Diesel Engine Power Prediction Based on Fuel Blends Using Neural Network

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ABSTRACT

Diesel engines are extensively used across various sectors—including transportation, petrochemicals, power generation, military, and heavy machinery—with particularly widespread application in the automotive industry. An internal combustion engine burns a mixture of fuel and air to efficiently generate mechanical energy. Engine performance, measured by power output, torque, and fuel efficiently enhances with improved combustion efficiency. To predict diesel engine performance, this study employs a neural network model. The objective is to analyze engine behavior across various fuel blends and identify the most accurate machine learning-based prediction model. The best performance of the biodiesel fuel blends with diesel is in MIX-5, which is 69.8 kW in 4900 rpm. Based on testing on experimental data, the best neural network topology is obtained with three hidden layers. In this neural network topology, training is carried out on the engine performance and the regression value is 0,98416.

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1. Introduction

The internal combustion engine uses a mixture of fuel and air to burn as efficiently as possible to produce mechanical energy. Engine performance, including power, torque, and fuel consumption, improves as the combustion process becomes more efficient. However, introducing excessive fuel into the combustion chamber can lead to reduced performance and increased operational costs. Consequently, a significant number of combustion engine users favor diesel engines due to their superior fuel efficiency (Bhagat et al., 2023; Khan & Goga, 2023; Mouzong & Ayissi, 2025). In contrast to gasoline (Otto engines), which burn the fuel and air mixture with sparks, diesel engines use pressure (compression ignition). In compression ignition engines, the fuel burns immediately due to the higher temperature of the combustion chamber compared to the fuel's autoignition temperature. The air is compressed to a temperature that exceeds the fuel's autoignition threshold. Compared to spark ignition engines, diesel engines are more robust and efficient and are widely utilized in agricultural machinery, industrial applications, and maritime transportation. However, diesel exhaust pollutants, such as NO_x, smoke, and SO_x, pollute the environment. According to reports, greener fuels are strongly encouraged by strict government rules on exhaust emissions (Can et al., 2021; Usha Kumari, 2017). Fuels with additives by volume tend to provide better efficiency and emit less nitrogen oxides and particulates (Daud et al., 2022). Diesel engines are widely used in various sectors such as mining, power generation, and transportation. Economic growth can be achieved through transportation. The use of transportation is increasing due to increased industrial activity (Naryanto, Delimayanti, et al., 2023). Diesel engines and fuel are widely used because they are considered cheaper and have greater power than gasoline engines. Diesel engines use diesel as their primary fuel, but an energy crisis is currently emerging. The rapidly declining supplies of natural gas, diesel, and gasoline present one of the greatest challenges facing the modern world, namely the energy crisis. However, environmental deterioration is another factor contributing to resource depletion and attention-grabbing (Durkin et al., 2020). The use of fuel in internal combustion engines will have an impact on the environment. The Indonesian government has set a target of achieving a 23% renewable energy mix by 2025, which includes initiatives such as the Mandatory Biodiesel Program designed to enhance energy security and improve environmental quality. Numerous studies have shown that biodiesel may aid in lowering greenhouse gas emissions, advancing sustainable rural development, and enhancing income distribution. Biodiesel has different chemical compositions than diesel, so higher biodiesel blending is expected to affect emissions and diesel engine performance (Amrulloh et al., 2024; Naryanto, Bahtiar, et al., 2023). For reducing numerous hazardous emissions, the use of biodiesel and other additives contributes to the creation of a sustainable environment and lessens the negative consequences of global warming, including climate change (Fayyazbakhsh & Pirouzfar, 2017; Siddartha et al., 2022; Solaymani, 2023; Tan et al., 2019). Biodiesel is one of the most valuable renewable energy sources, easily usable in existing diesel engines without requiring modifications. As two-thirds of the population in the developing world depend on agriculture for their livelihood, biofuels derived from crops create new markets and opportunities for agricultural products, while also promoting rural development. Given the slow depletion of the world's petroleum reserves and the increasing environmental contamination, there is a pressing need for suitable alternative fuels in diesel engines (Azad et al., 2012). The increasing need for fossil energy with the decline in fossil fuels will increase efforts to use higher biodiesel mixtures. In general, an increase in the proportion of the biodiesel mixture will result in a decrease in the engine performance. Subsequently, the decline in engine performance needs to be predicted in its damage. Diesel engine performance prediction is needed to determine the health of the vehicle and can be used to predict damage. One of the methods used for performance prediction is neural networks. Similar to the extensive network of neurons in the brain, ANN is a network of interconnected nodes. ANN is a machine learning and pattern recognition computer model that is modeled after the central nervous systems of animals, particularly the brain. They are typically depicted as networks of interconnected "neurons" that can process information to calculate values from inputs. Through a learning process, an ANN is set up for a particular use case, such as pattern recognition or data classification. In biological systems, learning entails modifying the synaptic connections between neurons. A neural network can accomplish jobs that a linear output cannot, which is one of the general benefits of ANN (Mhatre et al., 2015). This research aims to identify the accuracy of prediction models for selecting the optimal fuel mixture in diesel engines using machine learning neural networks.

2. Experimental

This study adopts a mixed-method approach that integrates experimental testing with simulation. Experimental data were gathered to assess the performance of biodiesel-diesel fuel blends in a diesel engine. These data were subsequently used to develop a predictive simulation model. Five fuel blend variations were prepared using a stationary bed reactor operated at a constant temperature of 70 °C and a rotational speed of 300 rpm for 30 minutes. Torque and power measurements were obtained using Dynotest equipment. Detailed specifications of the test engine are provided in Table 1. In this study, the fuel blends comprise B20 biodiesel blended with Solar (marketed as Dexlite in Indonesia). Table 2 shows Biosolar (BS) and diesel fuel (DX) using percentages for every 1 L of fuel. The fuel is blends using constant temperature and speed control. The temperature used in each mixture is 70 degrees Celsius and 300 rpm for 30 minutes. An illustration of an experimental setup procedure, data analytics, and prediction is presented in Figure 1.

Table 1: Specifications of the Test Engine

Engine Model	Toyota Diesel 2 KD-FTV
Engine Type	4 Stroke, In-line type, 16 Valve DOHC
Cylinder Number	4 Cylinder
Fuel System	Common Rail Type
Displacement	2494 cc
Bore and stroke	92 mm x 93.8 mm
Compression Ratio	18.5: 1

Table 2: Fuel Blends Control

Fuel Blends	Temperature Blends (ºC)	RPM Blends (RPM)	Time (Minutes)	Annotation
BS 90: DX 10	70	300	30	MIX-1
BS 80: DX 20	70	300	30	MIX-2
BS 70: DX 30	70	300	30	MIX-3
BS 60: DX 40	70	300	30	MIX-4
BS 50: DX 50	70	300	30	MIX-5

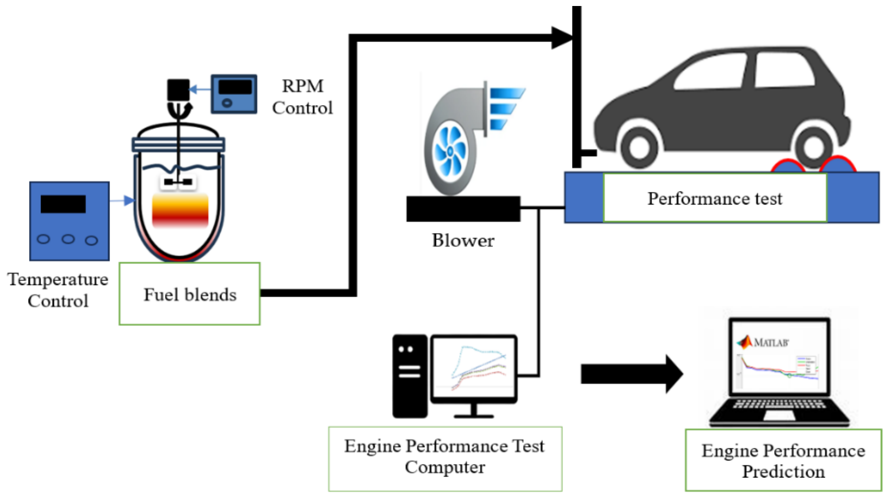


Figure 1: Experimental Setup

Figure 2 illustrates a predictive model for diesel engine performance developed using machine learning techniques, specifically artificial neural networks (ANN). The model incorporates two key input parameters: engine speed (RPM) and fuel blend composition. These inputs are processed through the neural network to capture complex, non-linear relationships between operating conditions and performance metrics such as torque and power output. The model architecture includes hidden layers, which are optimized to enhance prediction accuracy. This approach supports real-time optimization of engine settings and fuel mixtures, contributing to improved efficiency and reduced environmental impact.

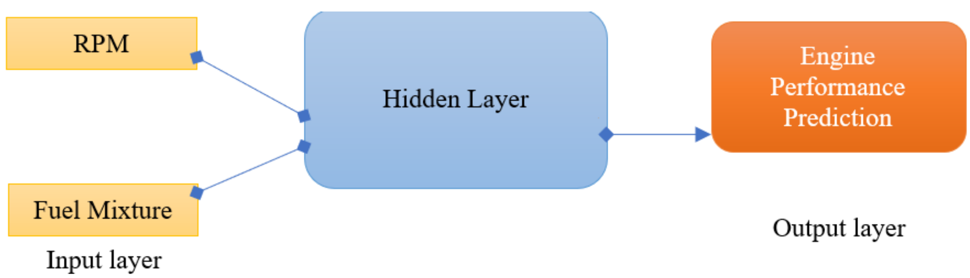


Figure 2: Proposed Engine Performance Prediction using ANN

ANN has been trained and tested on a typical PC using MATLAB software, and more neurons have been tested in the hidden layer during the training phase in order to precisely define the output. Following a successful training process, the network was evaluated using test data, and comparisons were made using statistical techniques and the network's output. The terms Root Mean Square Error (RMSE) and R-squared (R^2) (Can, Öztürk and Arcaklioğlu, 2021). This research uses an artificial neural network (ANN) built and run in the MATLAB Neural Network Toolbox. This environment was chosen because of its high computational capabilities and the availability of various functions for efficiently designing, training, and evaluating artificial neural network models. The toolbox also allows users to flexibly customize the network architecture, number of neurons, activation functions, and training algorithms to suit their research needs. The artificial neural network architecture used is a feedforward neural network (FFNN), consisting of three main layers: an input layer, a hidden layer, and an output layer. The input data used are diesel engine operating parameters, namely engine speed (in RPM) and biodiesel blend percentage, while the output data is engine performance in the form of power. The data used in this study were obtained from diesel engine performance tests with varying engine speeds and biodiesel blend levels. The data was then processed and used as a training dataset for an ANN to build an engine performance prediction model. The network training process is carried out using the Levenberg–Marquardt Backpropagation algorithm. The training data comprised 70% of the total data, 15% was used as validation data, and the remaining 15% was used as testing data. Mean square error (MSE) is selected as the overall loss function assessed after each forward pass during the training phase (Song et al., 2019):

$$\mathrm{MSE} = \frac{1}{K}\sum_{K=1}^{K}(x_k - y_k)^2 \tag{1}$$

where x_k is the true Engine Performance Prediction value while y_k is the output of the proposed network at time k. In the testing process, the RMSE and mean absolute error (MAE) (Chai & Draxler, 2014) are used to evaluate the performance of the proposed network.

$$\text{RMSE} = \sqrt{\frac{1}{K}\sum_{K=1}^{K}(x_k - y_k)^2} \quad (2)$$

MAE measures how close the estimation is to the true values neglecting the sign. In contrast, the RMSE is more sensitive to large errors and characterizes the variation of errors (Jierula et al., 2021):

$$\text{MAE} = \frac{1}{K}\sum_{K=1}^{K}|x_k - y_k| \quad (3)$$

3. Results and Discussion

The engine performance tests were conducted using fuel blends prepared under controlled temperature and rotational speed conditions, with the addition of specific additives. These blending parameters were found to influence vehicle performance. This study compares the effects of different fuel mixtures, temperature settings, and rotational speeds on engine output. The results of the diesel engine performance tests are presented in Table 3 and Figure 3. Fuel mixtures prepared under controlled temperature and rotational conditions significantly influence engine performance. The study found that increasing the proportion of diesel in the blend generally enhances maximum engine output. For example, the MIX-1 blend demonstrated better performance than mixtures without additives. However, when additives are introduced, engine performance tends to decline as diesel content increases. In contrast, blends with lower diesel content show improved performance, suggesting a complex interaction between additive concentration and fuel composition.

Table 3: Maximum Power of Difference in Diesel Engines

Fuel Mixture	Maximum Power (kW)
MIX-1	68.0
MIX-2	68.8
MIX-3	69.2
MIX-4	69.6
MIX-5	69.8

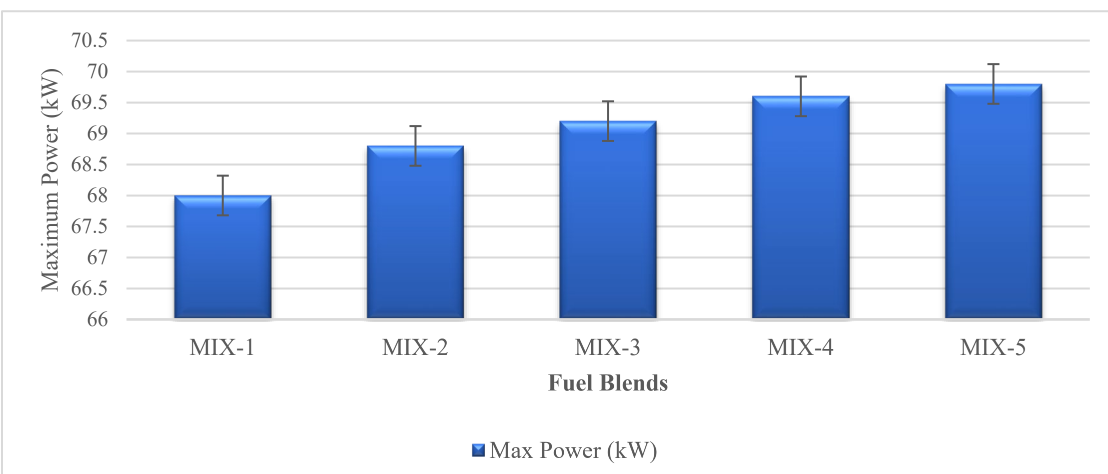


Figure 3: Maximum Power of Diesel Engine with Fuel Blends

The addition of Dexlite enhances diesel engine performance. Increasing the proportion of Dexlite in the fuel blend leads to improved engine output. Overall, higher diesel content in the mixture correlates with better performance characteristics. The best performance of the biodiesel fuel mixture with diesel is in MIX-5, which is 69.8 kW. From the results of the study, diesel engine performance fluctuates due to the blends process that use temperature control and rotation control. Therefore, the fuel blends method with temperature and rotation control affects engine performance. This is because Dexlite has better fuel characteristics compared to biodiesel, especially in terms of calorific value.

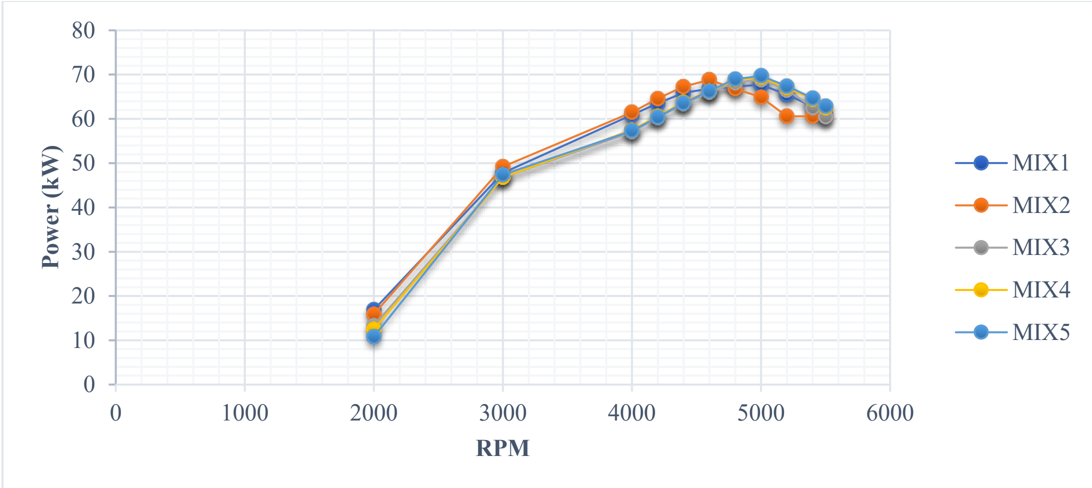


Figure 4: Engine Performance with Fuel Blends

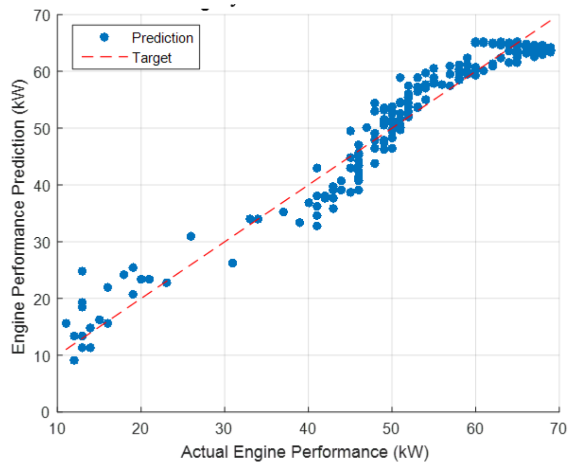
Figure 4 shows the difference in diesel engine power with temperature and rpm controls. The results show that using temperature and rpm controls tends to increase and stabilize the power produced. This is because the fuel mixture can be homogeneously mixed. This indicates that the fuel mixture is not perfectly mixed. This is also caused by the addition of additives. The results of the study show that the more biodiesel the engine power will decrease, this is in accordance with the research of Hassan and Al-Abboodi (Hassan & Al-Abboodi, 2025).

Table 4: Variation in the Number of Observations and Training

Data	Number of Observations (RPM and Engine Power)	Training Error (MSE)	RMSE	R^2
1	26	77.49	2.67	0.876
2	51	58.24	6.43	0.864
3	76	46.23	6.93	0.856
4	101	57.75	6.48	0.84
5	126	46.16	6.8	0.833
6	152	47.52	6.98	0.829
7	177	49.08	7.13	0.806
8	202	48.54	7.02	0.817
9	227	47.62	7.12	0.823
10	252	55.20	6.94	0.805
11	278	43.06	7.17	0.816
12	303	50.36	6.97	0.829
13	328	50.23	6.94	0.832
14	353	44.12	7.07	0.816
15	378	45.91	7.01	0.819
16	404	44.93	7.03	0.822
17	429	51.82	6.88	0.825
18	454	46.82	7.07	0.81
19	479	50.07	6.97	0.817
20	504	47.47	6.96	0.813

Table 4 presents the training results of the neural network-based prediction model prior to hidden layer optimization. The model achieved an average R^2 value of 0.80, indicating moderate predictive accuracy. Despite using 502 data points, the model exhibited a relatively high Mean Squared Error (MSE) of 47.47. To improve performance, the neural network architecture was refined by varying the number of hidden layers. The dataset was partitioned into 70% for training, 15% for validation, and 15% for testing to ensure robust model evaluation. Figure 6 illustrates the comparison between actual and predicted engine power trends. Table 5 presents the training error and regression (R) scores for different neural network configurations based on the number of hidden layers. Given the significant influence of hidden layer depth on regression accuracy, the model with three hidden layers was selected. This configuration yielded a regression value close to 1, along with a low Mean Squared Error (MSE) and Mean Absolute Error (MAE), indicating a well-trained model that closely matches the target output. Additionally, Table 5 details the variation in neuron counts across the hidden layers.

(a)



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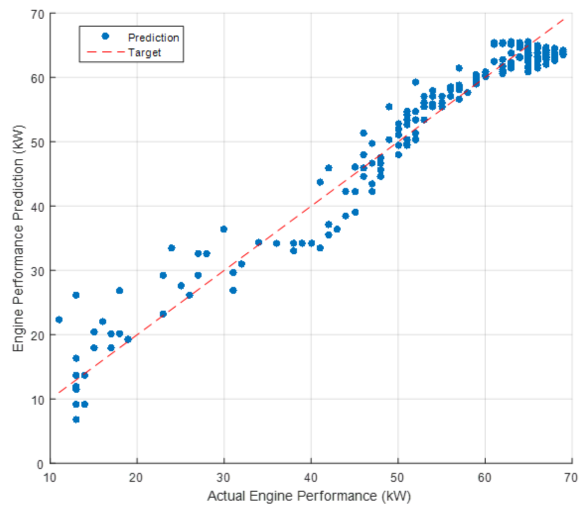
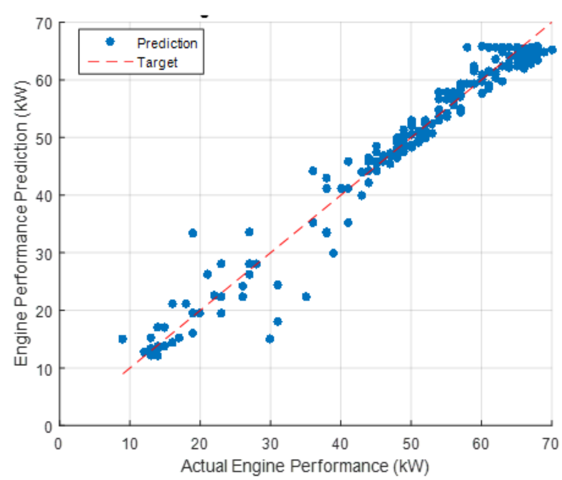


Figure 5: Comparison of Hidden Layers to Engine Performance Prediction with Neural Networks: (a) Engine Performance Prediction with 1 Layer; (b) Engine Performance Prediction with 2 Layers

(a)



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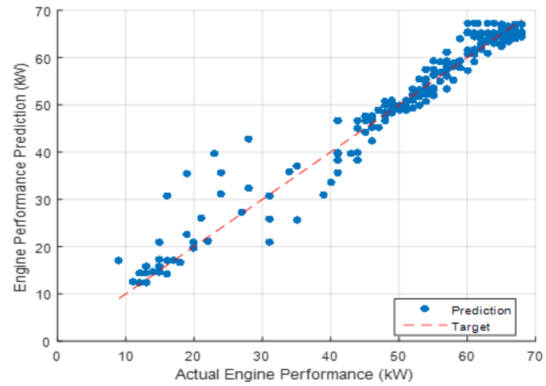

Figure 6: Comparison of Hidden Layers to Engine Performance Prediction with Neural Networks: (a) Engine Performance Prediction with 3 Layers; (b) Engine Performance Prediction with 4 Layers

Table 5: Variation Results in the Number of Neurons

Number of Hidden Layer	Training Error (MSE)	MAE	Epoch	R		
				Training	Validation	Test
1	15.30	3.06	29	0.976	0.975	0.972
2	15.17	3.03	16	0.977	0.9732	0.971
3	10.46	2.26	23	0.984	0.982	0.978
4	12.31	2.29	13	0.987	0.976	0.987

Experimental results indicate that the optimal neural network (NN) topology consists of three hidden layers. Using this configuration, the model was trained on engine performance data and achieved a high regression value of 0.98317, as shown in Figure 7, indicating strong predictive accuracy.

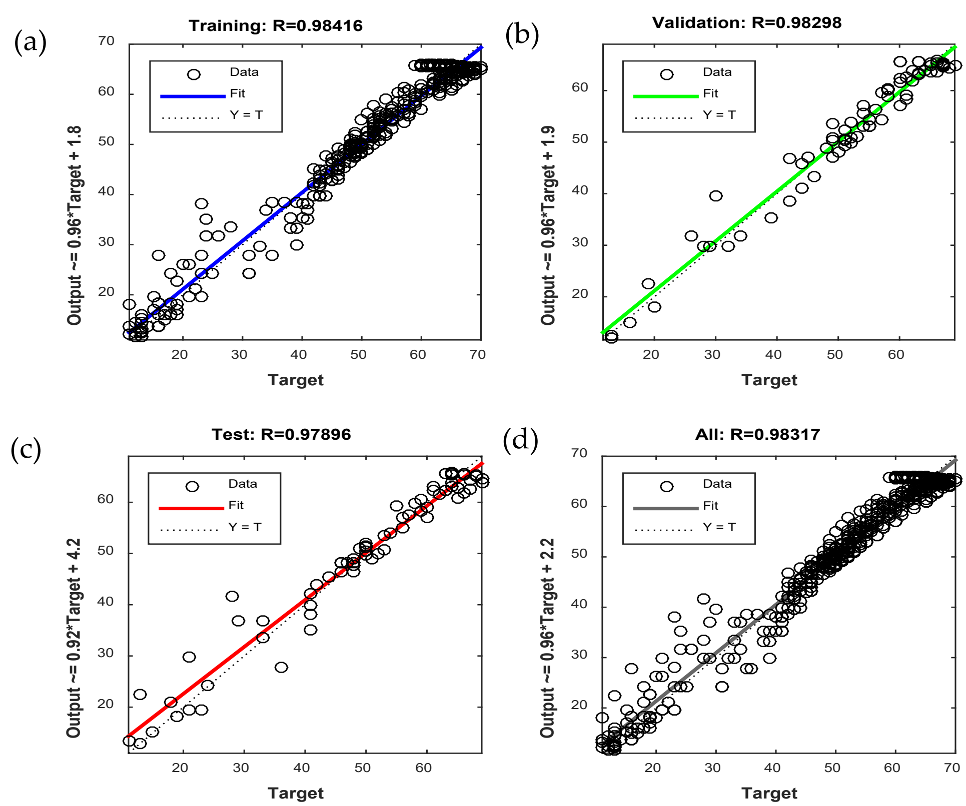

Figure 7: Selected Neural Network Regression Result of Engine Performance Based on rpm and Fuel Blends: (a) Training Data; (b) Validation Data; (c) Test Data; (d) All Data

Combustion, a chemical oxidation process, requires sufficient oxygen to produce carbon dioxide (CO_2) and water vapor. Incomplete combustion, often due to limited oxygen supply, leads to the formation of harmful byproducts such as carbon monoxide (CO) and unburned hydrocarbons (HC). Biodiesel offers a cleaner alternative to conventional diesel fuel, as it contains higher oxygen content, a greater cetane number, and lower sulfur levels, enabling more complete and efficient combustion. As a result, biodiesel can significantly reduce emissions of CO, HC, and particulate matter (PM/smoke), although it may lead to slightly higher nitrogen oxide (NO_x) emissions. The production of biodiesel through esterification—such as from palm oil—follows established methods used for other renewable feedstocks and aligns with sustainable development goals aimed at promoting clean energy (Laskowski & Zimakowska-Laskowska, 2025; Wirawan et al., 2024).

4. Conclusions

Based on the research results, the best experimental ideal mixture used Mix-5 fuel. The R^2 value for the neural network model with 3 hidden layers was 0.983. The model with three hidden layers produced the best performance with a Mean Squared Error (MSE) value of 10.46, a Mean Absolute Error (MAE) of 2.26, and a correlation coefficient (R) of 0.984 for training data, 0.982 for validation, and 0.978 for testing, respectively. The test results show that the model prediction has a low error rate and high correlation to actual data, so that the Neural Network is proven to be effective as a diesel engine performance prediction tool. The results of this study indicate that the application of Artificial Neural Network (ANN) is able to provide high accuracy in predicting the power performance of diesel engines based on variations in fuel mixtures. Therefore, this study opens up opportunities for further development in several directions, include integration with emission prediction and thermal efficiency for performance optimization as well as environmental aspects. Development of real-time monitoring models with the Internet of Things. Multi-parameter optimization using hybrid ai for combustion efficiency and fault detection.

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