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Predictive modeling of specific fuel consumption in compression ignition engines using neural networks: a comparative analysis across diesel and polymer-based fuels

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Abstract

The study utilized neural network modeling to forecast the fuel consumption in compression ignition engines fueled by diesel, HDPE PO, PP PO, and LDPE PO. Using empirical data, a neural network model was constructed and used to estimate specific fuel consumption (SFC). Employing orthogonal arrays and parameter adjustments ensured accurate prediction of SFC, which was validated through experimentation. The multilayer perceptron network, coupled with traditional backpropagation, facilitates the nonlinear mapping of inputs to outcomes. In the LM10TP architecture, the key metrics from the training set included an impressive R-squared value of 1, indicating a perfect fit with a root mean square error (RMSE) of 0.0012 and a mean square error (MSE) of 1.5143E-06. Similarly, the validation set exhibited robust performance metrics with an R-squared value of 0.9999, an RMSE of 0.0011, and an MSE of 1.2185E-06. These metrics underscore the efficacy of neural networks in both the training and validation phases, affirming their utility as reliable predictive tools for SFC. Overall, this study highlights the effectiveness of neural network modeling for accurately predicting fuel consumption in compression ignition engines across diesel and polymer-based fuels. By leveraging empirical data and sophisticated modeling techniques, this study contributes to advancing predictive capabilities in the field, offering valuable insights for optimizing engine performance and fuel efficiency.

1. Introduction

In recent years, the quest for sustainable and eco-friendly alternatives to conventional fossil fuels has spurred extensive research on alternative fuels for engines. This paper provides a comprehensive overview of studies exploring the feasibility and effectiveness of various fuel blends, additives, and engine optimization techniques aimed at reducing emissions and enhancing performance.

This review begins with Ghobadian *et al* (2009), who introduced diesterol, a promising eco-friendly fuel blend comprising fossil diesel, sunflower methyl ester biodiesel, and ethanol derived from potato waste. Their study emphasized the importance of boosting the fuel oxygen content to reduce engine emissions, with experimental findings supporting the optimal blend ratio for enhanced fuel stability and lowered emissions across the engine's operating range. Subsequent studies by Shahir *et al* (2014) and Channapattana *et al* (2015a, 2015b) explored diesel-biodiesel-ethanol blends and the effects of fuel injection pressure on engine emissions and performance, respectively. These studies highlight the potential of biodiesel as a sustainable alternative to fossil diesel, showing comparable performance and emission characteristics while addressing global fuel shortages and environmental concerns. Cheikh *et al* (2016) and Ma *et al* (2018) further contributed to the discourse by examining waste cooking oil biodiesel blends and the integration of biodiesel/alcohol blends as viable alternatives for internal combustion engines. Their research underscores the cost-effectiveness and environmental benefits of utilizing alternative fuels, paving the way for cleaner combustion and emissions

reduction. Moreover, Dey *et al* (2019) and Campili *et al* (2021) investigated the performance and emission characteristics of diesel-palm biodiesel-ethanol blends and neem biodiesel-diesel blends with nickel oxide nanoparticles, respectively. These studies offer valuable insights into optimizing the fuel composition and additive concentrations to enhance engine efficiency while mitigating harmful emissions. Finally, Srinidhi *et al* (2021a, 2021b, 2022a, and 2022b) presented a series of experimental investigations focusing on the utilization of nanoparticles and exhaust gas recirculation in neem biodiesel blends. Their findings underscore the potential of nanoparticle-induced blends for superior performance and emission reduction compared to traditional methods, further advancing the frontier of alternative fuels and engine optimization techniques. This literature review synthesizes a diverse range of studies aimed at exploring innovative approaches to mitigate environmental impacts and address energy challenges through the development and implementation of alternative fuels and engine optimization strategies.

Over the past few years, plastic waste has become a pressing environmental concern, and researchers have explored innovative disposal methods. This literature review examines the potential of waste plastic oil (WPO) from plastic pyrolysis as an alternative diesel engine fuel, focusing on a study by Modi and Patel (2023). Their research investigated plastic pyrolysis oils (PPOs) from various polymer-based fuels and evaluated their emissions and composition in comparison to diesel fuel. The key findings include higher CO emissions with LDPE and HDPE PPOs under heavy loads, whereas PP PPOs exhibited lower NO_x emissions. Despite the increased hydrocarbon content in the PPOs, lighter loads resulted in reduced unburned hydrocarbons. Overall, PPOs offer promise in reducing emissions, addressing plastic waste, and providing practical diesel engine alternatives. Unlike some alternatives, the WPO is compatible with existing engine systems, making it a practical solution. This underscores its potential as a cleaner fuel option and emphasizes the need for further research in this area.

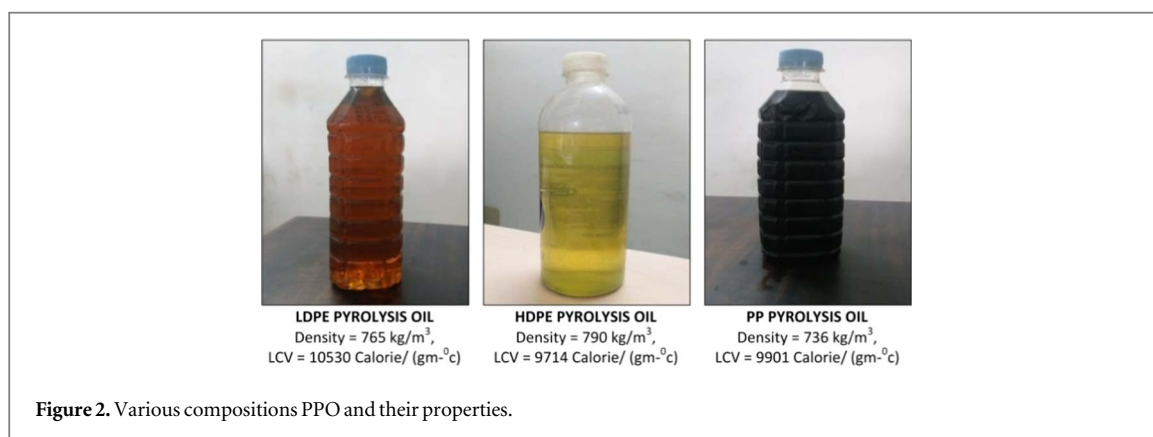
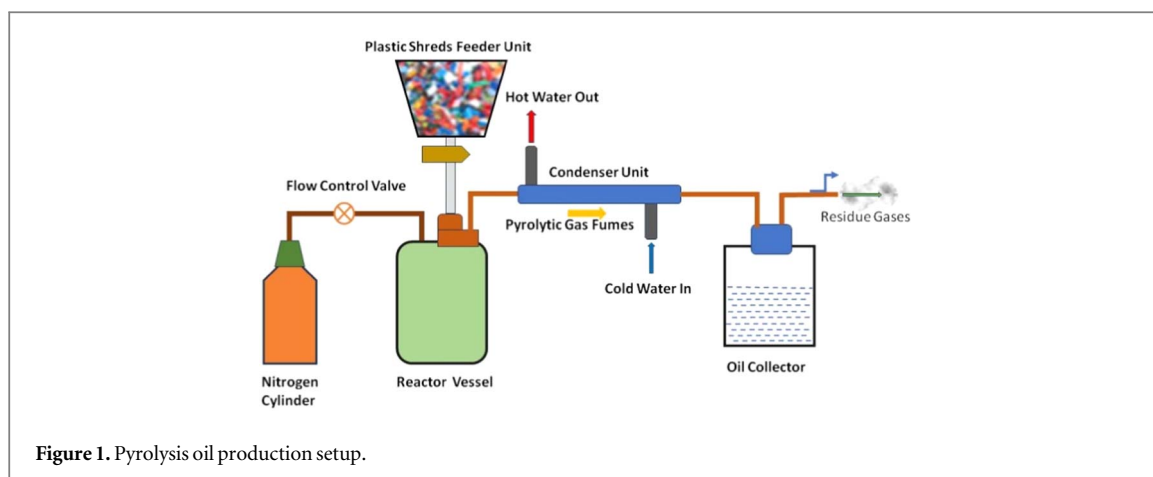
In recent years, the pursuit of sustainable fuel alternatives has driven researchers towards innovative solutions that transcend traditional disciplinary boundaries. This literature review highlights the pivotal role of artificial neural networks (ANNs) in advancing the understanding and application of alternative fuels in diesel engines, underscoring a transdisciplinary approach to fuel research. Parlak *et al* (2006) used an ANN to forecast the specific fuel consumption (SFC) and exhaust temperature of diesel engines at different injection times. Their study underscores the efficacy of ANNs in thermal engineering, offering rapid and consistent results that align closely with experimental data. Oğuz *et al* (2010) addressed engine testing challenges for biofuels by developing an ANN model to predict diesel engine performance. By leveraging experimental data, their ANN model accurately estimated the engine parameters, providing a cost-effective alternative to traditional testing methods. Subsequently, Pai and Rao (2011) and Javed *et al* (2015) investigated the application of ANN modeling to predict engine performance and emissions with alternative fuels, such as Jatropha Methyl Ester biodiesel blends and hydrogen dual-fuel diesel engines. These studies highlight the versatility of ANNs in forecasting the complex interactions within dual-fuel engine systems. Roy *et al* (2015) introduced an ANN model to predict the emission and performance parameters of diesel engines operating in CNG dual-fuel mode, further emphasizing the integration of advanced computational techniques in fuel research. Tosun *et al* (2016) compared the predictive capabilities of linear regression and ANN models in assessing engine performance and emissions with various fuel blends, demonstrating the superior accuracy of ANNs in modeling complex relationships. Finally, Bhowmik *et al* (2017) and Channapattana *et al* (2017) further underscored the significance of ANNs in fuel research by studying the influence of ethanol in diesel-kerosene blends and optimizing the DI-CI engine parameters using ANN prediction models.

Collectively, these studies exemplify a transdisciplinary approach to fuel research, wherein ANNs serve as versatile tools for predicting engine performance, optimizing fuel blends, and enhancing sustainability across diverse applications. This literature review elucidates the pivotal role of ANNs in advancing the frontiers of fuel research, transcending disciplinary boundaries for a more holistic understanding, and the application of alternative fuels in diesel engines.

Although existing studies have demonstrated the efficacy of ANNs in predicting engine performance and emission quantity (SFC), exhaust temperature, and emissions, there is a lack of comprehensive research that integrates insights from multiple disciplines to develop ANN models specifically tailored for predicting SFC in CI engines fueled with diesel and polymer-based fuels. Given the complexity of the factors influencing SFC, including fuel properties, engine design, and operating conditions, a transdisciplinary approach that combines expertise from fields such as mechanical engineering, computer science, and materials science is essential for developing robust predictive models.

Therefore, the identified literature gap underscores the need for future research to adopt a transdisciplinary approach towards developing ANN models tailored for predicting SFC in CI engines fueled with diesel and polymer-based fuels.

This study provides a comprehensive synthesis of cutting-edge research on alternative fuels and engine optimization techniques, highlighting their benefits and technological advancements. By exploring diverse fuels



and the role of artificial neural networks (ANNs), this study paves the way for innovative solutions in sustainable combustion technologies.

Furthermore, this review underscores the critical need for further transdisciplinary research to refine predictive models and accelerate the development of cleaner, more efficient fuel alternatives for diesel engines. Collectively, these efforts are crucial for addressing current environmental challenges and advancing the state-of-the-art in combustion technology for future generations.

2. Material and methods

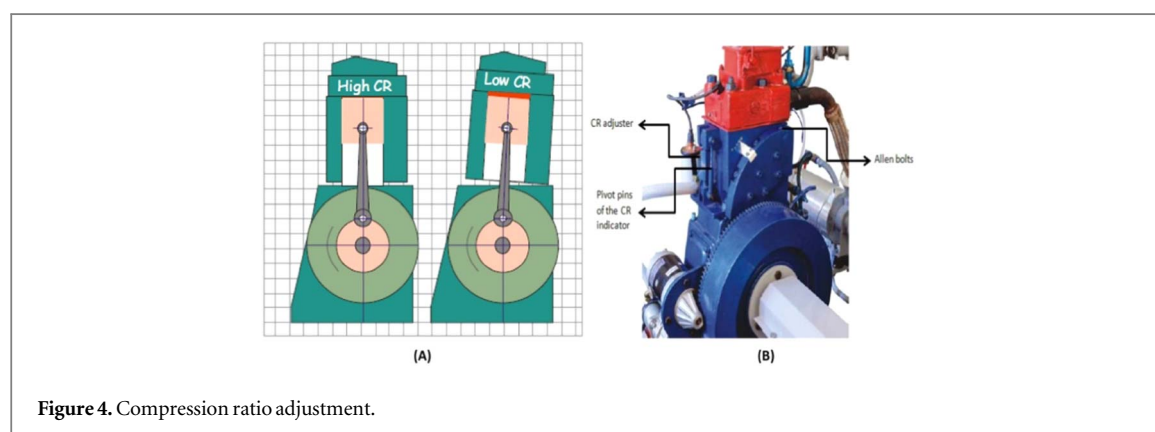
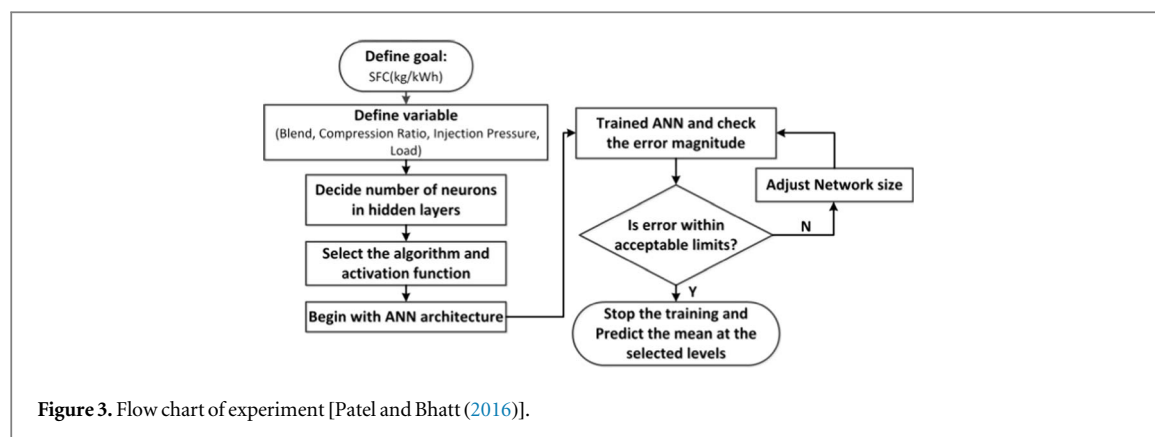
Various types of plastic waste are used as raw materials in the pyrolysis process to produce plastic pyrolysis oil. Pyrolysis is a method that involves the thermal decomposition of organic matter in the absence of oxygen. In this process, a closed container filled with plastic waste is heated from the bottom. The heat causes the plastic to vaporize, and these vapors are then cooled using a condenser. Inside the condenser, the vapors condense into plastic pyrolysis oil, which is collected in a bottle located at the bottom of the condenser.

Figure 1 illustrates the setup for pyrolysis oil production, which features a pyrolysis chamber equipped with a heat source and a condenser. Various types of waste plastics, including low-density polyethylene, high-density polyethylene, and polypropylene, were fed into the combustion chamber to generate pyrolysis oil, which was subsequently tested alongside the diesel fuel in the engines.

The various compositions and properties of PPO are shown in figure 2. The Taguchi approach, which is a set of statistical and mathematical methods for parametric optimization, was utilized. In addition, an NN was used to investigate the correlation between a set of quantitative experimental parameters and the responses.

Taguchi's L64 orthogonal array is used in the experimental flowchart shown in figure 3 to carefully organize tests with different fuel types, injection pressures, compression ratios, and loads. These experiments utilize both diesel and different types of plastic pyrolysis oils, exploring diverse combinations of injection pressures, compression ratios, and load conditions.

The experimental setup utilizes the Research Engine Test Setup (240PE) from Apex Innovation, Sangli, which integrates a single-cylinder, four-stroke VCR (variable compression ratio) research engine. This setup



includes an eddy current dynamometer with an arm length of 18.5 cm, enabling precise speed control from 800 to 2000 rpm. These components collectively offer a reliable platform for accurately controlling and measuring engine performance under varied operational conditions. Key instrumentation includes sensors for combustion pressure, crank angle, airflow, fuel flow, temperatures, and load measurements. These sensors are strategically positioned to capture essential data points crucial for comprehensive performance analysis.

All instrumentation interfaces seamlessly with a high-speed data acquisition device for real-time data capture at an optimized sampling rate, ensuring accuracy and responsiveness.

Experimental runs are conducted at a consistent engine speed of 1500 rpm to maintain uniformity and facilitate comparative analysis. This operational stability at a standardized speed serves as a baseline for evaluating the impacts of varied parameters such as compression ratio, injection pressures, and load.

The VCR engine incorporates an innovative tilting cylinder block arrangement designed to modify the compression ratio dynamically, as shown in figure 4. This mechanism allows for adjustment without interrupting engine operation or altering the combustion chamber geometry significantly. Adjustments are made by carefully manipulating Allen bolts and adjusting nuts based on preset compression ratio settings indicated on the CR indicator pivot pins, ensuring repeatability and precision in experimental setups.

In this experimental setup, the injection pressure dynamics of the Direct Injection (DI) system are monitored and controlled using a Piezo sensor located at the injector nozzle/fuel rail interface. Data acquisition is carried out with a NI USB-6210 (16-bit) system sampling at 250 kS/s, allowing for comprehensive analysis of injection pressure variations and their influence on engine performance metrics.

Load application on the eddy current dynamometer is facilitated by a precision load cell, which converts mechanical load into electrical signals. This transducer provides accurate, real-time feedback on the force or torque exerted on the dynamometer, essential for evaluating engine durability and operational limits under diverse load conditions.

Fuel consumption is quantified using a calibrated glass burette, measuring volume flow in milliliters. The engine's fuel consumption rate is determined by timing the depletion of a specific fuel volume, factoring in the fuel's specific gravity. This method, combined with stopwatch measurements, offers a straightforward yet effective means of assessing fuel efficiency and consumption patterns in controlled experimental environments.

Table 1 lists the variables used in the experimental setup and their corresponding values. The fuel type, compression ratio, injection pressure, and load were considered. Each factor had four levels considered in the

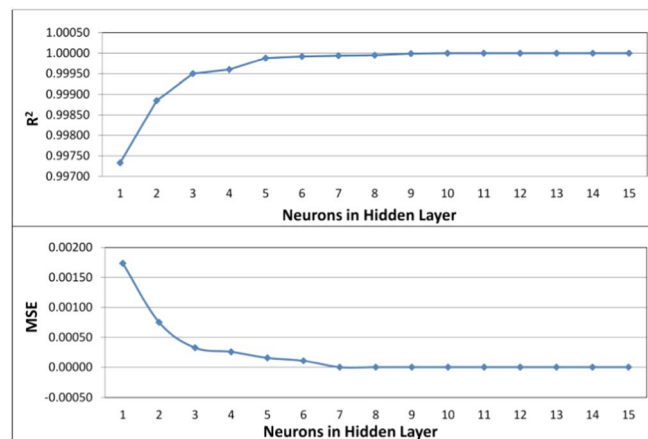


Figure 5. MSE and versus hidden layer neurons.

Table 1. Variables and levels.

Variables	Level			
	1	2	3	4
A: Type of Fuel	1 (DIESEL)	2 (LDPE PO)	3 (HDPE PO)	4 (PP PO)
B: Compression Ratio	15	16	17	18
C: Injection Pressure (bar)	180	200	220	240
D: Load (kg)	0	4	8	12

experimental setup. Table 2 lists the sets of parameters and their respective specific fuel consumptions for the 64 experimental sets.

3. Results and discussion

A review of the literature consistently affirms the superior predictive capabilities of ANN models compared to regression models. Consequently, ANN models are consistently preferred for predicting equivalent productivity. This section details the initial steps of data preparation, simulation of the model, subsequent processing methods, and various elements encompassing the design and training phases in constructing the ANN predictive models.

Before feeding the data into an ANN for training, it is essential to normalize the data, usually within the range of -1 to 1 or 0 to 1 . This normalization process guarantees that the data are within a consistent and manageable scale for effective ANN training.

The data are commonly normalized using equation (1) by scaling the data to fall within $[-1, 1]$. While the specifics of the normalization process may vary based on the equation employed, the overarching objective is to transform the data into a standardized range conducive to the efficient training and convergence of the ANN.

$$X_n = 2 \times \left[\frac{X - X_{\min}}{X_{\max} - X_{\min}} \right] - 1 \quad (1)$$

Where X_n is the variable's normalized value, X is the value of the variable, $X_{\min}$ is the minimum value of the variable, and $X_{\max}$ is the variable's maximum value.

3.1. Neural network modeling

The 64 orthogonal array experimental data points were classified into two categories: training and validation. MATLAB's Neural Network Toolbox was used to train and validate the various network configurations with different numbers of hidden neurons. For training, 48 data points were used, and 16 datasets were randomly selected for validation. Using training data reduces processing time and enhances the generalization of the model. The Levenberg–Marquardt (LM) optimization approach was employed to determine the biases and weights, which were adjusted iteratively during training to minimize the errors between the objective and predicted outputs. Choosing a single hidden layer simplifies the neural network architecture, making training

Table 2. Summary of the experiments.

Sr no	Experimental run	Factors				SFC (kg/kWh)
		A	B	C	D	
		Training data sets				
1	2	1	1	2	2	0.7631
2	3	1	1	3	3	0.4781
3	4	1	1	4	4	0.4092
4	5	1	2	1	2	0.7637
5	7	1	2	3	4	0.4414
6	8	1	2	4	1	15.9842
7	9	1	3	1	2	0.4814
8	11	1	3	3	1	8.2872
9	12	1	3	4	2	0.7088
10	13	1	4	1	4	0.4389
11	14	1	4	2	1	8.9635
12	16	1	4	4	3	0.4744
13	17	2	1	1	1	8.5068
14	18	2	1	2	2	0.6188
15	19	2	1	3	3	0.4642
16	21	2	2	1	2	0.5427
17	23	2	2	3	4	0.3997
18	24	2	2	4	1	11.7309
19	25	2	3	1	3	0.4458
20	26	2	3	2	4	0.3926
21	28	2	3	4	2	0.6368
22	29	2	4	1	4	0.3215
23	30	2	4	2	1	13.6036
24	32	2	4	4	3	0.4026
25	33	3	1	1	1	18.0943
26	35	3	1	3	3	0.4409
27	36	3	1	4	4	0.3952
28	37	3	2	1	2	0.7079
29	38	3	2	2	3	0.3935
30	40	3	2	4	1	9.3343
31	42	3	3	2	4	0.3746
32	43	3	3	3	1	14.2211
33	44	3	3	4	2	0.6267
34	45	3	4	1	4	0.4401
35	47	3	4	3	2	0.7291
36	48	3	4	4	3	0.4534
37	49	4	1	1	1	9.6329
38	50	4	1	2	2	0.6572
39	52	4	1	4	4	0.3296
40	54	4	2	2	3	0.3882
41	55	4	2	3	4	0.3167
42	56	4	2	4	1	8.5447
43	57	4	3	1	3	0.3843
44	59	4	3	3	1	8.3119
45	60	4	3	4	2	0.6332
46	61	4	4	1	4	0.3285
47	63	4	4	3	2	0.6896
48	64	4	4	4	3	0.3809
Validation Data Sets						
49	1	1	1	1	1	17.4198
50	6	1	2	2	3	0.4742
51	10	1	3	2	4	0.4206
52	15	1	4	3	2	0.7064
53	20	2	1	4	4	0.3440
54	22	2	2	2	3	0.4124
55	27	2	3	3	1	6.7708
56	31	2	4	3	2	0.5671
57	34	3	1	2	2	0.6044
58	39	3	2	3	4	0.3498
59	41	3	3	1	3	0.4878

Table 2. (Continued.)

Sr no	Experimental run	Factors				SFC (kg/kWh)
		A	B	C	D	
		Training data sets				
60	46	3	4	2	1	14.3220
61	51	4	1	3	3	0.4005
62	53	4	2	1	2	0.6296
63	58	4	3	2	4	0.3070
64	62	4	4	2	1	9.9480

Table 3. The relationship between errors and the number of neurons in the hidden layer.

No. of Neurons in hidden layer	MSE	R ²
1	0.00173524	0.99690
2	0.00075002	0.99842
3	0.00032686	0.99907
4	0.00025831	0.99917
5	0.00015763	0.99948
6	0.00010794	0.99962
7	5.0951×10^{-06}	0.99964
8	8.595×10^{-06}	0.99975
9	2.3633×10^{-06}	0.99989
10	1.5843×10^{-06}	1
11	4.2562×10^{-06}	1
12	1.2858×10^{-17}	1
13	2.2548×10^{-16}	1
14	1.8404×10^{-26}	1
15	4.1581×10^{-24}	1

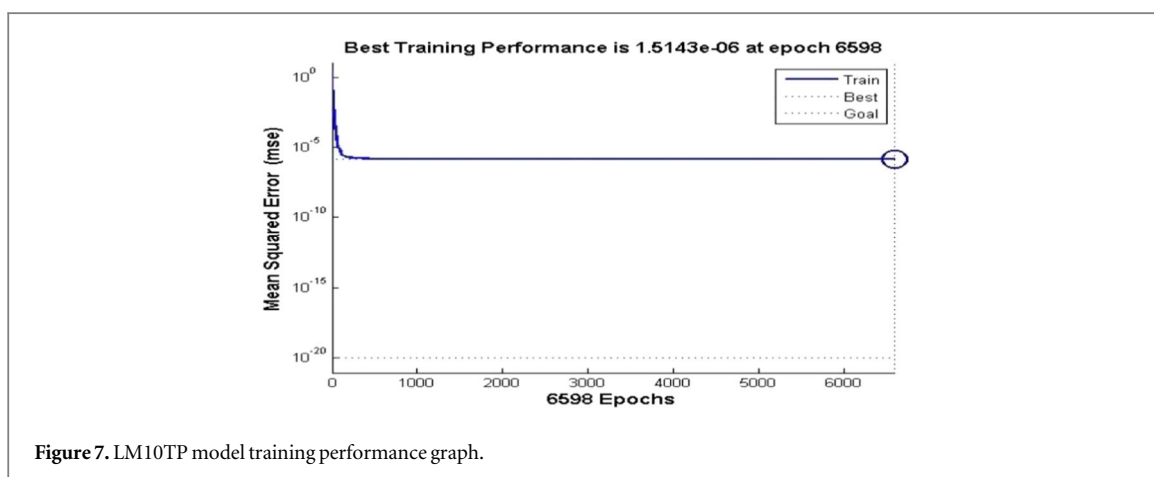
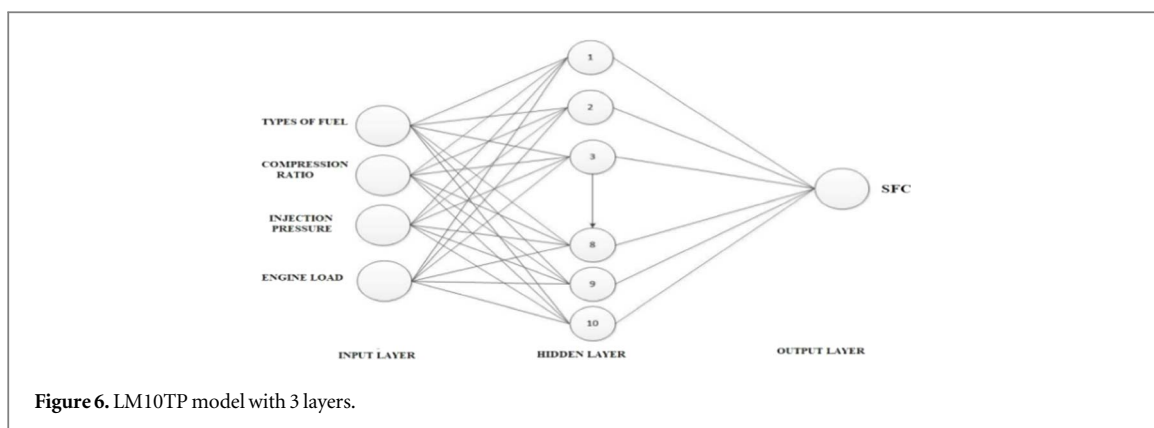
more efficient while reducing the risk of overfitting. This approach maintains model interpretability and is supported by empirical evidence showing competitive performance in classification tasks. Thus, the decision for a single hidden layer is grounded in balancing effectiveness, efficiency, and interpretability. Previous studies have demonstrated that the Levenberg–Marquardt method can rapidly yield accurate results when the number of neurons in the hidden layers is appropriately chosen. The performance analysis, represented by the Mean Squared Error (MSE) and R-squared (R²) scores, corresponds to the number of neurons in the hidden layer, as shown in table 3.

The effects of the number of neurons in the hidden layer on the R-squared and mean squared error (MSE) are shown in figure 5. As the number of neurons in the hidden layer increases to 10, the Levenberg–Marquardt (LM) technique causes R-squared to approach 1 and MSE to approach 0. However, during training, this algorithm tended to overfit the predicted data, leading to insufficient generalization. Overfitting occurs when the network excessively memorizes the training data, resulting in poor predictions for new situations. Therefore, it is essential that the NN model be tested on a fresh dataset as it is being trained. Initially, this ensures that the selected structure performs well in diverse settings, followed by fine-tuning the structure selection. In this study, we focus on a single hidden layer with 10 neurons.

3.2. Neural network training

Figure 6 illustrates the constructed ANN model, which consists of three layers: one input layer, one hidden layer, and one output layer. The input layer has four neurons, the output layer has one neuron, and the hidden layer has ten neurons for this investigation.

The tansig transfer function was used between the input and hidden layers of the model, and the purelin transfer function was used between the output and hidden levels. The target and input datasets were created for training once the data had been normalized. These target datasets comprised normalized, measured-specific fuel consumption thresholds for both training and validation datasets. The objective of this study was to address the prediction challenge with the aim of minimizing the final error to an extremely low value. The neural network training performance graph for the LM10TP model is shown in figure 7. After 6598 epochs, the training was stopped because the performance goal was achieved. At epoch 6598, the LM10TP model achieved a maximum



training performance of 1.5143E-06. The graph is a useful diagnostic tool for tracking the progress of training and location errors.

3.3. Mathematical model for output prediction

The achieved result appears reasonable because both the training and testing set errors demonstrated analogous characteristics, showing no significant signs of overfitting. Following the initial training of the LM10TP model, a retraining phase of 6598 epochs was conducted, resulting in a performance mean squared error (MSE) of 1.5143E-06 during training.

During the training phase of a neural network, the optimization process focuses on adjusting and retaining optimal weights in the interconnections among neurons across different layers. The significance of these weight values lies in their crucial role in enabling the trained ANN models to make precise predictions. In the LM10TP model, table 4 displays the weights and biases (learning parameters) of the neural network. The generation of the ANN output involved the formation of a neural network matrix with assigned weights and biases. This procedure includes applying the weight and bias matrix in tandem with the transfer function, as elaborated on by Patel and Bhatt (2016).

3.4. Evaluation of ANN model

Evaluating the predictive capacity of an ANN requires employing test data that has not been introduced to the network beforehand. At this stage, the outcomes are scrutinized to gauge the network's efficacy. Statistical approaches such as MSE, root mean square error (RMSE), and R-squared are frequently utilized. These metrics provide quantitative assessments of the accuracy and dependability of ANN predictions by comparing the predicted values with the actual data from unseen test sets. A MATLAB script was used to analyze the errors produced by the prediction model. After the training phase, the simulated outcomes of the ANN were exported to the MATLAB workspace for thorough evaluation. Comparisons were made using specific values, and the errors were calculated using equations (2)–(4).

$$MSE = \frac{1}{n} \sum_{i=1}^{i=n} (a_i - p_i)^2 \quad (2)$$

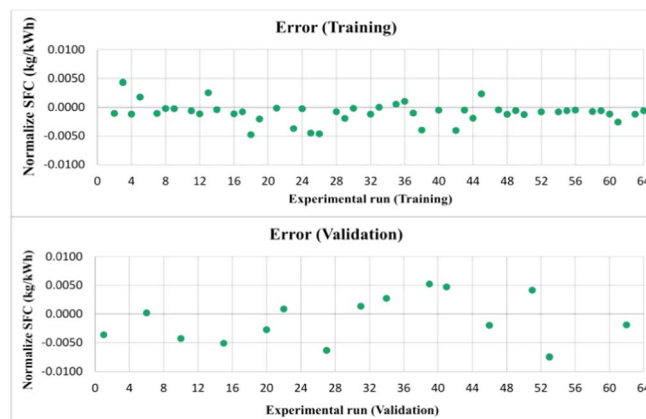


Figure 8. LM10TP model prediction errors in training and validation.

Table 4. Learnable parameters of LM10TP.

Weight values for					Bias values	
Hidden Layer (iw)				Output layer (lw)	Hidden layer (b1)	Output layer (b2)
6.22	3.12	3.14	2.88	−8.67	2.18	
14.48	16.07	−12.27	−34.13	0.17	−29.10	
−3.34	0.33	2.20	2.79	39.44	9.59	
10.55	−2.67	−2.76	−9.76	−0.04	−2.26	3.27
1.45	1.97	−1.73	−6.59	−0.33	−5.16	
−35.13	−45.04	6.26	29.29	−0.00	17.94	
−1.92	0.54	0.43	3.65	−0.06	0.50	
7.74	3.12	3.14	2.83	−27.37	3.19	
−0.03	0.01	0.06	14.72	−43.83	16.58	
7.22	3.06	3.08	2.79	36.03	2.89	

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^{i=n} (ai - pi)^2} \quad (3)$$

$$R^2 = 1 - \frac{\sum_{i=1}^{i=n} (ai - pi)^2}{\sum_{i=1}^{i=n} (pi)^2} \quad (4)$$

The errors in the prediction model were evaluated using MATLAB software. The simulated ANN results were exported to the MATLAB workspace after training. Subsequently, all the findings, comprising training and experimental data, were validated for three types of error terms. Figure 8 illustrates the prediction errors of the LM10TP model observed during the training and validation phases. During training, the LM10TP architecture exhibited a mean square error (MSE) of 1.5143×10^{-06} , a root mean square error (RMSE) of 0.0012, and a coefficient of determination R-squared of 1. Similarly, for the validation phase, the MSE, RMSE, and coefficient of determination R-squared for the LM10TP architecture were calculated as 1.2185×10^{-06} , 0.0011, and 0.9999, respectively.

This model exhibits strong performance in both training and validation for predicting specific fuel consumption. Figure 9 shows a comparison of the LM10TP model's predicted specific fuel consumption with the actual targets during the training and validation phases. Distinct colors and markers were employed to illustrate this comparison, highlighting that the outcomes projected by the ANN were closely aligned with the actual targets. Analyzing the network response in greater detail is beneficial, and the errors in both the training and validation sets can be used to evaluate the performance of the trained network. This analysis was conducted using the postreg routine, which receives the network output and the corresponding objectives and offers three options. The first two values, b and m, represent the slope and y-intercept, respectively. This procedure was performed for both training and validation by comparing network outputs with the targets provided.

Figure 10 illustrates the linear regression with three parameters, m, b, and R, for both the training and validation phases of the LM10TP model. During training, R equals one, indicating a perfect correlation between the objectives and outputs. However, the validation graphs and parameters demonstrated that the LM10TP

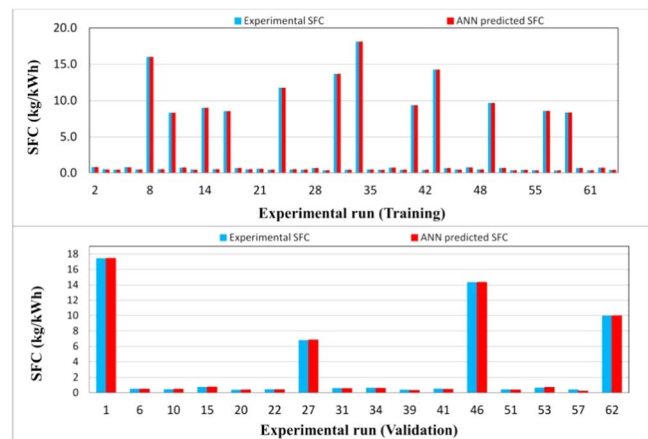


Figure 9. Actual versus ANN predicted result in training and validation.

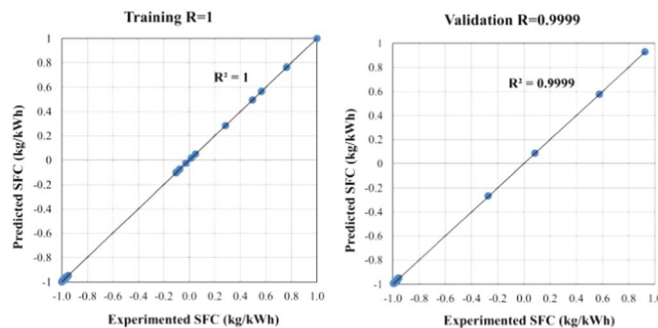


Figure 10. LM10TP model linear fitting.

model exhibited a linear fit with $R = 0.9999$. This confirms that the LM10TP model is exceptionally well suited for accurately predicting fuel usage.

3.5. Comparison of ANN model with RSM model

The comparison of ANN (Artificial Neural Network) and RSM (Response Surface Methodology) using metrics like MSE, RMSE, and R-squared error is explored in various studies across different domains. For instance, Patel and Brahmabhatt (2016) examined both models to predict surface roughness in roller burnishing, highlighting ANNs' capability in handling complex relationships and potentially achieving lower MSE and RMSE values. In contrast, Maran *et al* (2013) applied ANN and RSM to predicting mass transfer parameters during osmotic dehydration, showcasing RSM's interpretability and ANN's predictive power. Similarly, Okewale *et al* (2019) compared RSM and ANN for predicting mild steel corrosion inhibition, emphasizing the trade-offs between model transparency and accuracy. These studies underscore the importance of selecting the appropriate modeling approach based on the specific characteristics and requirements of the problem at hand in research and industrial applications.

The comparison in table 5 highlights that the ANN model achieves notably lower MSE and RMSE values compared to the RSM, indicating its superior accuracy in predicting specific fuel consumption (SFC). Moreover, the perfect R-squared value of 1 for ANN suggests an ideal fit to the data, while RSM achieves a high R-squared value of 0.9935, indicating slightly less precise predictions. These results underscore the ANN's capability to effectively capture and model the intricate relationships inherent in SFC data, likely due to its flexibility in handling nonlinear patterns compared to RSM's more structured approach.

4. Conclusions

The objective of the current investigation was to develop an ANN model for predicting specific fuel consumption (SFC) in compression ignition engines. Utilizing the L64 orthogonal array, an ANN model for SFC was constructed. The findings of the ANN model for predicting the SFC are as follows:

Table 5. Comparison of ANN and RSM.

Model	Prediction error		
	MSE	RMSE	R ²
ANN	0.00000265	0.0016	1
RSM	0.00013102	0.0115	0.9935

- Based on the experimental results, the neural network model significantly reduces the time and effort required.
- During training, the MSE and R-squared values for the LM10TP architecture were 1.5143×10^{-06} and 1, respectively.
- In the validation, the MSE and R-squared values for the LM10TP design were 1.2185×10^{-06} and 0.9999, respectively.
- The projected specific fuel consumption values obtained from the ANN closely matched the experimental data.
- Consequently, the utilized ANN model emerged as the best substitute for predicting specific fuel consumption based on diesel engine settings.
- Overall, the Experimental-ANN hybrid model demonstrated excellent accuracy in predicting the specific fuel consumption of diesel engines.

In conclusion, while this study demonstrates the effectiveness of the ANN model in predicting specific fuel consumption (SFC) based on variables such as types of fuel, compression ratio, injection pressure, and load, it is important to note its limitations. Introducing new control variables could potentially impact the model's performance. Additional model retraining and revalidation would be necessary to ensure accurate predictions with these additional variables.

Data availability statement

The experimental data generated and analyzed in this study were collected by the authors and are available upon request. Researchers interested in obtaining access to the dataset for further analysis or collaboration can contact the corresponding author [maulikmodi325@gmail.com] for data sharing. We are committed to promoting transparency and facilitating scientific inquiry, and welcome inquiries regarding the dataset. The data that support the findings of this study are available upon reasonable request from the authors.

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Ethical compliance

The study was approved by the Ethics Committee of Kadi Sarva Vishwavidyalaya.

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Conflict of interest declaration

The authors declare that they have no affiliations with or involvement in any organization or entity with any financial interest in the subject matter or materials discussed in this manuscript.

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