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Research Article

Combined application of ANN prediction and RSM optimization of performance and emission parameters of a diesel engine using diesel-biodiesel-propanol fuel blends

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ABSTRACT

In this study, an artificial neural network (ANN) was used to estimated the performance and exhaust emission parameters of a diesel engine running on diesel, biodiesel, and propanol fuel mixtures. In addition, the parameters estimated by ANN were tried determining the optimum operating parameter by using Response Surface Methodology (RSM). In the experimental study, propanol was added in 3 different ratios (5%, 10% and 20%) into 100% diesel, 80% diesel and 20% biodiesel fuel blends. In addition, engine tests, were made at 5 different engine speeds with 400 min^{-1} intervals between 1000 min^{-1} and 2600 min^{-1} revolutions at full load. In addition, HC (Hydrocarbon), CO (Carbon Monoxide), NO_X (Nitrogen oxides) and Smoke emissions were measured during in the working. ANN model was developed for estimation of engine output parameters depending on fuel mixture ratios and engine speed. In the ANN results, the regression coefficients (R^2) of the proposed model were found to be between 0.924 and 0.99. When the obtained ANN results were compared with the experimental results, it was seen that the maximum mean relative error (MRE) was 6.895%. It has been shown that the applied model can predict with a low error rate. The RSM results showed that the optimum operating parameters were 2034-min^{-1} engine speed, 74.667% diesel, 11.36% biodiesel and 15% propanol fuel mixture. In addition, in the validation tests of the model where the desirability was 0.7833%, the highest error rate was obtained as 7.37% as a result of NO_X. As a result of the study, it was seen that RSM supported ANN is a good method for estimating diesel engine parameters working with diesel/biodiesel/propanol mixtures and determining optimum operating parameters.

1. Introduction

In the last quarter century, the limited fossil-based resources, have encouraged researchers to explore different alternative fuels [1-6]. In addition, increasing environmental concerns as a result of the use of petroleum-based fuels are the other and main reason for these studies. Studies on reducing emissions from motor vehicles are being studied by many researchers with different methods [7-10]. In addition to these studies, esters of vegetable and animal oil, especially for diesel engines, were remarkable. Vegetable oil methyl esters, however, are encountered a number of issues, including low energy content, high density and viscosity, iodine value, and poor volatility. [11, 12]. While vegetable oil methyl esters can be used alone as fuel in the studies, they can also be used by mixing with diesel fuel in certain proportions. Especially in diesel/biodiesel fuel blends, it can provide almost the same engine torque and power, while causing an increase in specific fuel consumption (due to lower energy content) [13]. However, the general consensus in the studies is that there is a decrease in HC (hydrocarbon), CO (carbon monoxide) and soot emissions while using biodiesel and diesel biodiesel fuel mixtures, while NOX emissions increase [2, 14, 15]. The use of biodiesel as a fuel is a suitable fuel choice among biofuels due to these advantages. However, with long-term use of biodiesel in the engine, some negative consequences (such as accumulation of injectors, sticking of pistons and rings, dilution in engine oil) can be seen. Therefore, there may be a need to improve the fuel properties of vegetable oils [16]. For this reason, a fuel that can be mixed with biodiesel and has complementary properties is needed to minimize the difficulties arising from the diesel-biodiesel

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fuel mixture. Most of the researchers working in this field prefer alcohol as an additional fuel or oxygen additive [14, 17]. Especially since the high viscosity of biodiesel needs to be reduced, many researchers have recently started to use alcohol in compression ignition engines by mixing it with biodiesel [18, 19]. Propanol is a 3-carbon alcohol with a high energy density, straight chain structure, making it a potential alternative to light alcohols (methanol and ethanol). The most economical method for producing propanol from petrochemicals is called oxo synthesis [20]. But in order to make this alcohol, sustainable methods have been devised due to worries about the depletion of fossil fuel stocks. From sources like biomass or household solid waste, propane can be manufactured [21]. Although propanol is seen as a good alternative among alcohol fuels, its ratio in diesel or biodiesel is limited. According to the European diesel fuel quality norm EN590, mixtures above 45% by volume do not meet the requirements for kinematic viscosity and lubricity at higher mixing ratios [22]. For this reason, although propanol is seen as a good alternative fuel, its ratio in the fuel mixture is an important parameter.

A statistical analytic tool known as an artificial neural network (ANN) is used to accurately anticipate output results based on input values that have undergone training. It is also a supervised machine learning technique that shows sharp results due to its highly sensitive algorithm. ANN allows to reduce the time and cost required for multiple experiments and increase the overall efficiency of the system [23, 24]. Therefore, ANN can solve a wide variety of problems for engineering applications where traditional and numerical techniques have become tedious and time consuming. The time cost reduction of ANN has been used in the estimation of performance and emission parameters in internal combustion engines as in many different engineering fields in recent years [25-27]. ANN is capable of producing correct motor behavior. This allows it to act as an inexpensive virtual sensing system for on-board measurement of engine performance and emission characteristics in real time. However, Response Surface Methodology (RSM), a statistical analysis tool, is widely used to know the effect of each input variable on the output effect, especially when the output response is affected by three or more independent variables. It is also widely used to determine and predict the optimum combination of input variables for desired properties from RSM output parameters [27, 28]. Furthermore, RSM (Response Surface Methodology) is more advantageous compared to other methods in terms of simultaneously changing and optimizing effective parameters with the minimum number of experiments, to achieve maximum information [29-31]. In many studies in the literature, there are many studies with RSM approach for the optimization of engine responses by using biodiesel fuel in diesel engines. Atmanlı et al. [18] stated that they utilized RSM to optimize the triple fuel mixture with the goal of achieving maximum performance and minimum emissions. According to their findings, the optimal mixing ratio of diesel-Butanol-cotton oil methyl ester, with a predictability level of 0.98, is 65.5%, 23.1%, and 11.4% (by volume), respectively. Similarly, Simsek and Uslu, [32] determined the optimum injection pressure, biodiesel ratio and engine load parameters for maximum Brake Thermal Effect (BTE) and minimum emission parameters in their optimization study using RSM optimization technique. In their results, they reported that the error rates for different parameters were between 1.5% and 7.26%, and that RSM was an effective method to optimize various motor parameters. In their study, Yilmaz et al. [29] utilized the RSM (Response Surface Methodology) approach to determine the optimal blending ratio of eight different fuel mixtures prepared by adding alcohol to a diesel-biodiesel blend. They successfully developed a complete second-degree mathematical model with a 95% confidence level based on the obtained results. They stated that the validation test results yielded a successful outcome with a low error rate. Similarly, Rajesh Kumar et al., [33] conducted an optimization study for the minimum BSFC and NOX effect of injection timing and EGR (Exhaust Gas Recirculation) in their studies with biofuels prepared by adding alcohol such as dimethyl-carbonate, isobutanol and n-pentanol to diesel fuel. The optimum operating parameters for minimum BSFC and NOx were obtained as 0.988 for isobutanol/diesel mixture at 22° BTDC and 0% EGR valve opening. They stated that there was an error rate of about 5% between the estimated and mean experimental values. When the studies in the literature are examined, it is seen that the RSM-based optimization technique is widely used to improve the engine performance and emissions of different engine operating parameters with diesel/biodiesel dual and triple fuel mixtures such as diesel/biodiesel/alcohol. However, there are not enough studies in which the ANN technique to predict the diesel engine input and output parameters of Artificial Intelligence (AI) techniques and the RSM technique to optimize it together. In addition, in this study, two different techniques were used and compared to determine the optimum parameters to eliminate some the negative effect of biodiesel. In this context, in this study, the estimation of the optimum biodiesel and alcohol ratio for maximum engine performance and minimum BSFC and emission parameters and the optimum parameters were determined according to these estimation results. It is aimed that the results obtained in the study are an important approach to improve the emission results, especially to determine the fuel mixture ratios and to contribute to the literature in this field.

2. Materials and Methods

2.1 Experimental Setup

In experimental studies, sunflower oil methyl ester obtained by transesterification method was used. Propanol alcohol was obtained from Sigma-Aldrich company with 99% purity. In experimental studies, test fuels are 100% diesel (D), 80% diesel + 20% biodiesel (B80), 75% diesel + 20% biodiesel + 5% propanol (P5), 70% diesel + 20% biodiesel + 10% propanol (P10).) and 65% diesel + 20% biodiesel + 15% propanol (P15). Some properties of the fuels used are given in Table 1.

Prepared test fuels were carried out in a single-cylinder four-stroke air-cooled ANTOR 3 LD 510 brand experimental engine. Test engine specifications are given in Table 2. An electric dynamometer is used in the test system with a torque of 26 kW, 80 Nm and a maximum speed of 5000 rpm. The schematic view of the engine test stand used in the experimental studies is given in Figure 1. In the test system, fuel consumption, engine torque and engine power data were instantly recorded digitally with the interface program used. The interface program used is shown in Figure 2. The test was carried out at 5 different engine speeds (1000-1400-1800-2200-2600 min^{-1}) in full load position. The tests were waited until the engine temperature was reached, then measurements were made.

Exhaust emission measurements were made at all engine speeds. Mobydic brand gas analyzer, whose characteristics are given in Table 3, was used for emission measurements. All tests were repeated three times and the average value was calculated and used.

Table 1. Physical properties of use fuels

Properties	D2	Biodiesel	Propanol
Molecular weight (kg/kMol)	210	------	74.12
C (%)	86.13	77.1	64.82
H (%)	13.87	12.1	13.49
O (%)	0	10.8	21.59
Cetan number	52	56	12
Density (kg/m^3) 15 °C	835	884	803.7
Viscosity (mm/s2) 40 °C	2.72	4.51	1.74
Lower calorific value (Mj/kg)	42.49	38.65	30.63
Evaporation heat (kj/kg)	375	-----	727.88

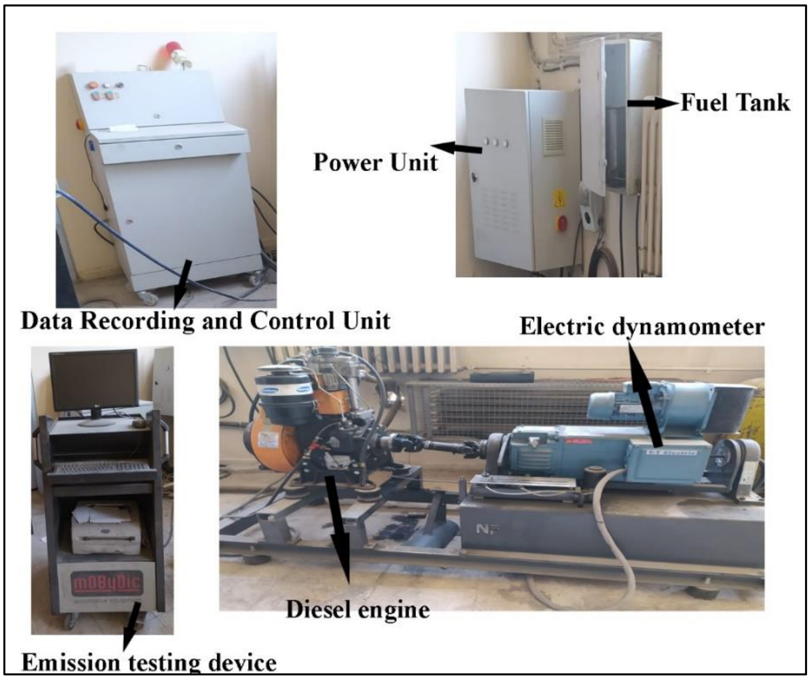

Figure 1. Schematic view of the experimental setup

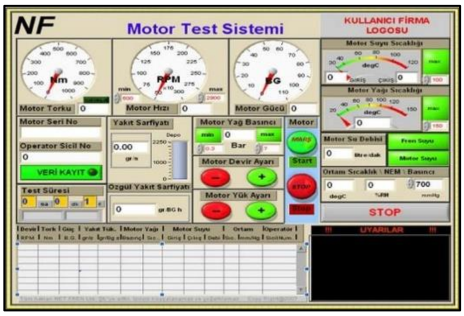

Figure 2. The interface program used.

Table 2. Properties of test engine

Engine Type ANTOR 3 LD 510	
Cylinders Number	1
Cylinder Diameter x Stroke	85 x 90 mm
Cylinder Displacement	510 cm^3
Compression Ratio	17:01
Maximum Engine Speed	3200 min^{-1}
Maximum Engine Power	12 Hp
Maximum Engine Torque	35 Nm 1800 min^{-1}

Table 3. Emission device measuring ranges

MOBYDIC 5000 GAS ANALYZER	
CO % Vol	0 – 10
CO_2 % Vol	0 – 20
HC ppm	0 – 20000
O_2 % Vol	0 – 21
NOx ppm	0 – 5000
Lambda	0 – 5
n %	0 – 100
k 1/m	0 – 20
Particle mg/m^3	0 – 1000

2.2 ANN

ANN is one of the AI methods inspired by the biological nervous system and used for solving various engineering problems, especially for which traditional modeling techniques are inadequate [34]. ANN is widely used in different engineering fields [35]. It is a mathematical and computational modeling technique that has been widely used in the automotive industry, especially in the processing of performance and emission parameters of internal combustion engines [36]. There is no limit to the number of layers in modeling with ANN. Generally, three layers are used in modelling. These layers are called input, output and hidden layers [37]. ANN progresses through three distinct stages. The first stage is modelling, the second stage is the learning (training stage) and the last stage is the testing stage. In the first stage, a model was created according to the input and obtained results (output) parameters (factors) used in the testing phase. In the training phase, the model was run to generate a target estimate based on the network input parameters. The output parameters obtained in the test procedure and the estimated values with the model prepared were compared, and the training phase was stopped when the error between the predicted results and the test results reached an acceptable value. In order to measure the prediction success of the created model, the regression coefficients MRE (Mean Relative Error) and RMSE (Root Mean Square Error) created with the goals and outputs of the ANN model and given in Equation 1-3 were used [38].

$$R^2 = 1 - \left(\frac{\sum_{i=1}^{n} (t_i - o_i)^2}{\sum_{i=1}^{n} (o_i)^2} \right) \quad (1)$$

$$MRE(\%) = \frac{1}{n} \sum_{i=1}^{n} \left| 100 \frac{t_i - o_i}{t_i} \right| \quad (2)$$

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

Here, 'n' is the amount of data in the information set, 'o' is the predicted output data, and 't' is the actual output. In the prepared model, engine speed, diesel, biodiesel and propanol ratios as input layer parameters, Engine Power (EP), Engine Torque (ET), Brake Specific Fuel Consumption (BSFC), Hydrocarbon (HC), Nitrous oxides (NOx) as output layer parameters, Carbon monoxide (CO) and soot emissions were selected. The schematic view of the developed ANN is shown in Figure 3. A commonly used feedforward backpropagation network type was chosen to explain complex problems in system modeling and description [39]. Generally, the Levenberg-Marquardt (Trainlm) training function is applied for precise predictions where the mean square error (MSE) determines the failure function of the network [40]. The (4-16-7) topology was used to estimate the input-output parameters. Four neurons make up the input layer, sixteen neurons make up the hidden layer, and six neurons make up the output layer in this example. Because it is a differentiable, continuous, and nonlinear function, the logarithmic sigmoid (logsig) activation function outperforms other functions in creating the right model, according to the majority of studies [41].

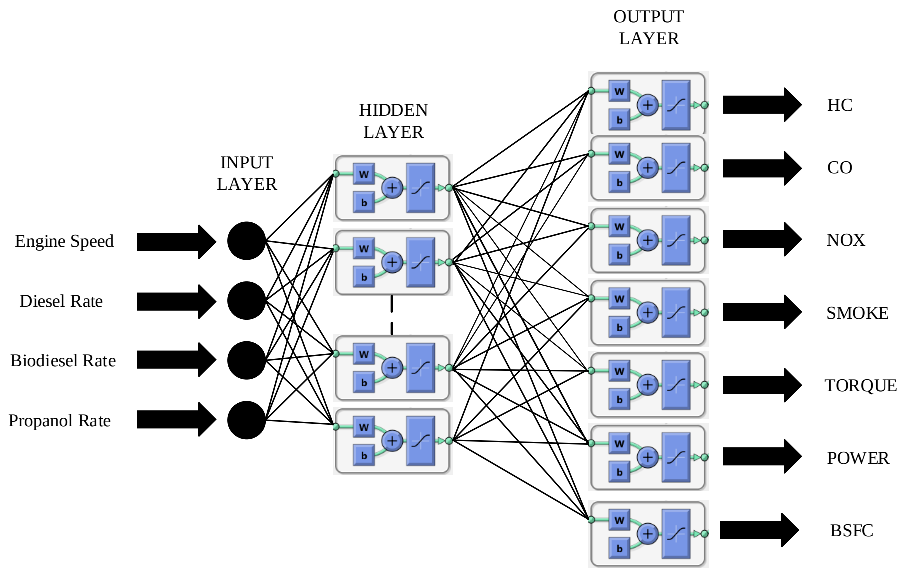

Figure 3. The schematic representation of the ANN

Table 4. Properties of neural network

Network	4 inputs, 7 outputs and 1 hidden layer
Network Type	Feed-forward back propagation
Data	Training: Randomly selected data from the experimental data at the rate of 80%. Test: Randomly selected data of 10% from experimental data. Confirmation: Randomly selected data of 10% from experimental data.
Training function	Trainlm
Adaptation learning function	Learngdm
Transfer function	Logsis
Performance function	Mean Square Error
Stopping criteria	Stop training the network when the validation error starts to increase.

Table 5. Input parameters

Input Factor	Code	Levels		
Engine Speed (min-1)	A	1000	1800	2600
Biodiesel (%)	B	0	20	-
Diesel (%)	C	75	70	65
Iso-propanol (%)	D	5	10	15

2.3 RSM

Response Surface Methodology (RSM), which has achieved successful results in applications in many different fields, is a computer-based application. This application is widely used for modeling and optimization of the performance and emissions of internal combustion engines [13, 40, 41]. RSM establishes a relationship between input and output parameters. It optimizes the responses according to the input factors, according to the relationship between the input and output parameters. For this purpose, RSM uses the least squares technique. According to RSM, each of the motor input parameters is assumed to be computable and can be expressed by the equation given below [42]:

$$y = f(X_1, X_2, \dots, X_n) \quad (4)$$

Here; X_1 X_1 …. X_n respectively, the input parameters and y are the output parameters. The first step in RSM consists of the field or independent variables of the process and empirical statistical modeling in order to develop empirical relationships for estimation and optimization, and to develop an appropriate approximation relationship between response and process variables. A quadratic equation model is applied for this relationship as shown below [38].

$$y = \beta_0 + \sum_{i=1}^{k} \beta_i x_i + \sum_{i=1}^{k} \sum_{j \geq 1}^{k} \beta_{ij} x_i x_j + \sum_{i=1}^{k} \beta_{ii} x_i^2 + \varepsilon \quad (5)$$

The linear coefficient, the quadratic coefficient j, the regression coefficient β, the number of parameters k, and the error ε found in the response are all given in this equation. Central Composite Design (CCD), which provides results that are considerably more exact when compared to other experimental designs, has been used in this investigation. The optimization is mainly aimed at maximizing ET and EP while minimizing BSFC, NOX, CO, HC and Soot emissions. At the same time, it is aimed to establish functional relationships between ANN estimated target parameters (ET, EP, BSFC, NOx, HC, CO and is) and design parameters. Input variables were chosen as engine speed (ES), Biodiesel ratio and Propanol ratio. Input variables and levels are given in Table 5. ET, BSFC, HC, CO, NOX and S are selected as output parameters of the model.

3. Results and Discussion

3.1 ANN Result

In this study, an ANN was designed by using the data obtained from experimental studies to predict diesel engine parameters. The general regression plot obtained from the designed ANN is given in Figure 4. When the general regression graphs obtained from the ANN given in Figure 4 are examined, the correlation coefficients are 0.99996 for training, 0.9983 for validation, and 0.98999 for testing. The overall (Training, Validation and Testing) correlation coefficient was 0.99863. The fact that the correlation coefficient is close to 1 indicates that the accuracy is high [38]. The fact that these values are very close to 1 shows high accuracy in modelling the outputs obtained from the designed ANN results. Baranitharan et al. [26] stated in their study that the correlation coefficient (R-value) of 0.99 indicates the success of the Artificial Neural Network (ANN) model in predicting diesel engine performance. They further emphasized that the R-value of the motor performance and emission characteristics demonstrates the accurate prediction of the output responses by the ANN model [43]. Additionally, the obtained prediction values from the ANN model show a high level of agreement with the experimental values [44] (Figure 5 and Figure 6).Comparison results of experimental results and estimation results for EP, BSFC, ET are given in Figure 5. When the comparison charts of the experimental results and estimation results for ET, EP, BSFC given in Figure 5 are examined, it is seen that the experimental results and the ANN estimation results are highly similar. The R^2 value was obtained as 0.924, 0.99 and 0.907, respectively. Results from the ANN model show that the use of ANN is sufficient to predict ET, EP and BSFC. In a study by Akçay et al., [7] they stated that the R^2 value of all the equations used was 0.98 0.99. As a result, diesel engine operation can be estimated with acceptable error value for further investigation using obtained equations or given algorithms. Also Rao et al., [28] they used a multi-layered sensing (MLP) network for nonlinear matching between input and output parameters in a study where they examined the performance and emissions of an engine with biodiesel and isopropanol added. In their results, they stated that ANN can predict engine performance and emissions with a correlation coefficient in the range of 0.98-0.999. The RMSE values obtained from the ANN results were 0.82 Nm, 0.224 kW and 11.96 g/kWh for ET, EP and BSFC, respectively, while the MRE values were 1.907%, 5.96% and 4.14%, respectively. Similarly, comparison charts of experimental results and estimation results for emission results (CO, HC, NOX and soot) are given in Figure 6. When the comparison charts of the experimental results and the estimation results for HC, CO, NOX and soot emissions given in Figure 6 are examined, it is seen that the experimental results and the ANN estimation results are in high agreement. The R^2 values obtained from the designed ANN model were obtained as 0.9895, 0.9433, 0.948 and 0.9596, respectively. The obtained R^2 values show that the model used is sufficient for estimating the relevant emissions. The RMSE values for HC, CO, NO_X and soot emissions were obtained as 1.47 ppm, 0.23%, 118.23 ppm and 0.17%, respectively. Similarly, MRE values were obtained as 3.86%, 23.36%, 3.19% and 5.82%, respectively. Similar results have been reported in previous studies [38, 42, 45]. Comparisons of the estimation results and experimental results obtained with the ANN model used are given in Table 6 for exhaust emissions, and engine performance comparisons are given in Table 7. The equation used to determine the % error value in the comparison is given in Equation (6).

$$error = \frac{test\ result - predicted\ result}{test\ result}\ x\ 100 \tag{6}$$

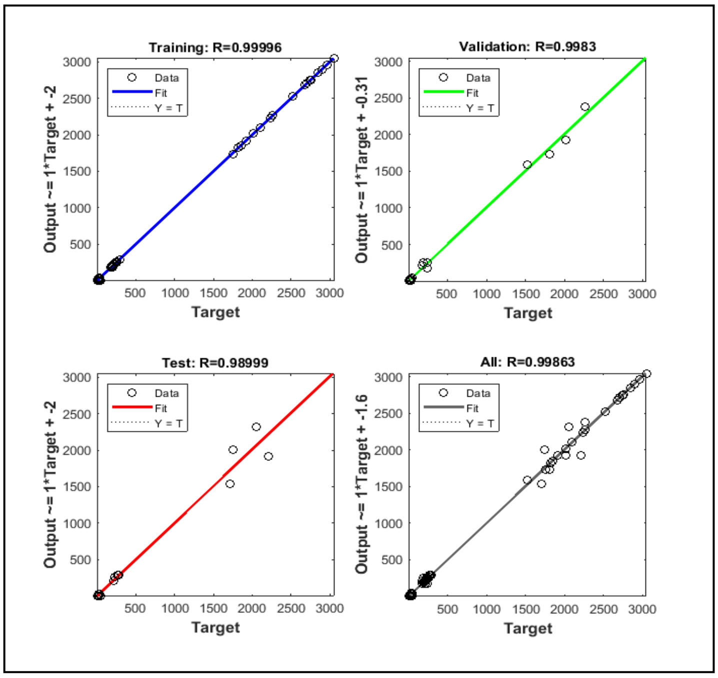

Figure 4. Regression graphs of training, testing, validation, and all results of ANN

Table 6. Comparison of experimental and prediction results for exhaust emissions

Engine Speed (min^{-1})	Biodiesel Ratio (%)	Diesel Ratio (%)	Propanol Ratio (%)	Value	HC (ppm)	CO (%)	NOx (ppm)	Smoke (%)
1000	20	75	5	ANN	46.273	2.198	1623.81	3.265
				Experimental	45	2.35	1742	3.36
				Error (%)	2.82	6.46	6.78	2.82

Table 7. Comparison of experimental and prediction results for engine performance

Engine Speed (min^{-1})	Biodiesel Ratio (%)	Diesel Ratio (%)	Propanol Ratio (%)	Value	ET (Nm)	EP (kW)	BSFC (g/kWh)
1000	20	75	5	ANN	24.03	2.545	266.62
				Experimental	22.78	2.55	278.87
				Error (%)	5.48	0.19	4.39

When the comparison results of the experimental and estimation results given in Table 6 and Table 7 are examined, it is seen that the output parameters for the input parameters of 1000 min^{-1} engine speed 75% diesel, 20% biodiesel and 5% propanol have low error rates for both engine performance and exhaust emissions appears to be predictable. Experimental results for HC, CO, NO_X and Smoke emissions were 45 ppm, 2.35%, 1742 ppm and 3.36 %, respectively, while in the ANN estimation results, they were 46,273 ppm, 2.198 %, 1623.81 ppm and 3.265 %, respectively. It is seen that the estimation results are close to each other with the experimental results. The % error rates were obtained as 2.82, 6.46, 6.78 and 2.82, respectively. Similarly, in the comparison made for engine performance, it is understood that it can be predicted with high accuracy. While the experimental results for ET, EP and BSFC were obtained as 22.78 Nm, 2.55 kW and 278.87 g/kWh, respectively, the ANN estimation results were obtained as 24.03 Nm, 2.545 kW and 266.62 g/kWh, respectively. It is seen that the % error rates are 5.58, 0.19 and 4.39, respectively. Previously, Kurtgoz et al., [46] reported that the ANN models they designed in a study they designed gave good results with high correlation and low error rates for the prediction of performance values in spark ignition biogas engine.

3.1 RSM Result

Analysis of variance (ANOVA) results for engine performance (ET, EP and BSFC) and emissions (HC, CO, NO_X and smoke) are given in Table 8.

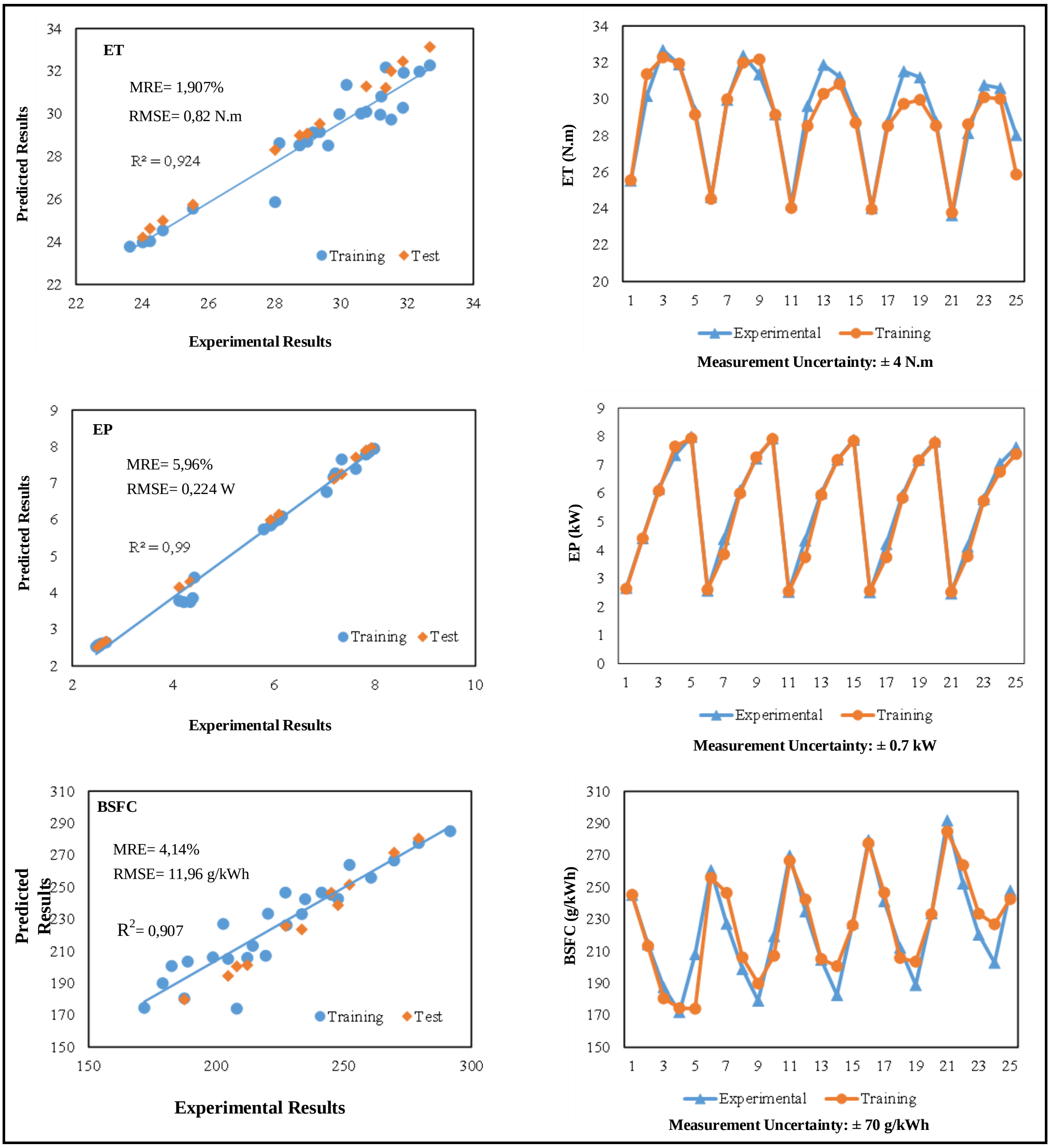

Figure 5. ANN prediction results with experimental results for engine performance results

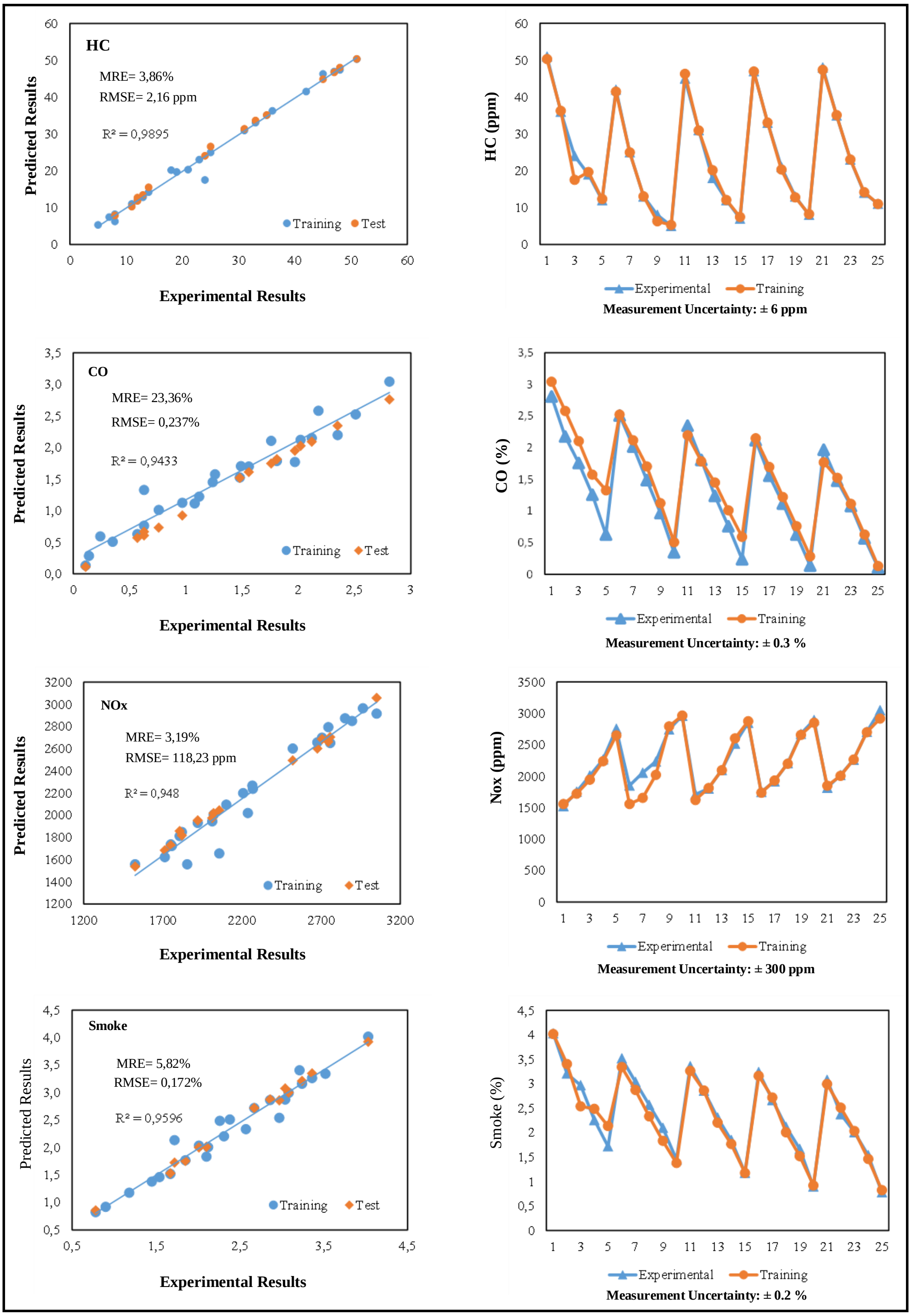

Figure 6. ANN prediction results with experimental results for exhaust emission results

When the ANOVA results given in Table 8 are examined, it is understood that the model and linear coefficients of all outputs are important. It is seen that the p values given in Table 8 are less than 0.05. Analysis of variance (ANOVA) provides numerical information for the probability value [47]. In the ANOVA results, the p value is a parameter that indicates whether the model is important or not. A “p” value greater than 0.05 indicates that the model is unimportant. If a factor's p-value is less than 0.05, it means that the factor has a high impact on the model under development [48]. In the developed model, it is understood that the biodiesel, diesel and propanol ratios are insignificant for all outputs, and the engine speed is important for all outputs. The correlation coefficients of the proposed model for engine performance and exhaust emissions are given in Table 9.

Table 8. Analysis of Variance for engine performance and exhaust emissions

	DF	ET	EP	BSFC	HC	CO	NO_X	Smoke
		p-value	p-value	p-value	p-value	p-value	p-value	p-value
Model	9	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Linear	4	0.000	0.000	0.000	0.000	0.000	0.000	0.000
(A) Engine Speed	1	0.000	0.000	0.000	0.000	0.000	0.000	0.000
(B) Biodiesel	1	0.243	0.811	0.880	0.062	0.886	0.609	0.481
(C) Diesel	1	0.293	0.749	0.806	0.130	0.703	0.716	0.575
(D) Propanol	1	0.424	0.748	0.841	0.224	0.948	0.724	0.485
Square	2	0.000	0.002	0.000	0.000	0.349	0.089	0.633
A^2	1	0.000	0.000	0.000	0.000	0.154	0.031	0.479
C^2	1	0.812	0.656	0.698	0.670	0.949	0.991	0.529
2-Way Interaction	3	0.084	0.745	0.954	0.894	0.096	0.046	0.386
AxB	1	0.328	0.682	0.908	0.522	0.039	0.307	0.607
AxC	1	0.290	0.671	0.896	0.518	0.042	0.357	0.584
AxD	1	0.241	0.635	0.903	0.528	0.049	0.429	0.617

Table 9. Correlation coefficients of the proposed model for engine performance and exhaust emissions

	ET	EP	BSFC	HC	CO	NOX	İs
R^2 (%)	97.29	98.62	92.56	98.72	99.37	97.33	98.57
Adj.R^2 (%)	95.67	97.79	88.10	97.95	98.99	95.73	97.72
Pred.R^2 (%)	90.75	95.98	78.92	96.83	97.18	92.33	95.25

The modified version of R^2 (Adjusted R^2) shows the conformity of the estimators with the conventional estimation. Significant factor (Predictors R^2) shows how well a regression model predicts responses from new observations. Adj. R^2 and Pred. When the R^2 values are examined, it is understood that the values for ET, EP, BSFC, HC, CO NO_X and is are compatible at an acceptable level. The highest difference between these values is approximately 9.18%. In a previous study, Adj. R^2 and Pred. It has been reported that the difference between the R^2 values is less than 20% and therefore these values are reasonably compatible [49]. Second-order regression equations produced by RSM to estimate the output parameters depending on the input parameters are given in Equation 7-13, respectively.

HC = 1076- 0.255Engine Speed – 8.23Biodiesel – 11.7Diesel – 8.76Propanol + 0.000012Engine Speed* Engine Speed + 0.0198 Diesel * Diesel + 0.00179 Engine Speed*Biodiesel + 0.00187 Engine Speed*Diesel + 0.00194 Engine Speed*Propanol (7)

CO = -42.5 + 0.0221 Engine Speed + 0.418Biodiesel + 0.475Diesel + 0.431Propanol- 0.0000001Engine Speed*Engine Speed – 0.00011Diesel*Diessel – 0.000225Engine Speed*Biodiesel – 0.000229Engine Speed*Diesel – 0.000234Engine Speed*Propanol (8)

NOx = 18564- 12.8Engine Speed- 186Biodiesel – 170Diesel - 138Propanol + 0.000177 Engine Speed*Engine Speed – 0.02Diesel*Diesel + 0.138Engine Speed*Biodiesel + 0.128Engine Speed *Diesel + 0.117Engine Speed*Propanol (9)

Smoke = 44.7- 0.0109Engine Speed – 0.265Biodiesel – 0.570Diesel – 0.346Propanol + 0.0000001Engine Speed*Engine Speed + 0.00177Diesel*Diesel + 0.000087Engine Speed*Biodiesel + 0.000095Engine Speed *Diesel + 0.000092Engine Speed*Propanol (10)

ET = -257 + 0.1122Engine Speed + 2.14Biodiesel + 2.91Diesel + 2.69Propanol – 0.000008Engine Speed*Engine Speed – 0.0030Diesel*Diesel – 0.000740Engine Speed *Biodiesel – 0.000831Engine Speed *Diesel – 0.000983Engine Speed *Propanol (11)

EP = -69 + 0.0247Engine Speed + 0.383Biodiesel + 0.95Diesel + 0.574Propaol – 0.000001Engine Speed*Engine Speed- 0.00298Diesel*Diesel – 0.000164Engine Speed*Biodiesel – 0.000176Engine Speed *Diesel – 0.000210Engine Speed *Propanol (12)

$$BSFC = 1856 - 0.49Engine\ Speed - 5.1Biodiesel - 23.3Diesel - 8.0Propanol + 0.000074Engine\ Speed*Engine\ Speed + 0.095Diesel*Diesel + 0.0017Engine\ Speed*Biodiesel + 0.0020Engine\ Speed*Diesel + 0.0020Engine\ Speed*Propanol \quad (13)$$

The applied RSM model was used to determine the optimum parameters of engine speed, diesel, biodiesel and propanol ratios, taking into account the predictive values of the developed ANN model. In the RSM model, the optimization is designed to maximize the engine performance parameters ET, EP, and minimize it for the BSFC and emission parameters (HC, CO NO_X and smoke). Optimum operating parameters obtained from the optimization results are given in Figure 7.

When the optimization results given in Figure 7 are examined, it is seen that 2034 min^{-1} engine speed, 11.3% biodiesel ratio, 74.667% diesel ratio and 15% propanol ratio are obtained. The best responses corresponding to the optimum operating parameters are 171.642 g/kWh for BSFC, 7.54kW for EP, 32.27 Nm for ET, 1.14% for soot emissions, 2488.8 ppm for NO_X emissions, 1.08% for CO emissions, and HC emissions It was found as 7.51 ppm for the obtained optimization results show that the engine performance and exhaust emission parameters are significantly affected by the input parameters. Dubey et al., [50] developed a regression model to analyze the effects of input parameters on BSFC, BTE, smoke, NOx , CO and HC in their study where they evaluated the effect of diesel biodiesel binary fuel mixture on engine performance and emissions experimentally and analytically. They stated that the input parameters were effective on BSFC, BTE, smoke, NOx, CO and HC and were statistically significant. In addition, they stated that the maximum desirability of the dual fuel mixture was 0.928, and the adequacy of the model was below 6% with validation tests. In addition, a combined desirability (D) value close to 1 is an indicator of optimization acceptability. In the obtained optimization results, the combined desirability was obtained as 0.7833. The obtained desirability value shows that the optimization works well. Confirmation test results of RSM results are given in Table 10. It can be seen that the validation test results can be obtained with a very low error rate for both engine performance and exhaust emission results. It is seen that the highest error rate for all results was in the ET response with 6.36%. When similar studies in the literature are examined, it is seen that the results obtained are close to the literature [47, 48, 51]. In a study by Şimşek et al [52] using RSM, they stated that the maximum error between the experimental results and the optimum results was 4.96%. In the results obtained, they stated that the RSM model could successfully model a single-cylinder diesel engine.

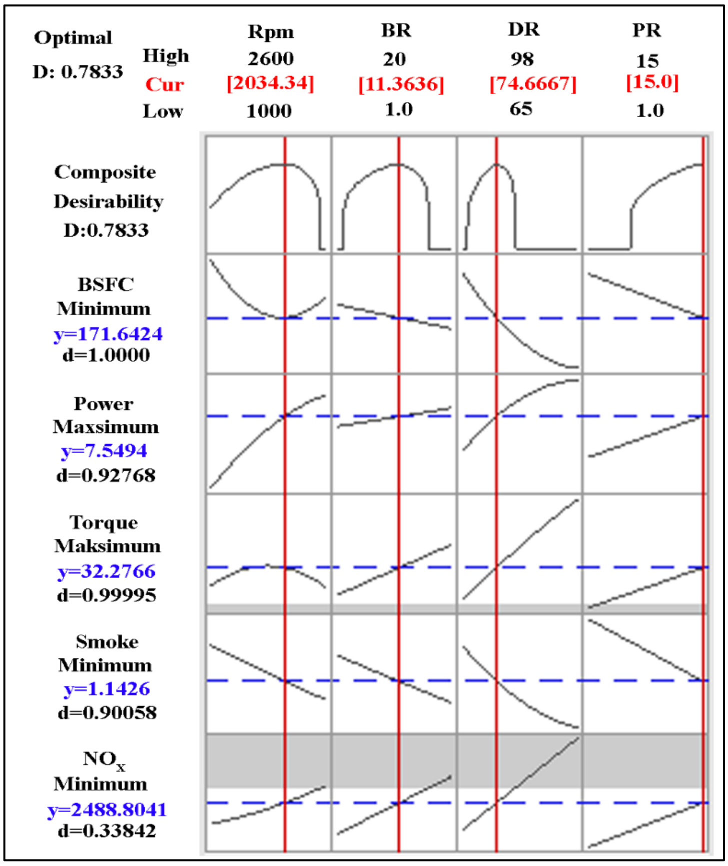

Figure 7. Optimization results

Table 10. RSM validation test results

Engine Speed (min^{-1})	Biodiesel Ratio (%)	Diesel Ratio (%)	Prop. Ratio (%)	Value	ET (Nm)	EP (kW)	BSFC (g/kWh)	HC (ppm)	CO (%)	NO_X (ppm)	Smoke (%)
1000	20	75	5	Opt.	24.2	2.53	269.76	44.225	2.276	1613	3.3
				Exp.	22.7	2.55	278.87	45	2.35	1742	3.36
				E. (%)	6.36	0.78	3.26	1.72	3.15	7.37	1.78

3. Conclusion

In this study, it is aimed to determine the optimum operating parameters of a diesel engine working with diesel biodiesel and propanol fuel mixtures. For this reason, an ANN model was developed and it was aimed to reduce the number of experiments to determine engine parameters. Optimum operating parameters of the obtained ANN results were determined with an RSM-based optimization model. In the ANN results, the R^2 values for ET, EP, BSFC, HC, CO, NO_X and soot emissions were obtained as 0.924, 0.99, 0.907, 0.989, 0.943, 0.948 and 0.959, respectively. The RMSE values of the ANN results were obtained as 0.82 Nm, 0.224 kW, 11.96 g/kWh, 1.47 ppm, 0.23%, 118.23 ppm and 0.17%, respectively. The MRE values of the ANN results were obtained as 1.907%, 5.96%, 4.14%, 3.19%, 26.37%, 3.86%, 5.82%, respectively. When the ANN and experimental results are compared, it is seen that the performance and exhaust emissions of a diesel engine operating with a diesel/biodiesel/propanol mixture can be predicted with a low error rate. In the RSM-based optimization results, the optimum engine operating (input) parameters were obtained as 2034 min-1 engine speed, 74.667% diesel ratio, 11.36% biodiesel ratio and 15% propanol ratio. On the other hand, the output parameters were obtained as 32.28 Nm, 7.55 kW, 171.64 g/kWh, 7.51 ppm, 1.08%, 2488.8 ppm and 1.14% for ET, EP, BSFC, HC, CO, NOX, and smoke, respectively. In the confirmation tests of the RSM results, it was seen that the results were close to the results obtained from the experimental study. In the validation test, the highest error rate was obtained as 6.36%. During the validation tests, it was observed that the error rate of the responses obtained with RSM was lower compared to ANN. Additionally, training the ANN model requires a larger amount of data (test results). However, RSM allows for predictions with a limited number of test results. Considering both the monetary and time aspects, RSM is believed to be more prominent.

Declaration

The author declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article. The author also declared that this article is original, was prepared in accordance with international publication and research ethics, and ethical committee permission or any special permission is not required.

Author Contributions

First Author and second author developed the methodology. Second author performed the experimental study. First Author and third author performed the analysis studies. First Author and second author supervised and improved the study. Authors wrote the manuscript together. Second author proofread the manuscript.

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