ANN Based Prediction of Engine Performance and Exhaust Emission Responses of a CI Engine Powered by Ternary Blends

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Abstract

In this study, experimental data was collected from a single cylinder diesel engine fueled by pyrolytic oil, neat diesel and butanol fuel blends. The experiments were conducted at various engine loads, namely from 0.25 kW to 1.25 kW by 0.25 kW increment. The engine performance and exhaust emission data obtained were modeled using an artificial neural network (ANN) algorithm. CO, NO_x, BSFC, and BTE were considered in the ANN model. The results were discussed in terms of R^2, MBE, and RMSE metrics. R^2 value of the performance and exhaust emission responses' prediction were 0.986, 0.963, 0.991, and 0967 for BTE, BSFC, NO_x, and CO, respectively, and in addition, all MBE value was very close to zero and smaller than 1.14. As a conclusion, the present paper showed that performance and exhaust emission responses of ternary fuels can be accurately predicted using an artificial neural network

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1. Introduction

Despite the increasing number of vehicles in the world, the decrease in the reserves of primary energy sources and increasing emission standards for vehicles have accelerated the search for alternative fuels. Fuels such as electrical energy, hydrogen, bio diesels, alcohol based fuels, biogas, liquid petroleum gas and compressed natural gas are used as alternative fuels in internal combustion engines and studies are carried out on these fuels. Quality criteria expected from alternative fuels can be listed as sustainability, accessibility, performance and compliance with emission standards. In order to ensure sustainability and to be more environmentally friendly, the evaluation of wastes as fuel (energy from waste) makes energy from waste more attractive in alternative fuels [1-3]. Energy can be regained from garbage, wastewater, factory waste, animal manure and many other worthless process

products. One of these wastes is used tires. Problems such as used vehicle tires occupying a lot of space in the storage yards and causing environmental pollution, indissolubility in nature, increasing the risk of fire, making millions of tires become waste in the world every year makes it necessary to evaluate waste tires.

Waste tires can be used as fuel in internal combustion engines by pyrolysis method [4]. Doğan et al. 2012, Wang et al. 2016, Adam et al. 2017, Murugan et al. 2008, Frigo et al. 2014, Karagöz, et al. 2020, in their studies, they examined the use of pyrolytic fuel from waste tires in internal combustion engines [4-9]. Researchers reported that pyrolytic fuel obtained from waste tires showed similar properties to diesel fuel. Besides, the researchers stated that with the addition of pyrolytic fuel to diesel fuel, some emission values improved while NO_x emission increased. Doğan 2011, Yusri et al. 2019,

carried out experiments on internal combustion engines by adding butanol to diesel fuel and emphasized that fuels containing high levels of oxygen have the potential to significantly reduce NO_x emissions [10,11]. In obtaining the experimental data of the subject study, it was aimed to improve NO_x emissions by adding butanol to the diesel pyrolytic fuel mixture.

Internal combustion engine tests, in which alternative fuels are tested, are complex, difficult and expensive processes where the engine, dynamometer units, many sensors, analyzers and thermocouples have to be used together. Instead of doing all the steps of expensive and time consuming engine tests, some of the test results can be used for training and the results of the untested parts can be predicted by using estimation methods. ANN, one of these estimation methods, is frequently used in engineering due to its high accuracy and simple use. With the well-trained ANN algorithm, the engine responses can be accurately predicted in a short time [12].

Based on the ANN studies in the recent literature, it can be said that generally predictability of exhaust emissions (HC, CO, NO_x) [13-15], performance (BTE (Brake Thermal Efficiency), BSFC (Brake Specific Fuel Consumption) [13-16], and combustion (CP_{max}) characteristics [13,17,18], for various test fuels was tested. For example, Ağbulut et al., 2020b predicted CPmax, BSFC, CO, HC and NO_x parameters by using an ANN algorithm for various test fuels, different engine loads and different injection pressures in a diesel engine [19].

In this study, experiments were carried out in a diesel engine using diesel - pyrolytic fuel - butanol fuel mixture. From the experimental data obtained, an ANN based prediction has been performed using engine load and test fuel as input parameters and effective efficiency, specific fuel consumption, CO and NO_x as output parameters.

2. Materials and Methods

2.1. Test Fuels and Test Engine

The fuels used in the tests were created by volumetric blending of pyrolytic fuel, diesel and butanol. Volumetric content and abbreviations of test fuels are given in Table 1. The triple fuel mixture was kept in the magnetic mixer for 15 minutes to ensure homogeneity. Diesel engine-generator set was used in the experiments. In the study, a single cylinder, 18:1 compression ratio, 7.8 cm cylinder diameter, 6.2 cm stroke, direct injection, air cooled engine was used. 4 kW of power can be obtained from the engine at 3000 rpm. The tests were started when the engine temperature stabilized and three repetition were averaged for each fuel and load condition. Experiments were carried out at four different loads of

0.50, 0.75, 1.00 and 1.25 kW to examine the operating conditions of the engine under different load conditions. The tests were performed at a constant 3000 engine speed. The fuel consumption of the engine was measured in mass with precision scales. Exhaust emission measurements were carried out with Bilsa brand exhaust emission analyzer. The schematic view of the experimental test rig is shown in Figure 1. The properties of test fuels are given in Table 2 [20].

Table 1. Test fuels, blending-percentages and abbreviations

		Test Fuel (TF)– Abb.					
		TF1	TF2	TF3	TF4	TF5	TF6
By volume, %	Pyrolytic oil	0	15	15	15	30	45
	n-Butanol	0	5	10	15	15	15
	Neat diesel	100	80	75	70	55	40

Table 2. Some important fuel properties.

		Property			
		Density (kg/m³; 15°C)	Cetane number	Viscosity, (cSt @40°C)	Lower heating value (MJ/kg)
Test Fuel	TF1	835.00	54.92	2.929	45.94
	TF2	843.40	51.19	2.776	44.54
	TF3	842.20	49.69	2.740	43.90
	TF4	841.00	48.19	2.703	43.26
	TF5	850.60	45.96	2.587	42.50
	TF6	860.20	43.72	2.470	41.74
Test Method		TS EN ISO 12185	EN ISO 5165 TS EN 15195	TS 1451 EN ISO 3104	EN 5165
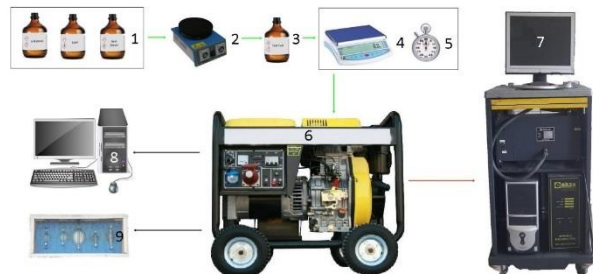
1	Neat diesel, n- butanol, pyrolytic fuel	2	Magnetic stirrer
3	Test fuel	4	Precision scales
5	Timekeeper	6	Test engine
7	Exhaust analyzer	8	Data logger and computer
9	Engine loading set		

Fig. 1. Schematic view of the experimental rig.

In the study, brake specific fuel consumption was calculated using Eq. 1., and brake thermal efficiency was also calculated using Eq. 2 [3].

$$BSFC = \frac{\dot{m}_f \ 10^3}{P_e} \qquad (1)$$

$$BTE = \frac{1000*3600}{BSFC*LHV} \qquad (2)$$

Where $\dot{m}_f$ is fuel mass consumption and it's unit is kg/h, P_e is the brake effective power and it's unit is kW, LHV is lower heating value and it's unit is kJ/kg.

2.2. Artificial Neural Network

ANN is probably the most frequently used tool for modeling the experimental responses, particularly with non-linear relationships both for regression and classification problems. ANN is a network structure and it consists of some process capability elements called neurons. However, the neural network structure model requires to be trained to set a nexus between inputs and responses. With this viewpoint, the mechanism of ANN is very similar to that of the human brain. After a well-done training process, the ANN algorithms is able to produce quick and reliable results even for the datasets containing missing data. Depending on the size of the networks, the number of layers may also grow to ANN. This case may result in memorizing for the network. Therefore, it is of great importance to find the optimum network size by avoiding both this situation and waste-training time. In this paper, the ANN used a feed-forward neural network and trained by the aid of the back-propagation algorithm (multi-layer perceptron) for all responses, and the optimum network size was found with trial and error for each engine response. Fig. 2 shows the ANN structure used in the present investigation.

In this study, an training of ANN has been performed with backpropagation algorithm and using 24 data from the experimental results. The dataset was randomly divided into two parts: training and testing data. 80% of all dataset was used for the training of algorithm, while the remaining 20% was used for the testing data. The LM learning algorithm was solved by a hidden layer of a small number of neurons. The grid search technique is used to tune the model parameters in this study. In the study, the optimum ANN network architecture in the prediction of BTE, BSFC, NO_x and CO responses have been found to be 2-7-1, 2-4-1, 2-2-1 and 2-4-1, respectively.
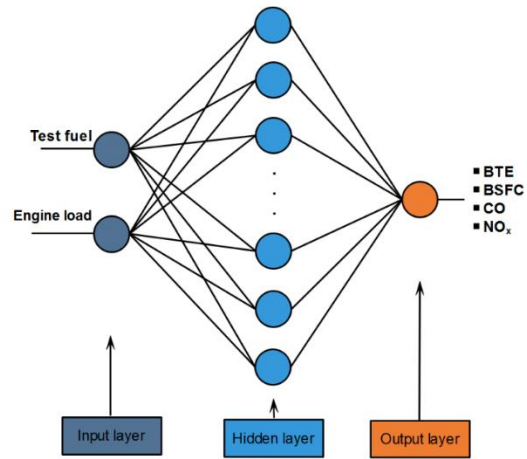

Fig. 2. Schematic view of ANN structure.

2.2.1. Evaluation Metrics

In the study, three metrics are used to discuss the performance of the prediction results. These are R^2, RMSE and MBE. Table 3 gives the equations and desired cases of these metrics [19, 21, 22].

Table 3. Equation and desired cases of the metrics.

Metrics	Equation	Desired case
R^2	$1 - \dfrac{\sum(y_i - x_i)^2}{\sum(x_i - \bar{x}_i)^2}$	R^2 is varying from 0 to 1. To be closest to the zero is the ideal case [21, 22].
*MBE	$\dfrac{1}{n}\sum_{i=1}^{n}(y_i - x_i)$	To be closest to the zero is the ideal case [21, 22].
**RMSE	$\sqrt{\dfrac{1}{n}\sum_{i=1}^{n}(y_i - x_i)^2}$	To be closest to the zero is the ideal case [21, 22].

* MBE: Mean bias error, **Root mean squared error

In Table 3, y_i and x_i are predicted and measured engine responses, respectively; $\bar{x}_i$ is the mean of measured engine response; n is the number of observations.

3. Result and Discussions

In the present investigation, the engine responses (performance and emission characteristics) are predicted with ANN algorithm. Three metrics (R^2, RMSE and MBE) are discussed to evaluate the prediction performance in the study. A summary of the prediction results is given in Table 4. As can be seen from Table 4, all responses have very satisfied results in terms of prediction side. That is, R^2, RMSE and MBE are varying from 0.963 to 0.991, from 0.019 to 19.968 and from 0.014 to 1.1356, respectively.

Table 4. Numerical results of evaluation metrics.

Response	Metrics		
	R^2	RMSE	MBE
BTE	0.986	0.174	0.0837
BSFC	0.963	17.968	0.084
NO_x	0.991	9.642	1.1356
CO	0.967	0.019	0.014

Figure 3 shows the curves of the data both measured and predicted for each response. As can be seen from Fig. 3, NO_x gives the worst results in terms of MBE metric, even if the prediction curve is closely followed to actual data owing to its high R^2 value of 0.991. As mentioned above, the best result for MBE metric is seen at the values of closing to zero [21]. That is why BTE has the best MBE result of 0.0837. This case is also supporting the R^2 and RMSE values of

0.986 and 0.174 for BTE, respectively. On the other hand, BSFC has the worst RMSE result of 17.968. Among all responses, the worst R^2 value is seen with 0.963 for RMSE even if it is very-satisfied result. In terms of R^2 metric, the most successful engine response is NO_x. The R^2 value of NO_x is 0.991. As well-known, MBE value can take positive or negative results. If MBE value is positive, then it means that mean of predicted values is higher than that of actual values. If it is negative, it means that mean of predicted values is smaller than that of actual values [22]. With this viewpoint, all results in terms of MBE metric are positive and varied from 0.014 to 1.1356 (See Table 4). CO emission is giving the most successful results in terms of MBE with the value of 0.014 among all responses. The worst one for MBE metric is NO_x with the value of 1.1356.
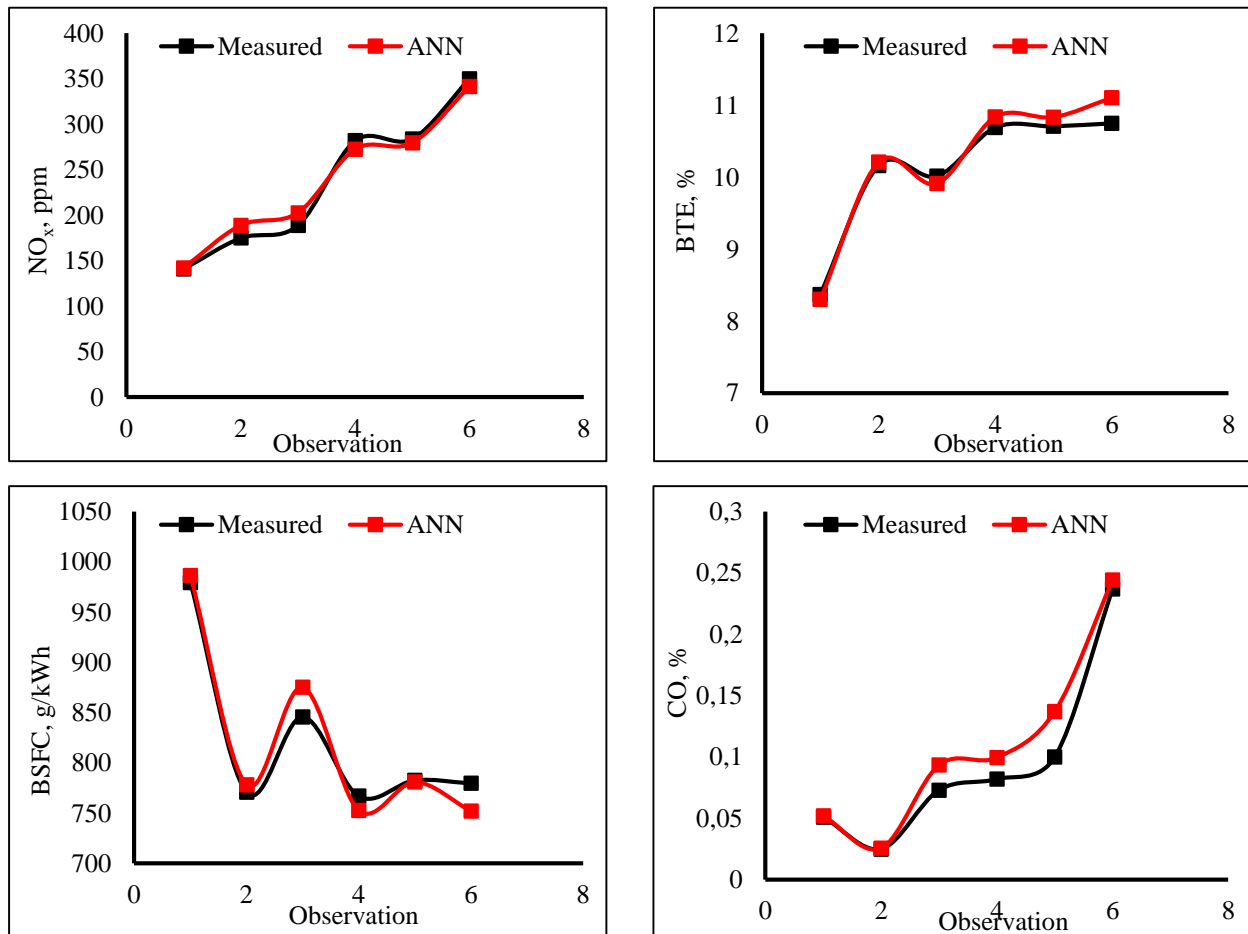

Fig. 3. Prediction results a) NO_x b) BTE c) BSFC and d) CO

4. Conclusion

In this study, experiments were carried out on a diesel engine using diesel - pyrolytic fuel - butanol fuel mixture. From the experimental data obtained, estimates were made with an artificial neural network used as engine load and test fuel as input parameters and brake thermal efficiency, specific fuel consumption, CO and NO$_x$ as output parameters. The following conclusions can be drawn from this study:

•The coefficient of determination for all responses is varying from 96.3% and 99.1%.

•The LM learning algorithm presented very satisfying results to train the neural network advanced and for evaluating the performance of the diesel engine.

•MBE values except for NO$_x$ are found to be very close to zero. The biggest MBE value is calculated to be 1.1356 in NOx and even this value is the very-satisfying result.

•Based on the prediction results, the engine response can be successfully predicted using an artificial neural network.

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