10B12 and

### Table 2: Fuel properties of the tested samples.

| Sample  | Density (kg/m³) | Flash point (°C) | Fire point (°C) | Viscosity (cSt) | Calorific value (kJ/kg) |
|---------|-----------------|-----------------|----------------|----------------|------------------------|
| D100    | 830             | 56              | 65             | 3.21           | 42500                  |
| P100    | 898.7           | 165             | 180            | 2.46           | 35668                  |
| C100    | 896.8           | 156             | 166            | 2.85           | 35085                  |
| P10B6   | 851             | 59              | 69             | 3.10           | 41251                  |
| P10B12  | 854             | 60              | 71             | 3.14           | 40698                  |
| P20B6   | 856             | 62              | 73             | 3.19           | 40615                  |
| P20B12  | 858             | 65              | 75             | 3.21           | 40097                  |
| C10B6   | 849             | 56              | 67             | 3.01           | 41013                  |
| C10B12  | 850             | 58              | 68             | 3.10           | 40423                  |
| C20B6   | 852             | 60              | 71             | 3.12           | 40132                  |
| C20B12  | 854             | 63              | 72             | 3.17           | 39716                  |

![Figure 2: Meshed model.](image)

![Figure 3: Temperature distribution of uncoated piston.](image)
**Figure 4:** Temperature distribution of coated piston.

**Figure 5:** Heat flux of uncoated piston.

**Figure 6:** Heat flux of coated piston.
C10B12 exhibit lesser CO emissions among all, and compared with, diesel outcomes.

5.1.3. Carbon Dioxide (CO$_2$) Emission. Figures 10(a) and 10(b) exhibit the variation of CO$_2$ emissions with respect to load deployed on the engine fueled with various blends. Generally, the emissions such as CO and CO$_2$ exhibit trade-off effects with each other. This seems to represent that CO$_2$ gets reduced when CO increases. It should happen; if appropriate oxygen is accessible in the blend, CO$_2$ will appear due to oxidization of CO [9]. But, here, in our study, no significant variations are observed. Moreover, as per trend statistics, the samples P10B12 and C10B12 possess marginal decrease in CO$_2$ emissions.

5.1.4. Hydrocarbon (HC) Emission. Figures 11(a) and 11(b) represent statistics of unburned hydrocarbon emissions (HC) with respect to load deployed on an engine fueled with various blends. As per the literature in various research articles, it was evident that phenomenal rise of HC emissions for the blends is concentrated with high percentage of $n$-butanol [7, 8, 10]. In compression ignition engines, HC emissions evolved due to unburned fuel that is confined inside the combustion chamber. In addition, the fuel sprayed inside the combustion chamber reaches the cold cylinder walls that can be settled as unburned hydrocarbons [9]. In our study, HC emissions are gradually increasing with the increase in the amount of $n$-butanol in the blend. This may be because of the slow and poor-air fuel mixing, because of the rise of the evaporated heat levels of $n$-butanol,
5.1.5. Smoke/Opacity Emission. Opacity emission depicts the quantity of soot accumulation in the exhaust gases. Also, it occurs due to the result of unburned hydrocarbons and absorption of some biotic compounds. Moreover, their rate may depend on the nature of the fuel tested. It was noticed that opacity emissions are decreasing with the increase in the concentration of butyl alcohol in the blend as depicted in Figures 12(a) and 12(b) [7, 8, 10]. This trend may arise because of the presence of O2 molecules in the butyl alcohol [9].

Figure 8: (a). NOx vs load for PPME samples. (b). NOx vs load for CIME samples.

Figure 9: (a). CO vs load for PPME samples (b). CO vs load for CIME samples.

Figure 10: (a) CO2 vs load for PPME samples (b). CO2 vs load for CIME samples.
5.2. Performance Analysis. In general, performance parameters such as BP, BMEP, and BTE tend to increase or remain the same with an increase in load, whereas BSFC decreases; this trend is at par with general performance of diesel engines [2–6]. In this study, the performance analysis has been carried out by connecting the test rig with IC engine soft.

5.2.1. Brake-Specific Fuel Consumption. Figures 13(a) and 13(b) show the variation of BSFC as a function of load. Here, the analysis is done at a rated speed and constant compression ratio of the same engine; that is the reason why BSFC trend relies on the trend statistics of rate of mass flow of a blend. It has been noticed that BSFC slightly increases or remains the same for all biodiesel blends in comparison with the diesel outcomes. This is because of the lower energy content in the biodiesel samples than that of diesel [9]. From the literature [7, 8, 10], it has been revealed that this increase may depend on the percentile increment of n-butanol in the sample. Another reason behind this trend is lower calorific value of n-butanol rather than a neat diesel, in which the analysis is done at the same load only, and, also, due to discrepancies in turbulence level that may lead to high cycle by cycle combustion imbalance during preliminary phases of the combustion phenomenon [7, 8]. Although the piston has been coated with a ceramic material, n-butanol additive played an influencing factor in the trend statistics of brake-specific fuel consumption.

5.2.2. Mechanical Efficiency. In general, the content of diesel and additives is directly proportional to all the performance parameters like BP, BMEP, and BTE [2–6]. The higher the volume percentage of diesel and additives, the higher the performance of the engine. If volume percentage of bio-methyl esters increases, then the diesel, as well as n-butanol, ratio decreases in the biodiesel sample; hence, a marginal increase in performance is only observed in this investigation. During combustion process, the exhaust gas temperatures are higher for the engine with ceramic coated components than the engine under normal conditions [26–30]. When increased exhaust gases temperature is considered, it is obvious that turbocharging and consequently total thermal efficiency of the engine are increased. Otherwise, the higher the mechanical efficiency on an engine, the higher the volume % of n-butanol in the tested sample [7, 8, 10] (both for PPME and CIME) as noticed in Figures 14(a) and 14(b).
5.3. Prediction Analysis. In order to estimate the exhaust gas emissions, artificial intelligence tools such as ANN and regression analysis have been applied.

5.3.1. Analysis Using ANN. ANN is treated as soft computing strategy that can be assisted by the biotic neural system. The operating condition of neural networks is related to the activity of neurons in human brain, in which each activity transfers weight along with bias that can evolve one over another. ANN can be easily applied in various engineering aspects to sort out the issues in many applications, pointedly in the areas where traditional statistical techniques are not enough to apply. It constitutes three layers (minimum) such as input, hidden, and output layers [19]. ANN has been employed as a processing strategy to study the performance and gaseous emissions in the domain of biodiesels fueled in an engine at various working conditions [11–13, 15–18, 20–25]. In the current study, ANN was applied to estimate the emission gases such as CO, \( \text{CO}_2 \), NO\(_x\), HC, and smoke density for all blend samples. Feed forward backpropagation in combination with “TRAINLM” training function has been used as algorithm, and mean square error treated as performance function [11, 12, 19–25]. Here, the number of hidden layers was fixed to two, whereas, for every hidden layer, neurons are varied to observe the better network architecture, in which the number of epochs at which the feasible outcomes are achieved is 1500 (based on validation). Load depicted on the engine (L), volume % of diesel oil (D), volume % of PPME or CIME (P/C), and volume % of n-butanol (A) were chosen as inputs, and required exhaust gases are treated as targets [11–18]. Figure 15 shows the flow process of ANN.

5.3.2. Regression Analysis. In addition to ANN, Minitab software is peculiarly utilized to generate second-order regression mathematical models with the experimental data the same as done in ANN [26]. The generated equations (1)–(5) are used to predict various emissions of PPME blends, whereas equations (6)–(10) are for the CIME blends based on the inputs as shown below. The predicted values of regression and ANN for all the blend ratios are tabulated, and an average of each emission parameter is extracted.

\[
\text{NO}_x = -661 - 684D \times D - 4121P \times P - 677L \times L - 1642D \times A + 2157D \times L + 2339P \times L + 1409A \times L, \tag{1}
\]

\[
\text{CO} = 0.609 - 0.604D \times D - 3.94P \times P - 0.0150L \times L - 1.66D \times A - 0.0220D \times L - 0.0751P \times L + 0.0533A \times L, \tag{2}
\]

\[
\text{CO}_2 = 1.42 - 0.08D \times D + 4.4P \times P - 1.32L \times L - 0.77D \times A + 8.38D \times L + 7.68P \times L + 7.03A \times L, \tag{3}
\]

\[
\text{HC} = 73.9 - 81.7D \times D - 477P \times P + 22.0L \times L - 126D \times A + 13.0D \times L + 13.0P \times L - 29.7A \times L, \tag{4}
\]

\[
\text{opacity} = -12.7 + 20.9D \times D + 126P \times P + 27.2L \times L + 40D \times A + 30.2D \times L + 42.3P \times L - 26.1A \times L, \tag{5}
\]

\[
\text{NO}_x = -889 + 1073D \times D + 7579C \times C - 831L \times L - 2244D \times A + 2291D \times L + 2416P \times L + 1718A \times L, \tag{6}
\]

\[
\text{CO} = 0.061 + 0.147D \times D + 0.74C \times C + 0.0050L \times L + 0.03D \times A - 0.0535D \times L + 0.0032C \times L + 0.038A \times L, \tag{7}
\]

\[
\text{CO}_2 = 5.59 - 4.77D \times D - 25.3C \times C - 1.27L \times L - 11.1D \times A + 8.77D \times L + 7.25C \times L + 4.29A \times L, \tag{8}
\]

\[
\text{HC} = 17.4 - 19.6D \times D - 13C \times C + 24.5L \times L + 2D \times A + 16.1D \times L - 11.2C \times L + 20.3A \times L, \tag{9}
\]

\[
\text{opacity} = 11.7 - 7.3D \times D - 38C \times C + 27.5L \times L - 21.1D \times A + 31.6D \times L + 41.2C \times L - 31.2A \times L. \tag{10}
\]
Predicting CO, CO2, NOx, HC, and smoke emissions

New input (P/C)
New input (L)
New input (A)
New input (D)

Part 1
Input (P/C)
Input (D)
Input (A)
Input (L)

Part 2
Trained ANN
Tested ANN
Predicting CO, CO2, NOx, HC, and smoke emissions

Part 3
Accuracy control
Save
sufficient
Not sufficient

Figure 15: Process chart of ANN.

Figure 13: (a) BSFC vs load for PPME samples. (b), BSFC vs load for CIME samples.

Figure 14: (a) Mech. eff. vs load for PPME samples. (b). Mech. eff. vs load for CIME samples.

Figure 16: (a). Prediction chart for PPME blends. (b) Prediction chart for CIME blends.
6. Conclusion

In this study, ANN and regression analysis have been incorporated in order to optimize the working parameters of CI engine with its piston coated with ceramic material and fueled with various novel blends. Various influencing factors such as load depicted on the engine and n-butanol concentration on exhaust gas emissions were examined. Due to increased combustion chamber temperature of ceramic coated engine, phenomenal reduction in soot and carbon monoxide emissions has been noticed. However, n-butanol additive plays an influencing factor in the trend statistics, rather than the coating applied on the piston. Second-order multiregression model for each parameter is developed, and, on the other hand, the combined effects of input characteristics on engine emissions are deeply discussed. Based on the experimental investigation, the following diagnoses are made:

(1) The existing CI engine modified with its ceramic coated piston works satisfactorily with biodiesel fuels, and the results show that it can produce less emission and improves performance.

(2) Significant improvement was found in mechanical efficiency of the engine tested with various n-butanol blends, whereas brake-specific fuel consumption slightly increases with the increase in the concentration of n-butanol in the blend sample. This is due to the lower heating value of n-butanol compared with diesel fuel.

(3) Emission parameters such as NOx, CO, and smoke have been significantly reduced, irrespective of loads deployed on the brake drum of an engine operated with n-butanol blends. The higher this reduction, the higher the amount of n-butanol in the sample.

(4) No significant variations were found in the statistics of CO2 emissions. On the other side, HC emissions have been increased drastically due to cushioning and flame quenching effect.

(5) By using ANN, 92.20–97.95% of an overall average accuracy was predicted for all emission parameters, whereas it was 80.81–97.03% by regression. Under all the circumstances, instead of the diesel fueled engine, the engine tested with P10B12 and C10B12 fuels gives optimistic responses.

Abbreviations:

ANN: Artificial neural networks
BMEP: Brake mean effective pressure
BP: Brake power
BSFC: Brake-specific fuel consumption
BTE: Brake thermal efficiency
CI: Compression ignition
CIME: Calophyllum inophyllum methyl ester
CO: Carbon monoxide
CO2: Carbon dioxide
DI: Direct injection

FAME: Fatty acid methyl esters
H2SO4: Sulfuric acid
HC: Unburned hydrocarbons
NaOH: Sodium hydroxide
NOX: Oxides of nitrogen
PPME: Pongamia pinnata methyl ester
RSM: Response surface methodology.

Data Availability

The data used to support the findings of this study are included within the article.

Disclosure

This study was performed as a part of the employment at Arba Minch University, Ethiopia.

Conflicts of Interest

The authors declare that there are no conflicts of interest.

References

[1] M. Chaker Ncibi and M. Sillanpaa, “Recent research and developments in biodiesel production from renewable bioresources,” Recent Patents on Chemical Engineering, vol. 6, no. 3, pp. 184–193, 2013.

[2] B. R. Aravindh Raj, P. Jeyaraman, N. Tamil Selvam, and K. Arun Kumar, “Performance and emission evaluation of a VCR diesel engine using mahua oil methyl ester,” International Journal of Mechanical Engineering & Technology, vol. 9, no. 3, pp. 143–155, 2018.

[3] S. Ashraf, M. Hussain, M. W. Mumtaz, and M. Shuaib, “Biodiesel production by alkali catalyzed transesterification of chicken and beef fats,” International Journal of Alternative Fuels and Energy, vol. 1, no. 1, pp. 14–20, 2017.

[4] S. K. Karmee and A. Chadha, “Preparation of biodiesel from crude oil of Pongamia Pinnata,” Bioresource Technology, vol. 96, no. 13, pp. 1425–1429, 2005.

[5] K. Sureshkumar, R. Velraj, and R. Ganesan, “Performance and exhaust emission characteristics of a CI engine fueled with Pongamia Pinnata methyl ester (PPME) and its blends with diesel,” Renewable Energy, vol. 33, no. 10, pp. 2294–2302, 2008.

[6] P. L. Naik and D. C. Katpatal, “Performance analysis of CI engine using Pongamia Pinnata (Karanja) biodiesel as an alternative fuel,” International Journal of Science and Research, vol. 2, pp. 445–454, 2013.

[7] D. C. Rakopoulos, C. D. Rakopoulos, E. G. Giakoumis, A. M. Dimaratos, and D. C. Kyritsis, “Effects of butanol-diesel fuel blends on the performance and emissions of a high-speed DI diesel engine,” Energy Conversion and Management, vol. 51, no. 10, pp. 1989–1997, 2010.

[8] K. Nanthagopal, B. Ashok, B. Saravanan, D. Patel, B. Sudarshan, and R. Aaditya Ramasamy, “An assessment on the effects of 1-pentanol and 1-butanol as additives with Calophyllum Inophyllum biodiesel,” Energy Conversion and Management, vol. 158, pp. 70–80, 2018.

[9] P. Ramakrishnan, R. Kasimani, M. S. Peer, and S. Rajamohan, “Assessment of n-pentanol/calophyllum inophyllum/diesel blends on the performance, emission, and combustion characteristics of a constant-speed variable compression ratio
Advances in Materials Science and Engineering

direct injection diesel engine,” *Environmental Science and Pollution Research*, vol. 25, no. 14, pp. 13731–13744, 2018.

[10] S. Imtenan, H. H. Masjuki, M. Varman, and I. M. Rizwanul Fattah, “Evaluation of n-butanol as an oxygenated additive to improve combustion-emission-performance characteristics of a diesel engine fuelled with a diesel-calyphyllum inophyllum biodiesel blend,” *RSC Advances*, vol. 5, no. 22, pp. 17160–17170, 2015.

[11] S. Uslu and M. B. Çelik, “Prediction of engine emissions and performance with artificial neural networks in a single cylinder diesel engine using diethyl ether,” *Engineering Science and Technology, An International Journal*, vol. 21, no. 6, pp. 1194–1201, 2018.

[12] S. Uslu, “Optimization of diesel engine operating parameters fueled with palm oil-diesel blend: comparative evaluation between response surface methodology (RSM) and artificial neural network (ANN),” *Fuel*, vol. 276, Article ID 117990, 2020.

[13] M. Aydin, S. Uslu, and M. B. Çelik, “Performance and emission prediction of a compression ignition engine fueled with biodiesel-diesel blends: a combined application of ANN and RSM based optimization,” *Fuel*, vol. 269, Article ID 117472, 2020.

[14] P. R. Ganji, R. K. V. Raju, and S. S. Rao, “Computational optimization of biodiesel combustion using response surface methodology,” *Thermal Science*, vol. 21, no. 1, pp. 465–473, 2017.

[15] R. K. Mehra, H. Duan, S. Luo, A. Rao, and F. Ma, “Experimental and artificial neural network (ANN) study of hydrogen enriched compressed natural gas (HCNG) engine under various ignition timings and excess air ratios,” *Applied Energy*, vol. 228, pp. 736–754, 2018.

[16] F. Yang, H. Cho, H. Zhang, J. Zhang, and Y. Wu, “Artificial neural network (ANN) based prediction and optimization of an organic Rankine cycle (ORC) for diesel engine waste heat recovery,” *Energy Conversion and Management*, vol. 164, pp. 15–26, 2018.

[17] S. M. Safieddin Ardebili, H. Solmaz, and M. Mostafaei, “Optimization of fusel oil–gasoline blend ratio to enhance the performance and reduce emissions,” *Applied Thermal Engineering*, vol. 148, pp. 1334–1345, 2019.

[18] S. M. Safieddin Ardebili, A. Taghipoor, H. Solmaz, and M. Mostafaei, “The effect of nano-biochar on the performance and emissions of a diesel engine fueled with fusel oil-diesel fuel,” *Fuel*, vol. 268, Article ID 117356, 2020.

[19] G. Li and J. Shi, “On comparing three artificial neural networks for wind speed forecasting,” *Applied Energy*, vol. 87, no. 7, pp. 2313–2320, 2010.

[20] M. Deb, P. Majumder, A. Majumder, S. Roy, and R. Banerjee, “Application of artificial intelligence (AI) in characterization of the performance-emission profile of a single cylinder CI engine operating with hydrogen in dual fuel mode: an ANN approach with fuzzy-logic based topology optimization,” *International Journal of Hydrogen Energy*, vol. 41, no. 32, pp. 14330–14350, 2016.

[21] I. M. Yusri, A. P. P. Abdul Majeed, R. Mamat, M. F. Ghazali, O. I. Awad, and W. H. Azmi, “A review on the application of response surface method and artificial neural network in engine performance and exhaust emissions characteristics in alternative fuel,” *Renewable and Sustainable Energy Reviews*, vol. 90, pp. 665–686, 2018.

[22] B. Ghabidian, H. Rahimi, A. M. Nikbakht, G. Najaﬁ, and T. F. Yusaf, “Diesel engine performance and exhaust emission analysis using waste cooking biodiesel fuel with an artificial neural network,” *Renewable Energy*, vol. 34, no. 4, pp. 976–982, 2009.

[23] M. Taghavi, A. Ghareghani, F. B. Nejad, and M. Mirsalim, “Developing a model to predict the start of combustion in HCCI engine using ANN-GA approach,” *Energy Conversion and Management*, vol. 195, pp. 57–69, 2019.

[24] K. Atik, N. Kahraman, and B. Ceper, “Prediction of performance and emission parameters of an SI engine by using artificial neural networks,” *Journal of Thermal Sciences and Technology*, vol. 33, 2013.

[25] D. Kakati, S. Roy, and R. Banerjee, “Development of an artificial neural network based virtual sensing platform for the simultaneous prediction of emission-performance-stability parameters of a diesel engine operating in dual fuel mode with port injected methanol,” *Energy Conversion and Management*, vol. 184, pp. 488–509, 2019.

[26] S. Yessian and P. A. Varthan, “Optimization of performance and emission characteristics of catalytic coated ic engine with biodiesel using Grey-Taguchi method,” *Scientific Reports*, vol. 10, no. 1, pp. 2129–2213, 2020.

[27] W. Koszela, P. Pawlus, R. Reizer, and T. Liskiewicz, “The combined effect of surface texturing and DLC coating on the functional properties of internal combustion engines,” *Tribology International*, vol. 127, pp. 470–477, 2018.

[28] P. Ponnusamy, R. Subramaniam, and N. Nedunchezian, “An experimental study on the effect of EGR on performance and emission on four stroke SI engine with various catalytic coatings,” *International Journal of Elixir Thermal Engineering*, vol. 43, pp. 6586–6589, 2012.

[29] M. Azadi, M. Baloo, G. H. Farrahi, and S. M. Mirsalim, “A review of thermal barrier coating effects on diesel engine performance and components lifetime,” *Autmotive Science and Engineering*, vol. 3, 2013.

[30] S. Soundar, P. Anand, and V. Ramesh, “Improving thermal efficiency of diesel engine by using ceramic coating on cylinder liner and piston head,” *International Journal of Mechanical Engineering & Technology*, vol. 8, pp. 834–845, 2017.