An assessment of six-cylinder diesel engine performance and vibration features by diesohol fuel employing neural networks

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Abstract: This study's main goal was to thoroughly assess the performance and vibration of a six-cylinder engine utilizing diesel-bioethanol fuel mixtures. These blends incorporated bioethanol in ratios below 15% and were created by combining anhydrous ethanol (C_2H_5OH) with standard diesel fuel in varying proportions. The study employed seven distinct blends to assess engine performance and vibration levels thoroughly. Multi-layered perception (MLP) neural networks were applied namely a feedforward back-propagation neural system. The chosen training algorithm was the Levenberg-Marquardt, while activation functions employed were logsig, tansig, and purelin transferring functions. The study findings revealed that the optimal neural network model consisted of two hidden layers comprising 15 neurons. The recommended transfer functions for the first and second hidden layers were logsig and logsig, respectively. Overall, this study demonstrated the neural system model's remarkable efficacy in accurately predicting the performance and vibration levels of engines operating on blends of diesel and bioethanol fuels, commonly known as diesohol fuel blends.
Keywords: ANN model, diesel engine, performance, vibration, kurtosis

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1 Introduction

Most energy needed is consumed by combusting fossil-based fuels, which also generate 98% of all carbon emissions (Taghizadeh-Alisaraei et al., 2017; Hosseini et al., 2017a). Diesel engines are often used, hence it has been determined that their emissions are a substantial contributor to air pollution (Chen et al., 2019; Hosseini et al., 2022; 2023). Therefore, researchers have focused on clean and renewable fuels in light of the greater need for energy, the negative environmental impact of carbon-based fuel usage, and the need to reduce emissions (Uslu and Celik 2018; Hosseini et al., 2017b; Taghizadeh-Alisaraei et al., 2017). Studies have shown that biofuels, including biodiesel and bioethanol, can potentially serve as a practical addition or substitute for fossil fuel-derived gasoline or diesel fuel (Ghobadian, 2012; Hassan et al., 2017; Taghizadeh-Alisaraei et al., 2017; Taghizadeh-Alisaraei et al., 2022). Due to its low viscosity, favorable cold-flow

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properties, and higher oxygen content, bioethanol exhibits a potential for achieving higher compression ratios and shorter burn times, thereby making it a promising alternative fuel (Silitonga et al., 2018; Wei et al., 2018). In this context, a blend of diesel and bioethanol with a bioethanol ratio of less than 15% is a prospective alternative fuel, namely diesohol fuel (Shadidi et al., 2014). The flexibility, accuracy, and rapid response capabilities of artificial neural networks (ANNs) have recently made them a highly appealing and effective approach for simulating and resolving complicated issues (Mohammadhassani et al., 2015).

ANNs is a computational machine that can generate, develop, and uncover new knowledge autonomously without requiring assistance like the human brain (Oğuz et al., 2010). ANNs is utilized in scientific and engineering applications to address diverse problems, particularly those that cannot be solved using conventional modeling methods (Oğuz et al., 2010). ANN is a robust and non-linear technique that enables the prediction of multiple output variables by utilizing multiple input variables (Alt et al., 2018). In the following, a review of various studies that have employed ANNs to analyze performance and air pollution features of biofuelled engines and the results of each study are discussed in detail. In this regard, Rao et al. (2017) employed an ANN to analyze a diesel engine's performance and exhaust pollution diesel engine running on biodiesel. They found that the back-propagation technique was optimal for training the network. The results showed a high correlation coefficient for engine performance and emissions prediction for exhaust gas temperature (EGT), brake specific fuel consumption (BSFC), brake thermal efficiency (BTE), HC, O_2, CO_2, CO, NO_X, and smoke, respectively. In a separate study, Oğuz et al. (2010) assessed the ANN to predict diesel engine performance using different biofuels. They applied various fuel types such as diesel, biodiesel, and biodiesel-bioethanol mixtures to create the ANN framework. The model could accurately anticipate power, torque, hourly fuel consumption, and SFC, leading the researchers to conclude that the developed model is suitable for predicting engine performance with different biofuels. Ghobadian et al. (2009) analyzed diesel engine features using biodiesel fuel with an ANN. They employed a normal Back-Propagation technique for the engine and an MLP for non-linear mapping between input/output components. The ANN model predicted engine performance and exhaust emissions well, with correlation coefficients (*R*) higher than 0.92 for engine torque, specific fuel consumption (SFC), CO, and HC emissions. The model's simulated and measured values showed good agreement with a predicted mean square error (MSE) of 0.0004. Karonis et al. (2003) utilized a neural network methodology to establish a correlation between diesel fuel quality and the exhaust pollution of a diesel engine, and their findings demonstrated that the model achieved very well predictions for CO, HC, NO_x, and PM.

Balamurugan et al. (2017) developed an ANN model to anticipate the performance and emission features of an adjustable compression ratio (VCR) engine using blends of biodiesel extracted from orange oil. They determined the Levenberg–Marquardt algorithm with logsig/tansig transfer function to generate the most accurate results. The ANN model was a reliable predictive tool for analyzing VCR engines' performance and emission characteristics using biodiesel blends, including BTE, BSFC, CO, NO_x, and HC emissions. Parlak et al., (2006) investigated using an ANN for predicting SFC and EGT in a diesel engine. They proposed a back-propagation neural network model with a 3–7–2 (input/hidden/output layer nodes) structure, which was the best model for the task. The results showed that the ANN model could predict SFC and EGT in diesel engines with a median percentage error of fewer than 2%, which agreed with the experimental results. Kiani et al., (2010) utilized an ANN model to predict an SI engine's engine brake power and exhaust emissions using gasoline-ethanol blends. Researchers found that the proposed algorithm provided a desirable emission model with a coefficient of correlation (R^2) of 0.98, 0.96, 0.90, and 0.71 for CO, CO_2, HC, and NO_x, respectively. Moreover, the ANN model accurately predicted the torque and brake power with a correlation coefficient of 0.99 and 0.96. Rezaei et al., (2015) performed a similar study utilizing homogeneous charge compression ignition (HCCI) engines using ethanol-butanol blends. The analysis demonstrated that the suggested simulations could accurately forecast HCCI engine performance parameters.

Literature reviews have shown that using ANNs for predicting engine performance and vibration parameters has gained significant attention in recent years. However, no research hasn't been conducted on using ANNs to anticipate the performance, root-mean-square (RMS), and Kurtosis of six-cylinder diesel engine vibration by diesohol blended fuels. Therefore, this study aimed to set out an ANN model for predicting the engine performance, RMS, and Kurtosis of a six-cylinder diesel engine's vibration using diesohol blended fuels. Developing such a model could provide valuable insights into the impact of diesohol mixtures on an engine's performance and vibration characteristics and aid in developing more efficient and sustainable engines.

2 Materials and methods

2.1 Experimental set-up

This study utilized a six-cylinder diesel engine. The engine has a governor system for controlling and stabilizing the rotational speed. The cylinder firing order of the engine follows the sequence of 4-2-6-3-5-1, and the valve timings are as follows: intake valve opening (IVO) 25 degrees before bottom dead center (BDC), exhaust valve closing (EVC) 28 degrees after top dead center (TDC), intake valve closing (IVC) 55 degrees after BDC, and exhaust valve opening (EVO) 120 degrees after TDC. To measure the engine's brake power and torque under different operating conditions, an eddy current dynamometer model WE400 was adopted. The engine's signals generated by vibration were obtained using triple accelerometers installed vertically, laterally, and longitudinally (*x*, *y*, *and* *z*) directions. The acceleration-time signals utilized for transforming to an analog/digital converter for storage on a computer (Figure 1).

2.2 Fuel preparation

In this study, the mixture of anhydrous ethanol (C_2H_5OH) and straight diesel (D100) were prepared by volume using a homogenizer. Fuel mixtures of straight diesel, D98E2 (98% straight diesel and 2% ethanol), and diesel inclusion ethanol up to 10% were utilized. The fuel blends' properties can be seen in our previous paper, cited in reference (Taghizadeh-Alisaraei and Rezaei-Asl 2016), for additional details on the properties of the fuel mixtures.

2.3 Experimental methods

The tests in this study were conducted under maximum load conditions and at five engine rotations (1600-2000 by 100 rpm intervals) with a fixed pressure at the injectors (35 MPa) for all fuel mixtures. Please note that the information used in this study adopted from our previous research cited in reference (Taghizadeh-Alisaraei and Rezaei-Asl, 2016). Performance factors such as torque, power, BSFC, and EGT were recorded during each test, along with the RMS of vibrations. After the engine stabilized, the data acquisition period was 1 minute for each test, with a frequency of 50 kHz. Acceleration data were stored during several working cycles of the engine, starting from the TDC of the piston's No.1. Figure 1 depicts the experiments of vibration data acquiring; also, the set-up and test method illustrate the same figure.

2.4 Vibration analyses

This section describes the RMS and kurtosis features of the diesel engine signals to analyze engine vibration.

2.4.1 RMS of vibration signal

The RMS and kurtosis parameters were utilized to analyze the engine vibration and evaluate its performance. These parameters can be defined using the following equations. The RMS is calculated based on Equation 1, which takes into account the number of data within a given time period (N) and the acceleration data at time t_k ($x(t_k)$) (Hosseini et al., 2020):

$$x_{RMS} = \left[\frac{1}{N} \sum_{k=1}^{N} x^2(t_k) \right]^{1/2} \tag{1}$$

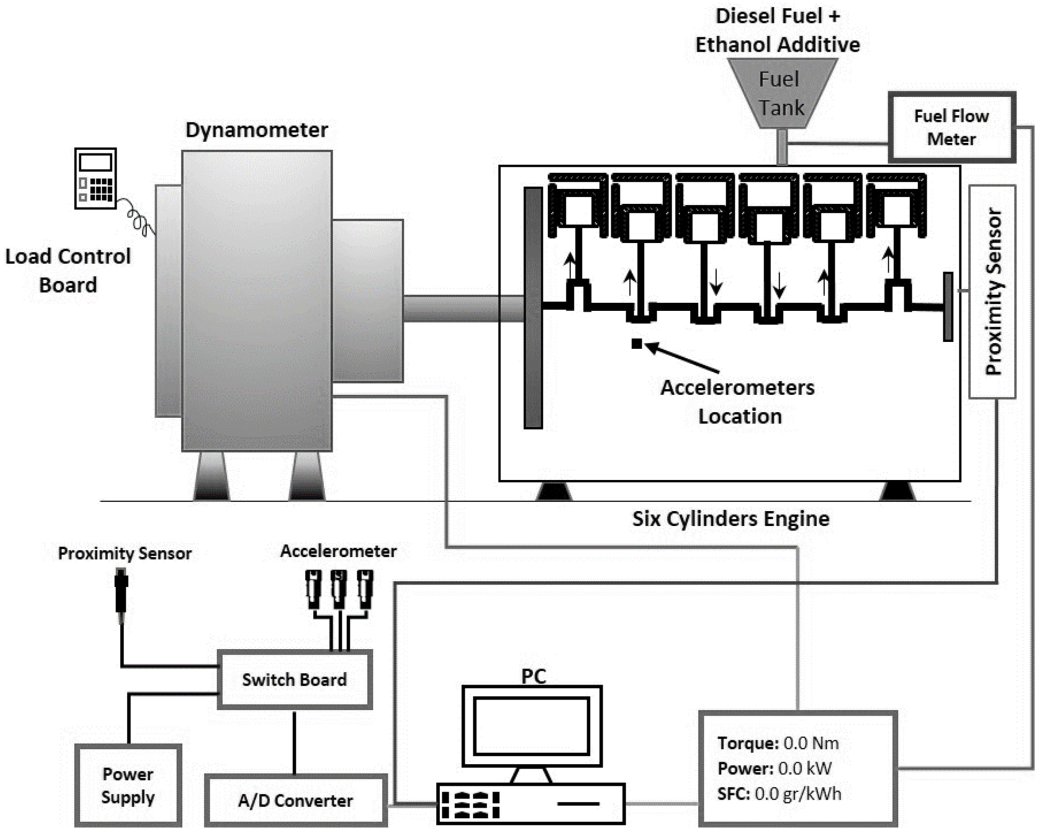


Figure 1 The devices and data collection set-up schematic for experiments

The root mean square (RMS) is a parameter that compares vibrations under different situations. RMS is directly related to the energy of the vibration signals, a function of its amplitude. It is determined by calculating the square of vibration data, which assigns higher emphasis to sudden peaks or shocks (Taghizadeh-Alisaraei and Rezaei-Asl, 2016). The total vibration acceleration (atotal), which is a combination of acceleration in three axes, can be expressed as the following Equation 2:

$$\alpha_{total} = \left(\alpha_{vertical} + \alpha_{lateral} + \alpha_{longitudinal}\right)^{1/2} \tag{2}$$

2.4.2 Kurtosis of vibration signal

The kurtosis parameter is highly susceptible to noise and requires preliminary signal treatment, such as band-pass filtering and envelope detection, to utilize its performance (Pachaud et al., 1997; Wang et al., 2015; Lorenzo and Calabro, 2007) entirely. Kurtosis characterizes the peakedness and thickness of the signal's distribution around the mean. A higher kurtosis value indicates that the peaks in the signal are taller and sharper. Thus, kurtosis can better distinguish between two signals.

For comparison of results with other common methods, the criterion of kurtosis was employed to assess the engine's performance based on the vibration signal, as described by Equation 3 (Hosseini et al., 2020):

$$Kurt = \frac{\left[\frac{1}{N} \sum_{k=1}^{N} x^4(t_k) \right]}{\left[\frac{1}{N} \sum_{k=1}^{N} x^2(t_k) \right]^2} \tag{3}$$

The total kurtosis of the acceleration signal ($Kurt_{total}$) can be defined as the combination of the kurtosis values of the three axes of acceleration signals, and it can be calculated using Equation 4:

$$Kurt_{total} = \left(Kurt_{vertical} + Kurt_{lateral} + Kurt_{longitudinal}\right)^{1/2} \tag{4}$$

3 ANN modeling

In this study, the primary objective is to utilize an ANN for the prediction of performance, RMS, and Kurtosis of a six-cylinder diesel engine's vibration. This was accomplished by creating a computer technique in Matlab software to anticipate the parameters mentioned above under various operation situations. One of the advantages of the ANN model is that it can learn about the system without prior knowledge of the process relationships. This makes it significantly faster than traditional simulation programs or mathematical models. Furthermore, the ANN model's input and output variables can be modified per the requirements (Oğuz et al., 2010). An ANN network comprises three essential elements: the input/one or more hidden/output layer. The input layer gets the values of the input variables, which are then analyzed by the hidden layer(s). The output layer calculates the final output. The various neural network models vary based on the types of nodes in the hidden layer, which are responsible for learning the underlying relationships between the input and output variables (Karonis et al., 2003; Aghbashlo et al., 2021). To develop an ANN model, two training and testing processes are needed by training network output values estimated based on input data. The testing step involves testing the network to determine the time to stop training or to store training data, which can later be used to estimate an output (Oğuz et al., 2010).

3.1 Input and output parameters

In this paper, the input layer of the ANNs consisted of five parameters: engine speed, ethanol percentage, lower heating value (LHV), fuel density, and fuel consumption. The output layer included eight parameters: engine power, BTE, RMS, and kurtosis of the engine's vibration in three axes, namely vertically, laterally, and longitudinally. Figure 2 displays the neural network architectural diagram. All of the data in the data sets were arranged prior to training the network, and the input parameters were normalized using an equation since the activation function of the output layer was linear (purelin) in all networks. Therefore, only the input parameters were normalized using Equation 5:

$$I_{norm} = \frac{I - I_{\min}}{I_{\max} - I_{\min}} \tag{5}$$

Equation 5 is used to normalize the input parameters before feeding them into the ANN model. In this equation, I_{norm} represents the data with normalization, I is the experimental or input data, I_{min} represents the lowest value of the exprimental data, and I_{max} represents the greatest value of the measured data. By this equation, the input parameters are scaled to the range of 0 to 1, which is required for the proper functioning of the ANN model with linear activation function in the output layer.

3.2 Selection of dataset and activation function

An ANN model is employed to predict the outcome variable. 100% of the dataset was available for analysis, including 70%, 15%, and 15% for train, valid, and test. An MLP with a feed-forward back-propagation neural network model was used for analysis. The levenberg-marquardt (trainlm) technique employed as the training algorithm. In this research, three different transfer functions were applied as activation functions, namely logsig, tansig, and purelin, and the corresponding equations are presented in Equations 6 and 7, where x denotes the input data.

$$logarithmicsigmoid = \frac{1}{1+e^{-x}} \tag{6}$$

$$tangentsigmoid = \frac{2}{1+e^{-2x}} - 1 \tag{7}$$

$$R = 1 - \left(\frac{\sum_{i=1}^{n} (T_i - O_i)^2}{\sum_{i=1}^{n} (T_i - \bar{O})^2} \right) \tag{8}$$

$$MSE = \frac{1}{n} \sum_{i=1}^{n} (T_i - O_i)^2 \tag{9}$$

3.3 Statistical analysis of output variables

In this research, the network was trained by different numbers of hidden layers and neurons to determine the best network. For comparison, mean squared error (MSE) and correlation coefficient (R-values) statistical techniques were used. The best network was determined based on the higher value of *R* and the lower value of MSE, as computed by Equations 8 and 9, respectively.

Equations 5 and 6 involve the following variables: n denotes the number of sampling tested; T_i represents the results obtained from the measurements (target); O_i corresponds to the values that were anticipated (output); and $\bar{O}$ denotes the mean of the expected values.

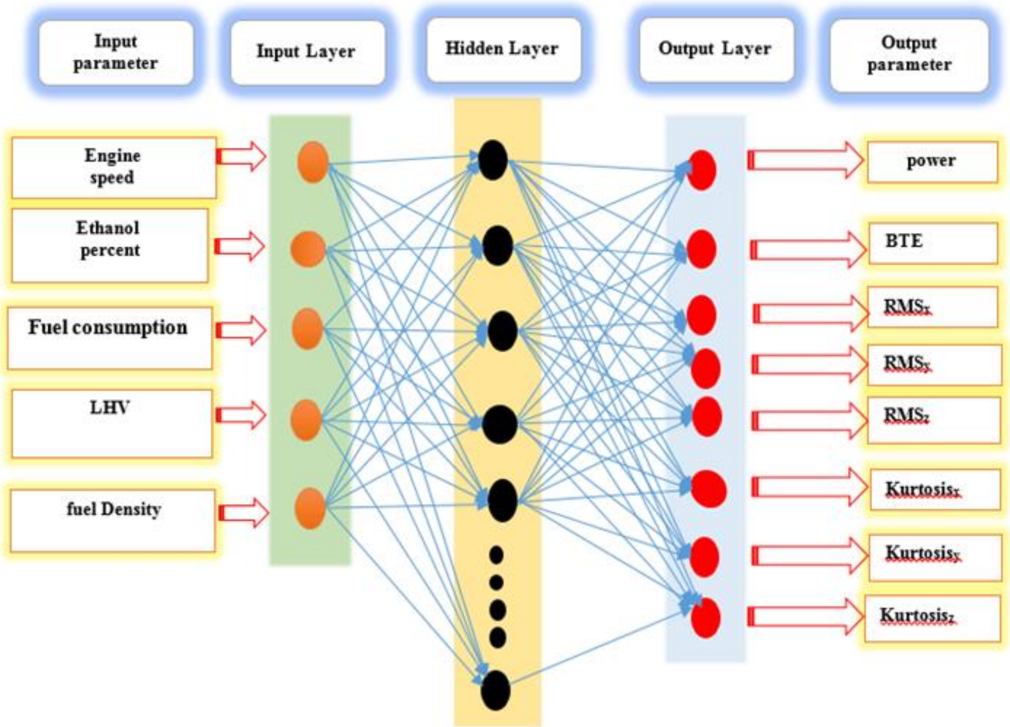


Figure 2 Topology of a neural network

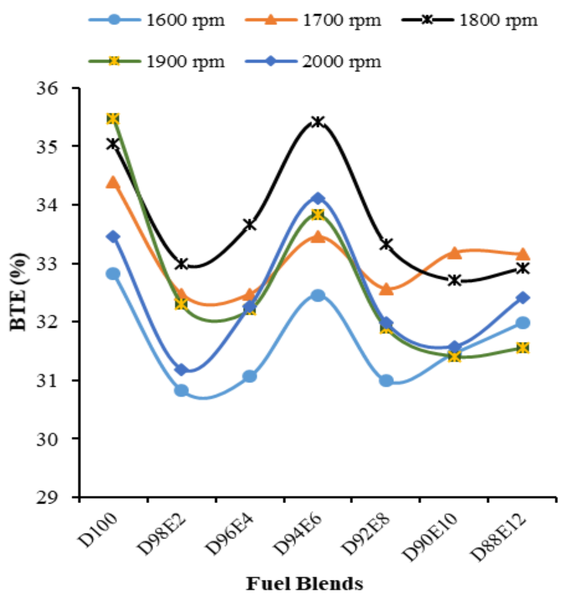
4 Results and discussion

Figure 3a displays the BTE with regard to the fuel blend and engine speed. The graph indicates that the BTE increases as the engine speed increases from 1600 to 1800 rpm and then decreases from 1800 to 2000 rpm. Typically, the BTE decreases at higher speeds due to reduced engine volumetric efficiency. The D98E2 and D90E10 fuels exhibit the lowest values of BTE with regard to fuel consumption, while the maximum value of BTE is obtained for D100 and D94E6 fuels. For fuel blends of D92E8, D90E10, and D88E12, the BTE value is reduced due to the lower quality of the fuel blends. For D88E12 fuel blend, the combustion quality decreases due to heterogeneous fuel. The mixing of ethanol with diesel fuel depends on its temperature, it increases with increasing temperature, but with decreasing temperature, it becomes biphasic, and the fuel quality decreases (Mccormick and Parish, 2001; Sathiyamoorthi and Sankaranarayanan, 2017).

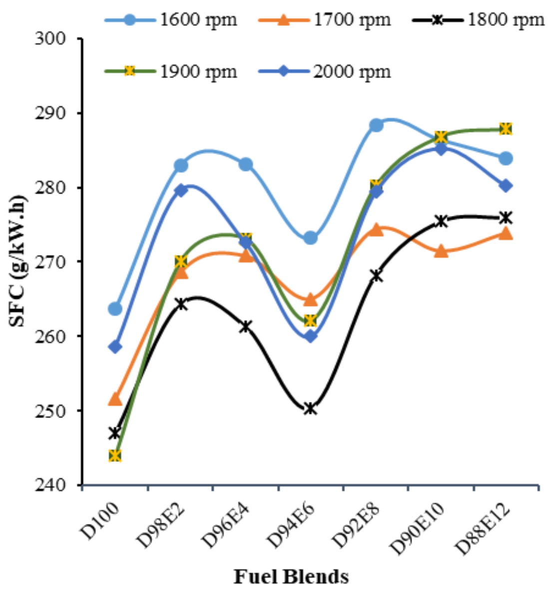
The SFC is maximum at the speed of 1600 rpm due to the lower produced engine power. The minimum SFC is for a speed of 1800 rpm due to higher produced power and lower fuel consumption. It is worth noting that the trend of SFC diagrams contrasts with the BTE diagrams (Figure 3b).

Decreased ethanol's heating value is important in increasing SFC. Although the use of oxygenate fuels like ethanol increases the oxygen content of the fuel and results in an ideal stoichiometric ratio, it also increases the air-fuel ratio, which can affect the combustion and emissions of the engine, ultimately leading to increased fuel consumption. As the dose of ethanol in fuel blends increases from 0% to 12%, the engine power also increases, but fuel consumption also rises, particularly for the three fuel blends of D92E8, D90E10, and D88E12. Among the D98E2, D96E4, D94E6, D92E8, D90E10, and D88E12 fuel blends, the minimum SFC is related to the D94E6 fuel blend due to its good balance between fuel consumption, combustion efficiency, and fuel quality. However, increasing the amount of ethanol to more than 6% reduces fuel quality, which is the main factor in the rise of SFC and the drop of BTE.

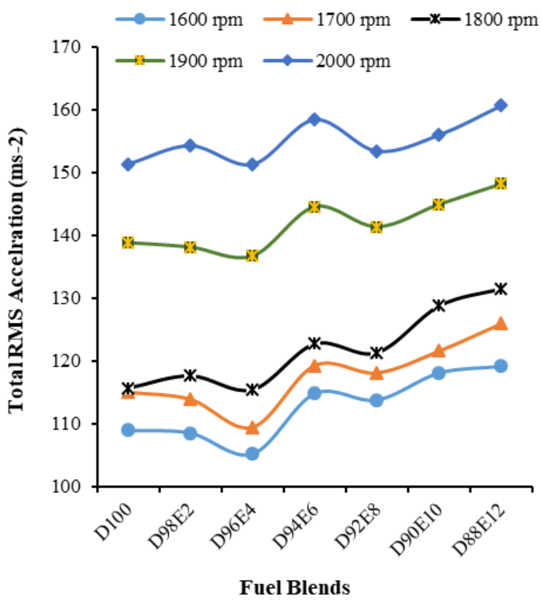
The RMS acceleration resultant, RMS_{Total}, was calculated for the vertical, lateral, and longitudinal directions using Equation 2. The RMS of vibration has a rising trend with increasing bioethanol dose in D100 fuel, leading to enhanced engine vibration (Figure 3c). Additionally, for all fuel blends, the kurtosis increases with ethanol dose in D100 fuel (Figure 3d). A sudden increase in kurtosis is observed for D94E6 fuel, indicating some irregularities in engine performance, and it operates in a more non-uniform manner and increases power.



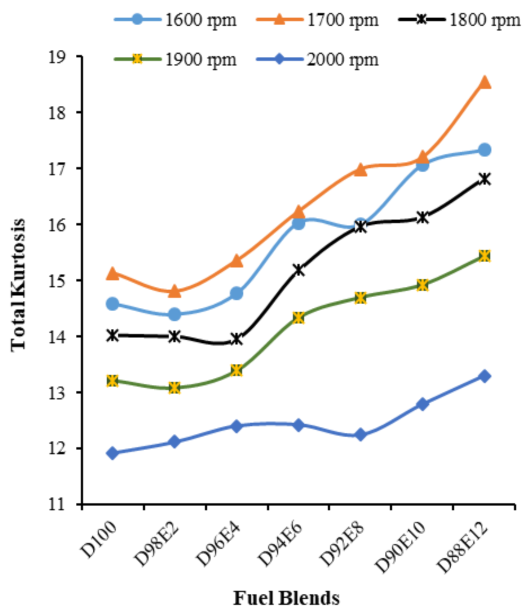
(a) BTE



(b) SFC



(c) total RMS



(d) kurtosis

Figure 3 values of BTE, SFC, total RMS, and kurtosis for all fuel blends

An ANN model was employed to analyze the performance, RMS, and Kurtosis of a diesel engine's vibration with diesohol fuel blends. All input parameters used in the ANN model impact the engine's performance, RMS of vibrations, and Kurtosis. Table 1 summarizes the impact of each input parameter on the output variables.

Table 1 The impact of each input parameter

Parameter	Range	Description
Engine speed	1600-2000 rpm	1600 to 1800 rpm, BTE ↑; 1800 to 2000 rpm, BTE ↓; 1600 to 2000 rpm, engine power ↑.
LHV	39.64-41.6 (MJ kg^{-1})	Bioethanol↑ from D100 to D88E12, LHV↓.
Fuel consumption	10.21-16.26 (kg h^{-1})	Adding bioethanol to D100, from 1600 to 2000 rpm, fuel consumption ↑.
Ethanol percent	0-12	Bioethanol↑ from D100 to D94E6, brake power↑; from D94E6 to D88E12, brake power ↓.
fuel density	0.8136-0.8201 (g cm^{-3})	Bioethanol↑ from D100 to D88E12, fuel density ↓.

Note: ↑ : indicating an increasing trend, ↓ : indicating a decreasing trend.

The impact of each input parameter on the performance, RMS, and Kurtosis of the diesel engine's vibration has been thoroughly examined and discussed in our previous study (Taghizadeh-Alisaraei and Rezaei-Asl, 2016). The results and comprehensive analysis are presented in reference, and the changes in the output parameters in various conditions are summarized in Table 2, which has been elaborated in our previous research (Taghizadeh-Alisaraei and Rezaei-Asl, 2016).

Table 2 Range of variations in output parameters like performance, RMS, and Kurtosis of engine's vibration

Parameter	Range	Description
Power	39.5-57.9	Bioethanol↑ from D100 to D94E6, brake power↑; from D94E6 to D88E12, brake power ↓. Reason: adverse blending of ethanol-diesel fuel at high doses of ethanol and non-heterogeneous fuel blend.
BTE	30.82-35.47	1600 to 1800 rpm, BTE ↑; 1800 to 2000 rpm, BTE ↓; BTE decreases at high speeds due to lower engine volumetric efficiency.
RMS	44.154-106.5	Bioethanol↑ from D100 to D88E12, the RMS of vibration ↑.
Kurtosis	5.248-13.719	Bioethanol↑ from D100 to D88E12, the kurtosis of vibration ↑.

Note: ↑: indicating an increasing trend, ↓: indicating a decreasing trend.

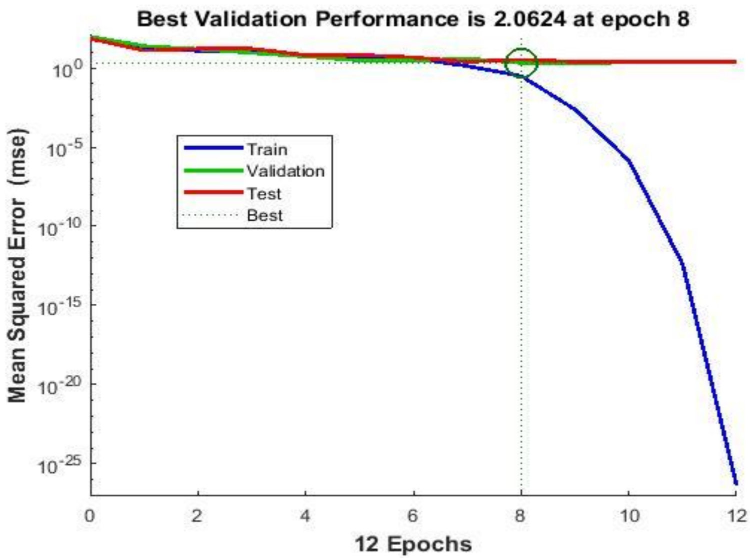
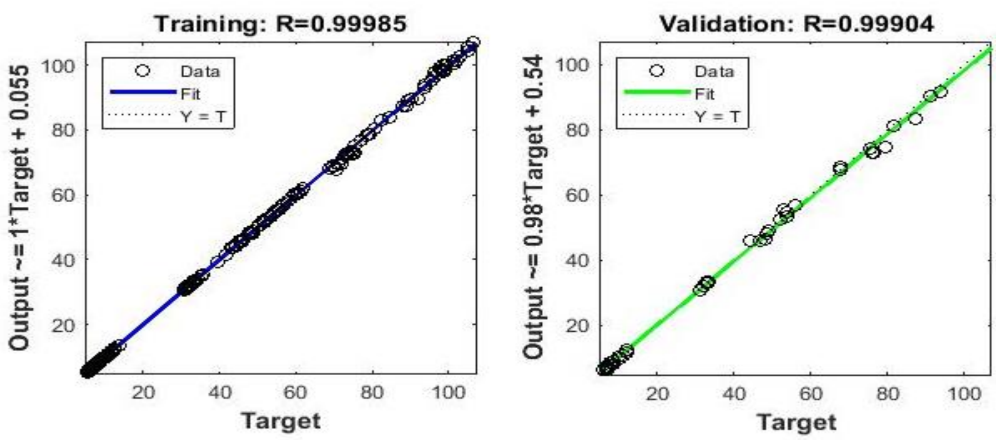


Figure 4 Performance of the optimum network



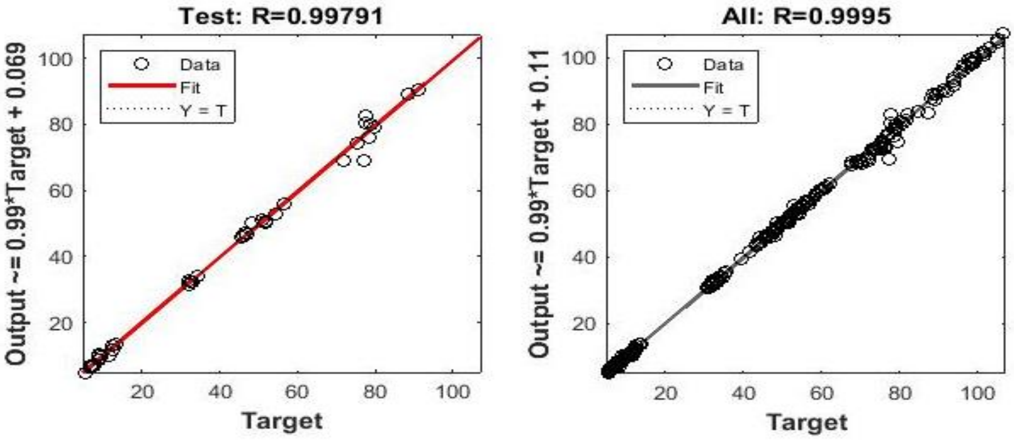


Figure 5 Overall R values of optimal ANN model

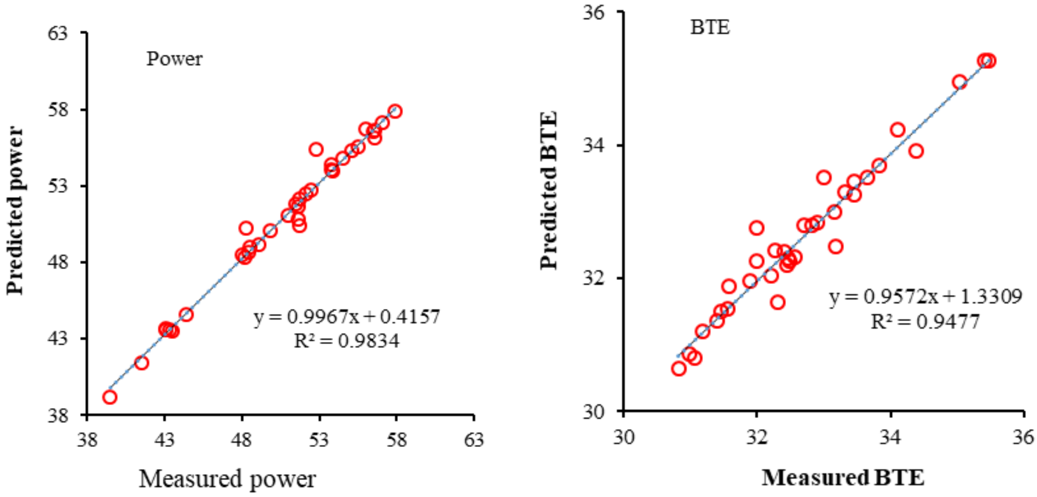
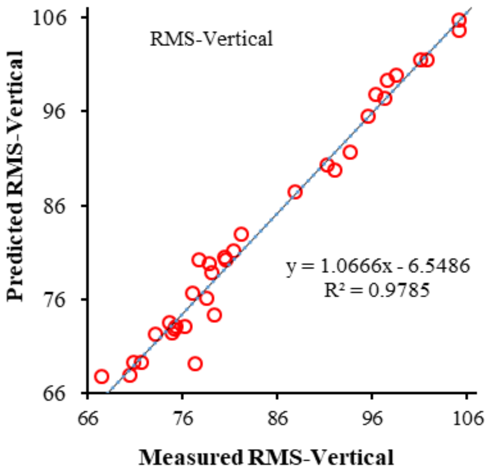


Figure 6 Displays the experimental results and predicted values of the Performance parameter

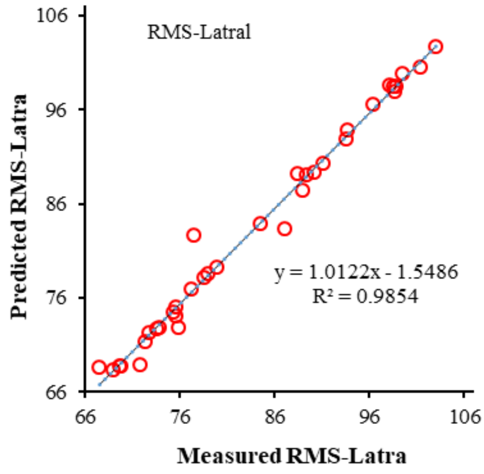
Multiple network models were employed to obtain the most accurate prediction by the ANN model. The outcomes and evaluations of various network models are presented in Table 3. The ANN model was evaluated using multiple network models to select the optimum anticipated. The trainlm algorithm was used with the purelin transfer function for the output layer and the transfer functions of tansig and logsig for the two hidden layers. Two hidden layers with 15–15 neurons each and the transfer functions of logsig–logsig for the first and second hidden layers were found to be the ideal network architecture. Figures 4 and 5 illustrate the performance and overall R-values of the optimum ANN network. The R-values of the optimum structure for training, validation, and testing were 0.999, 0.999, and 0.998, respectively. For train, valid, and test, the MSE values of the optimum network were 0, 2.062, and 2.448, respectively.

An analysis of regression was employed between the output and related targets to assess the network's response. The finding of this analysis indicated that the constructed model could anticipate the performance, RMS of vibrations, and Kurtosis of compression ignition (CI) diesel engine with sufficient accuracy. The expected outputs of the ANN were compared to the experimental data for performance, vibrations, and Kurtosis, presented in Figures 6 and 7.

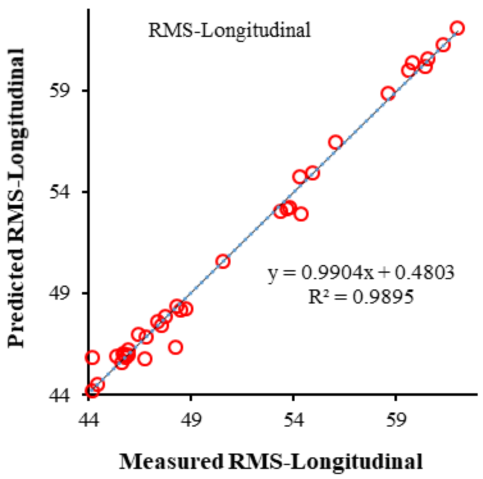
The performance regression coefficients for power and BTE using the ANN were 0.991 and 0.973, respectively. The RMS of vibrations and Kurtosis regression coefficients for RMSx, RMSy, RMSz, Kurtosisx, Kurtosisy, and Kurtosisz using the ANN were 0.989, 0.992, 0.994, 0.903, 0.962, and 0.963, correspondingly. These results indicate that the optimal ANN model strongly correlated with the predicted model and experimental data.



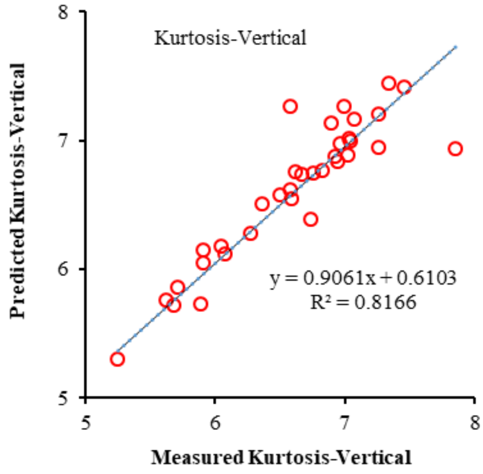
(a) RMS-Vertical



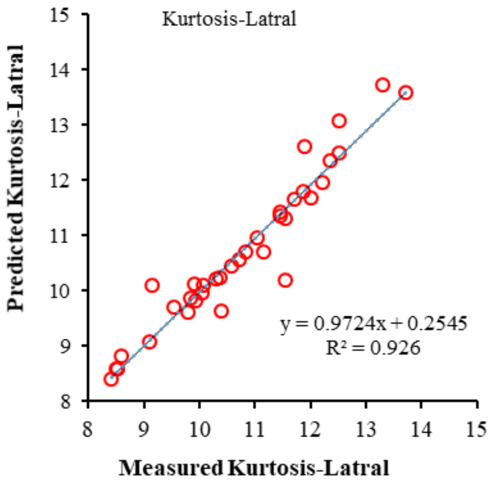
(b)RMS -Lateral



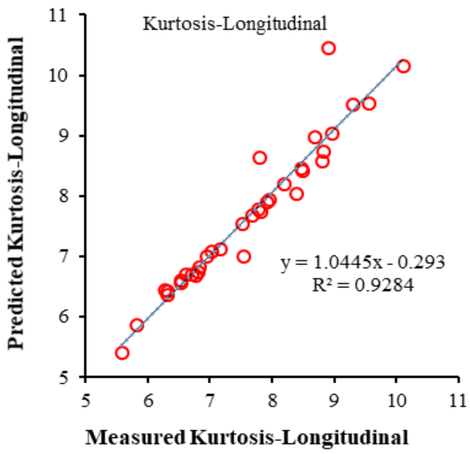
(c) RMS-Longitudinal, kurtosis of the engine



(d) Kurtosis-Vertical



(e)Kurtosis-Lateral



(f) Kurtosis-Longitudinal

Figure 7 Displays the experimental results and predicted values of the vibrations and Kurtosis of the engine vibrations of the engine

Based on the regression analysis results, it can be concluded that the ANN is a powerful tool for predicting the performance, RMS of vibrations, and Kurtosis of engines with reasonable regression coefficients. The high regression coefficients obtained for the various parameters indicate that the ANN model could capture the underlying patterns and relationships between the input and output variables in the dataset, leading to accurate predictions. Therefore, the ANN model can be useful in predicting the behavior and performance of engines, which can have significant practical implications for industries such as automotive and transportation. It is worth mentioning that, due to the widespread practical use of compression combustion engines in various agricultural engineering sectors, this research's results can be used in developing and adjusting engines with different practical conditions in agricultural engineering.

Table 3 Brief of various networks evaluated to yield the criteria of network performance

Networks number	Activation function	Neurons in hidden layers		MSE			R		
		Layer 1	Layer 2	Training	Validation	Testing	Training	Validation	Testing
1	a/b	5	-	0.5551	2.6503	3.3427	0.99969	0.99866	0.99759
2	a/b	10	-	0.1229	8.2202	5.1181	0.99962	0.99702	0.99752
3	a/b	20	-	0.0029	6.8496	3.0467	0.99963	0.999777	0.99895
4	a/b	30	-	0.0004	2.4587	4.9500	0.99996	0.99912	0.99767
5	c/b	5	-	0.4286	5.3832	4.3969	0.99926	0.99721	0.99727
6	c/b	10	-	0.0996	5.1054	8.9605	0.9999	0.99768	0.99476
7	c/b	20	-	0.0098	7.8996	9.6203	0.99984	0.99602	0.99606
8	c/b	30	-	0.0000	7.0798	8.3383	0.9996	0.99596	0.99626
9	c/c/b	10	10	0.0926	8.2989	2.8820	0.9994	0.99652	0.99775
10	c/c/b	15	15	0.0000	2.0624	2.4481	0.99985	0.99904	0.99791
11	c/c/b	20	20	0.0000	8.0083	7.0152	0.99963	0.99547	0.99631
12	c/c/b	20	25	0.0044	8.3046	6.6949	0.99858	0.99492	0.99609
13	c/c/b	25	20	0.0000	9.2814	4.9946	0.99979	0.99551	0.99721
14	c/c/b	25	25	0.0000	13.1199	10.7911	0.99956	0.99396	0.99505
15	c/c/b	20	30	0.0000	12.3391	5.0176	0.99938	0.99568	0.99764
16	c/c/b	25	30	0.0000	22.5487	14.9324	1	0.98749	0.98475
17	c/c/b	30	30	0.0003	6.0896	11.7499	0.99986	0.99679	0.9919
18	a/a/b	10	10	0.0317	4.8273	9.9892	0.99985	0.99737	0.99463
19	a/a/b	15	15	0.0118	11.7747	7.7339	0.99717	0.99685	0.99593
20	a/a/b	20	20	0.0000	13.3989	7.4388	0.99992	0.99375	0.99641
21	a/a/b	20	25	0.0000	8.5352	5.5769	0.99821	0.99558	0.99627
22	a/a/b	25	20	0.0000	7.4846	9.3666	1	0.99783	0.99576
23	a/a/b	25	25	0.0000	10.6364	12.8336	0.99693	0.99027	0.98548
24	a/a/b	20	30	0.0000	7.1790	4.3499	1	0.99762	0.99735
25	a/a/b	25	30	0.0000	11.8147	16.9473	1	0.99397	0.98768
26	a/a/b	30	30	0.0000	14.8898	13.4523	1	0.99271	0.99365
27	a/c/b	10	10	0.1351	9.0990	7.0104	0.9981	0.996	0.99596
28	a/c/b	15	15	0.0039	15.9094	4.0175	0.99229	0.99668	0.99296
29	a/c/b	20	20	0.0000	14.3756	12.4895	0.99699	0.99313	0.99399
30	a/c/b	20	25	0.0016	5.8147	19.6947	0.99692	0.9964	0.9863
31	a/c/b	25	20	0.0000	11.9491	8.0112	1	0.99494	0.99611
32	a/c/b	25	25	0.0000	5.9878	6.9302	0.99959	0.99728	0.99625
33	a/c/b	20	30	0.0000	2.1248	3.3423	0.99978	0.99895	0.99842
34	a/c/b	25	30	0.0000	8.2412	9.7932	0.99934	0.99576	0.99618
35	a/c/b	30	30	0.0000	4.7512	5.6869	1	0.99741	0.99698
36	c/a/b	10	10	0.1194	4.5388	8.3300	0.99871	0.99841	0.99641
37	c/a/b	15	15	0.0021	9.4714	8.9846	0.9998	0.99545	0.99507
38	c/a/b	20	20	0.0000	7.7820	13.0252	1	0.99683	0.97407
39	c/a/b	20	25	0.0000	3.6960	8.1147	1	0.99762	0.9954
40	c/a/b	25	20	0.0000	10.1197	6.3902	0.99998	0.99496	0.997
41	c/a/b	25	25	0.0000	3.2329	6.9756	1	0.99817	0.99806
42	c/a/b	20	30	0.0000	18.6084	20.1389	0.999457	0.99154	0.9904
43	c/a/b	25	30	0.0000	5.2361	4.4124	0.99961	0.99757	0.99733
44	c/a/b	30	30	0.0000	6.7297	5.4205	0.99929	0.99716	0.999

Diesel engine performance and vibration characteristics are highly dependent on engine controlling factors, including fuel type, qualities of fuel, engine rotation, intake temperature, and environmental factors affecting the engine. As a result, utilizing ANN can be a valuable approach to lessen the time and financing required for extensive test-bed research, especially when particular variables need to be checked (Mohamed et al., 2012). The use of a proposed ANN model can minimize the need for vast amounts of training data, in contrast to the common approach of employing a look-up table in the ECU of the IC engines, which typically necessitates experimental data to anticipate or modify engine performance, manage pollution, and mitigate knocking phenomena utilizing engine vibration signals (Rezaei et al., 2015). The present study demonstrates the ability of the proposed artificial neural network model to cut back on the cost and time of ECU calibration. In contrast to the conventional approach, which requires an extensive collection of data sets for predicting and calibrating engine performance, emissions control, and engine knocking reduction using engine vibration signals, the proposed ANN model requires less data for training of the network. Therefore, the presented ANN model can offer significant time and cost savings for engine control strategies involving large variations (Hosseini et al., 2020).

5 Conclusion

The object of the present research was to use a neural network technique that could predict the performance, RMS, and Kurtosis of the body vibration of a six-cylinder diesel engine using a blended fuel called diesohol (diesel-ethanol). The dataset used for training, validation, and testing the ANN model was divided into 70%, 15%, and 15%, respectively. An MLP neural network with a feed-forward back-propagation model was used, employing the Levenberg-Marquardt (trainlm) technique as the training algorithm, and logsig, tansig, and purelin transfer functions as activation functions. The optimal network architecture was found to have two hidden layers, with 15 neurons each, and a transfer function of logsig-logsig for the first and second hidden layers, respectively. The correlation coefficient for the best structure for train, valid, and test were 0.99985, 0.99904, and 0.99791, respectively. The MSE values of train, valid, and test of the best model were 0, 2.062, and 2.448, respectively. The regression coefficient values for RMS and Kurtosis of the engine's vibration using ANN were found to be 0.989, 0.992, 0.994, 0.903, 0.962308, and 0.963 for RMS_x, RMS_y, RMS_z, $Kurtosis_x$, $Kurtosis_y$, and $Kurtosis_z$, respectively. The findings of this study indicate that ANNs are a potent instrument for forecasting engine performance and body vibration. The predicted model shows a strong correlation with measured data, emphasizing the accuracy of the ANN as a predictive tool in this field. Future studies can be done with different renewable fuels to investigate the six-cylinder diesel engine's performance, emissions, and vibrations and analyze exergy, environmental exergy, and economic exergy with an evolutionary developed algorithm.

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