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Prediction of CI Engine Performance and Emission Characteristics Powered by WPO and Diesel Fuel Blends by ANN

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Abstract

The emissions and operational performance characteristics of a four-stroke compression ignition engine employing a mixture of pure diesel and catalytic pyrolysis oil obtained from municipal plastic waste. In the current study, a framework of an Artificial Neural Network (ANN) is employed to simulate. The maximum amount of oil produced at 350°c - 500°c. The liquid fuel that was produced physical characteristics were like those of diesel, such as density (790 kg/m^3) and calorific value (39.6 mj/kg) which helped the fuel blend burn more completely and effectively, improving performance and combustion characteristics. an Artificial Neural Network (ANN) model was built and used to anticipate emission characteristics (smoke, hc, co, nox) and performance metrics including (brake power, brake thermal efficiency and brake specific fuel consumption) for inputs parameters load and volume of selected blends. for the most accurate prediction of emissions and performance parameters the back-propagation algorithm was employed. The regression coefficients (r^2) of 0.99801, 0.9983, 0.95753, and 0.97467 for bthe, bsfc and emission, which were extremely close to 1. According to the research work, an unmodified diesel engine might run on a blend of the suggested alternate fuel and diesel blend. Additionally, it indicates that artificial neural networks are helpful in modelling and predicting the emissions or performance of wpo in diesel engines, which may lead to the use of wpo30 fuel in automotive engines.

***Major Finding:** ANN is a powerful tool for modelling the performance parameters of ci engine powered by waste plastic oil-diesel fuel blends. It proved the strong correlation between the predictions made by ANN and actual experimental data in modeling of new fuel in ci engine.*

Keywords: *ANN Prediction, CI Engine, Municipal Plastic Oil, Performance Parameter*

1.0 Introduction

Worldwide, there are 1.0 billion light-duty cars and approximately 320 million trucks on the road. By 2040, it is expected that the numbers will exceed 1.7–1.9 billion, with india expected to have a notable increase in growth. internal combustion engines are the industry's mainstay now, although future technology is unclear[1]. There is widespread use of internal combustion engines in power generation, transportation and agriculture. Utilization of fossil fuels derived from petroleum in ic engine has resulted in several issues, including air pollution, environmental damage, health issues for humans and other biological species and global economic difficulties. consequently, significant efforts are being made to reduce combustion engine exhaust emissions. gasoline and diesel fuels which are extensively utilized within the automotive sector and are recognized as the

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primary agents of climate change and detrimental to the ecosystem[2]. To address the increasing need for energy while minimizing the environment's detrimental effects of fossil fuels, it is imperative that emphasize the use of alternative or renewable energy sources. Numerous studies have been conducted to identify alternative fuels that might potentially decrease and substitute traditional fuels in an internal combustion engine[3]. These fuels are currently undergoing testing to determine their optimal performance and emissions characteristics.

This work presents blending of diesel with fuels derived from municipal plastic waste through catalytic co-pyrolysis of waste plastics chosen for alternative fuelling in compression-ignition engines. The impact of mixing waste plastic oil with diesel fuel on brake power, bsfc, bthe and emissions were investigated through experiments conducted on various combinations in a compression ignition engine. when utilizing mixes of pyrolytic oil and diesel fuel for the ci engine. experimental process requires a significant amount of time and financial resources[4,5]. To avoid this, ANN model is used with explicit aim to predict and evaluate outcomes in relation to changes input factors. ANN effectively utilized in this work to predict the outcomes of performance and emission characteristics. When compared to traditional polynomial methods, ANN offers several benefits because it is less difficult, expensive, and time-consuming. an artificial neural network, or ANN, was used to predict and adjust the chosen output parameters.

The ANN technique is used to fit a non-linear complex connection. The use of ANNn in predictive modelling intended for complex non-linear systems has attracted significant attention. This is due to the ANN's ability to approximate non-linear data using a variety of functions. ANN have been employed to predict several performance and emission metrics, including brake power, bthe, bsfc, Hydrocarbon (Hc) emissions, Carbon Monoxide (CO) emissions, Nitrogen Oxides (NO_x) emissions and smoke intensity. In addition to this, forecasts have been made for the bsfc, bthe and emissions for ci engine using different fuel blends such as wpo10, wpo20, wpo30 and wpo40. this study, we tested four different selected blends combinations of diesel and pyrolytic fuel blend on ci engine due to its best performance in terms of selected parameters. We collected experimental data on the engine's relevant inputs and used this data to train a neural network, a trained network that is beneficial for forecasting blended fuel performance and emissions.

2.0 Materials and Procedures

The data presented in this study are the outcomes of actual experiments carried out in the research and development laboratory in the automobile engineering department. The tests were conducted using different combinations of waste plastic oil and diesel fuel to examine the operation of a single-cylinder, four-stroke diesel engine.

2.1 Preparation of Catalytic Pyrolysis Oil

Within the scope of this research, specific municipal plastic wastes were pyrolyzed using catalysts in a thermo-catalytic manner to create test fuels. The process of dissolving heat without the presence of oxygen is called pyrolysis. by using silica-alumina as a catalyst[6]. Wpo is produced. the brown-black waste plastic oil sample is shown in Figure 1. The properties of Wpo include being a secure, non-hazardous, environmentally degradable, and sustainable fuel that can be effortlessly utilised in unmodified diesel engines[7,8]. A measured quantity of commercially available diesel fuel and wpo (volume basis)



Figure 1. Waste plastic oil sample.

was taken in a container. Using a mechanical stirrer, the blend was stirred at higher speed (1400-1500) rpm for 30 min. blends of diesel fuel made by mechanical stirring are added after the wpo is produced. Wpo10 means, 10% wpo and 90% diesel fuel make up the blend sample that was left over after testing was completed. A different blend sample of diesel fuel with wpo selected as ratios of 10–40 percent and utilised as fuel for the experimental design on ci engine.

2.2 Experimental Investigation

The experimental configuration comprises a single diesel engine. Figures 2 and 3 display the configuration of a conventional CI engine powered by diesel and blended fuels. engine has been synchronized manually with an eddy current dynamometer to set the load from 0% to a maximum of 120%. The technical specifications of the engine test configuration are shown in Table 1. The speed was 1500 Revolutions Per Minute (RPM) to use the data for current work. measurements were conducted on many variables including brake power, brake thermal efficiency, volumetric efficiency and emissions were measured.

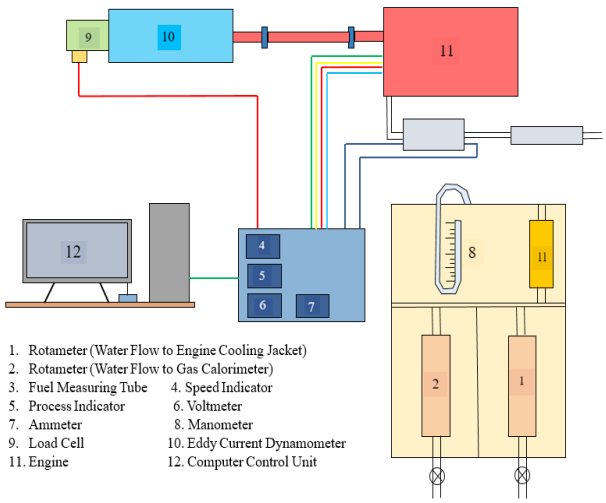


Figure 2. Experimental test setup configuration.

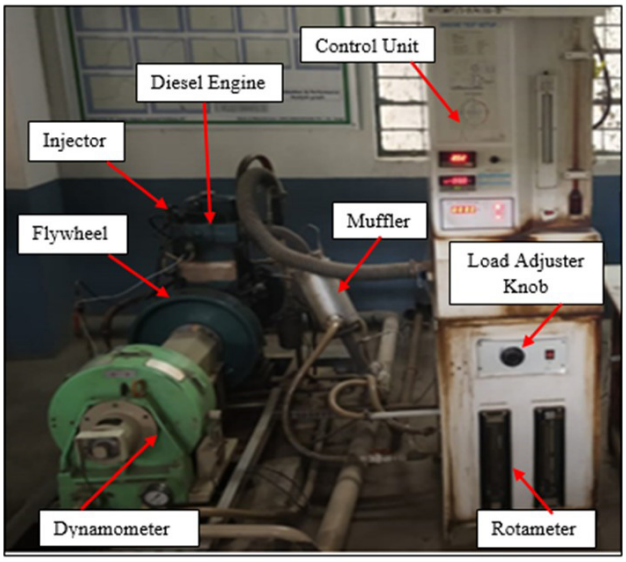


Figure 3. Photographic view of test setup.

Table 1. Technical details of setup

Parameters	Specifications
Engine Make and Type	Kirloskar made, 1- Cylinder, Four Stroke
Bore	87.5 mm
Stroke	110 mm
Power	5.2 kw @ 1500 rpm
Cooling	Water Cooled
Compression Ratio	17.5 :1
Dynamometer Type	Eddy Current Dynamometer
Calorimeter Type	Pipe in Pipe Type Calorimeter
Temperature Sensors	k-Type Thermocouple and RTD (pt100)

2.3 Artificial Neural Network Technique

A relatively recent development is the use of artificial neural network techniques to simulate internal combustion engine operation. This methodology is employed to forecast the efficiency and emissions of diesel engines[9,10].

Another name for an ANN is a neural network, the structure and operational characteristics of biological brain networks are intended to be replicated by this mathematical model. An ANN is self-possessed interconnected artificial neurons which utilize the connectionist computing paradigm to process information[11]. The input layer, hidden layer and output layer are the three primary layers of an artificial neural network[12].

The influence of an input set or another processing element on a processing element in a preceding layer is described by the weights (w1, w2, wn). The summing function aggregates the data by multiplying each input value with its corresponding weight value and then combining them with[13] signals are emitted from the input layer and travel through one or more concealed layers before reaching the output layer. The weights (xj) are multiplied by the incoming signals or input (wij), which is then added to the bias (wbi) contribution. The summation function is defined by Equation 1.

$$NETi = \sum_{j=1}^{n} w_{ij} x_j + wb_i \quad (1)$$

A neuron's output is calculated using Equation 1, after its entire input is subjected to an activation function. The activation function curvilinearly matches the input and output layers. It also processes the net input of the cell to determine its output. the performance of the network is greatly impacted by the activation function choice.

To forecast the performance parameters of bsfc, bte and brake power as well as the emission characteristics smoke, hc, CO and NO_x in this research work, chosen input factors were the load and percentage of blends. The inaccuracy that occurs throughout the learning process is referred to as root-mean squared[14]. To obtain the most accurate prediction from the network, various topologies were assessed and trained based on the experimental findings. back-propagation approach employed to train artificial neural network model.

2.4 Findings and Conversation

The subsequent sections discuss the outcomes gained form engine performance including bsfc, bthe, brake power and emission characteristics (hc, CO, NO_x and smoke) of the produced blended with diesel fuel. This section provides a detailed discussion on the estimation of performance parameters for an experimental testing of engine, using several graphs.

2.4.1 Brake Power Performance

Figure 4 illustrates fluctuation in brake power for diesel and wpo mixes under different loads.

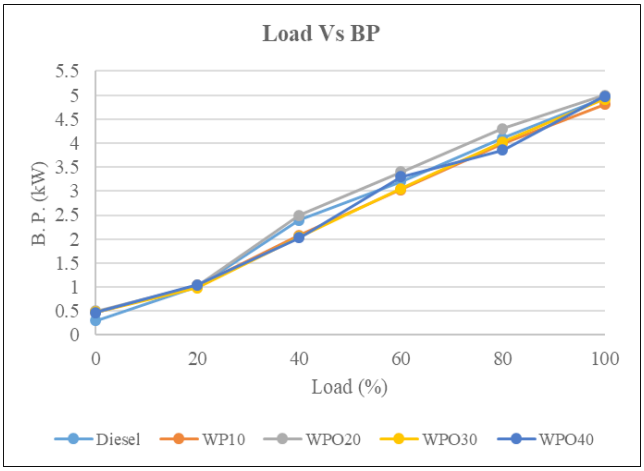


Figure 4. Load vs brake power.

At zero load (0%), the brake power for diesel fuel (wpo0) ranges from 0.25 kw to 4.88 kw. wpo100 brake power, on the other hand, ranges from 0.47 to 4.98 kw. furthermore, brake power is comparable to diesel fuel at 75% full load and wpo20. better blend atomization, which releases more heat energy than diesel, may be the cause of this[15]. diesel fuel has a lower boiling point than wpo20 fuel blends made from waste plastics. wpo 20 blends exhibit the highest bp of all engine loads mentioned while keeping a steady speed.

2.4.2 Brake Thermal Efficiency Performance

Figure 5 displays the braking heat output for diesel and wpo blends at various loads. when associated to standard fuel, the graph indicates that wpo has a slight improvement in break thermal efficiency. Diesel fuel has a thermal efficiency of 30.08% when fully loaded, wpo20

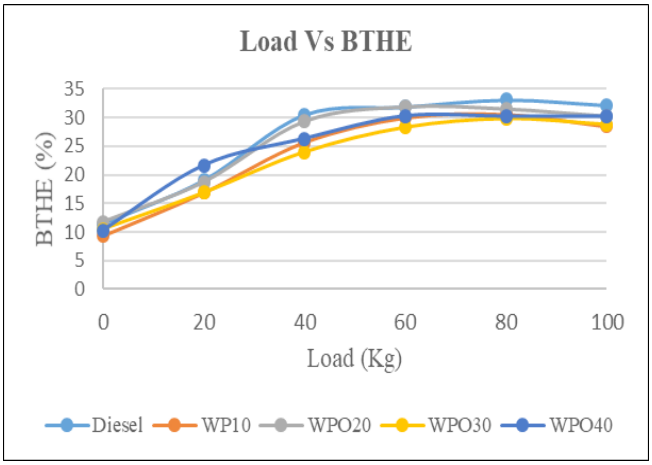


Figure 5. Load vs bthe.

blend outperforms all other combinations, with a 30.23% increase in efficiency that is most apparent under fully loaded conditions. The brake thermal efficiency rises with higher conversion rates and lower heat loss when the load is raised[16].

2.4.3 Bsfc Performance

Figure 6 presents the bsfc for different loads of wpo and diesel fuel mixtures. It was observed that bsfc dropped as soon as the load increased. The bsfc of diesel is 0.75 kg/kwh under no load conditions and 0.27 kg/kwh under full load conditions. The highest value of wpo50 is 0.29 kg/kwh when operating at full load, while it's no-load value is 0.82 kg/kwh. When compared to diesel, the bsfc for wpo20 dropped by 6% at 40% load condition, and this

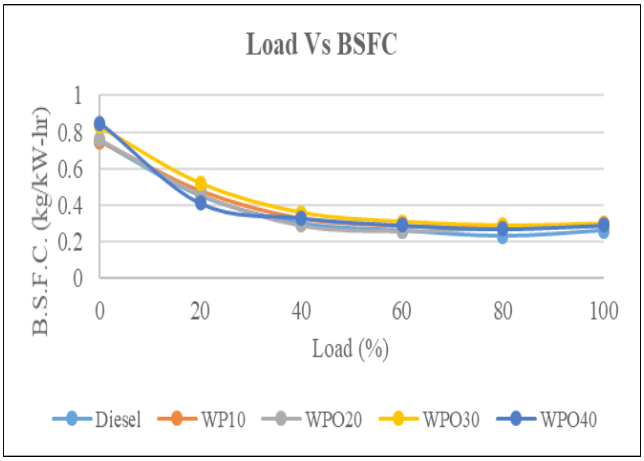


Figure 6. Load vs. bsfc

trend remained relatively consistent at full load. Found that, in comparison to full load conditions, the decline in bsfc was more pronounced at lower load.

2.4.4 CO Emission

The CO emissions for various test fuels and engine loads are displayed in Figure 7.

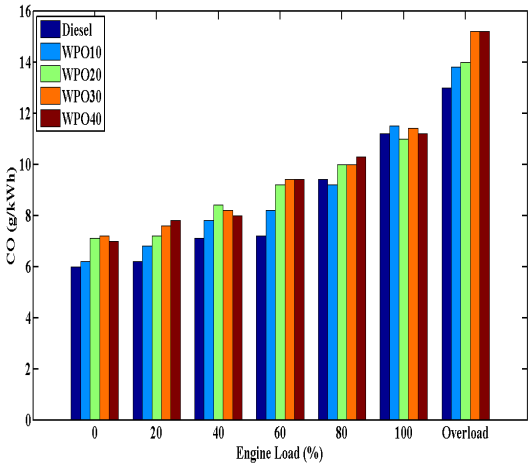


Figure 7. Load vs CO emission.

For all test fuels, engine CO emissions rise as load increases[17]. wpo10 exhibits the lowest average CO emissions of all the wpo blends. diesel emits an average of 8.58 g/kwh of CO at all engine loads; for the wpo10, wpo20, wpo30, and wpo40 blends, this increased to 9.07 g/kwh, 9.57 g/kwh, 9.86 g/kwh, and 9.84 g/kwh respectively. the increased emission of CO at maximum load could be attributed to higher fuel consumption. low oxygen levels in wpo's hydrocarbon and inadequate fuel mixing capacity cause incomplete combustion, which raises CO emissions.

2.4.5 Hc Emission

Figure 8 illustrates how engine load affects hydrocarbon (hc) emissions for various test fuels. at higher loads, there is a significant increase in hydrocarbon emissions due to incomplete combustion and oxygen shortage[18]. This leads to incomplete fuel combustion, which releases greenhouse gases.

Conversely, greater power demands at higher loads necessitate a greater fuel quantity, which results in a

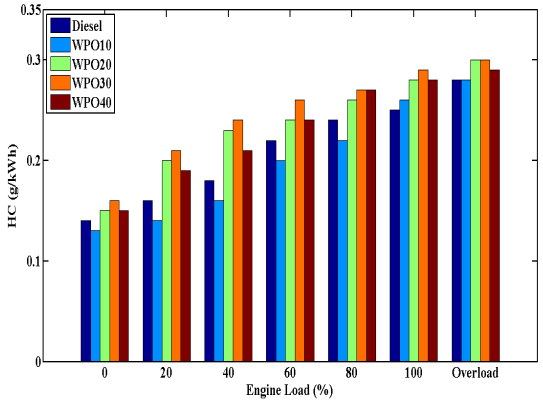


Figure 8. Load vs hc emission.

richer mixture at higher loads. diesel produces average uhc emissions of 0.21 g/kwh, wpo10 produces 0.198 g/kwh, wpo20 produces 0.237 g/kwh, wpo30 produces 0.247 g/kwh, and wpo40 produces 0.233 g/kwh.

2.4.6 NO_x emission

Figure 9 displays the amount of NO_x emissions emitted by the engine at varying engine loads, using various test fuels. experimental findings indicate that NO_x emissions exhibit an upward trend when engine load escalates from no load to full load, as well as during engine overload. More fuel is needed when the engine is running harder,

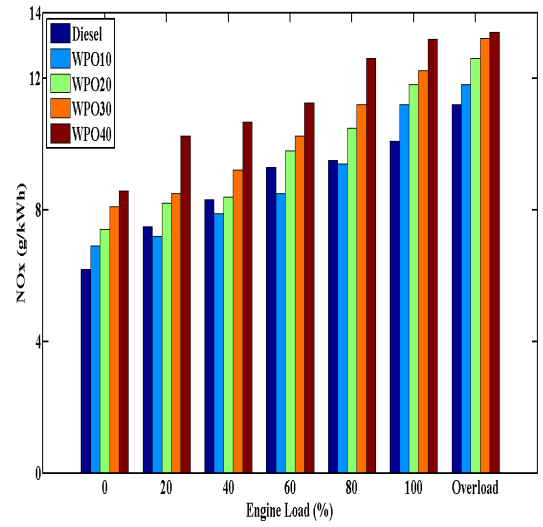


Figure 9. Load vs nox emission.

which increases the cylinder temperature and releases NO_x emissions. 8.87 g/kwh for diesel, 8.98 g/kwh for wpo10, 9.81 g/kwh for wpo20, 10.38 g/kwh for wpo30, and 11.42 g/kwh for wpo40 blend are the average NO_x emissions from the engine. engines utilizing a wpo40 blend were found to release significantly higher levels of no_x. increasing the proportion of wpo blend in diesel fuel resulted in a rise in NO_x emissions.

2.4.7 Smoke Intensity Emission

The phenomenon of smoke is exclusively constituted of particulate matter in the form of solid soot that is maintained in a state of suspension within the gaseous emissions[19]. Figure 10 shows the smoke emission from the engine for various fuels as the operational demand on the engine escalates, it measured in Bosch Smoke Units (bsu).

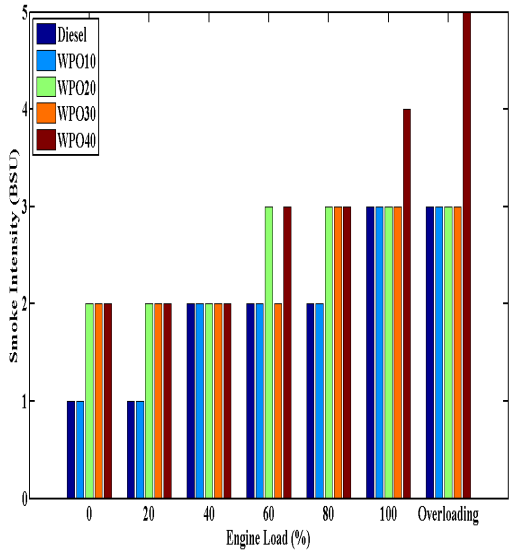


Figure 10. Load vs smoke intensity.

It is evident that when the load on engine increases, the extent of smoke emissions also intensifications. engine emits an average of 2 bsu of smoke with diesel and wpo10, 2.57 bsu with wpo20, 2.43 bsu with wpo30, and 3 bsu with wpo40. It is evident that diesel emits less smoke than wpo mixes. The lack of a homogenous amalgamation of fuel and air within the engine cylinder constitutes the fundamental reason for this predicament. but at higher load ranges, there was a noticeable white smoke emission

since there wasn't enough air present and the combustion was irregular[20, 21].

3. ANN Modelling for Prediction of Performance

Four distinct formulations of Waste Plastic Oil (WPO) blended with pure diesel fuel (wpo10, wpo20, wpo30, and wp40) were investigated within a four stroke ci engine and the resultant data was employed to calibrate a predictive neural network model. the emissions and performance metrics were utilized to construct an effective neural network architecture. This neural network framework was developed to forecast the outcomes of the ci engine assessments utilizing the feed-forward back-propagation technique, which was trained on the datasets amassed from the experimental trials. in this model, 85% of the dataset was randomly designated as the training set, while the remaining 15% was allocated for prediction and validation purposes[22].

To assess the accuracy and effectiveness of the ANN technique, the only variable that can be changed is the number of neuron units in the hidden layer. The only variable that can be modified is the number of neurons in the hidden layer[23]. Figure 11 shows the training phase of neural network which indicated the required time, performance and number of epochs.

The next sections provide an analysis of the predicted results obtained from the Artificial Neural Network (ANN) modelling for bthe, bsfc, brake power no_x, co, hc and smoke intensity.

3.1 Modelling of ANN for Performance Parameter

The mse for the training of algorithm using bthe results is found to be very low, with values of 0.9987 for training, 0.99874 for validation and 0.9567 for testing r^2-value, which indicates the accuracy of the neural model in predicting wpo performance, is obtained 1 for all phases. This concludes that the training of the neural model was successful for all blends. through mathematical modelling, the coefficient of determination (r^2) which is specified below, is used to determine the ANN's performance. Through mathematical modelling, the performance of the ANN was ascertained using the coefficient of determination (r^2), which is defined below[24].

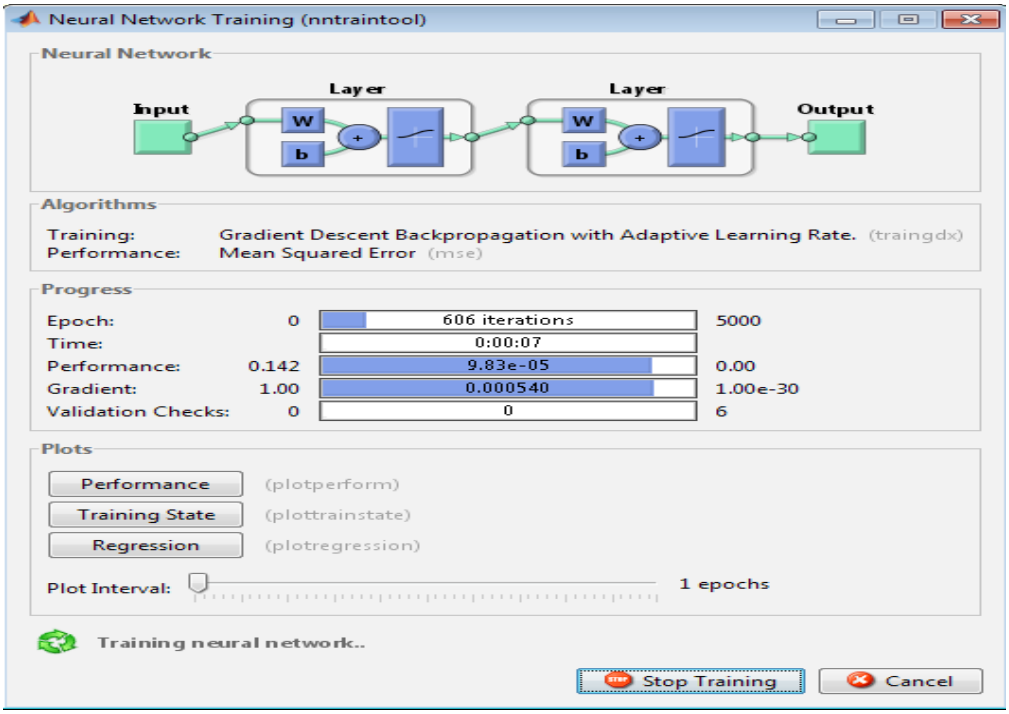


Figure 11. Training phase of neural network.

$$R^2 = 1 - \sum_{i=1}^{n} \left(\frac{(y_{ei} - y_{pi})^2}{(y_m - y_{pi})^2} \right) \quad (2)$$

Where y_{ei} actual output value, y_{pi} predicted output value, and y_m average experimental output value and n number of experimental dataset. mean squared error (mse) values obtained for predicting bsfc were relatively low. mse values were 1.09863e-06 for training, 1.9632e-04 for testing, and 4.3562e-04 for validation. a consistent trend of higher bthe, bsfc and brake power was seen as the load increased, across all selected blends. This is because

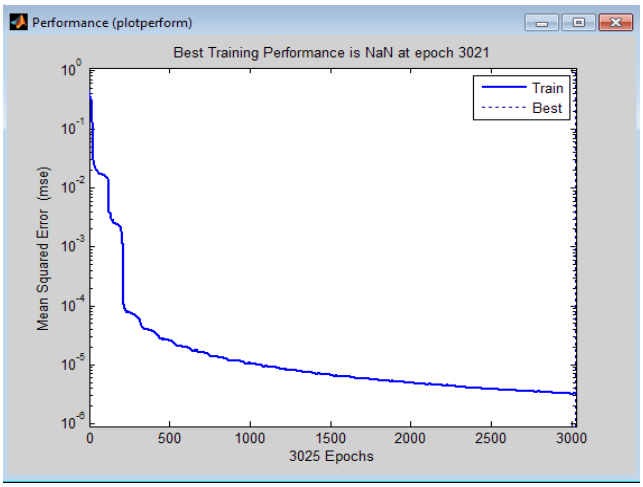


Figure 12. Prediction performance of neural network.

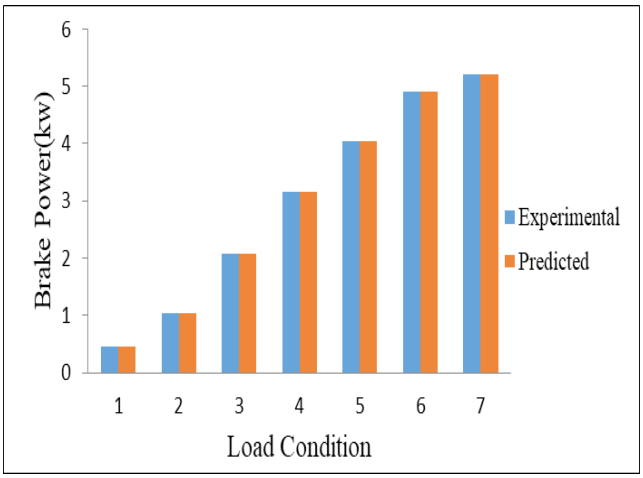


Figure 13. Correlation between experimental with predicted results of bp.

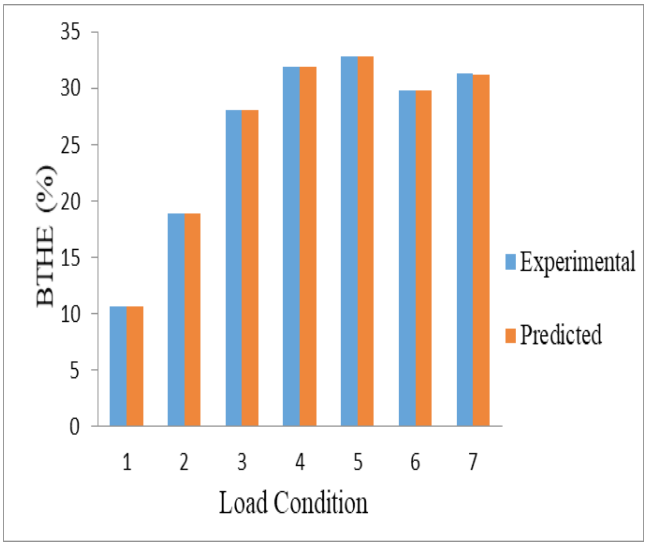


Figure 14. Relationship between experimental and predicted results of bthe.

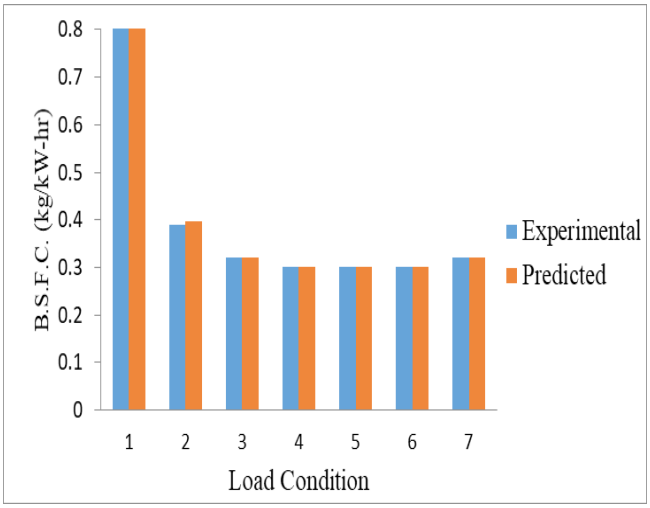


Figure 15. Correlation between experimental with predicted results of bsfc.

of higher load conditions. The training for the bte, bp, bsfc and all selected emission forecast were successful, within the 3021 epoch cycles. the training achieved the lowest possible Mean Squared Error (MSE) value closer to one, as depicted in Figure 12. in addition, the prediction error summary for each parameter is discussed following graph. The error histogram exhibited a uniform distribution, implying few mistakes during computation. Additionally at 3025 epochs, the prediction validation performance peaked. achieving the least possible mean squared error of 0.99987.

Figures 13, 14 and 15 display the comparison results of wpo30 for both experimental and prediction result of trained network. It displayed a comparative analysis of a subset of the engine's performance metrics for the wpo30 at load levels of 0%, 20%, 40%, 60%, 80%, 100%, and 120% at 1, 2, 3, 4, 5, 6, and 7 load conditions respectively. The comparison of bp, bthe and bsfc prediction with experimental results are plotted in Figure 13, 14 and 15. It illustrates the correlation between the targeted output values of bthe, bsfc and brake power accordingly, during the training testing and validation stages. The implementation phases of the artificial neural network resulted in an r^2 value of 0.99756 for bthe, 0.99871 for brake power and 0.98812 for bsfc prediction.

The testing state predictions are impartially accurate, they are the closest to the experimental brake power value within the network's specified error. the ANN back propagation technique was employed to significantly enhance the accuracy of predicting the output parameters[25]. There is a significant correlation obtained between predicted and tested results.

Regression analysis was used to compare the network output with the appropriate targets to look more closely at the network response[26]. The results indicated established model accurately forecasted performance of CI engines under various engine loads and wpo mixtures. The study of the whole network returned a correlation coefficient of 0.9899 which indicates that the model successfully predicted the engine performance.

3.2 Modelling of ANN for Emission Characteristics

The proposed ANN tool for predicting levels of hc, CO, NO_x and smoke demonstrated high correlation coefficients 0.99824, 0.96547 and 0.96531 to training, test and validation data sets respectively. overall network accuracy was 0.9775. in addition, the mean squared error (mse) was 0.9863, indicating that the network successfully acquired the understanding of the link between the variables.

The ANN back propagation technique was employed to significantly enhance the accuracy of predicting the output parameters. Figures 16, 17, 18 and 19 illustrate the disparities between the anticipated and observed values for emission performance. the experimental and predicted results are slight variance with another and fall within a reasonable error range in terms of mse and coefficient of determination (r^2)[2,6]. As a result, the network receives the anticipated response for the carbon monoxide emission for various blends of fuel. wpo30 the correlation coefficients (r^2) for hc, no_x, co, and smoke

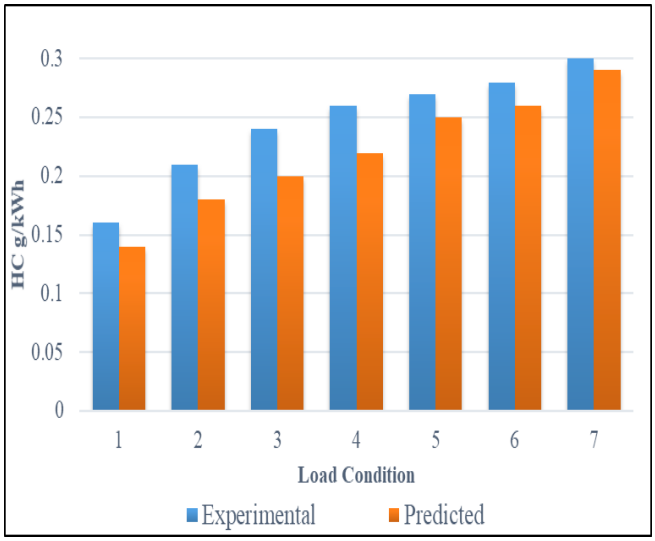


Figure 16. Relationship between experimental and predicted values of hc.

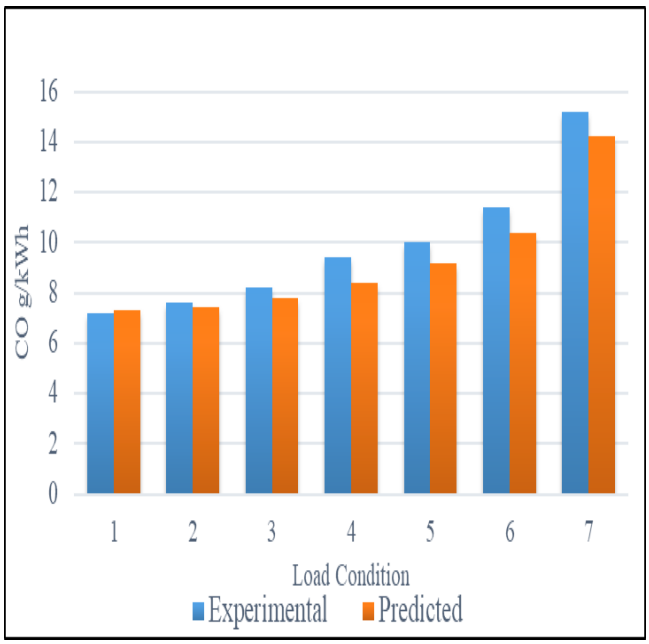


Figure 17. Relationship between experimental and predicted values of CO.

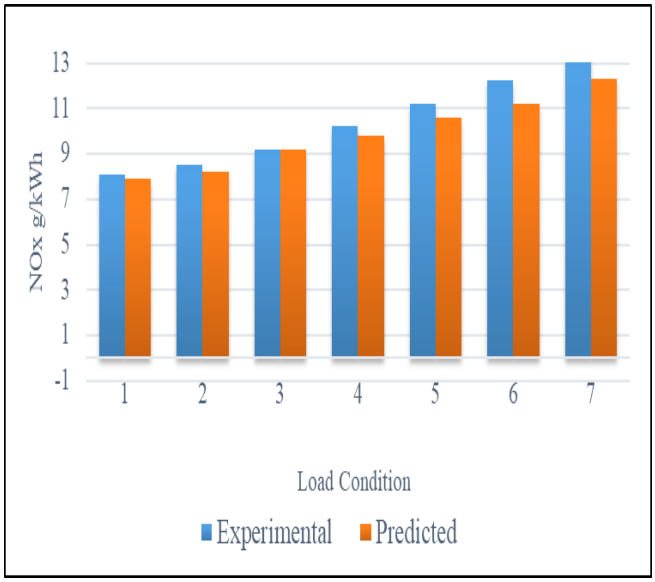


Figure 18. Relationship between experimental and predicted values of NO_x .

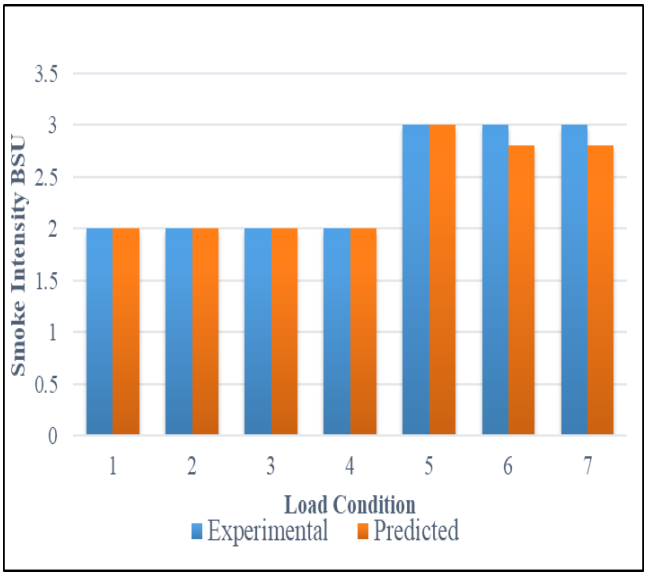


Figure 19. Relationship between experimental and predicted values of smoke.

were determined designate 0.99636, 0.99217, 0.98764 and 0.99735 respectively. The experimental and predicted emission values were determined at full load as for hc 0.26 and 0.28 g/kwh, for CO 11 and 10.5 g/kwh, for NO_x 12.5 and 11.5 g/kwh and for smoke 3.5 and 3 bsu.

With these results Figures 16, 17, 18 and 19 indicated model effectively showcased its capacity to generalize load and wpo blend concentration, leading to appropriate emissions as evidenced by the high r^2 values[6,10]. Graphs from the comparison of experimental data and predicted data demonstrate that ANN applications are accurately employed in single-cylinder diesel engines that utilize wpo-diesel fuel blends.

Finally, this study determined that the ANN capacity to forecast bsfc, brake power, bthe and pollutants was usually satisfactory. regression analysis was conducted to evaluate the experimental and expected data, revealing a significant relationship among experimental values and predicted values of selected input parameters in CI engine.

4.0 Conclusion

The results demonstrated better performance in terms of bthe, brake power and bsfc at all engine loads including engine overload condition. also found that additional amounts of co, hc, no_x, and smoke emission increased.

Research was conducted to design and train ANN model using the acquired data. input data used in formation of ANN obtained by experimental testing. The findings show that the experimental and projected results are highly correlated. It shows that the back-propagation training algorithm effectively predicted engine brake power, bsfc and bthe across various engine loads and fuel blend ratios. the r^2 values for the ANN estimations for bsfc, bte and bp are 0.98812, 0.99803 and 0.99871 respectively. it indicates that r^2 values are nearly equal to one. To forecast the emission performance hc, CO, NO_x and smoke, the acquired data was fed into a neural network. the load and wpo-diesel fuel blends were chosen as the inputs. for hc, NO_x, CO and smoke, the corresponding r^2 values were found to be 0.99636, 0.99217, 0.98764, and 0.99735.

However, in every instance, it was observed that the r^2 values at various points of the prediction process were closely approaching one for all predictions. despite achieving the lowest possible mse, a uniform distribution was consistently evident in the error histogram. according to the current analysis, the utilized neural network model exhibited a high level of efficiency in prediction of performance and emission characteristics of produced wpo- diesel fuel blends. A comparison between generated results by ANN and actual experimental data demonstrates that ANNs can effectively model diesel engines powered

by wpo- diesel fuel blends. The discrepancy between the experimental and projected findings for all parameters is minimal and insignificant. Therefore, the utilization of artificial neural networks assists in evaluating ci engine performance and exhaust emissions by reducing the necessary efforts, engineering time, and cost.

5.0 References

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Abbreviations

ANN	Artificial Neural Network
CV	Calorific Value
IP	Indicated Power
CI	Compression Ignition
bsfc	brake specific fuel consumption kg/kw-h
wpo	Waste Plastic Oil
bthe	brake thermal efficiency
bp	Brake Power
CO	Carbon Monoxide
NO_x	Nitrogen Oxide Emission
hc	hydrocarbon emission
r^2	coefficient of determination
MSE	Mean Square Error