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Artificial Neural Network-Based Modeling of Performance Spark Ignition Engine Fuelled with Bioethanol and Gasoline

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ABSTRACT

Machine learning technology can distinguish the relationship between engine characteristics and performances. Therefore, the goal of the present work is to predict the performance parameters of a single-cylinder 4-stroke gasoline engine at different ignition timings using a blended mixture of gasoline and bioethanol by an artificial neural network (ANN). Experimental data for training and testing in the proposed ANN was obtained at a dynamic speed and full load condition. An ANN model was developed based on standard Back-Propagation algorithm for the spark ignition engine. Multi-layer perception network (MLP) was used for non-linear mapping between the input and output parameters. An optimizer in the family of quasi-Newton methods (lbfgs) and the rectified linear unit function were used to assess the percentage error between the desired and the predicted values. The network input parameters are engine speed, fuel, and ignition timing. Furthermore, torque, power, specific fuel consumption (SFC), thermal efficiency (ηth), and energy consumption (EC) are taken as output parameters. The results show that ANN is the proper method for predicting SIE performance because it has accurate prediction results that are very similar to experimental results. Moreover, from the observation results, the ANN model can predict the engine performance quite well with correlation coefficient (R)=0.962139 and MSE=0.003967 for data testing.

Keywords: *Artificial neural network, bioethanol, gasoline, spark ignition engine, performance.*

I. Introduction

The highly efficient use of bioethanol in spark ignition engines (SIE) is attributed to its low sulfur content and flammable properties, rendering it a viable alternative fuel [1]–[3]. Therefore, numerous research efforts have been undertaken to develop suitable models and configurations for the fuel system and the spark ignition engine (SIE) using bioethanol. Moreover, rural communities have even produced and used it as an alternative fuel to replace kerosene [4]. Some are about the effect of a mixture of ethanol and gasoline on the combustion characteristics of laminar flames [5]. Furthermore, research regarding the effect of using ethanol and gasoline on flame speed [6], dynamic and spray characteristics [7], NOx emissions, and their impact on fuel efficiency [8]. Moreover, research has also been carried out on bioethanol by modifying the degree of ignition to the usual standards in gasoline engines [4], [9]. The results of these studies all show that the combustion rate increases for all bioethanol-gasoline mixtures, and exhaust emissions are reduced

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significantly. Unfortunately, conducting experiments of this nature demands substantial expenses, energy resources, and the utilization of costly testing equipment [10], [11].

Hence, a potential solution to address this issue involves employing machine learning techniques to forecast machine performance in advance, prior to its actual implementation [12]. Machine learning (ML) techniques have the capability to discern the correlations between engine attributes, like fuel ratio and engine rotational speed, and their impact on both performance and exhaust emissions. Machine learning can consider intricate variables that affect performance and exhaust emissions, including variations in fuel composition and environmental factors like temperature and humidity [13]. Furthermore, machine learning can assess alternative engine designs and control strategies in order to enhance performance and minimize emissions. Research findings indicate that machine learning models can generate highly precise predictions and prove invaluable in the optimization of engine performance and reduction of exhaust emissions [14]. Certain researchers utilize machine learning for forecasting engine performance in smart vehicles [15]. They consider engine speed and fuel mixture variations as input variables, while output variables include power, torque, fuel consumption, and exhaust emissions. The findings reveal that the regression values for a majority of the parameters closely align with the experimental data. Moreover, the use of machine learning modeling enables the prediction of brake power, torque, fuel consumption, and spark ignition engine (SIE) exhaust emissions. The results demonstrate a strong correlation between the predicted values and the experimental ones [16]. Furthermore, modeling was conducted using a Feed-Forward Neural Network (FFNN) to forecast engine performance parameters, including engine speed, torque, and fuel consumption in biodiesel-fueled engines. The outcomes indicate that FFNN effectively optimized the setup to predict the relationship between the training data and the experimental data [17].

Moreover, machine learning is also employed for modeling and forecasting the performance of spark ignition engines (SIE) using ethanol as fuel [18]. The engine performance parameters that are modeled include specific fuel consumption, effective power, average effective pressure, and exhaust gas temperature. Furthermore, advanced machine learning methods, specifically the extreme learning machine (ELM) [19] and least-squares support vector machine (LS-SVM) [20], are employed to model the machine based on experimental data. The outcomes reveal that machine learning yields the most effective model for predicting engine performance and exhaust emission characteristics. Notably, even models like K-ELM and cuckoo search (CS) can achieve performance levels comparable to LS-SVM.

Additionally, engine performance can be represented through Artificial Neural Networks (ANNs). The predictive capability of an artificial neural network (ANN) is developed through training on experimental data and subsequently validated using independent data [21]. The ANN model can handle multiple input variables for predicting several output variables. Predictions made by a trained ANN are typically much quicker compared to conventional simulation programs or mathematical models, as they do not require time-consuming iterative calculations to solve differential equations using numerical methods. However, it's essential to choose an appropriate neural network topology to balance model accuracy and simplicity [22]. Moreover, the flexibility of ANNs allows for the addition or removal of input and output variables as necessary. ANN modeling is applied for predicting brake power, torque, brake-specific fuel consumption, and engine emissions. From the concise overview provided, it's evident that machine learning has been successful in forecasting machine performance, assisting researchers in discovering phenomena at an early stage.

Hence, the objective of this study is to forecast the performance of spark ignition engines (SIE) constructed from a blend of gasoline and 85% bioethanol (BE85). In the subsequent modeling, the input parameters involve a combination of gasoline and bioethanol (BE85) and variations in engine speed ranging from 3000 rpm to 8000 rpm. The output parameters utilized for evaluating engine performance encompass torque, effective power, thermal efficiency, and specific fuel consumption.

II. Material and Methods

2.1. Material

The raw material for producing bioethanol consists of 85% coconut flower sap and 15% gasoline. Initially, bioethanol acquired through natural fermentation typically contains 43-45% ethanol content. To increase the ethanol content to 94-95%, a distillation process involving a fractionation column is employed. The fuel mixture, composed of 85% bioethanol and 15% gasoline, is manually prepared by mixing it in a test tube and shaking it. Testing of the fuel properties is conducted at the PT fuel testing laboratory, Pertamina West Surabaya, with the results detailed in Table 1. The engine performance tests are carried out using a 125 cc spark ignition engine, involving variations in engine speed under wide throttle openings and changes in choke carburetor settings, such as 3/4 and 7/8. The adjustment of the choke carburetor aims to achieve adequate fuel supply while minimizing the inclusion of bioethanol as an oxidizer. The experimental procedure is depicted in Figure 1, and, as a general practice, the engine tests are conducted three times.

Table 1. Fuel properties

Properties	Gasoline	BE-85
Research octane number (RON)	88-100	105
Flash point (°C)	-23	12.78
Caloric value (cal/gr)	10500	8939
Density at 15 °C (kg/m^3)	715	780
Viscosity at 20 °C (cSt)	0.6	0.546
LHV, MJ/kg	28	15.3

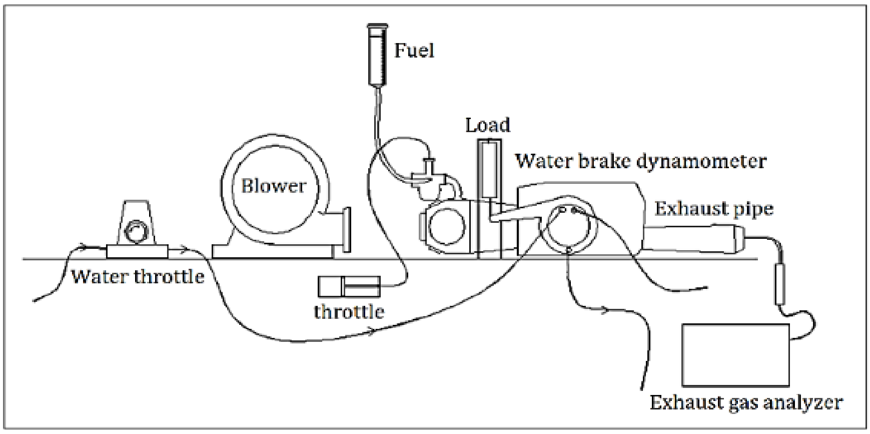

Fig 1. Experimental scheme

2.2. Methods (Artificial Neural Network)

Artificial Neural Network (ANN) is a logic programming technique designed to emulate the functioning of human brain processes, such as learning, memory, decision-making, and inference, independently and without external assistance. ANN incorporates several vital characteristics, including data-driven learning, the ability to generalize, and the capacity to work with infinite variables, among others. At its core, an artificial nerve cell serves as the fundamental unit in the operation of an ANN, much like a biological neuron. It receives input from various sources, combines this input in a specific manner, performs non-linear operations on the result, and ultimately presents the final output. Artificial nerve cells typically comprise five key elements: input, weight, sum function, activation function, and output (as depicted in Figure 2).

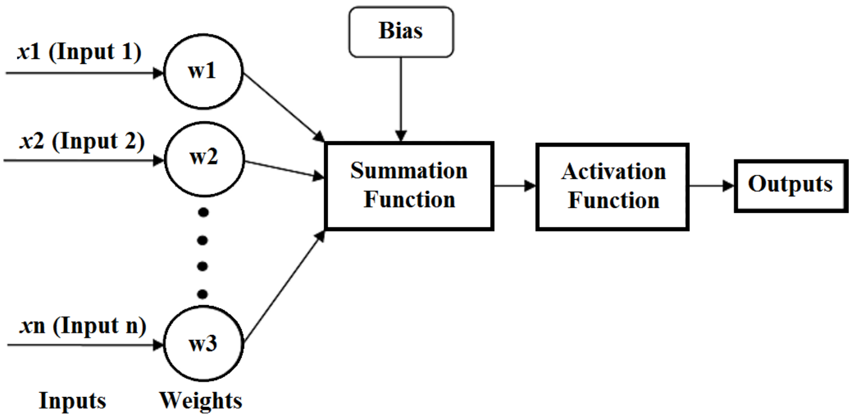

Fig. 2. ANN cell structure

The Artificial Neural Network (ANN) typically consists of three primary layers: the input, hidden, and output layers. The input layer receives data from external sources. Neurons, the processing elements in the input layer, transmit data from these external sources to the hidden layers. The weight represents the value of the connection between individual cells. The output is generated by using data from neurons in both the input and hidden layers, incorporating elements such as bias, summation, and activation functions. In the output layer, the network generates the final output by processing data from the hidden layer, which is then sent to an external destination. The sum function calculates the net input of a cell, and the addition function used in this research is expressed in Equation (1).

$$NT_i = \sum_{j=i}^{n} W_{ij} X_j + W_{hi} \quad \ldots\ldots \quad (1)$$

The activation function serves as a crucial component that establishes the connection between the input and output layers. It plays a pivotal role in determining the output of a cell by processing the input net into the cell. The choice of the appropriate activation function has a substantial impact on the network's performance. Commonly used activation functions include the rectified linear unit function, the sigmoid function, and the hyperbolic tangent function. The selection of the activation function depends on the specific neural network to be designed. The sigmoid function is a widely adopted transfer function in many applications. In this study, the ANN model employs the rectified linear unit function, which is represented in Equation (2).

$$f(NT_i) = \max\,(0, NT_i) \quad \ldots\ldots \quad (2)$$

One of the major advantages of artificial neural networks is their capacity to learn and the availability of various learning algorithms. Beyond the choice of ANN architecture, the learning algorithm plays a pivotal role in determining its practical success. To achieve an output value that closely approximates the desired numerical value, it is essential to identify the optimal number of neurons in the hidden layer.

The performance metrics, Regression co-efficient (R) and Mean squared error (MSE) were calculated using equation (3) and equation (4).

$$R = \sqrt{1 - \frac{\sum_{i=1}^{n}(Y_i - X_i)^2}{\sum_{i=1}^{n} X_i^2}} \quad (3)$$

$$MSE = \frac{1}{n}\{\sum_{i=1}^{n}(Y_i - X_i)^2\} \quad (4)$$

III. Result and Discussions

3.1. Prediction of SIE Performances by ANN

The experimental results are presented in Table 2. Based on the experimental results, we make predictions, and the most suitable ANN architecture for predicting SIE performance is illustrated in Figure 3.

Table 2. The experiment result

RPM Engine	Fuel	Ignition timing (°)	Torque (Nm)	Power (Hp)	η_{th} (%)	SFC (kg/hp.hr)	EC (kcal/hr)
4000	Gasoline	9	6.5	3.7	24.6	0.28	12000
4500	Gasoline	9	6.7	4.12	25.5	0.265	12100
5000	Gasoline	9	6.3	4.3	26	0.255	11999
5500	Gasoline	9	6.1	4.4	25	0.257	12500
6000	Gasoline	9	5.5	4.55	24	0.265	13500
6500	Gasoline	9	5.1	4.7	23	0.275	15000
7000	Gasoline	9	4.8	4.8	22	0.286	16000
7500	Gasoline	9	4.1	4.6	21	0.3	16500
4000	BE50	9	5.9	3.2	24.7	0.296	8200
4500	BE50	9	5.7	3.53	26.5	0.289	8700
5000	BE50	9	5.5	3.9	26.5	0.28	8990
5500	BE50	9	5.25	4	25	0.295	9500
6000	BE50	9	4.91	4.15	24.8	0.3	10000
6500	BE50	9	4.49	4.08	24.5	0.31	11000
7000	BE50	9	4	3.9	21.5	0.32	12000
4000	BE50	12	6.1	3.4	25	0.283	8500
4500	BE50	12	5.85	3.77	27.4	0.275	9000
5000	BE50	12	5.7	4	27	0.262	9550
5500	BE50	12	5.5	4.3	26.5	0.27	9800
6000	BE50	12	5.25	4.35	26	0.28	10500
6500	BE50	12	4.85	4.4	25.5	0.29	11500
7000	BE50	12	4.2	4.2	22	0.307	12500
4000	BE50	15	6	3.27	25.2	0.288	8350
4500	BE50	15	5.8	3.64	26.5	0.285	8550
5000	BE50	15	5.6	4.01	26.5	0.265	8900
5500	BE50	15	5.38	4.2	26	0.282	9500
6000	BE50	15	5.1	4.24	25.6	0.292	10000
6500	BE50	15	4.7	4.22	25.7	0.303	10700
7000	BE50	15	4.13	4.07	21.3	0.312	11900

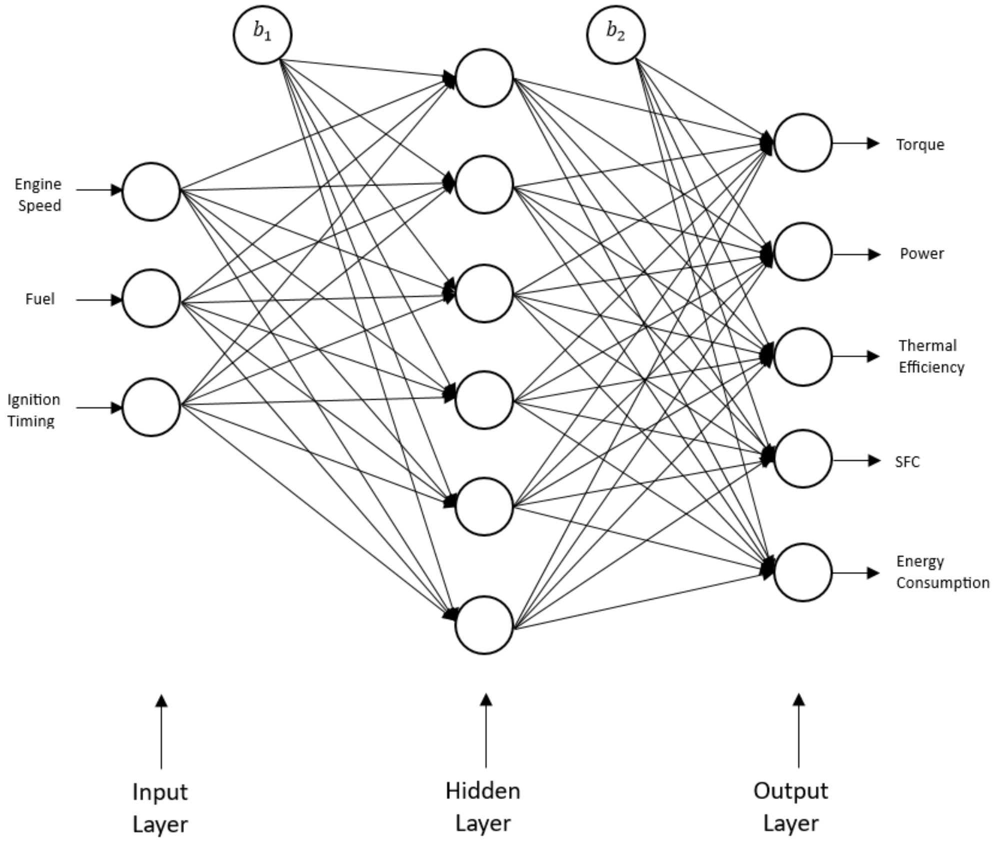

Fig. 3. The best architecture for predicting SIE performance

The ANN model is considered a reasonable and reliable approach to non-linear problems. The network input parameters are engine speed, fuel, and ignition timing. Sedangkan torque, power, specific fuel consumption (SFC), thermal efficiency (η_{th}), and energy consumption (EC) are taken as output parameters.

In this study, 29 experimental data sets were used to prepare training and testing data for ANN (see Table 2). The ratio of training and testing data was chosen as 70%:30%, that is, 21 and 8 experimental data sets were randomly selected for training and testing data, respectively. The ANN model has been developed using Python. In the back-propagation model, input and output scaling greatly affects ANN performance. As mentioned above, the rectified linear unit function (RELU) was used in this study. The input and output datasets are normalized between 0 and 1 before the training and testing process to obtain optimal predictions. During the training phase, the number of neurons in the hidden layer is incrementally increased (from 6 to 50) to achieve the best performance.

Furthermore, determining the number of hidden layers is crucial in evaluating model performance, in which the selection process involves a series of trials to achieve a minimum and maximum MSE R-value to indicate the model's prediction accuracy. Therefore, an artificial neural network (ANN) with 14 hidden layers can produce optimal prediction values, as depicted in Table 3. The table shows the prediction results for both training and testing approaches with satisfactory accuracy.

Table 3 shows the results of testing the ANN model with hidden layer node = 14, producing a value of R = 0.962139 for testing data, R = 0.981746 for training data, and MSE = 0.002655 for training data, MSE = 0.003967 for testing data. ANN predictions are carried out for torque, power, SFC, thermal efficiency, and energy consumption. Furthermore, when comparisons of the ANN predictions and trial results for testing sets of output performance and exhaust emissions parameters are verified in Figures 4 to 8. The most outstanding point is that the predicted results are close to the trial results, and Figure 4 to 8 show that their R values were more than 0.95.

Table 3. SIE performance using ANN model

Training Algorithm	Transfer Function	Number of Neurons	Regression		MSE	
			Training	Testing	Training	Testing
lbfgs	RELU	10	0.973806	0.927735	0.003795	0.007438
		32	0.987211	0.929663	0.001865	0.007247
		21	0.981313	0.931313	0.002718	0.007083
		19	0.980492	0.936122	0.002836	0.006604
		34	0.993142	0.945991	0.001003	0.005612
		35	0.991655	0.946335	0.00122	0.005577
		45	0.987964	0.947364	0.001756	0.005473
		47	0.988387	0.949433	0.001695	0.005263
		46	0.989309	0.958094	0.001561	0.004381
		48	0.981614	0.959043	0.002934	0.004284
		14	0.981746	0.962139	0.002655	0.003967

The most remarkable thing is that the prediction results are very close to the experiment results. The network's prediction ability for SIE performance parameters was found to be acceptable. This means that the choice of three input parameters as dynamic influences for predicting SIE performance provides reasonable results.

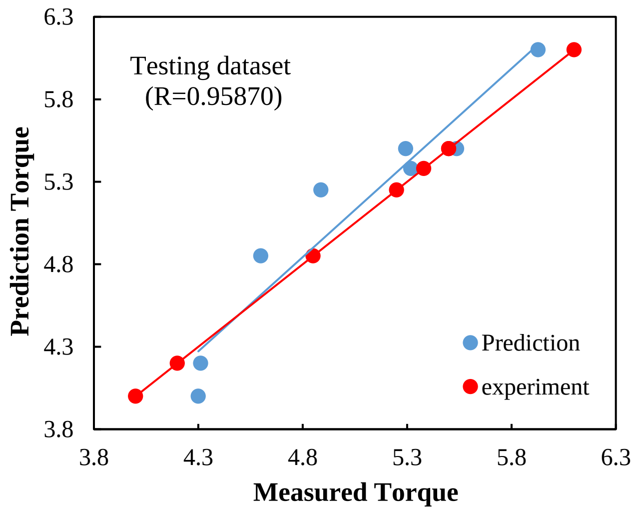

Fig. 4. Comparison of predicted and experimental results for testing sets of engine torque

Based on Figure 4, it can be seen that the predicted results are close to the experimental results, which is related to Table 2; it can also be seen that the torque value continues to increase along with the increase in engine speed. In addition, this data also shows that when

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the ignition reaches an angle of 12 degrees, the crankshaft rotation angle increases, and mass flow increases, which increases engine load, evident through a significant increase in torque.

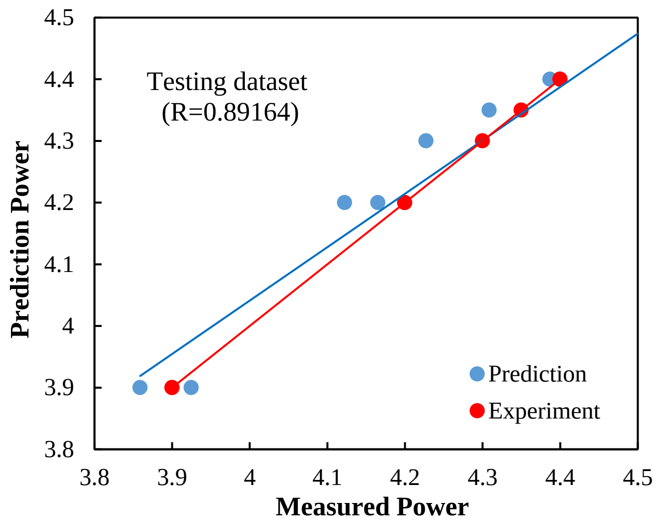

Fig. 5. Comparison of predicted and experimental results for testing sets of engine power

Meanwhile, from Figure 5, it is also known that the prediction results are pretty close to the experimental results, and this is confirmed by the data in Table 2, where it can also be seen that the research results show that the BE50 engine reaches the lowest performance at low rpm, around 4000 rpm, with a power of 3.20 hp. At the same engine speed, a bioethanol-fueled engine produces about 3.70 hp. Furthermore, at high rpm, ranging from 6000 rpm to 6500 rpm, the BE50-fueled engine reaches the highest performance.

Molecularly, these results show that the hydroxyl group content in bioethanol has succeeded in increasing the magnetic force between fuel molecules so that engine power increases. This analysis is from previous research that discussed the performance of fuel mixtures with hydroxyl groups in aromatic compounds [23]–[25].

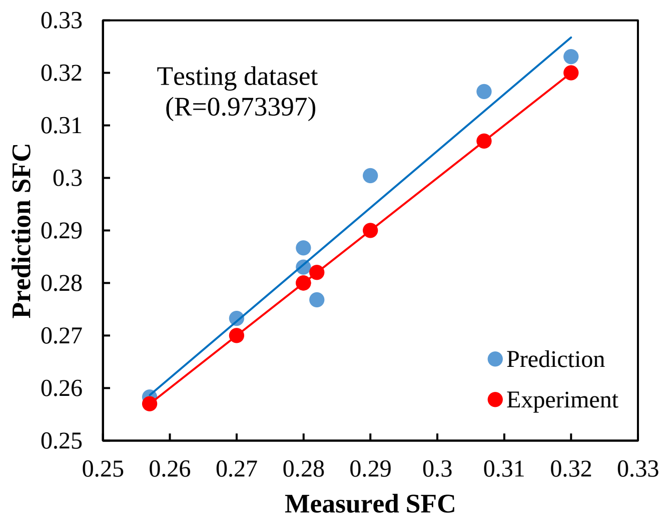

Fig. 6. Comparison of predicted and experimental results for testing sets of specific fuel consumption

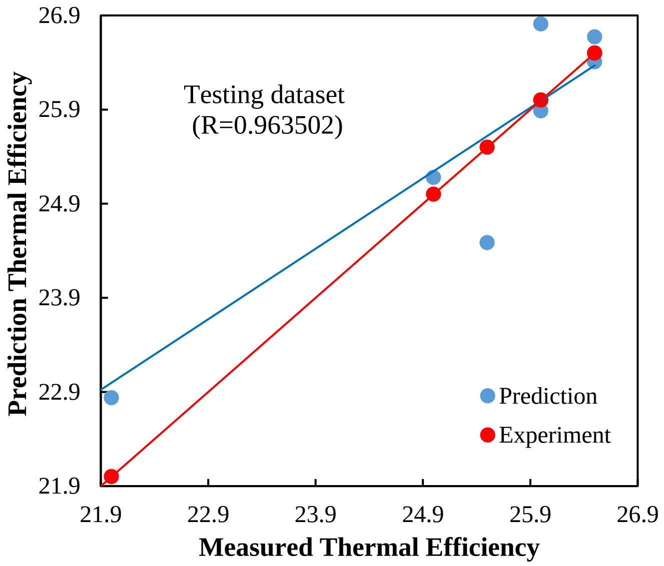

Fig. 7. Comparison of predicted and experimental results for testing sets of thermal efficiency

Figures 6 and 7 show how changing ignition timing affects fuel consumption and thermal efficiency. These results also show that ANN is very accurate in predicting engine performance, where it can be seen that there are similarities between the prediction results and engine test data in the laboratory. In Table 2, bioethanol shows the highest fuel consumption level at around 16,500 kcal/hour at 7500 RPM, while BE50 reaches about 12,000 kcal/hour at 7000 RPM after 12 ignition times. It can be seen that using BE50 reduces energy consumption by approximately 25.44%.

These results confirm that OH groups play a role in creating fuels with high thermal efficiency and lower energy consumption (see Table 2 and Figure 8). This analysis is reasonable because the polar and branched OH groups demonstrate the reactive nature of the BE50 molecule, as evidenced by its higher thermal efficiency than gasoline. This analysis follows our previous research using liquid metal-based additives and is discussed differently [26]–[28].

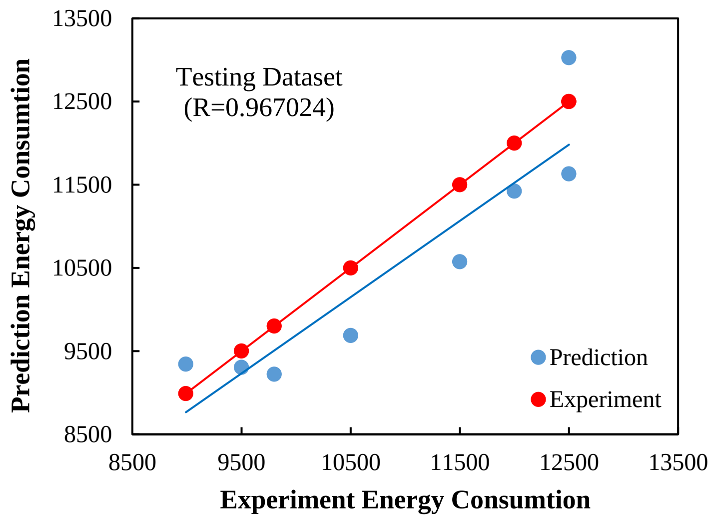

Fig. 8. Comparison of predicted and experimental results for testing sets of energy consumption

The network is successfully trained and then tested data is used to evaluate the selected network. Using the results obtained from the network, the comparison is carried out using statistical methods. Network performance is evaluated using the average percentage of errors. The mean percentage error is the average ratio between the 2 errors and the experimental value. This result shows how large the error is related to the correct value, and it is expressed as a percentage value. The average percentage error is less than 0.3% and 0.2% for the training and test data, respectively. Therefore, the results obtained from the optimal ANN model can easily be considered to be within acceptable limits [29]. A lower mean percentage error value indicates that there is a better correlation between the trained or tested value and the measured value. These results and analysis are reasonable because they follow previous research, which also used ANN to predict combustion pressure parameters in spark ignition engines fueled by 20% ethanol (E20) [30].

IV. Conclusions

Research on the use of the ANN method to predict the performance of SIE fueled by BE50 has been completed, and it can be concluded that the research results conclude that ANN is one of the appropriate methods for predicting SIE performance. The results reflect how big the error is about the value it should be, expressed in percentage form, around 0.003 for training data and 0.002 for test data. The research findings demonstrate a strong correlation between the predicted and experimental data. Analysis of the experimental data using ANN reveals a favorable correspondence between the data generated by the ANN and the measured values. This developed model minimizes the need for extensive experimentation and proves to be an efficient tool for forecasting engine performance and emission characteristics under diverse operational conditions involving various biodiesel blends.

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