Journal of Research and Applications in Mechanical Engineering
ISSN: 2229-2152 (Print); 2697-424x (Online)
(2025) Vol. 13, No. 2, Paper No. JRAME 25-13-020
[DOI: 10.14456/jrame.2025.20]

Research Article

Predicting Performance and Emission Characteristics of Compression Ignition Engine Using Artificial Neural Network with Biodiesel Blends from Used Temple Oil

S. B. Anjappa*
D. K. Ramesha
K. Ganesh
B. C. Channakeshava
Department of Mechanical Engineering, University of Visvesvaraya College of Engineering, Bangaluru 560001, India

Received 24 August 2024
Revised 23 October 2024
Accepted 27 October 2024

Abstract:
Power generation is highly dependent on compression ignition engines, which are mostly compression ignition engines with no power output that release dangerous toxic gases such as petrol and diesel, contaminating the atmosphere by disturbing local ecosystems and contributing to environmental problems. Efforts to solve this problem have focused on alternative fuels, and oil-based biodiesels are a popular choice owing to their sustainability and diesel-like performance. Towards this objective, the present study is focused on development of artificial neural network models for the performance and emission characteristics of biodiesel to reduce the physical testing which demand high resource inputs by making property based predictions more accurate. The brake specific fuel consumption (6–5–1), brake thermal efficiency (6-3-1) and exhaust gas temperature (6-5-1) are the best ANN model architectures for forecasting different performance metrics. The model obtained MSE of 0.0397, RMSE of 0.1993, MAD of 0.1234 and MAPE of 0.5599 for brake thermal efficiency prediction. According to the sensitivity analysis, the model for brake thermal efficiency and exhaust gas temperature is sensitive to fuel consumption. The ANN model for brake specific fuel consumption is significantly sensitive to torque, and the model for brake specific energy consumption is sensitive to breaking power, which provides credence to the wider use of a biodiesel as a practical substitute of fuel, especially for products made from used temple oil. This change may contribute to a greener future by lowering a greenhouse gas emission and promotes better energy practices.

Keywords: ANN, Performance and emission characteristics, Machine learning, Temple oil, Biodiesel blends, Compression ignition engine

1. Introduction

This has been essential in the development of metropolitan areas for industry, which necessitates a rise in population and the need for fossil fuel-based electricity [1]. As industrialization continues at its current rate, there will be a greater need for energy, and shortages of some natural resources will pose a serious threat to future energy supplies [2]. To meet the growing demand for electricity due to high pace industrialization and increasing populations will be necessary to provide sustainable and efficient power generation methods [3]. Significant progress has been made in the areas of performance, resilience, size, molecularity, and output optimization in the power generation industry [4].

* Corresponding Author: S. B. Anjappa
e-mail address: mechvism@gmail.com

The modern day internal combustion (IC) engines are the backbone of current power production that is used to drive various modes of transportation ranging from small commercial vans to huge industrial fork lifts. These versatile engines run on different forms of liquid fossil fuels including petrol or diesel [5]. Nevertheless, burning these traditional fuels does not occur without serious environmental consequences since their combustion produces toxic mixtures. NOx, CO, SO_2, heavy metals and greenhouse gases like carbon dioxide and methane are all emanations of burning gasoline and diesel. The environment accumulates these harmful substances which destroys the fragile ecological equilibrium leading to issues such as acid rain, global temperature swings as well as an augmenting greenhouse effect. The necessity to monitor and lower the quantities of toxins produced by internal combustion engines stems from the long-term consequences that these environmental stresses can have on all living things.

One possibility to be looked at is that, renewable, low-emission alternative fuels are developed and adopted. Significant examples of innovative fuel sources analyzed by researchers as potential substitutes for standard gasoline and diesel include hydrogen, propane, biodiesel, and methane hydrates among others. In this regard the use of microbial electrolysis cells (MECs) is particularly significant because it uses electromotive microorganisms' metabolic processes to convert ammonia into a clean burning gas which is hydrogen. Since ammonia has low splitting potential it is an efficient and cost effective substrate for this mode of producing hydrogen [6]. On the other hand, optimizing various factors such as: microbial community composition; electron donors' presence; electrode materials; pH and temperature; and hydraulic retention time is very crucial in maintaining ammonia-splitting reaction without excessive energy loss. The need to find alternative fuels has become more pressing as the globe struggles to offset the negative environmental effects of burning fossil fuels and reduce greenhouse gas emissions. In order to overcome the obstacles involved in the creation and application of these greener, more sustainable power sources, researchers are putting up endless effort. For Khatri etal. [7] recently used ANN model to evaluate the performance of CI engine running on Karanja oil and Karanja biodiesel, and they were able to obtain an impressive correlation value of 0.9948. These developments highlight the enormous potential of alternative fuels to transform the energy landscape and open the door to a more ecologically conscious future. To address the growing worries about environmental sustainability and the depletion of fossil fuels, researchers have been looking into a variety of alternative fuel sources in recent years. In one such study, the inedible seeds of the Chrysobalanus icaco plant were used to create a new biofuel. It was carried out by Okonkwo et al. [8]. The performance parameters of this biodiesel fuel were predicted by the authors through the application of sophisticated statistical modeling techniques. A high coefficient of determination ($R^2 = 0.903$) in their research indicated a very good fit between the observed and anticipated values. In addition, the MAE was 0.650 and RMSE for the best model was a meagre 1.3723, indicating how accurate the model was in predicting the performance of the biodiesel. The efficacy and emissions of two different biodiesel blends made from feedstocks including Karanja, Neem, Mahua and jatropha in a different study [9]. When compared to pure diesel fuel, their findings revealed a noteworthy 34.05% average decrease in carbon monoxide (CO) emissions, a 42.54 % increased in carbon dioxide (CO_2) levels, and a 21.29 % increased in nitrogen oxide (NOx) emissions. These results show that these biodiesel blends have the potential to lower hazardous pollutants, but they also show that there are trade-offs, such as higher NOx emissions, which may need for further optimization. In order to enhance the performance of a diesel engine, an innovative strategy that combined the usage of nanomaterials and miture of the microalgae Chlorella vulgaris with biogas [10]. Combining nanomaterials and biogas decreased fuelling by 14 percent thus new fuel mixtures may boost the ability of engines to perform more efficiently. conversely for the A20 blend, this resulted to higher brake-specific fuel consumption (BSFC) due to the higher viscosity of the fuel blend. Krishnamoorthi et al. [11] made an assessment of the emission characteristics and efficiency of using a blend of chaulmoogra oil and diethyl, through an artificial neural network (ANN) modeling. Thus, their investigation produced regression coefficient values of the following range: 0.910 to 0. 999, meaning this model had almost 100 percent accuracy in identifying the blend characteristics. Javed et al. have elaborated a model to assess the operational efficiency of a hydrogen dual fuel engine when fueled with Jatropha Methyl Ester biodiesel. In the model, the overall regression coefficient came came slightly to 0.9936, A MSE of 0. Equally important, the values for RMSD are 0.0011 and MAPE are 4.8630% [12].

Böyükdipçi et al. [13] investigated the application of ammonia (NH_3) additions to sunflower biodiesel in a diesel engine. Their research showed that the vibration parameters of the engine were adversely affected by the additive. But the accuracy ratios of the B90A10, B85A15 and B95A5 blends were astonishingly high (99.206%, 99.675% and 99.505%, respectively) showing that certain combinations of biodiesel additive and engine performance enhancer have potential. In the study conducted by Balabin et al [14] the thermo physical properties of biodiesel were well analyzed using near infrared spectroscopy in combination with artificial neural network (ANN) forecasting model. The ANN model achieved optimal root mean squared errors of prediction (RMSEP) of just 0.42 kg m^{-3} for density, 0.068 $mm^2 s^{-1}$ for viscosity, 45 ppm for water %, and 51 ppm for methanol content, according to the researchers' outstanding findings. These incredibly precise forecasting abilities highlight ANN modeling's potential as an effective tool for assessing and improving biodiesel properties. In addition, research by Mathew et al. [15] found that the presence of fuel-bound oxygen in biodiesels significantly decreased the generation of soot. This is an important discovery because traditional diesel fuels pose a serious environmental risk due to soot emissions. The inherent oxygen content in biodiesels, derived from their vegetable oil feedstocks, appears to play a pivotal role in mitigating this pollutant. The growing interest in biomass-based alternative fuels, with vegetable oils being the most prominent, is driven by their renewable nature and abundant availability [16]. Many nations, including India, have implemented regulations mandating the blending of vegetable oil-based biofuels with conventional diesel, aiming to encourage the widespread adoption of these sustainable energy sources. To further encourage the switch to alternative fuels like biodiesel, governments have also implemented a number of support measures, including tax breaks, grants, subsidies, and financing for research and development [17]. Vegetable or non-edible oil transesterification results in biodiesels with heating values that are strikingly similar to conventional diesel fuel. The energy content and combustion behavior of these mono-alkyl esters of long-chain fatty acids are comparable to those of diesel [18]. According to studies, biodiesels based on soybean and rapeseed methyl ester have brake thermal efficiencies that are just 4-7% lower than those of traditional diesel [19]. Additionally, the lubricity and cetane number of biodiesels are comparable to those of diesel, ensuring compatibility with most existing engine systems [20]. With these favorable properties, biodiesels have emerged as a highly promising alternative to fossil-based diesel, offering the potential to reduce our reliance on finite resources while mitigating environmental concerns associated with traditional fuels [21]. The field of engine performance modeling and optimization has seen significant advancements in recent years, with researchers exploring various machine learning techniques to enhance predictive capabilities [22]. The appropriate biodiesel ratio is an important factor in engine performance and emissions, and the researchers discovered that the K-ELM approach was extremely effective in calculating this value. Furthermore, Silitonga et al. [23] demonstrated that K-ELM can successfully forecast a range of engine performance indicators, including smoke opacity, carbon monoxide (CO), nitrogen oxides (NOx), brake thermal efficiency (BTE), and brake-specific fuel consumption. With mean absolute percentage error (MAPE) values ranging from 1.363% to 2.090%, the K-ELM model displayed outstanding predictive power for these critical parameters. By utilizing ant colony optimization, enhanced a predictive artificial neural network (ANN) for diesel engine pollution prediction, advancing the investigation of sophisticated modeling methodologies [24]. This model's outputs were NOx and soot emissions, while its inputs were engine speed, power, fuel mass injection rate, and intake air temperature. The ANN model surpassed conventional correlation-based methods, according to the researchers, who also observed that it achieved remarkable R-squared values of 0.98 and 0.96 for NOx and soot emissions, respectively. This demonstrates how well ANN-based models are able to forecast the intricate correlations between emissions and engine operating factors. Vignesh et al. [25] pushed the envelope even farther by creating a DNN with four hidden layers and a special neuron configuration of 100-500-200-50. A worldwide calibration technique for split injection control, an essential component of optimizing engine performance, was developed using this DNN-based model. In comparison to the conventional response surface methodology (RSM) technique, the authors showed that the DNN approach led to the selection of a more exact optimum point, resulting in a wider power band with improvements of 11.13% and 12.90% in power and deliverable torque, respectively. This demonstrates how deep learning can be used to maximize the possibilities for optimizing engine performance. In another study regarding the usage of ANN, as well as the CMA-ES to forecast emissions and to finish the studies in this sector completed by Zheng [26]. The effectiveness of this hybrid technique to emulate complex engine emissions is further confirmed by the researcher’s report of theminimal error rate between expected and experimental values, ranging from 3 to 10%. One highly significant area of research with numerous applications is the capacity to create precise computer models for predicting the performance and emission characteristics of biodiesel fuels. Though considerable efforts have been devoted to investigate the possibility of replacing the fossil fuel with biodiesel in I C engines there is still a significant high accurate predictive means. This paper seeks to resolve the above predicament through the use of intricate artificial neural network (ANN) model that forecasts fuel consumption, CO, NOx, UHC and soot emissions, besides BTE, BSFC, BSEC, and fuel consumption by relying on inherent properties. Developing such sophisticated computational models represents a significant step forward, as it would reduce the industry's reliance on physical testing, which can be both challenging and redundant. The specific objectives of this research are multi-faceted - not only will ANN-based models be created to predict both performance and emissions, but sensitivity analyses will also be performed to identify the most influential input parameters, providing valuable insights. The ultimate objective is to show that these ANN models are accurate and feasible in predicting the behavior of biodiesel fuels, which would speed up the development and optimization of this promising renewable energy source as a competitive substitute for traditional diesel.

This work also pinpointed the most suitable ANN architectures for each of the forecast accuracy indices in terms of MSE, RMSE, MAD and MAPE with low prediction errors. Analysis of sensitivity showed that fuel consumptions greatly affect models of BTE and EGT, while torque does affect the model of BSFC. This paper reveals the applicative significance of biodiesel, mainly from waste feedstock comprising used temple oil. By enhancing the predictive models in use, it assists in reducing the levels of greenhouse gas emission together with encouraging the use of cleaner energy.

2. Materials and Methods

2.1 Engine Experimental Setup

A single-cylinder, four-stroke engine with model number TAF1 HSD, 4 was used in the investigation shown in figure 1. Kirloskar, a renowned indian company, provided the 4 kW constant speed engine used for the testing work [27]. This engine was specially fitted with a range of cutting-edge measuring and controlling apparatuses, which made it the perfect configuration for the study. This engine was used for additional agricultural tasks in addition to its experimental applications, demonstrating its adaptability and suitability for a variety of practical applications. Table 1 provides a reference for the comprehensive specs of this experimental CI (compression ignition) engine [28]. The principal fuel source for the current investigation is biodiesel based on used temple oil (UTO), as chosen by the researchers. Since this biodiesel is made from non-edible oil rather than vegetable oil suitable for food use, it is considered a second-generation type. Transesterification, which involves combining vegetable oil and methanol with a NaOH catalyst to form the final biodiesel product, is the method used to produce the biodiesel [29]. Several blends, such as B20, B25, B30, B35, B40 and B100 were used in physical test of this UTO biodiesel at four different engine load settings: they are 25%, 50%, 75% and 100% respectively [30]. Standard diesel fuel was also employed to compare and analyze the qualities and performance of these substitute fuels in internal combustion engines. This is so because the energy content to heat output ratio can be determined accurately by using conventional diesel fuel.

Fig. 1. Experimental Setup Diagram

Table 1: Engine specifications

Manufacturer	Kirloskar TV1
Power range	4 kW 1500 rpm
Displacement volume	661 cm^3
Compression ratio	17.5:1
Standard injection timing	23° bTDC
Cooling type	Air-cooled

2.2 Engine performance parameters

A number of indicators are available for assessing efficiency of an internal combustion engine, and each one offers insightful information [31]. The BSFC is one such metric that quantifies the rotational power efficiency or output shaft of the engine. The BSFC is a measure of fuel efficiency; lower BSFC values correspond to higher brake power. This is because less fuel and energy are needed to generate the desired power output. By directly comparing the BSFC of different engines, engineers and researchers can assess which designs are optimizing the conversion of fuel into useful mechanical work [32]. The engine's capacity to capture the energy content of the fuel input and transform it into power produced at the braking point is assessed by the Brake Specific Energy Consumption (BSEC), another related metric. Lower BSEC values signify higher efficiency, as they demonstrate the engine is extracting more usable energy from the same amount of fuel. This is a crucial consideration, as maximizing the energy utilization helps improve overall powertrain performance and reduce fuel consumption [33]. The Brake Thermal Efficiency (BTE) develops these ideas further and calculates the proportion of work developed to the heat produced by the burning of fuel. Greater BTE percentages show that the engine is using its fuel's chemical energy more efficiently to produce mechanical power as opposed to wasting it as waste heat or as a result of inefficiencies. This efficiency metric provides a holistic view of how well the engine is leveraging the energy potential of the fuel [34]. Finaly, the combustion characteristics of the engine can be explained by the exhaust gas temperature. The EGT stands for Exhaus. easy gases temperature which indicates temperature of gases released during the process of combustion. For air-cooled engines, EGT serves as a valuable comparative indicator of the combustion situation, as higher temperatures generally signify more complete fuel burning. However, it's important to note that the expelled gases, many of which are greenhouse gases, can contribute to the overall heating of the engine and the environment, underscoring the need for continued efficiency improvements.

2.3 Engine emission parameters

Smoke is an inevitable byproduct that arises when combustion occurs in an oxygen-deficient environment. This smoke density, measured in Hartridge Smoke Units (HSU), is a crucial indicator for analyzing and understanding emissions from various sources, particularly engines [35]. A multitude of intricately intertwined elements affect the HSU value, such as the engine's operating circumstances, the fuel's physiochemical properties, and the particular design features of the combustion chamber. For instance, engines running at higher loads or with sub optimal air-fuel ratios will typically produce denser, more opaque smoke due to incomplete combustion. Similarly, fuels with different compositions, such as higher aromatic content or increased viscosity, can also impact smoke density by altering the fuel atomization, vaporization, and mixing processes within the cylinder. Additionally, the geometric configuration of the combustion chamber, including factors like swirl and turbulence patterns, can affect in-cylinder mixing and, consequently, smoke formation. Closely monitoring and managing smoke density is essential, as excessive smoke not only indicates inefficient combustion but can also contribute to environmental pollution and health concerns [36]. The absorption coefficient (m^{-1}) is another significant parameter that measures how much the fuel absorbs electromagnetic radiation during combustion, in addition to smoke density. More energy released by the fuel per unit of mass is indicated by a greater absorption coefficient, which could result in better combustion and lower emissions.

2.4 Dataset

The experimental compression ignition (CI) engine arrangement used in the Kirloskar series of studies provided the data for this investigation. Throughout the trials, this engine was run at a steady 1500 revolutions per minute (rpm). The engine was methodically subjected to various loads by the researchers as they meticulously measured and recorded the engine's working parameters. This extensive dataset contains important engine performance indicators including speed, torque, load, power and fuel consumption rate in addition to critical fuel factors like calorific value [37]. Important performance metrics including brake-specific fuel consumption, brake-specific energy consumption, brake thermal efficiency (BTE), and exhaust gas temperature were also recorded by the researchers. The dataset also included metrics linked to emissions, such as the absorption coefficient and smoke density. The entire dataset was divided into three separate sets by the researchers to enable more thorough analysis: 70% were put aside for training, 15% were set aside for validation, and the remaining 15% were set aside for final testing [38]. This strategic data partitioning allows for robust model development, tuning, and evaluation to gain reliable insights from the experimental findings. The researchers then employed correlation analysis to uncover the numeric relationships between the various parameters. The correlation matrix provides a quantitative measure of the degree and direction of correlation, ranging from -1 to +1. Negative values indicate an inverse relationship, while positive values signify a direct correlation between parameters [39]. Importantly, this correlation analysis holds true regardless of the underlying data distribution, providing a generalized understanding of how the different parameters influence one another. Building on this foundation, the researchers were able to develop a deeper, more nuanced comprehension of how the engine's input variables, performance metrics, and emission characteristics are interrelated. As highlighted by Jahirul et al., this type of correlation analysis can be a powerful tool, potentially enabling the use of advanced techniques like artificial neural networks (ANNs) to reliably predict fuel properties and engine performance without the need for extensive, time-consuming experimental evaluations. Even while the relationships aren't always strictly linear, the correlation matrix shown in Table 2 makes it abundantly evident that every single input parameter assessed affects the emissions and performance of the CI engine.

Table 2: Matrix of correlation for every parameter: an initial stage in visualizing the linear relationship between various factors.

	CV (kJ/kg)	**Load (%)**	**Torque (N-m)**	**Speed (rpm)**	**Power (kW)**	**Fuel Consumption (l/h)**	**BSFC (kg-kW/h)**	**BSEC (kJ/kWh)**	**BTE (%)**	**EGT (ºC)**	**Smoke density (HSU)**	**Absorption coefficient (m^{-1})**
CV (kJ/kg)	1.0000											
Load (%)	0.000	1.0000										
Torque (N-m)	0.000	0.9993	1.0000									
Speed (rpm)	0. 0978	-0. 9480	-0.9420	1.0000								
Power (kW)	0.0030	0.9982	0.9996	-0.9343	1.0000							
Fuel Consumption (l/h)	-0.0261	0.9983	0.9962	-0.9570	0.9942	1.0000						
BSFC (kg-kW/h)	-0.1444	-0.8680	-0.8815	0.7206	-0.8911	-0.8479	1.0000					
BSEC (kJ/kWh)	0.1039	-0.8743	-0.8880	0.7518	-0.8969	-0.8607	0.9678	1.0000				
BTE (%)	-0.1284	0.9019	0.9147	-0.7895	0.9225	0.8893	-0.9570	-0.9900	1.0000			
EGT (ºC)	-0.0963	0.9594	0.9501	-0.9654	0.9436	0.9707	-0.7260	-0.7560	0.7895	1.0000		
Smoke density (HSU)	-0.0042	0.7151	0.6900	-0.7979	0.6741	0.7420	-0.3443	-0.3450	0.3874	0.8483	1.0000	
Absorption coefficient (m^{-1})	-0.0133	0.7253	0.7004	-0.8060	0.6849	0.7526	-0.3427	-0.3499	0.3909	0.8580	0.9846	1.0000

2.5 Development of ANN models for CI engine

Machine learning offers many techniques for building a predictive model like decision trees, neural nets, regression models, and many more clustering algorithms. Particular conditions and parameters are implementation regarding the need to model the performance and efficiency of a compression ignition. The main prerequisite was that the model had to be very interpretable so that the interactions between the different parameters could be clearly understood. Additionally, the model had to be capable of handling non-sequential data, rather than being limited to sequential data inputs. Equally important was the need for computational efficiency, ensuring the model could be deployed without excessive resource demands [40]. In order to simulate and analyze engine operations and get important insights into their behavior, engine modeling is a must. MATLAB 2021b is used for these simulations, which aid in the assessment of engine performance and emissions through computational modeling. The training and validation phases of the artificial neural network (ANN) model had a significant impact on its efficacy. Based on experimental results, researchers adjusted network settings during validation, such as the hidden layer's neuron count. Using an activation function, an activation function is used to conduct a non-linear transformation after a linear transformation is carried out by a single neuron in the ANN technique [41]. The model is a flexible option because of this combination's ability to capture both linear and non-linear data. Additionally versatile and adaptive, ANN models work well at replicating intricate, a non linear interactions between inputs and outputs. Simple layers in the ANN govern how the inputs are converted into predictions, and the interpretation of each layer can offer important insights into the structure of the data. Based on its activation properties, each layer adds to the ultimate prediction; the overall prediction is the result of aggregating these layers according to their weights and biases. The Feed Forward Back Propagation (FFBP) model is among the common techniques for solving non- linear problems that is being applied in the current study. This is because the fuel and/or engine parameters that can be used as inputs can cause a wide variety of non-linear effects on the operation of the IC engine and hence, ANN is an appropriate tool in modeling the behavior of an IC engine.

2.6 Network

The basic design of the FFBP neural network architecture used in this present work as shown in figure 2. The input layer, the hidden layer, and the output layer are the three separate layers that make up the FFBP models.

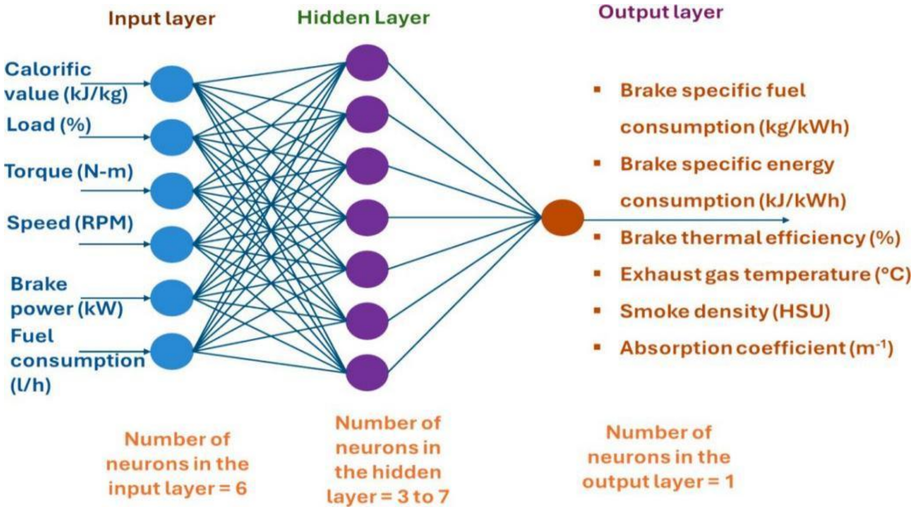

Fig. 2. FFBP neural structure of 6 nodes in input layer, 1 node in output layer and 7 nodes in hidden

For each parameter that needs to be predicted, the input layer consists of six (6) input neurons, while the output layer has (1) neuron. To explore the optimal network topology, five different configurations were developed and tested - 6-3-1, 6-4-1, 6-5-1, 6-6-1, and 6-7-1, with the 6-7-1 topology shown in the figure 2.

$$\text{Number of hidden layer neurons} \leq \text{Number of input layer neurons} + 1 \quad (1)$$

$$\text{Number of hidden layer neurons} = \frac{Number\ of\ hidden\ layer\ neurons}{\sqrt{Number\ of\ input\ layer\ neurons \times Number\ of\ output\ layer\ neurons}} \quad (2)$$

One important feature that can have a big impact on how well an ANN model performs is the quantity of the buried layer's neurons. The Kolmogorov theorem states that the formulas in equations (1) and (2) can be used to calculate the ideal quantity of the buried layer's neurons. These computations led to the decision to vary the hidden layer's neuron count from three to seven. This method aids in making sure the ANN models can accurately represent the problem's underlying complexity [42]. The Levenberg-Marquardt backpropagation algorithm, which is renowned for its quicker convergence and less training epoch requirements as compared to other optimization techniques, was used to train the ANN models. Furthermore, the learning function which was used in controlling the training of the model was the gradient descent with momentum weights. Another important consideration for developing ANNs is the choice of the transfer function since it defines the way the input signals are processed to provide the network's response. In this study, the tan-sigmoid transfer function was utilized due to its continuous and differentiable nature, which typically exhibits better performance with non-linear problems. The Mean Squared Error (MSE) was chosen as the performance index to evaluate the models' accuracy during the training phase.

2.7. Methodology

The topic description given above indicates a clear-cut process of building FFBP ANN model to predict the performance and emission profile of a CI test engine fueled with different percentages of UTO based biodiesel fuel blends. The Supplementary Information document that is cited provides a thorough flowchart of this recommended methodology. The first step in the process is gathering a solid dataset with the necessary input parameters, like engine operating conditions (load, speed, torque, brake power), fuel properties (calorific value), and the desired output parameters, such as exhaust gas temperature (EGT), smoke density, absorption coefficient, and brake-specific fuel consumption (BSFC). The model can create significant links between engine operating circumstances, fuel properties, and the performance and emissions that emerge from these associations thanks to this extensive dataset. After that, a correlation matrix is created to measure the interdependencies among the different parameters. This helps to determine which input-output variables are suitable and offers important insights into the physics at play. Deciding the number of neurons in the hidden layer depending on the amount of initial and final variables is one of the strategies used in enhancing the ANN design. The ANN models are then trained and simulated using MATLAB 2021b's Neural Network Tool kit. Several performance metrics are calculated to assess the model's accuracy and predictive capacity after the training phase. These include the mean absolute deviation (MAD), mean squared error (MSE), mean absolute percentage error (MAPE), and root mean square error (RMSE). Choosing of the optimal model is made from the perspective of the maximum R coefficients and the minimum values of errors. A comparison of maggio actual with actual and predicted values, with conventional diesel as the reference, is done on graphs to ensure that the model’s performance is accurate. This enables a visual analysis of the model's ability to capture the trends and subtleties of the engine's performance and emissions characteristics when operating on various UTO based biodiesel fuel mixtures. Lastly, a sensitivity analysis is carried out for every input parameter with respect to the optimal models, offering insightful information about the relative significance and impact of different fuel qualities and operating conditions on the emissions and engine performance. Utilizing this data will optimize fuel mixes and engine settings for greater economy and lower emissions. According to the study process, it is therefore necessary to assess the biodiesel blends in terms of its performance and emanation at both fully loaded and part loaded condition. This comparison is useful in explaining biodiesel characteristics on the functionality and performances of vehicle engines under varying loads. High loads often cause high fuel consumption and emissions and, at the same time, low loads may give various thermal efficiencies. From such differences, improvements can be made on ANN models in order to give better estimations and increase the suitability of biodiesel usage the most stable source of energy in place of conventional energy at various types of operations.

2.8 Indexes for evaluating ANN models

Several statistical indicators were used to extensively analyze the performance of the created artificial neural network (ANN) models.

$$R= \frac{n\sum xy-\sum x\sum y}{\sqrt{(n\sum x^2-(\sum x)^2)\,(n\sum y^2-(\sum y)^2)}} \tag{3}$$

$$MSE = \frac{\sum (x-y)^2}{n} \tag{4}$$

$$RMSE = \sqrt[2]{\frac{\sum (x-y)^2}{n}} \tag{5}$$

$$MAD = \frac{\sum |x-y|}{n} \tag{6}$$

$$MAPE = \frac{1}{n} \times \sum \left| \frac{x-y}{y} \right| \times 100 \tag{7}$$

The correlation coefficient (R), where "n" is the total number of data points, "x" denotes the desired value, and "y" denotes the anticipated value.

Equation (3) was utilized to assess the linear relationship a value of 1 denoting a perfect positive correlation between the model's predictions and the actual target values. The mean-squared error (MSE), which calculates the average difference between expected and observed values and provides a general sense of model accuracy, was given by equation (4). The root-mean-squared error (RMSE), which is determined by equation (5), was also computed to provide more context. This measure shows the standard deviation of the prediction errors and is expressed in the same units as the original data. In addition, compared to the MSE, the mean absolute deviation (MAD), which was calculated using equation (6), offered a reliable indicator of the average absolute difference between predicted and actual values and was less susceptible to outliers. Lastly, prediction accuracy was reported as a % using the mean absolute percentage error (MAPE), which was obtained from equation (7). This provided a simple and understandable metric for evaluating model performance. Through the examination of these diverse statistical metrics, the researchers were able to acquire a thorough comprehension of the advantages, disadvantages, and general applicability of the ANN models.

3. Result and Discussion

3.1 Prediction of some of the essential performance parameters of the engines

The performance of artificial neural network models to predict important engine parameters when the engine was operated on biodiesel of different blends produced from used temple oil was investigated. Researchers employed basic statistical measures to evaluate the models such as correlation coefficient (R), mean squared error (MSE), root mean square error (RMSE), mean absolute deviation (MAD) and mean absolute percentage error (MAPE). They systematically studied the impact of altering the size of the buried layer from three neurons to seven neurons. It was pointed out that the most effective possibility for prediction of the engine's brake-specific fuel consumption (BSFC) was the 6-5-1 neural network topology, which includes 6 input neurons, 5 neurons in the only hidden layer, and 1 output neuron. On the basis of such parameters, this particular model emerged highly successful, with a desirable R-All or an overall correlation coefficient of 0. 9970, MSE of 4. 36E-05, RMSE of 0. 0066, MAD of 0. 0052 and the Mean Absolute Percentage Error of 1 was obtained. 2499. The 6-3-1 topology was determined as the most effective one in the evaluation of BSEC with the R-All of 0. 9932, MSE of 0. 2121, RMSE of 0. 4606, MAD of 0. 3031 and mean absolute percentage error (MAPE) of 1. 6702. The 6-3-1 design was also the best topology for predicting the brake thermal efficiency (BTE) by having the highest value of R-All of 0. 9988, MSE of 0. 0397, RMSE of 0. 1993, MAD of 0. 784 their values were 1234, and MAPE of 0. 5599. Singly, and despite the current lack of R-All penalties at all, impressively. 9965, MSE of 23. 6187, RMSE of 4. 8599, MAD of 2. Avg actual flows equaled 8763 for calibration, 9395 for validation, and MAPE of 0. 9917 was also found to be the best model and 6-5-1 was also concluded to be the best candidate to forecast the exhaust gas temperature (EGT) second to BSFC. The study also highlighted a notable observation the correlation coefficients during the training phase sometimes surpassed those in the testing and validation phases, indicating a potential discrepancy in the topologies. In order to tackle this, the researchers stressed that the R-All value which offers a thorough evaluation of the model's prediction accuracy and generalization abilities across all data subsets should serve as the primary guide when choosing the ideal topology. Let's look closely at the performance parameters of the IC engine that runs on different blends of biodiesel from used temple oil (UTO). The details are below in Figure 3, which explains it all quite well. A clearer comprehension of the patterns and connections between the compositions of the biodiesel blends and engine performance data was made possible by these visuals. For example, it was found that the BSFC decreased as engine load increased, which was explained by improved combustion efficiency and decreased heat loss at higher loads. Comparably, when the load increased, the BSEC showed a declining trend, indicating better overall performance and fuel efficiency [43]. In contrast, the BTE showed a positive association with load, indicating improved engine performance and energy conversion under greater load circumstances. It was also discovered that, in keeping with expectations, the EGT increased as the engine load increased. These conclusions from the thorough investigation offer helpful advice for enhancing the efficiency of IC engines using mixes of biodiesel made from UTO. The remarkable precision and accuracy of the ideal artificial neural network (ANN) model is validated by the strong agreement between the predictions and the target values. The biofuels under consideration, B20 (20% biofuel, 80% diesel) and B100 (pure biofuel), appear to have remarkably similar properties to conventional diesel fuel, as evidenced by the lack of any significant deviation or separation between the trend lines for the different biofuel blends on the y-axis, which represents key performance metrics like brake-specific fuel consumption (BSFC), brake-specific energy consumption (BSEC), brake thermal efficiency (BTE), and exhaust gas temperature (EGT) [52,53].

This suggests that these biofuel mixes can be smoothly incorporated into compression ignition (CI) engines as alternate fuels without significantly affecting the engine's overall performance. These results are in line with the model's performance as reported by Javed et al. [44], who were able to accurately simulate the emissions and operation of a dual-fuel engine powered by hydrogen and a blend of Jatropha Methyl Ester biodiesel. In support of this, the additional data shown in Fig. 3 confirms a high correlation with engine load where, in general, all fuels of diesel, B20, B25, B30, B35, B40 and B100 to exhibit similar trends for BTE, BSFC, BSEC and exhaust gas temperature [45]. The striking similarities observed across this wide range of biofuel blends support the conclusion that these renewable fuels can be easily incorporated into CI engine applications as viable and effective alternatives to conventional diesel, without sacrificing engine performance or efficiency.

3.2 Emission Parameters prediction with ANN

The research examined the emission properties of a compression ignition (CI) engine operating on various biodiesel mixes derived from used temple oil. The two primary emission parameters that were looked at were smoke density and absorption coefficients. These data are crucial for understanding the engine's combustion characteristics and exhaust emissions. To represent these emission parameters, the researchers created a variety of neural network topologies using three to seven neurons. The performance evaluation metrics for these models are included in Table 4 of the study, demonstrating their high prediction accuracy of the engine's emission behavior [46]. For smoke density, the 6-3-1 topology exhibited the strongest correlation, with an R-All value of 0.9946. This model also demonstrated low error metrics, with an MSE of 3.0261, RMSE of 1.7396, MAD of 1.4677, and MAPE of 8.7520. Similarly, for absorption coefficient prediction, the 6-6-1 topology outperformed the others, achieving an R-All of 0.9932 and impressively low error values of 0.0008 for MSE, 0.0282 for RMSE, 0.0221 for MAD, and 5.9503 for MAPE. These exceptional results indicate that the proposed models are highly accurate and well-suited for modeling the non-linear relationships inherent in engine emission characteristics [47]. The study's conclusions were further corroborated by a comparison with an earlier study that used engine speed and load data to predict fuel consumption and emissions from a spark ignition engine; the current model's demonstrated performance was comparable with those earlier findings, demonstrating the approach's robustness and applicability. Also, the trends in smoke density as well as the absorption coefficient were also analyzed whereby the engine load was considered. As depicted in Figures 4(a) and 4(b), both parameters exhibited a positive correlation with increasing load, indicating that higher engine loads lead to greater smoke density and absorption coefficient. Importantly, the minimal deviation observed between the trend lines for different biodiesel blends (B20 and B100) and diesel suggests that these biofuels exhibit very similar properties to conventional diesel fuel. This finding implies that the tested biodiesel blends can be used as viable alternatives to diesel in CI engines without significantly impacting the engine's emissions profile [48]. In addition, Figure 3 of the supplemental information also corroborates these findings as it presented the dependence of smoke density and absorption coefficient on load as a function of fuel type and load, although the fuels used in evaluating this work included diesel, B20, B25, B30, B35, B40 and B100 [49]. This large set of data is useful in comprehending the emission profile of CI engines fuelled with different biodiesel blends and can guide the design of improved engines that have a reduced emission footprint.

3.3 Sensitivity analysis

Sensitivity analysis assists in forecasting an output parameter, while trying to determine one input parameter. The feasibility and the optimal model were evaluated by calculating the remaining parameter value with one of the input parameter fixed at time using the test set. To dig deeper, we checked out how these values line up with each other. We did this with something called the correlation coefficient (R-All) as well as MSE & RMSE [50]. You can also find the sensitivity analysis for the ideal model topologies regarding BTE, EGT, BSFC, & BSEC forecasts in Table 5 [51]. Hypothesis testing made it possible to establish that the input parameter torque influenced the best accurate model for predicting BSFC (6-5-1). In order to ensure the overall output tops the total figure in terms of fuel consumption, there has to be a balance between torque and BSFC [52]. Originally, torque means the force that tries to rotate an object or the revolve force of the engine. The exhaust gas temperature of 6-5-2-1 is closely linked with fuel consumption while the prediction of BSEC of 6-3-2-1 is significantly affected by the braking power. It can be seen that ideal torque and fuel affect the brake thermal efficiency model to a larger extend. Table 6 illustrates sensitivity analysis performed on the top models regarding the emission, absorption coefficient and smoke density. The model that achieved the highest accuracy in forecasting two highly sensitive to engine speed smoke density (6–3–1) and extremely sensitive to engine load absorption coefficient (6–6–1) of the tested vehicle was topology. This work was mainly concerned with refining artificial neural network (ANN) models to predict several engine system performance indicators. According to the investigation of several ANN topologies, the researchers found in their study which ANNs viewed better forecasts for given indicators [53]. for the prediction of BFSC, brake specific energy consumption (BSEC), brake thermal efficiency (BTE) and exhaust gas temperature (EGT), respectively, the best ANN model topologies were found to be 6-5-1, 6-3-1, 6-3-1 and 6-5-1. For the BTE prediction, using calculated MSE, MAD, MAPE and RMSE the values were found to be 0.0397, 0.1993, 0.1234 and 0.5599, in that order. The findings also suggest a significant correspondence between the model's outputs as well as the actual observed values; quite expectedly, the BTE prediction yielded the highest R-All of 0. 9988. The research also anticipated that technique with 6-3-1 topologies and the 6-6-1 topologies was ideal for predicting absorption coefficient and smoke density, respectively. as indicated in analyses of the emission parameters, the prediction of the smoke density using the ANN of 6-3-1 topology holds the more value of R-All correlation coefficient of 0.9946. the corresponding of RMSE, MSE, MAPE for the smoke density prediction was 3.0261, 1.7396, 1.4677 and 8.7520, in that order.

Even if ANNs have shown a lot of promise, it is still worthwhile to investigate alternative machine learning techniques, including Decision Trees and Support Vector Machines, in order to perform comparative analyses and obtain a deeper comprehension of the dynamics of CI engine [54]. To fully realize the promise of these computational tools in real-world CI engine applications, future research should concentrate on optimizing neural network architectures, refining training methodologies, and investigating the integration of diverse machine learning approaches [55]. The creation of reliable real-time data processing and collection strategies will be essential to this project in order to facilitate the smooth integration of these cutting-edge methods into the engine control systems.

Table 3: displays the models used to anticipate emissions.

parameter	Model	No. of neurons	R - Train	R - validations	R - Tests	R - ALL	MSE	RMSE	MAD	MAPE
BSFC (kg-kW/h)	BSFC-6–3-1	3	**0.9996**	0.9952	0.9529	0.9919	0.0001	0.0104	0.0049	**1.1198**
	BSFC-6–4-1	4	0.9984	0.9987	0.9431	0.9682	0.0005	0.0213	0.0083	1.8187
	BSFC-6–5-1	5	0.9974	**0.9998**	0.9976	**0.9970**	**0.0000**	**0.0066**	0.0052	1.2499
	BSFC-6–6-1	6	0.9620	0.9909	0.9607	0.9658	0.0007	0.0273	0.0233	5.9579
	BSFC-6–7-1	7	0.9985	0.9943	**0.9994**	0.9937	0.0001	0.0092	**0.0048**	1.1731
BSEC (kJ/kWh)	**BSEC-6–3-1**	3	**0.9965**	**0.9972**	0.9984	**0.9932**	**0.2121**	**0.4606**	**0.3031**	**1.6702**
	BSEC-6–4-1	4	0.9955	0.5606	0.9773	0.9893	0.2702	0.5198	0.3083	1.9908
	BSEC-6–5-1	5	0.2075	0.8910	0.6371	0.2914	14.8957	3.8595	2.3660	11.5680
	BSEC-6–6-1	6	0.9922	0.9378	**0.9998**	0.9787	0.4814	0.6938	0.4037	2.2602
	BSEC-6–7-1	7	0.5861	0.7940	0.7511	0.6412	19.7816	4.4477	3.4422	22.4025
BTE (%)	**BTE-6–3-1**	3	0.9992	**1.0000**	0.9774	**0.9988**	**0.0397**	**0.1993**	**0.1234**	**0.5599**
	BTE-6–4-1	4	0.8967	0.9990	0.9980	0.9394	2.8713	1.6945	1.0036	4.6516
	BTE-6–5-1	5	0.9981	0.9999	**0.9986**	0.9083	0.0535	0.2313	0.1765	0.8419
	BTE-6–6-1	6	0.8835	0.9920	0.9666	0.9298	5.0974	2.2577	1.6914	7.7218
	BTE-6–7-1	7	0.9999	0.9317	0.9146	0.9766	0.7654	0.8749	0.3340	1.5205
EGT (ºC)	EGT-6–3-1	3	0.9987	0.6994	0.9308	0.9919	45.0672	6.7132	3.3875	1.1332
	EGT-6–4-1	4	0.9933	0.9959	**0.9995**	0.9920	46.3064	6.8049	4.9097	1.6096
	EGT-6–5-1	5	0.9994	0.9919	0.9839	**0.9965**	**23.6187**	**4.8599**	**2.9395**	**0.9917**
	EGT-6–6-1	6	0.9973	0.9706	0.9985	0.9912	49.9486	7.0674	4.6041	1.5226
	EGT-6–7-1	7	**1.0000**	**1.0000**	0.3214	0.9831	91.3481	9.5576	3.5016	1.1857

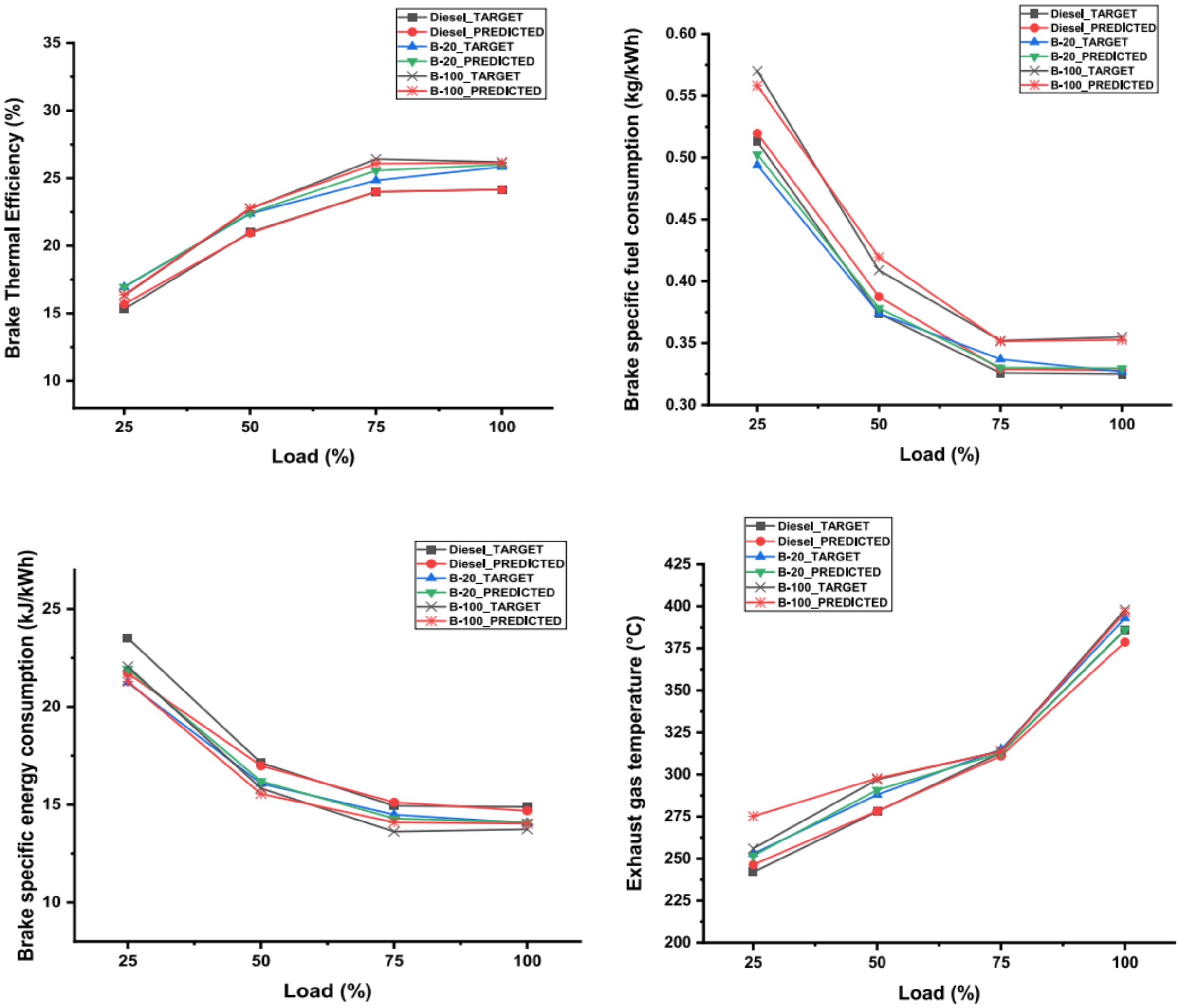

Fig. 3. predicted values and observed of BTE, BSFC, BSEC and EGT.

Table 4: lists the emission prediction models performance evaluation indices.

parameter	Model	No. of neurons	R - Train	R - validations	R - Tests	R - ALL	MSE	RMSE	MAD	MAPE
smoke density (HSU)	**SD- 6–3-1**	3.	**0. 9956**	**0. 9997**	0.9967	**0.9946**	3.0261	1. 7396	1.4677	8.7520
	SD-6–4-1	4	0.9975	0.9965	**0.9991**	0.9930	**2.7116**	**1.6467**	**1.0883**	**5.8984**
	SD-6–5-1	5	0.9871	0.9985	0.9829	0.9799	13.9407	3.7337	2.8539	18.5829
	SD-6–6-1	6	0.6599	0.9881	0.9977	0.7508	102.5749	10.1279	4.8282	32.1169
	SD-6–7-1	7	0.9936	0.9982	0.9901	0.9928	4.1567	2.0388	1.5730	9.6690
Absorption coefficient (m^{-1})	AC-6–3-1	3	**0.9992**	0.9988	0.9853	0.9893	0.0064	0.0802	0.0386	9.5293
	AC-6–4-1	4	0.9916	0.9953	0.9869	0.9893	0.0051	0.0712	0.0499	12.6555
	AC-6–5-1	5	0.9902	0.9988	1.0000	0.9932	0.0032	0.0563	0.0363	9.2059
	AC-6–6-1	6	0.9934	**0.9999**	**1.0000**	**0.9932**	**0.0008**	**0.0282**	**0.0221**	**5.9503**
	AC-6–7-1	7	0.9751	0.9998	0.9994	0.9840	0.0091	0.0952	0.0697	19.4951

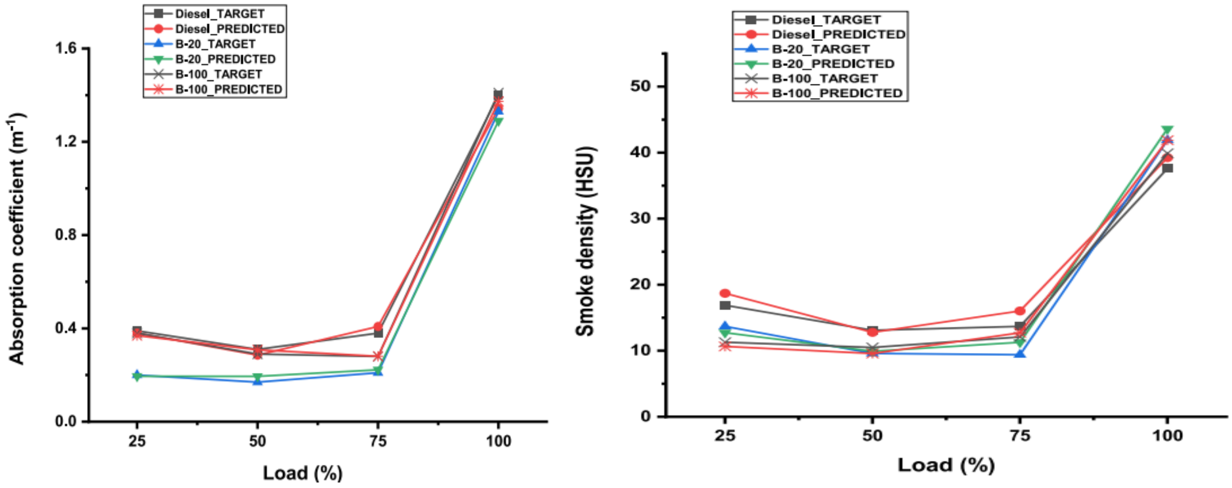

Fig. 4. Predicted values and observed values of absorption coefficient and smoke density

Table 5: Sensitivity analysis for the predicttion of BTE, BSFC, BSEC and EGT

Prediction parameter		Parameter name (on hold)	R - ALL	MSE	RMSE
BSFC (kg/kWh)	BSFC-(6-5-1)	CV in kJ/kg	0.9947	0.0001	0.0091
		Load in %	0.9957	0.0001	0.0076
		Torque in N-m	**0.9805**	**0.0012**	**0.0346**
		Speed in RPM	0.9972	0.0000	0.0064
		Brake Power in KW	0.9947	0.0001	0.0089
		Fuel consumption in l/h	0.9953	0.0001	0.0071
BSEC (kJ/kWh)	BSEC-(6-3-1)	CV in kJ/kg	0.9826	0.4021	0.6341
		Load in %	0.9839	0.4364	0.6606
		Torque in N-m	0.9925	0.1745	0.4177
		Speed in RPM	0.9944	0.1277	0.3574
		Brake Power in KW	**0.7615**	**12.5246**	**3.5390**
		Fuel consumption in l/h	0.7630	6.1141	2.4727
BTE (%)	BTE- (6-3-1)	CV in kJ/kg	0.9869	**0.8934**	0.9452
		Load in %	0.9874	0.5227	0.7230
		Torque in N-m	0.9979	0.0638	**0.2526**
		Speed in RPM	0.9906	0.2992	0.5470
		Brake Power in KW	0.9911	0.2920	0.5404
		Fuel consumption in l/h	**0.9836**	0.5227	0.7230
EGT (^{O}C)	EGT - (6-5-1)	CV in kJ/kg	0.9922	39.6486	6.2967
		Load in %	0.9890	69.5387	8.3390
		Torque in N-m	0.9961	21.7855	4.6675
		Speed in RPM	0.9936	37.5758	6.1299
		Brake Power in KW	0.9029	1380.0000	37.1820
		Fuel consumption in l/h	**0.7510**	**2360.0000**	**48.6272**

Table 6: Sensitivity analysis for absorption coefficient, smoke density, and emission parameter prediction.

Prediction parameter		Parameter name (on hold)	R - ALL	MSE	RMSE
smoke density (HSU)	SD - (6-3-1)	CV in kJ/kg	0.9830	0.9830	0.9830
		Load in %	0.9420	0.9420	0.9420
		Torque in N-m	0.8031	0.8031	0.8031
		Speed in RPM	0.4310	514.0440	22.6725
		Brake Power in KW	0.9758	18.5262	4.3042
		Fuel consumption in l/h	0.5960	321.5964	17.9331
Absorption Coefficient (m^{-1})	AC - (6-6-1)	CV in kJ/kg	0.9863	0.0087	0.0933
		Load in %	0.7965	0.1159	0.3404
		Torque in N-m	0.9918	0.0057	0.0755
		Speed in RPM	0.9983	0.0008	0.0288
		Brake Power in KW	**0.9905**	**0.0008**	**0.0288**
		Fuel consumption in l/h	0.9330	0.0333	0.1825

4. Conclusions

The importance of artificial neural networks in increasing the stock of biodiesel as a renewable energy source for CI engines is therefore underlined by this work. The models of ANN that were developed systematically and optimized in this work make it possible to provide the prediction of biodiesel fuel performance and emission characteristics with a high degree of accuracy, rarely seen when working on this topic. Specific patterns of applied some ANN architectures such as 6-5-1 for brake specific fuel consumption (BSFC) represent the reliability and stability of the modeling methodology. It is possible to draw the conclusions about describing of highly excellent correlation coefficients that is 0, 17000 for brake thermal efficiency (BTE) is obtained in addition to low values for MSE such as just 0. 0397 for BTE, the above -stated indices evidently affirm the reliability and prognostic capability of the developed ANN models. This study's sophistication is further demonstrated by the sensitivity analysis that was done, which provides insightful information about the most important parameters. This information can be used to advise and direct future model optimizations and revisions.

The pursuit of the sustainable development goals (SDGs) will be greatly impacted by these ground-breaking discoveries since they directly support SDG 7's promotion of environmentally friendly energy sources and SDG 13's mitigation of greenhouse gas emissions. This work contributes to the improvement of sustainable energy practices and opens the door to a more environmentally friendly future by minimizing the need for resource-intensive physical testing. In line with the worldwide necessity to shift towards greener energy alternatives and accomplish sustainable development goals, the research promotes the wider usage of biodiesel as a clean, renewable substitute for traditional fossil fuels.

Declaration of competing interest

The authors declare the they have no known competing financial interests in this paper or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgments

This work was done by Anjappa S B. etl. We are thankful to the authorities of University of Visvesvaraya College of Engineering, and University of Agricultural Sciences, GKVK, Bangalore, India for providing all facilities for completing this work.

Declaration of generative AI in scientific writing

The authors declare the they didn’t use AI tools to analyse and data as Part of the research work.

References

[1] Prasad RK, Agarwal AK. Effect of hydrogen enrichment of compressed natural gas on combustible limit and flame kernel evolution in a constant volume combustion chamber using laser ignition. Fuel. 2021;302:121112.

[2] Andal EGT. Industrialisation, state-related institutions, and the speed of energy substitution: the case in Europe. Energy. 2022;239:122274.

[3] Rinke N, Petrielli GP, Dourado A, Leduc S, Di Fulvio F, Daniele D, et al. Bioenergy-livestock integration in Brazil: Unraveling potentials for energy production and climate change mitigation. J Clean Prod. 2023;422:138586.

[4] Sayyed S, Das RK, Kulkarni K. Performance assessment of multiple biodiesel blended diesel engine and NOx modeling using ANN. Case Stud Therm Eng. 2021;28:101509.

[5] Singh RR, Clarke RM, Chadee XT. A just energy transition for a hydrocarbon rich SIDS. Energy. 2023;279:128069.

[6] Jåstad EO, Bolkesjø TF. Modelling emission and land-use impacts of altered bioenergy use in the future energy system. Energy. 2023;265:126349.

[7] Sousa J, Lagarto J, Carvalho E, Martins A. SWHORD simulator: A platform to evaluate energy transition targets in future energy systems with increasing renewable generation, electric vehicles, storage technologies, and hydrogen systems. Energy. 2023;271:126977.

[8] Jin G, Huang Z. Asymmetric impact of renewable electricity consumption and industrialization on environmental sustainability: evidence through the lens of load capacity factor. Renew Energy. 2023;212:514-22.

[9] Dey S, Reang NM, Majumder A, Deb M, Das PK. A hybrid ANN-Fuzzy approach for optimization of engine operating parameters of a CI engine fueled with diesel-palm biodiesel-ethanol blend. Energy. 2020;202:117813.

[10] Rao KP, Babu TV, Anuradha G, Rao BA. IDI diesel engine performance and exhaust emission analysis using biodiesel with an artificial neural network (ANN). Egypt J Pet. 2017;26(3):593–600.

[11] Latvytė E, Zhu X, Wu L, Lan R, Vale P, Graves JE. A low-temperature ammonia electrolyser for wastewater treatment and hydrogen production. Int J Hydrogen Energy. 2024;52(2):265–82.

[12] Zhan G, Li D, Tao Y, Zhu X, Zhang L, Wang Y, et al. Ammonia as carbon-free substrate for hydrogen production in bioelectrochemical systems. Int J Hydrogen Energy. 2014;39(23):11854–9.

[13] Böyükdipi Ö, Tüccar G, Soyhan HS. Experimental investigation and artificial neural networks (ANNs) based prediction of engine vibration of a diesel engine fueled with sunflower biodiesel–NH_3 mixtures. Fuel. 2021;304:121462.

[14] Balabin RM, Lomakina EI, Safieva RZ. Neural network (ANN) approach to biodiesel analysis: analysis of biodiesel density, kinematic viscosity, methanol and water contents using near infrared (NIR) spectroscopy. Fuel. 2011;90(5):2007–15.

[15] Mathew BC, Thangaraja J, Sivaramakrishna A. Combustion, performance and emission characteristics of blends of methyl esters and modified methyl esters of karanja and waste cooking oil on a turbocharged CRDI engine. Clean Techn Environ Policy. 2019;21:1791–807.

[16] Pai PS, Rao BS. Artificial neural network based prediction of performance and emission characteristics of a variable compression ratio CI engine using WCO as a biodiesel at different injection timings. Appl Energy. 2011;88(7):2344–54.

[17] Usmani RA, Mohammad AS, Ansari SS. Comprehensive biofuel policy analysis framework: a novel approach evaluating the policy influences. Renew Sustain Energy Rev. 2023;183:113403.

[18] Ude CN, Onukwuli DO, Okey-Onyesolu FC, Nnaji PC, Okoye CC, Uwaleke CC. Prediction of some thermo-physical properties of biodiesel using ANFIS and ANN cum sensitivity analysis. Cleaner Waste Syst. 2022;2:100006.

[19] Thangaraja J, Zigan L, Rajkumar S. A machine learning framework for evaluating the biodiesel properties for accurate modeling of spray and combustion processes. Fuel. 2023;334:126573.

[20] Hoang AT, Nižetić S, Ong HC, Tarelko W, Le TH, Chau MQ, et al. A review on application of artificial neural network (ANN) for performance and emission characteristics of diesel engine fueled with biodiesel-based fuels. Sustain Energy Technol Assess. 2021;47:101416.

[21] Nema VK, Singh A, Chaurasiya PK, Gogoi TK, Verma TN, Tiwari D. Combustion, performance, and emission behavior of a CI engine fueled with different biodiesels: a modelling, forecasting and experimental study. Fuel. 2023;339:126976.

[22] Wong PK, Wong KI, Vong CM, Cheung CS. Modeling and optimization of biodiesel engine performance using kernel-based extreme learning machine and cuckoo search. Renew Energy. 2015;74:640–7.
[23] Silitonga AS, Masjuki HH, Ong HC, Sebayang AH, Dharma S, Kusumo F, et al. Evaluation of the engine performance and exhaust emissions of biodiesel–bioethanol–diesel blends using kernel-based extreme learning machine. Energy. 2018;159:1075–87.
[24] Mohammadhassani J, Dadvand A, Khalilarya S, Solimanpur M. Prediction and reduction of diesel engine emissions using a combined ANN–ACO method. Appl Soft Comput. 2015;34:139–50.
[25] Vignesh R, Ashok B. Deep neural network model-based global calibration scheme for split injection control map to enhance the characteristics of biofuel powered engine. Energy Convers Manage. 2021;249:114875.
[26] Zheng B, Chen JY, Song Z, Mao E, Zhou Q, Luo Z, et al. Prediction and optimization of emission in an agricultural harvest engine with biodiesel–diesel blends by a method of ANN and CMA-ES. Comput Electron Agric. 2022;197:106903.
[27] Channapattana SV, Pawar AA, Kamble PG. Optimisation of operating parameters of DI-CI engine fueled with second generation bio-fuel and development of ANN based prediction model. Appl Energy. 2017;187:84–95.
[28] Taheri-Garavand A, Heidari-Maleni A, Mesri-Gundoshmian T, Samuel OD. Application of artificial neural networks for the prediction of performance and exhaust emissions in IC engine using biodiesel–diesel blends containing quantum dot based on carbon doped. Energy Convers Manage X. 2022;16:100304.
[29] Chakraborty A, Roy S, Banerjee R. An experimental based ANN approach in mapping performance–emission characteristics of a diesel engine operating in dual-fuel mode with LPG. J Nat Gas Sci Eng. 2016;28:15–30.
[30] Sevinc H, Hazar H. Investigation of performance and exhaust emissions of a chromium oxide coated diesel engine fueled with dibutyl maleate mixtures by experimental and ANN technique. Fuel. 2020;278:118338.
[31] Hazar H, Tekdogan R, Sevinc H. Investigating the effects of oxygen enrichment with modified zeolites on the performance and emissions of a diesel engine through experimental and ANN approach. Fuel 2021;1(303):121318.
[32] Xiang JX. Estimation of minimum and maximum correlation coefficients. Statist Probab Lett 2019;1(145):81–8.
[33] Jahirul MI, Rasul MG, Brown RJ, Senadeera W, Hosen MA, Haque R, et al. Investigation of correlation between chemical composition and properties of biodiesel using principal component analysis (PCA) and artificial neural network (ANN). Renew Energy 2021;1(168):632–46.
[34] Hariharan N, Senthil V, Krishnamoorthi M, Karthic SV. Application of artificial neural network and response surface methodology for predicting and optimizing dual-fuel CI engine characteristics using hydrogen and bio fuel with water injection. Fuel 2020;15(270):117576.
[35] Uslu S, Celik MB. Performance and exhaust emission prediction of a SI engine fueled with I-amyl alcohol-gasoline blends: an ANN coupled RSM based optimization. Fuel 2020;1(265):116922.
[36] Viswanathan VK, Kaladgi AR, Thomai P, Aˇgbulut Ü, Alwetaishi M, Said Z, et al. Hybrid optimization and modelling of CI engine performance and emission characteristics of novel hybrid biodiesel blends. Renew Energy 2022;1(198):549–67.
[37] Baweja S, Trehan A, Kumar R. Combustion, performance, and emission analysis of a CI engine fueled with mustard oil biodiesel blended in diesel fuel. Fuel 2021;15(292):120346.
[38] Kumar MV, Babu AV, Kumar PR. The impacts on combustion, performance and emissions of biodiesel by using additives in direct injection diesel engine. Alex Eng J 2018 Mar 1;57(1):509–16.
[39] Ayazi M, Rasul MG, Khan MM, Hassan NM. Experimental investigation of fuel consumption and emissions of diesel engine fueled with ternary fuel blends of diesel, biodiesel and bioethanol. Energy Rep 2023;1(9):470-5.
[40] Fu J, Yang R, Li X, Sun X, Li Y, Liu Z, et al. Application of artificial neural network to forecast engine performance and emissions of a spark ignition engine. Appl Therm Eng 2022;25(201):117749.
[41] Chen S, Ren Y, Friedrich D, Yu Z, Yu J. Sensitivity analysis to reduce duplicated features in ANN training for district heat demand prediction. Energy and AI 2020;1(2):100028.
[42] Sharma P, Sahoo BB. Precise prediction of performance and emission of a waste derived biogas–biodiesel powered dual–fuel engine using modern ensemble boosted regression tree: a critique to Artificial neural network. Fuel 2022;1(321):124131.
[43] Bidarvatan M, Thakkar V, Shahbakhti M, Bahri B, Aziz AA. Grey-box modeling of HCCI engines. Appl Therm Eng 2014;70(1):397–409.
[44] Mohan B, Badra J. An automated machine learning framework for piston engine optimization. App Energy Combustion Sci 2023;1(13):100106.

[45] Alonso JM, Alvarruiz F, Desantes JM, Hernández L, Hernández V, Molto G. Combining neural networks and genetic algorithms to predict and reduce diesel engine emissions. IEEE Trans Evol Comput 2007;11(1):46–55.

[46] Hosseini M, Chitsaz I. Knock probability determination in a turbocharged gasoline engine through exhaust gas temperature and artificial neural network. Appl Therm Eng 2023;5(225):120217.

[47] Lee TK, Kramer D, Ohl G, Filipi ZS. Optimal calibration of high DOF engines considering fuel economy and combustion stability. IFAC Proceedings Volumes 2009;42(26):224–34.

[48] Manvitha MS, Pujitha MV, Prasad NH, Anju BY. A predictive analysis on CO2 emissions in automobiles using machine learning techniques. International Conference on Intelligent Data Communication Technologies and Internet of Things (IDCIoT).IEEE 2023 (pp. 394-401).

[49] Alruqi M, Sharma P, Deepanraj B, Shaik F. Renewable energy approach towards powering the CI engine with ternary blends of algal biodiesel-diesel-diethyl ether: bayesian optimized Gaussian process regression for modeling-optimization. Fuel 2023;15(334):126827.

[50] Gao Y, Wang R, Li Y, Han E, Song M, Yang Z, et al. Regulating dynamic equilibrium of active hydrogen for super-efficient nitrate electroreduction to ammonia. Chem Eng J 2023;15(474):145546.

[51] Okonkwo CP, Ajiwe VI, Obiadi MC, Okwu MO, Ayogu JI. Production of biodiesel from the novel non-edible seed of chrysobalanus icaco using natural heterogeneous catalyst: modeling and prediction using artificial neural network. J Clean Prod 2023;20(385):135631.

[52] Sekar M, Selim MY, Elgendi M. Improving the performance of a diesel engine using nanomaterials and chlorella vulgaris microalgae blends assisted with biogas. Int J Hydrogen Energy 2024;49:496–506.

[53] Krishnamoorthi M, Malayalamurthi R, Sakthivel R. Optimization of compression ignition engine fueled with diesel-chaulmoogra oil-diethyl ether blend with engine parameters and exhaust gas recirculation. Renew Energy 2019;1(134):579–602.

[54] Javed S, Murthy YS, Baig RU, Rao DP. Development of ANN model for prediction of performance and emission characteristics of hydrogen dual fueled diesel engine with Jatropha Methyl Ester biodiesel blends. J Nat Gas Sci Eng 2015;1(26):549–57.

[55] Saravanan AP, Pugazhendhi A, Mathimani T. A comprehensive assessment of biofuel policies in the BRICS nations: implementation, blending target and gaps. Fuel 2020;15(272):117635.