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Experimental investigation and artificial neural network-based modelling of thermal barrier engine performance and exhaust emissions for methanol-gasoline blends

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ABSTRACT

In recent years, due to environmental concerns and the depletion of fossil fuels, alternative fuel use and alternative emission reduction methods have gained importance in the automotive industry. In addition, methanol is used as an alternative fuel in gasoline engines with coated piston engines. This study first presents an experimental investigation of engine performance and exhaust emissions for a partially thermal barrier lined piston engine operating on methanol-gasoline blends. In the second phase the obtained data is then used to develop an Artificial Neural Network (ANN) based model to predict engine performance and exhaust emissions for methanol-gasoline blends. The developed ANN model was trained and validated using MATLAB. The results of the experimental study showed that the use of methanol-gasoline blended fuel in the engine provides better engine performance and reduced exhaust emissions compared to gasoline fuel. According to the results obtained, an increase of 3.7 % in effective power and a decrease in NOx and HC emissions by 19 % and 18 %, respectively, compared to the STD case when both coating and alternative fuel are used in the engine. With the established ANN models, engine performance parameters and exhaust emission parameters were predicted with 99 % and 98 % accuracy respectively.

1. Introduction

The combustion process in internal combustion engines generate emissions that contribute to air pollution and climate change [1]. These generated emission values vary depending on the engine working-running conditions and fuels used [2]. Besides, these criteria are essential parameters that affect engine efficiency. Engines with higher efficiency provide better fuel economy and lower emission by converting a higher percentage of the fuel into energy [3]. Researchers have been conducting thermal coating works in engines in order to improve engine working-running parameters [4]. In addition, along with alternative fuel studies, both performance parameters and emission values are being improved [5].

Pistons coated with thermal barrier have been developed in order to reduce heat transfer from combustion chamber to the piston, and this decreases the heat load on piston and cylinder walls [6]. This effect reduces the amount of heat released by the engine [6,7]. Thermal barrier coating also increases the efficiency of the engine, and thus decreases the amount of fuel burnt and therefore the amount of emission released to the atmosphere. Coating all elements of combustion chamber in spark ignition engines leads to an increase in the tendency of knock in the engine. Therefore, partial coating methods are used in engines [8,9].

When studies conducted on partial coating method are examined, it is seen that Saravanan et al. investigated the effects of coating of the piston with biofuel in a gasoline engine on performance and emission. As a result of the study, they determined increases in effective efficiency values due to coating. They also found that in the case of using 10 % biofuel, there was a decrease in NOx emissions and increases in effective efficiency and HC emissions. In coated piston experiments, they determined decreases by 3.1 % and 3.6 %, respectively, in HC and CO emissions when 10 % biofuel blended fuel was used compared to the standard fuel use [10]. Sivakandhan et al. examined the effects on the performance and emissions in a coated engine and a diesel engine working with diesel fuel blended with sardine oil methyl ester. They coated the piston with 0.5 mm thick partially stabilized zirconium. As a result of the experiment carried out on the coated engine, thermal efficiency, heat dissipation, and cylinder interior pressure values increased with biodiesel and nanoparticle added fuel with respect to the standardized fuel [11]. Bayat and Yildiz investigated the effects of coating

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Nomenclature

ANN	Artificial Neural Network
BFG	Broyden-Fletcher-Goldfarb-Shanno
BFG3	3-Hidden-Neuron BFG
BP	Back Propagation
BR	Bayesian Regularization
C	Carbon
CGB	Conjugate Gradient BP
CO	Carbon Monoxide
CO_2	Carbon Dioxide
CSA	Crank Shaft Angle
H	Hydrogen
HC	Hydrocarbon
H_2	Hydrogen
LM	Levenberg Marquardt
LM3	3-Hidden-Neuron LM
MAPE	Mean Absolute Percentage Error
MSE	Mean Square Error
M1	Model 1 of ANN
M2	Model 2 of ANN
M3	Model 3 of ANN
M10	10 % Methanol+90 % Gasoline
M20	20 % Methanol+80 % Gasoline
NiCrAl	Nickel Chromium Aluminum
NOx	Nitrogen Oxides
OSS	One-step Secant BP
R^2	Regression Coefficient
RMSE	Root Mean Square Error
SFC	Specific Fuel Consumption
STD	Standard Piston Engine
TBL	Coated Piston Engine
Y_2O_3	Yttrium Oxide

Subscripts

A_t	the actual value
F_t	the forecast value
n	the number of fitted points

the surface of the piston with different materials in different thicknesses with finite elements analysis. As a result of their study, they found a decrease by 15 % in friction force according to pressure values in the coated engine [12]. Obulesa et al. experimentally investigated the effects of gasoline-methanol blends and thermal barrier coating in a one-cylinder and two-stroke spark ignition engine. They added methanol to the fuel at volumetric amounts of 10 %, 20 %, and 30 %. In addition, they coated the upper surface of the piston with brass material of 300 μm thickness. As a result of the study, the best result was obtained with the fuel blend of 20 % methanol + gasoline. With 20 % blend fuel and coating, improvements were observed in effective efficiency, specific fuel consumption (SFC), and mechanical efficiency [13]. Cesur investigated the effects of partial coating of the upper surface of the piston and water injection with an experiment. He determined improvements in effective power and effective efficiency in the partial coating method. When he examined the emission values, he found increases in NOx emissions depending on increased combustion chamber temperature with coating and decreases in HC emissions [14]. Abbas et al. experimentally investigated the effects of ceramic coating on performance and emissions in a single cylinder engine. As a result of the study, they found an increase in effective efficiency and NOx emissions with coating application [15]. Krishnamani et al. experimentally investigated the effects of coatings and alternative fuels on performance and emissions in an engine. As a result of the experimental study, they found that the effective data and NOx emissions increased with ceramic coating application while HC emissions decreased [16].

Petroleum-based fuels used in internal combustion engines lead to air pollution. In order to reduce the negative effects of these fuels, alternative fuels are used in engines [12]. In addition to the primary fuels of engines such as gasoline and diesel, alternative fuels such as methanol, ethanol, biodiesel, and hydrogen are fuels that are used in order to increase performance and decrease emission values [17,18]. Methanol is an alternative fuel recommended as a solution to decreasing environmental effect of vehicle emissions. Methanol has lower viscosity compared to gasoline. Therefore, its atomization and mixing with air is easier [19]. Alcohol fuels have higher oxygen content and H/C ratio [20]. Alcohol fuels are fuels that have high evaporation energy. Therefore, they decrease in-cylinder heat in suction and compression strokes. Thanks to this cooling property of alcohols, more air can be absorbed into the cylinder during suction stroke, and the engine's volumetric efficiency is improved [21]. The high flame rates of alcohols lead to earlier completion of combustion and increase the thermal efficiency of the engine [22–24].

When the literature is reviewed, it is seen that Nuthan Prasad et al. (2020) investigated the changes in performance and exhaust emissions when methanol blends were used as fuel in a one-cylinder four-stroke engine under full load conditions and varying compression ratios. As a result of the experimental study, they determined improvements in engine performance but increases in NOx emissions [25]. Elfasakhany (2015) experimentally examined the effects of using alcohol-gasoline blends at varying ratios in a gasoline engine on performance and emissions. As a result of the experiments, he found decreases in CO and HC emissions and increases in volumetric efficiency, engine torque, and effective power with alcohol-gasoline blends [26]. Zhao (2011) injected methanol-gasoline blends in varying ratios to the engine with the help of an electronic control unit. As a result of the experiment, he observed that when methanol ratio rose up to 50 %, due to the decrease in the energy content of methanol-gasoline blends, the combustion performance of the engine worsened [27]. Agarwal et al. (2014) analyzed the effects of 10 % and 20 % methanol-gasoline blends in a spark ignition engine under partial load conditions on engine performance and exhaust emissions in comparison to gasoline. As a result, they determined that the use of methanol-gasoline blends as fuel in the engine increased the thermal efficiency of the engine, and it decreased NO and CO emissions [28]. Vancoille et al. (2013) investigated the effects of methanol-gasoline blends in different ratios on engine performance and exhaust emissions. They determined that effective efficiency increased and NOx and CO_2 emissions decreased [23]. Canakci et al. (2012) examined the effects of using ethanol-gasoline and methanol-gasoline blends as a fuel in a gasoline engine. In the experiments they conducted, they used different loads, revolutions, and blend ratios. As a result, they determined decreases in emission values (CO, HC, and NOx) and increases in SFC [29]. Qadiri investigated the effects of two different types of alterative fuel additives to gasoline fuel on performance and emissions. In the study, they used 20 % methanol-80 % gasoline and 8 % ethanol-2% water-90 % gasoline blended fuels. As a result of the study, they found a slight improvement in performance and reductions in HC and NOx emissions with methanol-gasoline blended fuel [30].

The usability of alternative fuels in different combustion variations in internal combustion engines requires many experiments to be conducted on the determination of engine performance parameters and exhaust emissions. When many experiments are carried out, the costs increase [31]. Today, due to the fast developing artificial intelligence technologies, the results of experiments in different conditions can be estimated with existing experiment data in many fields. However, these estimations require speedy processing of numerous data. In this context, powerful computer processors and software are needed. One of these software widely used today is MATLAB-nntool application [32].

The fuel [33], performance [34,35] and emission parameters [36] of engines running on diesel, gasoline and other fuel types [37] and their combinations [38,39] can be estimated with artificial intelligence technologies such as ANN [40], machine learning [41], etc. ANN is an artificial intelligence system that can bring solutions to the problems in which there is linear or non-linear relationship between its input and output and works based on relations between neurons as in human brain [42]. Different ANN structures have been built in order to produce better solutions to different problems. The structure of an ANN varies according to the solutions it provides to the problem. However, it seems to be impossible to develop a model related to the ANN structure that can yield the best solution. Therefore, different ANN structures for a problem are tried, and it is attempted to find the best solution [43]. This situation requires computer solutions in ANN applications. MATLAB-nntool is widely used as it provides an opportunity to do trials by creating different network structures in a fast way and yields practical results for different inputs for the solution found [31,39,41,43].

Engine revolution, engine torque, fuel flow, suction manifold mean temperature, and cooling water entry temperature were used as input data in back propagation (BP) learning algorithm in ANN built in order to estimate the power, specific fuel consumption, exhaust gas temperature, and mean effective pressure of a 4-cylinder 4-stroke methanol engine. The results obtained show that ANN has high precision in estimating output data [44]. In experiments where gasoline-methanol-ethanol blends are used as fuels in a spark ignition engine, values such as break power, torque, specific fuel consumption (SFC), fuel flow rate, etc. Can be successfully estimated with an ANN in which engine revolution and methanol and ethanol ratios are used as inputs [45]. In the ANN built in order to estimate SFC value and exhaust emissions of a gasoline engine, different training algorithms were used to train BP. When the estimation results obtained were compared with experiment results, it was seen that ANN yielded successful results [46]. Estimation results in the ANN built to simultaneously estimate exhaust emissions of a direct injection diesel engine and trained with BP and Radial Basic Function validated the experiment data with very close values [47]. The torque of a one-cylinder engine that runs on gasoline-methanol blends in different blend ratios between 0 and 18 % can be estimated with high precision through an ANN in which brake power, SFC, brake thermal efficiency, exhaust gas temperature, exhaust emission values, engine revolution and load, and fuel blend ratio are used as inputs [48]. In studies conducted, it is seen that the ability of different inputs introduced to ANNs to estimate similar outputs one by one or as a whole is rather high.

In the literature, the reduction of emissions from internal combustion engines and alternative fuels to petroleum-based fuels have been investigated in detail. In this study, two alternative research methods were used simultaneously and an artificial neural network method was also used for the prediction of experimental data. In the experimental study, in order to reduce the exhaust emissions from the engine to the environment without reducing the engine performance, firstly, the standard engine piston was partially coated with ceramic material with high heat reserve. In this way, some improvements in performance and emission values were found. However, in order to achieve the desired results, secondly, gasoline-methanol mixtures were used as alternative fuel in the ceramic coated engine. As a result of the study, the opportunity to release less pollutant emission to the environment was revealed. Furthermore, in addition to the experimental work, ANN was used with an alternative approach in order to estimate both engine performance parameters and exhaust emissions. The experiment data obtained were combined with similar engine data borrowed from the literature and used in the training of three different ANNs according to the output status created in MATLAB-nntool, and experiment results of fuel with 20 % methanol were estimated in the trained network. Finally, estimation results and experiment results were compared.

2. Materials and methods

2.1. Experimental methods

In the experiments, a 2-cylinder, natural-suction, injection, and water-cooled spark ignition engine was used. The schematic view of the test bench where the experiment was carried out is presented in Fig. 1. The technical specifications of the test engine are given in Table 1.

An electric dynamometer with a capacity of 20 kW was used in the experiments. In order to measure the exhaust emissions released from the engine, MRU Delta 1600 L brand measurement device was used (Table 2). The emission measurement device measures CO and CO_2 values as percentage and HC and NOx values as ppm. NiCr–Ni type thermocouples were used in the experiments to measure temperature values in certain parts of the engine.

Electronic fuel injection system was used in order to inject methanol in different ratios to the engine. Electronic fuel injection system determines the position of the camshaft and the revolution of the engine through the electronic control unit decoder, and strokes are determined with top dead center sensor. Alcohol injectors were positioned on the suction manifold in a way to inject the fuel exactly to the back of the engine intake valve. Alcohol was started to be injected in ratios of 10 % and 20 % of the fuel consumed by the engine with suction valve in open position and after the piston passed the top dead center 5° CSA. The methanol used in the experiments was industrial-use type and 99.9 % pure. In the experiments, 10 % methanol+90 % gasoline (M10) and 20 % methanol+80 % gasoline (M20) blends were used. Technical specifications of gasoline and methanol fuel are given in Table 3.

In order to compare the results of the standard (STD), coated (TBL), and methanol injection (M10, M20) experiments, the engine was run under the same conditions (ignition advance, injection pressure, entry temperature, and pressure and air/fuel ratio). The experiments were carried out at constant ignition advance. The ignition advance of the engine was 10° crankshaft angle (CA). The experiments were carried out with the throttle valve in wide open position and at engine revolutions of 1400, 1,00, 2200, 2600, 3000 and 3400 rpm. The experiments were first started with gasoline fuel. Engine performance parameters and exhaust emissions were measured under full load conditions with gasoline fuel. After the experiments with gasoline fuel were completed, the engine piston was replaced with a coated piston and the engine was operated under the same conditions. In the last stage of the study, 10 % methanol and 20 % methanol were injected into the engine with coated piston and gasoline fuel, respectively, and performance and emission values were measured. The flowchart showing the experimental steps and results of the experimental study is given in Fig. 2.

The partial differentiation method was used to conduct uncertainty analysis during the experiments in order to distinguish between systematic and random uncertainties. Table 4 presents the outcomes of the analysis of uncertainty.

2.2. ANN structure

The inputs for the ANN application were chosen as the methanol ratio of the fuel, coated or uncoated piston, crank force read in the dynamometer and engine revolution according to the experiment data. According to these data, engine performance parameters (moment, engine power, SFC, effective efficiency) and exhaust parameters (HC, CO, NOx) were estimated.

Network structure determination and normalization were done according to the methodology of our previous study [49].

In engine experiments, the data on piston-uncoated gasoline fuel, coated gasoline fuel, 10 % methanol added gasoline fuel, and 20 % methanol added gasoline fuel were used. As the data on uncoated piston were few, uncoated 10 % and 20 % methanol added gasoline fuel experiment data obtained from our previous studies were used in the training of the ANN [50]. Of the 36 data in total, 18 belonged to

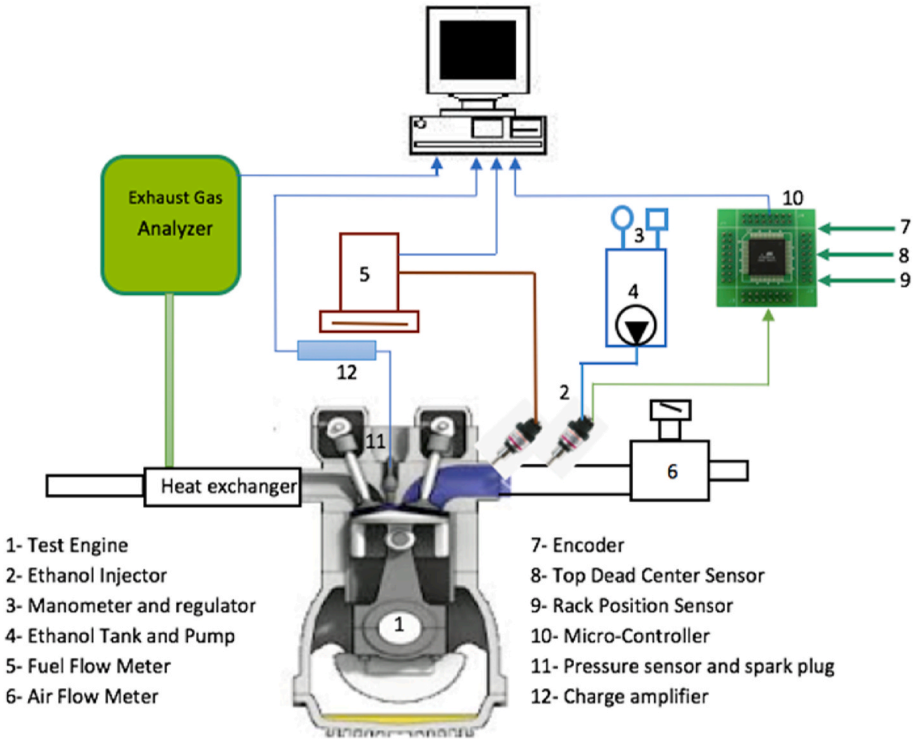

Fig. 1. Test bench.

Table 1
Test engine features.

Engine Type	Lombardini
Piston Diameter	72 mm
Stroke	62 mm
Number of Cylinders	2
Stroke Volume	0,55 dm^3
Power, 2400 rpm	15 kW
Compression rate	10.7/1
Cooling	liquid

Table 2
Exhaust gas analyzer device features.

Measurement	Measuring range	Sensibility
CO, %vol	0–15.00	±0.06 %
NOx, ppm	0–10000	±5
HC, ppm	0–2000	±12

The upper part of the piston was coated with Y_2O_3 (TBL) ceramic material of 8 mm width and 0.5 mm thickness. In order to coat the piston, atmospheric plasma spray method was used. H_2 % blend was used for the plasma gas. The piston coating consisted of a Y_2O_3 layer of 0.30 mm thickness over a NiCrAl bond layer of 0.20 mm thickness.

piston-coated engine and 18 to piston-uncoated engine. 30 data were used for training the ANN. MATLAB-nntool uses 70 % of the data fed into it for training, 15 % for test, and 15 % for validation (Fig. 2). These rates can be changed when desired. However, in this study, the default settings were used. The input data obtained from coated piston M20 fuel were fed to the network after its training was completed and the ANN was asked to estimate. Predictions were made on the trained network with data taken from the literature [20], and it was seen that the network worked correctly. The estimations obtained were evaluated.

2.2.1. *Creation of the network structure in MATLAB-nntool*

Considering that the factors that affect motor performance and

Table 3
Properties of fuels.

Property	Unit	Gasoline	Methanol
Chemical formula	–	C_7H_{17}	CH_3OH
Carbon content	% massive	85–88	37.5
Hydrogen content	% massive	12–15	12.6
oxygen content	–	–	49.9
Density (15 °C)	kg/m^3	750.8	796
Research octane number	–	95	108.7
Lower calorific value	MJ/kg	31.98	15.8
Stoichiometric	–	14.7	6.45
Latent heat of Vaporization	KJ/kg	349	1178
Auto-ignition temperature	^0C	257	464
Boiling point	^0C	45–207	64

exhaust emission results included in the problem outputs can be different from each other, input numbers were kept constant and three different models were established in terms of output numbers. In Model 1 (M1), each output corresponding to input parameters was separately estimated (Fig. 3). In this estimation model, while evaluating training results, trials where regression coefficient (R^2) was over 99 % in the training for engine performance parameters and over 96 % in the validation and test, and where it was over 98 % in the training for exhaust emission parameters and over 96 % in the validation and test were recorded, and simulation was performed. In Model 2 (M2), keeping input parameters constant, four motor performance parameters were estimated in one network, while three exhaust emission parameters were estimated in another network (Fig. 4). While deciding on the training level of the network in M2, in cases where R^2 coefficient was over 98 % in the training for engine performance parameters and 0 ver 97 % in the validation and test, and where it was over 97 % in the training for exhaust emission parameters and over 95 % in the validation and test, simulation was performed, and results were recorded and evaluated. In Model 3 (M3), where all outputs were estimated together (Fig. 5), in cases where R^2 exceeded 93 % in the training and 90 % in the validation and test, the network was deemed to be good, simulation was

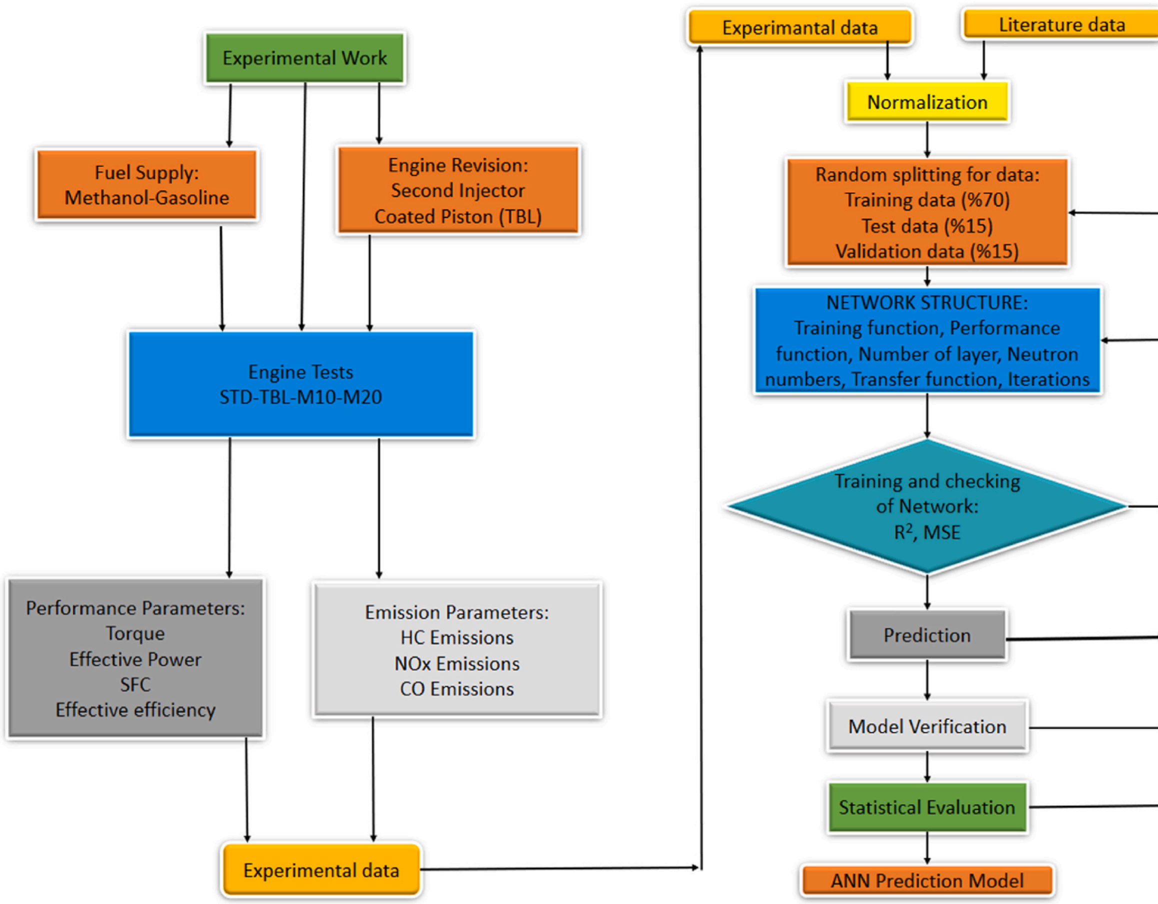

Fig. 2. Experimental flow chart.

Table 4
Uncertainties.

Parameters	Systematic uncertainties, ±
Engine Load, N	0.1
Engine Speed, rpm	1.0
Fuel Time, s	0.1
Temperature, 0C	1
Fuel consumption, g	0.01
Parameters	**Total Uncertainty, %**
SFC, g/kWh	1.2
Torque, Nm	1.0
Effective power, kW	1.3

performed, and the results were recorded.

In MATLAB-nntool, different networks can be established with different names in the same problem, trials can be made, and the results obtained can be saved as tables. There are 19 different types of network such as Cascade-forward backprop, Competitive, Elman Backprop, Feed-forward backprop, Hopfield, etc. Feed-forward backprop (BP) network type, which we thought could produce the best solution to our problem according to our pervious experiences and the results in the literature, was chosen. After the input data and target data files are introduced to the network, training function will have to be chosen among 14 alternatives such as Broyden-Fletcher-Goldfarb-Shanno (BFG), Bayesian Regularization (BR), Conjugate Gradient Backpropagation (CGB), One-step secant backpropagation (OSS), and Levenberg Marquardt (LM). As calculation is short and it generally yields correct results, MATLAB-nntool recommends LM function as default. However, by trying different functions, better results can be obtained. MSE, MSEREG, or SSE can be chosen as performance functions. In this study, the commonly used MSE was preferred. The number of layers was chosen as 2 for single hidden layer trials and as 3 for double hidden layer trials, and by changing neutron numbers, trials were made. Among LOGSIG, PURELIN, TANSIG, as it is commonly used and yields more correct results, TANSIG was chosen as transfer function (Fig. 2). After necessary selections were made, the network structure was displayed, and after seeing that it was appropriate, the network was recorded.

2.2.2. *MATLAB-nntool network training*

As training parameters, epochs count, goal, min-grad and max-fail were determined. Here, the number of epochs can be increased according to the problem. The goal is generally selected as zero in order to obtain the most correct result. As the probability of obtaining exactly correct result was low, max-fail and epochs count were determined as close to each other. When the results that were thought to be the best results were obtained, simulation data (M20 experiment data for coated engine) were loaded as input in the simulation window, and results were obtained and evaluated. By reviewing the results, the solutions that the network brought to the new problems were assessed. The network structure obtained was recorded for future use.

2.3. *Statistical evaluation of the estimations obtained from the ANN*

Different training algorithms were tried at different hidden neuron numbers in the BP model for M1, M2, and M3 models, and simulations were run in the ANN which was decided to be good. After de-normalizations of the results obtained from the simulation were performed, R^2, Mean Absolute Percentage Error (MAPE) and Root Mean Square Error (RMSE) values were calculated, and they were used as

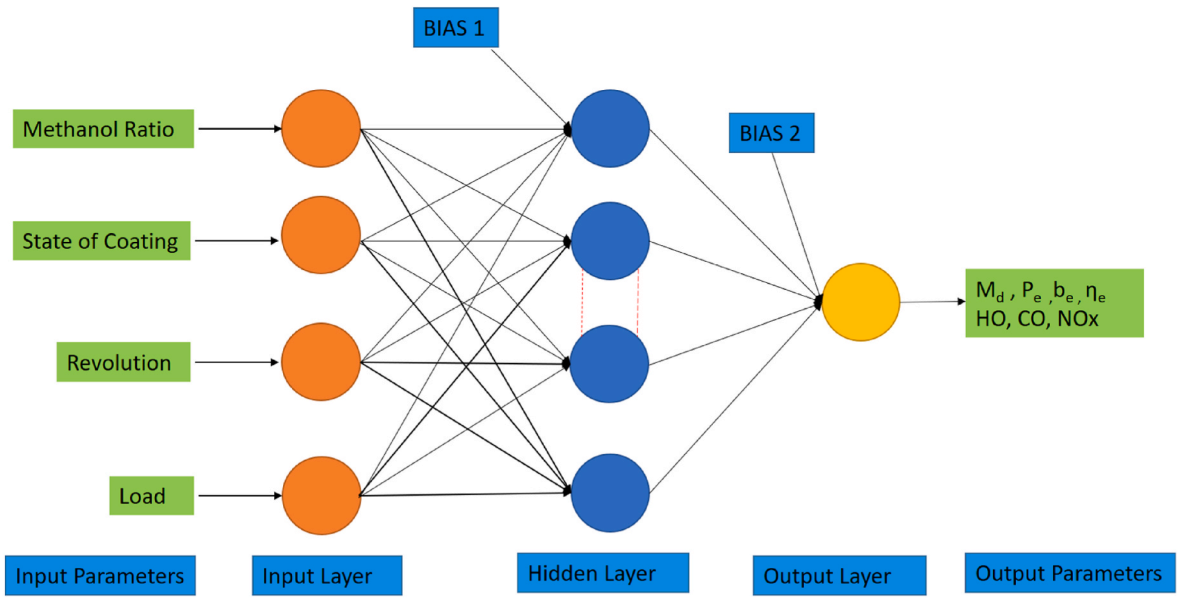

Fig. 3. Model 1 ANN structure.

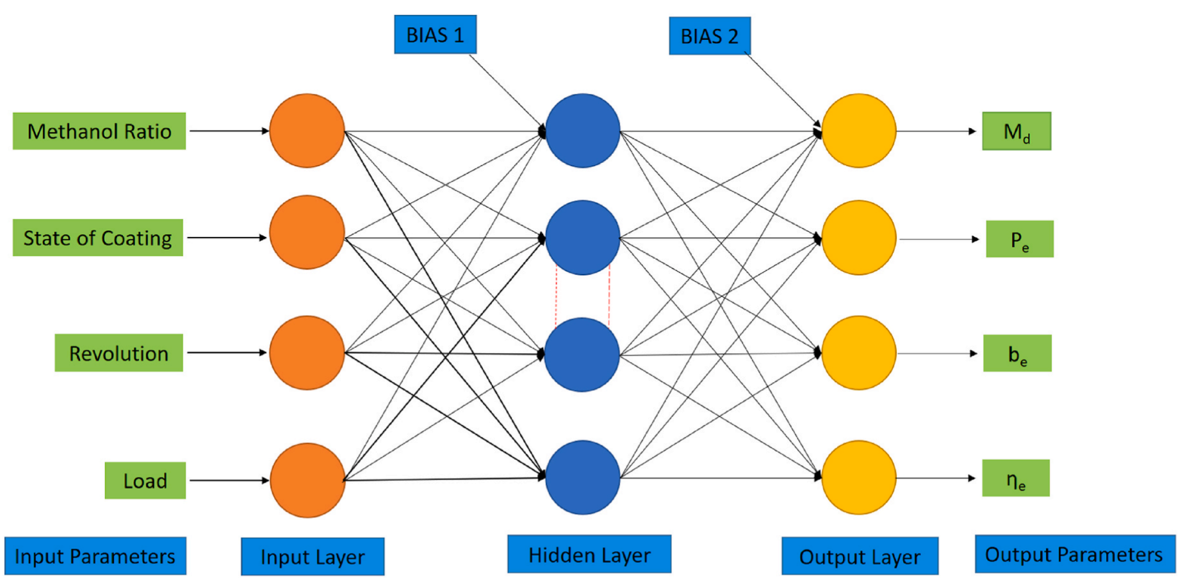

Fig. 4. Model 2 ANN structure.

decision-making tools in deciding which network was the best.

The following formula was used in calculating MAPE value [51]:

$$MAPE = \frac{1}{n}\sum_{t=1}^{n}\left|\frac{A_t - F_i}{A_t}\right| \tag{1}$$

n is the number of fitted points, A_t is the actual value, F_t is the forecast value.

The following formula was used in order to obtain RMSE results [51]:

$$RMSE = \sqrt{\frac{1}{n}\sum_{t=1}^{n}(A_t - F_t)^2} \tag{2}$$

R^2 was calculated with the following formula [52]:

$$R^2 = \left[\frac{n\left(\sum_{t=1}^{n}A_tF_t\right) - \left(\sum_{t=1}^{n}A_t\right)\left(\sum_{t=1}^{n}F_t\right)}{\sqrt{\left[n\sum_{t=1}^{n}A_t^2 - \left(\sum_{t=1}^{n}A_t\right)^2\right]\left[n\sum_{t=1}^{n}F_t^2 - \left(\sum_{t=1}^{n}F_t\right)^2\right]}}\right]^2 \tag{3}$$

MAPE, RMSE, and R^2 results obtained were presented as tables, and they were used as the decision-making tool for determining the network that gave the best result.

3. Result and discussion

3.1. Experimental results

In internal combustion engines, decreasing emission values released to the environment and increasing engine efficiency depend on increasing combustion efficiency. Methods of increasing combustion

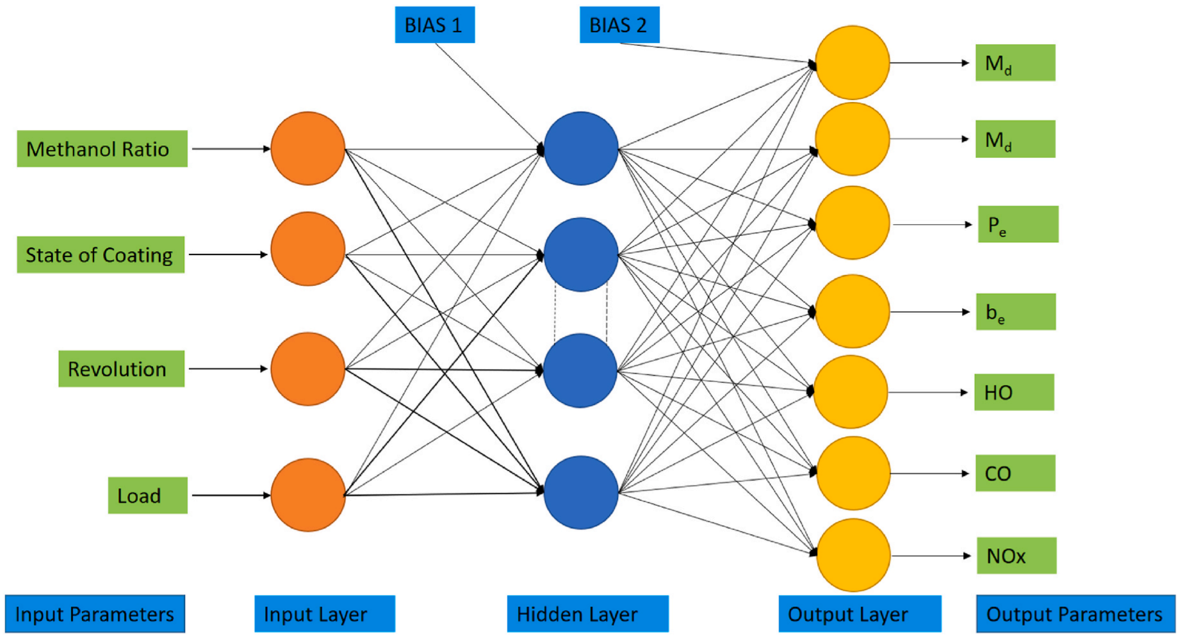

Fig. 5. Model 3 ANN structure.

efficiency in engines include increasing combustion chamber temperature and using alternative fuels. In the present study, upper section of the piston was partially coated with thermal material. The graph that shows the engine torque values obtained when the piston was coated with Y_2O_3 material is given in Fig. 6. In the coated engine, increases were observed in engine torque in all revolutions compared to the standard engine data. Maximum increase amount in the moment was determined to be 2.5 % at 2200 rpm. The reasons for the increase in the torque values of the coated engine compared to STD are decrease in internal piston temperature loss thanks to ceramic coating, getting the fuel to burn more by preventing flameout, and related energy increase. When we look at the literature, improvements in engine torque are obtained with ceramic coating or partial ceramic coating methods in engines. When Abbas et al. examined the in-cylinder pressure values with ceramic coating method in a diesel engine, they found that the in-cylinder pressure value of the coated piton engine was higher than the uncoated piston engine [15].

The changes in engine torque when methanol was injected to the coated engine in different ratios are presented in Fig. 6. When the graph was examined, in the case where M10 fuel was used, increases were observed in all engine revolutions, while in the case where M20 fuel was used, decreases were determined in torque values. With respect to STD engine data, maximum increase in engine torque was 3.7 % at 2200 rpm. The reason for the increase in engine torque with M10 fuel was the increase in combustion efficiency depending on O content in alcohol. In addition, high hidden evaporation temperature of methanol decreases the temperature of suction air and increases volumetric efficiency. On the other hand, the reason for the decreases in the engine torque with M20 fuel was the lower minimum temperature value of methanol compared to that of gasoline. Hence, lower energy of M20 fuel in comparison to gasoline fuel leads to generation of less power and moment. When the studies in which methanol-gasoline blended fuels are used as fuel in the engine are examined, it is seen that methanol mixed with gasoline fuel up to certain ratios causes improvements in engine torque. Studies conducted by Cesur and Kumar show that methanol-gasoline blended fuel increases engine torque [53,54].

Fig. 7 presents effective power values obtained in TBL piston engine and when M10 and M20 fuels were used in TBL piston engine. When the

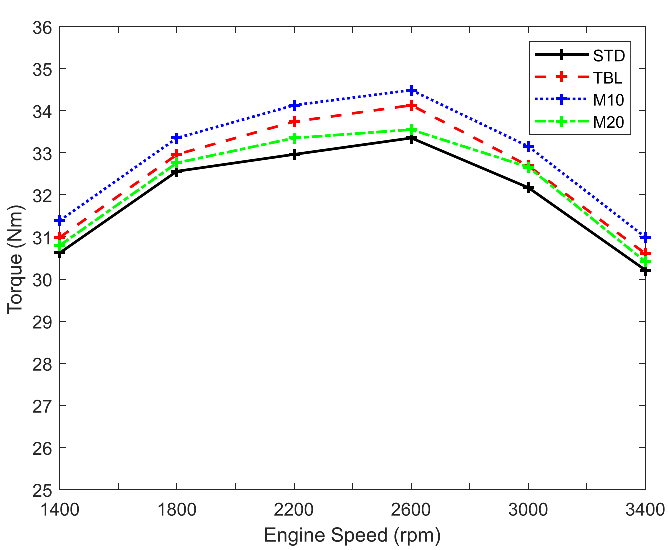

Fig. 6. Experimental torque variation.

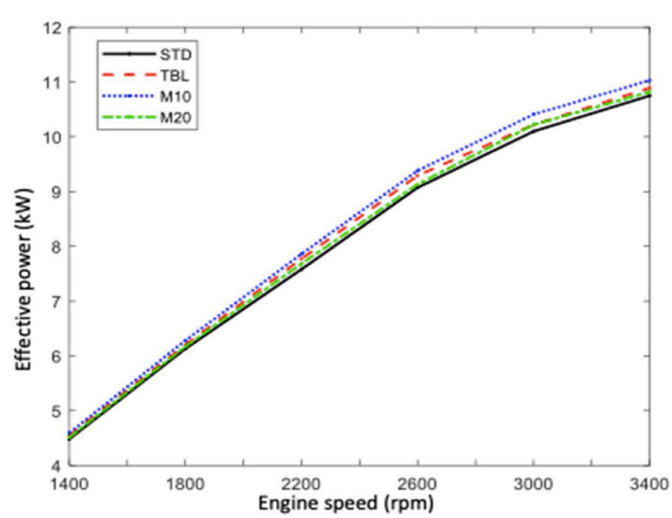

Fig. 7. Experimental power variation.

graph was examined, it was observed that there were increases in all revolutions (speeds) in the TBL piston engine in comparison to standard engine data. Dattatreya et al. investigated the effects of ceramic coating on piston on engine performance and as a result of the study, they found improvements in effective power with ceramic coating applications [55] When M10 fuel was used in the TBL piston engine, there were increases in the effective power, while in the case of M20 fuel use, decreases were observed. Maximum increase rate in the effective power with M10 fuel was 3.7 % at 2200 rpm. According to the literature, methanol-gasoline blended fuels cause an increase in effective power [53,54].

Fig. 8 shows SFC values in TBL piston engine and when M10 and M20 fuels were used in TBL piston engine. When the figure was examined, decreases were observed in SFC values in all engine revolutions. Maximum decrease was determined to be 2.3 % at 2600 rpm. The reason for the decreases was the improvement in combustion and the increase in fuel recycle efficiency. In the literature, ceramic coating method leads to improvements in specific fuel consumption. Krishnamani et al. found decreases in specific fuel consumption with ceramic coating process compared to STD engine [16]. When M10 and M20 fuels were used in TBL engine, while there were decreases in SFC values with M10 fuel, there was a slight increase with M20 fuel. Minimum SFC was achieved with M10 fuel. Maximum decrease ratio in SFC was 2.9 % at 2200 rpm compared to STD engine data. The reason for the decreases in SFC values when M10 fuel was used was the improvement in combustion efficiency. However, the reason for the increases when M20 fuel was used was that alcohol has a less low heating value compared to gasoline fuel. More fuel was needed to obtain the same amount of energy. Besides, the high stochiometric fuel/air ratios it has led to using more fuel for the same output power. When the studies using methanol-gasoline blended fuels are examined in the literature, it is seen that when methanol is mixed with gasoline fuel, specific fuel consumption decreases. Balki et al. obtained improvements in specific fuel consumption values with methanol-gasoline blends [56].

Effective efficiency values in TBL piston engine and TBL piston engine when M10 and M20 fuels were used are presented in Fig. 9. Increases were observed in the effective efficiency of TBL piston engine in all revolutions compared to the standard engine data. Maximum increase in effective efficiency was 2.38 % at 2200 rpm. Reduction in heat transfer as a result of thermal barrier coating increased combustion efficiency and fuel recycle efficiency. This in turn leads to increases in effective efficiency. In the case that M10 fuel was used in the engine, increases were observed in effective efficiency in TBL piston compared to STD engine data. The increase in volumetric efficiency increases the combustion efficiency of oxygen in the fuel content. Dananjayakumar et al. found increases in effective efficiency values compared to the uncoated piston engine when using ceramic coated pistons in the engine [57]. In M20 fuel use, on the other hand, decreases in effective efficiency were observed compared to TBL engine. The reason for the decreases was that due to less value of lower heat of methanol and high stoichiometric fuel/air ratios, more energy is needed in order to obtain the same amount of power. In the literature, Balki et al. found increases in effective efficiency when methanol-gasoline blended fuels are used in the engine [56].

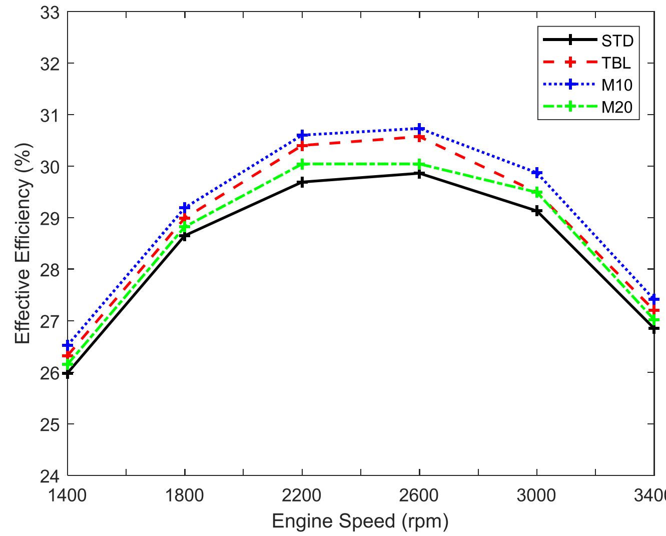

Fig. 9. Experimental effective efficiency variation.

The graph showing the HC emission values released from the exhaust when the piston is coated with Y_2O_3 material is presented in Fig. 10. Decreases in HC emission values were observed in the coated engine in all revolutions compared to the standard engine. Maximum decrease ratio in HC emissions was determined to be 11 % at 1400 rpm. The reason for the decrease in HC emissions with the coating method was the increase in the combustion chamber temperatures with the heat reserve created by the ceramic coating on the surfaces close to the cylinder walls and the related speed increase in oxidation reactions. Increased reaction speeds reduce HC emissions. In addition, the unburned fuel-air mixture that remained in the narrow areas around the combustion chamber was burnt due to the effect of heat. Periyannan et al. found reductions in HC emissions with ceramic coating applications. Karthickeyan, similar to

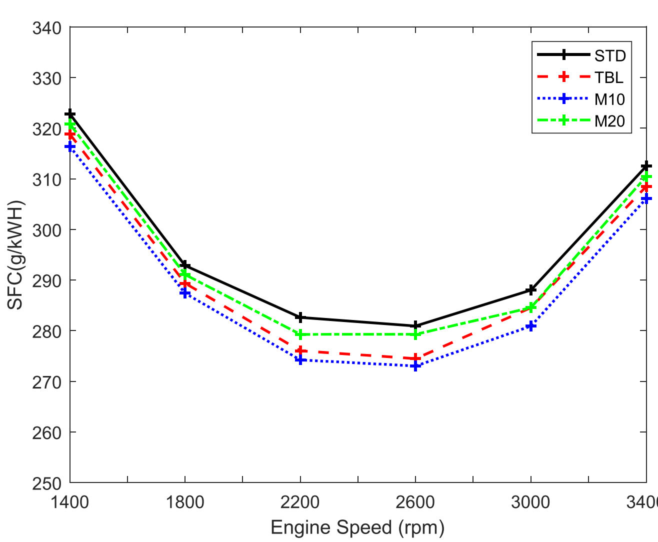

Fig. 8. Experimental SFC variation.

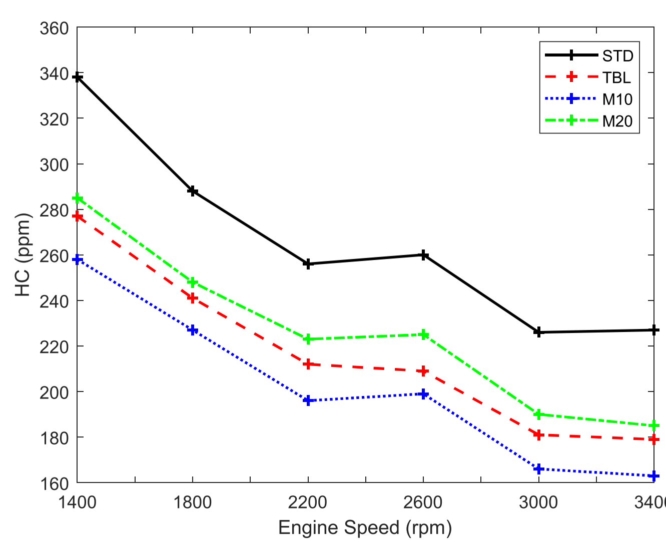

Fig. 10. Experimental torque HC variation.

the literature, found improvements in HC emissions with ceramic coating methods [58,59]. When M10 and M20 fuels were used in the engine, decreases in HC emissions were detected compared to the STD condition. Maximum decrease amount was determined in M10 fuel as 18 % at 3400 rpm. The reason for the reduction in HC emissions was the increase in combustion efficiency due to the different chemical and physical properties of alcohol from gasoline fuel. The reason for the increases was the high oxygen content of methanol and high combustion rate. High combustion rate is the combustion of H and C atoms in the fuel without turning into HC emissions by reacting with air in a fast way. Besides, high flame rate in the cylinder causes the combustion to be completed in a shorter time and thus decreases temperature loss on cylinder walls. When the literature was examined, it was seen that there were improvements in HC emissions with gasoline-methanol blended fuel [60].

Fig. 11 shows the graph showing NOx emission values when M10 and M20 fuels are used in STD engine, TBL piston engine and TBL piston engine. In the figure, it is seen that there are increases in NOx emissions released from TBL piston engine in all revolutions compared to the standard engine data. Maximum increase rate in NOx emissions was 7 % at 3400 rpm. The increases in NOx emissions resulted from the ceramic material coating on the upper surface of the piston, which led to increases in the combustion chamber temperatures. Increased combustion chamber temperatures increased the formation speed of NOx emissions, thus causing NOx emissions released from the engine to increase. When the literature is examined, increases in NOx emissions have been detected due to increasing in-cylinder temperatures with ceramic coating method [58,59,61]. When M10 and M20 fuels were used in the coated engine, decreases in NOx emissions which were increased with ceramic coating were determined in all revolutions. Maximum decrease amount in NOx emissions was found to be 19 % at 2200 rpm. The reason for the decreases in NOx emissions was high hidden evaporation heat of methanol. Methanol's absorbing more heat from the environment during evaporation leads to a decrease in adiabatic flame temperature. In addition, methanol blend fuel injected to the suction manifold during suction process decreases the temperature of the suction manifold. Decreased temperatures result in decreased NOx emissions. When the studies examining NOx emission changes were examined, it was seen that NOx emissions decreased with methanol-gasoline blends [62,63].

The graph showing CO emission values when M10 and M20 fuels were used in TBL piston engine and TBL engine is presented in Fig. 12. Improvements in CO emissions were achieved in all revolutions compared to the standard engine data when pure gasoline was used in TBL piston engine and M10 and M20 fuels were used in TBL piston engine. The reason for the improvements in CO emissions was the increase in reaction speeds as a result of the increase in combustion chamber temperature due to ceramic material coating. Increased combustion rate increases combustion efficiency. When the literature on CO emissions is examined, reductions in CO emissions emitted from the engine were found with ceramic coating applications [57,58]. The improvements obtained in CO emissions with methanol blend fuel resulted from the improvement in combustion efficiency due to methanol blend fuel. Rich oxygen content of methanol and its high combustion rate increase the speed and efficiency of combustion reactions. High flame rate in the cylinder leads to the completion of combustion in a shorter time. It is thought that due to high combustion rate, C particles in the fuel complete the combustion before they are converted into CO.

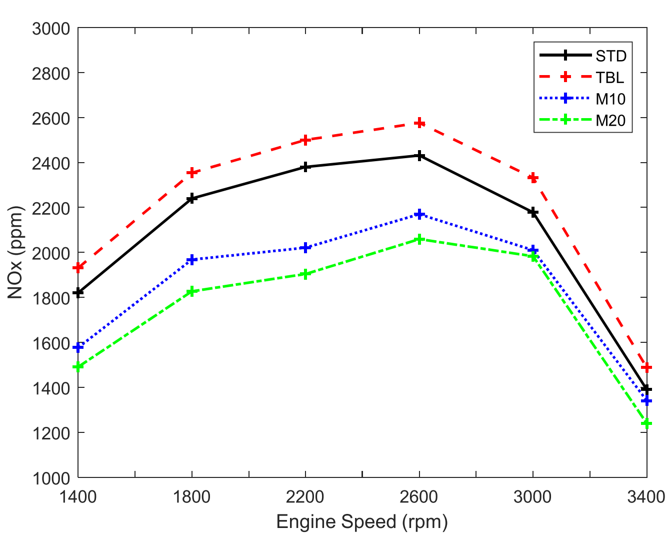

Fig. 11. Experimental NOx variation.

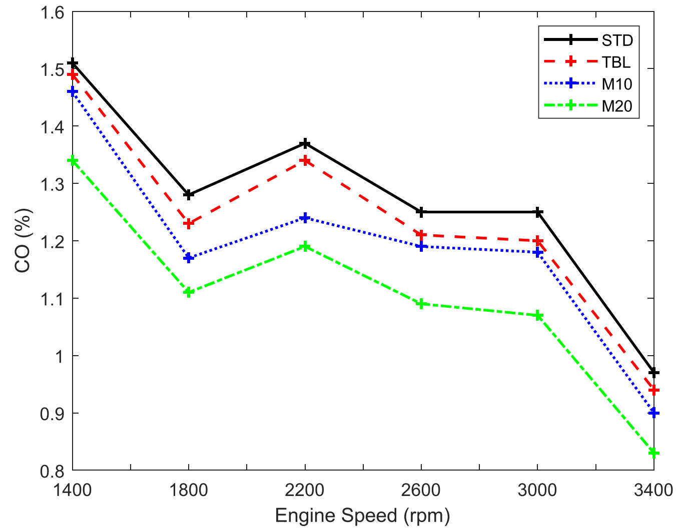

Fig. 12. Experimental CO variation.

3.2. ANN results

As moment is a value that is easy to calculate with a mathematical method, estimation in ANN was started with this value. Since R^2 values of training, test, and validation estimations obtained as a result of 3-neuron training were better, the simulation was carried out according to 3-neuron network. When the results obtained with different training algorithms during the estimations were evaluated, LM training algorithm, which yielded better results [64,65], was chosen. R^2 of the moment values estimated was 0.9999, MAPE value was 0.0129, and RMSE value was calculated as 0.0148, and the results that were best estimated in this system are presented in Table 1. The results obtained in the estimation of the moment in M2 could not catch up with the values in M1. Therefore, estimations were made with the number of hidden layers as three, four, and five, R^2 values were calculated as 0.9969, 0.9793, 0.929, MAPE values as 0.4005, 0.5864, 1.0497, and RMSE values as 0.1529, 0.5864, 10,497, respectively. In M2, as in M1, the 3-neuron network yielded the best results. In the results of the simulation of the estimations performed in five different network structures, R^2 was found in the range between 0.9394 and 0.9903, MAPE in the range between 0.5381 and 2.2835, and RMSE in the range between 0.2131 and 0.8451. Here, the training algorithm that gave the best results was BFG with its 3-neuron structure. In M1 and M2, in which output values consisted of engine performance parameters, while network structures close to each other yielded good results, in M3, where exhaust emission data were added to output parameters, similar network structure gave better results with different training algorithm.

Estimations regarding engine power that varies according to moment and revolution values were made similarly to moment estimations. Differently from the moment, the network structure that gave the best result in M1 was the one with 2 hidden layers, and in M2, it was the network with 4 hidden layers. In M3, hidden neuron number was three, and BFG instead of LM gave a better result as a training algorithm [43, 66]. In power estimations, differently from the others, although MAPE and RMSE values were found to be better in the network with 7-hidden-neuron LM training than the network with BFG3 training, the estimations of the network with 3-hidden-neuron BFG (BFG3) training, where R^2 was better, turned out to be better (Table 5).

In the trials made for the estimations of SFC values that are directly related with engine moment and efficiency, the network structures that yielded the best results were similar to the network structures of the moment. While LM3 network yielded R^2 as 0.9972&0.9971, MAPE as 0.4021&0.2909, RMSE as 0.5547&1.0284 in M1 and M2, R^2 was found as 0.9967, MAPE as 0.4262, and RMSE as 1.3995 in M3. It is seen that the differences between the models in terms of SFC estimations were not great [43].

Estimations of engine efficiency, which is directly associated with engine structure, quality, engine performance parameters, and exhaust emission parameters, displayed similarity to the network structure of engine power in M1, and they exhibited similarity to the moment network structure in M2. Statistical evaluation of estimations made in efficiency was better in M2 with respect to moment and power. This situation clearly shows that efficiency is more associated with other engine performance parameters [43](Table 5).

Among the network structures built for the estimation of motor performance parameters in M1, LM3 network yielding R^2 as 0.9999, MAPE as 1.0652, and RMSE as 0.5387 shows that it gave the best estimations. In LM 4 and LM5 networks, R^2 value stayed almost the same, while regarding MAPE value, the ranking of LM4, LM3, and LM5 was seen, and regarding RMSE value, the ranking of LM3, LM4, and LM5 was observed. This situation shows that in determining which network would give better results, R^2, MAPE, RMSE, and other values are not sufficient on their own, and that three of them should be evaluated together [46].

In M1 networks established in order to estimate exhaust emission values, the best results were obtained for HC with OSS3, for CO with OSS5, and for NOx with BFG5. R^2 was found as 0.9828 for HC, as 0.9495 for CO, as 0.9103 for NOx; MAPE value was determined as 1.9652 for HC, as 2.5427 for CO, and as 4.9249 for NOx; and, RMSE value was found as 5.2237 for HC, as 0.0374 for CO and as 43.3627 for NOx. R^2 being in the range between 0 and 1 leads to its change in small intervals, while the reason for the changes in MAPE and RMSE values with great intervals was that statistical evaluation was made after de-normalization process [66]. Therefore, as the error increases, MAPE and RMSE values increase as well. This situation facilitates decision-making process. If MAPE and RMSE values had been calculated before de-normalization, the situation would have to be evaluated with smaller numbers.

While the results obtained with OSS and BFG training algorithms in M1, where exhaust emission values were estimated separately, were good, estimations made with LM training algorithm in M2, where exhaust emissions were estimated as a whole, turned out to be better. The best network in M2 was LM7, which yielded R^2 as 0.9669, MAPE as 4.8888, and RMSE as 11.33. For CO, LM7 network yielded R^2 as 0.9544, MAPE as 4.6678, and RMSE as 0.057, while LM3 network gave R^2 as 0.9163, MAPE as 3.05, and RMSE as 0.0448. Here, although R^2 value was higher in LM7 network, as MAPE and RMSE values were lower, LM3 results were considered. Estimation results for NOx values in M2 were similar to CO in terms of network structure. Although R^2 value of LM7 network was better, LM3 network was more advantageous in terms of MAPE and RMSE values. In M2, where all three exhaust emission value estimations were evaluated together, for LM3 and LM7 networks, R^2 value was found as 0.9977 and 0.9983, MAPE values as 4.2817 and 4.8060, and RMSE as 54.1213 and 55.5568, respectively. In M2 LM7 network, while the relationship between experiment data and estimations increased for CO and NOx according to R^2 value, the difference between the values increased according to MAPE and RMSE values. Therefore, LM3 was taken as the best network in the estimation of CO and NOx estimations in M2.

In M3, where engine performance parameters and exhaust emissions were estimated together with the same inputs, interesting results for exhaust emissions were found. BFG3 network, which gave the best results in HC estimation, yielded R^2 as 0.9376, MAPE as 4.8746, and RMSE as 9.4932. Accordingly, as the model number increased, despite the decrease in R^2, improvements in MAPE and RMSE values were observed in M3 with respect to M2. In CO estimation in M3, on the other hand, R^2 value was close to M1 and higher compared to M2, but there were increases in MAPE and RMSE values. In NOx estimation, R^2 took a very weak value as 0.5424, while MAPE and RMSE came out to be more advantageous compared to M2 with the values of 9.8744 and 199.8031, respectively. Although R^2 value for NOx in LM7 network in M3 took a value of 0.6231, which was higher compared to BFG3, as MAPE and RMSE values were also found to be high, it was graphically observed that the estimations of this network were poorer. Although general R^2 value of the network in M3 varied between 0.96 and 0.98, MAPE value between 3.93 and 15, and RMSE value between 75 and 188, when the results were analyzed separately for each output, it was observed that R^2, MAPE, and RMSE yielded quite different results. This situation shows that statistical evaluation of the results separately in the estimation of sensitive data is important in terms of reliability.

The curve that appeared on the engine moment graph is a typical convex curve. The moment estimations are also expected to look similar to this curve. M20 experimental data were estimated with M1 with errors under 0.1 %. While 0.0108 % error was formed in the best estimation, it was determined to be 0.068 % in the worst estimation. These results show that the engine's moment value was estimated as very close to the experimental data by the ANN. In M2 model, the best estimation was made with 0.078 % error at 3400 rpm, while the worst estimation was made with 0.65 % error at 1800 rpm. When Model 3 results are examined, it is seen that the best estimation was made with 0.11 % error at 3400 rpm, while the worst estimation was made with 1.3 % error at 1400 rpm. In general, it is seen that as revolution increased, the estimations of the three models improved, while the estimations got poorer at low revolutions (Fig. 13).

The graph of power value calculated mathematically according to moment and revolution values increases as much as the revolution depending on the revolution, and it decreases after the maximum revolution. The lowest error in M1 was 0.068 % at 2600 rpm, while the highest error was 1.32 % at 3000 rpm (Fig. 14). While error rates in the estimation of power values in M2 varied between 0.14 and 2.6 %, the error rate went up to 10.21 % in M3. Accordingly, addition of exhaust emission values to the estimation model made power estimation difficult. The estimation of power calculated according to the moment value having a lower accuracy shows that ANN system works differently from mathematical models.

Error rates of estimations made with the three models are below 0.7 %. It is obvious that SFC curve, which has a concave curve, can be easily drawn [40] with the data estimated by the three models (Fig. 15). While the best estimation was made in M2 with 0.0839 % error at 3400 rpm, the worst estimation was made in M2 with 0.707 % error at 2200 rpm. All estimations having an error rate below 1 % shows that the ANN can excellently estimate SFC.

Estimations of the efficiency curve which is directly related with SFC overlap with SFC. The best efficiency estimation was made in M3 with 0.03 % error at 1800 rpm, while the worst estimation was made in M1 with 0.905 % at the same rpm. While M1 was the best model in terms of moment, power, and SFC, it is seen that all three models yielded very close results in efficiency estimation (Fig. 16). This situation shows that efficiency is directly related with both engine performance parameters and exhaust emission values. Estimation errors being lower than 1 % in all three models shows that efficiency can be directly estimated with input parameters.

Although NOx graph has a partially convex curve, data changes

Table 5
Statistical evaluation of estimations of engine performance and exhaust emission values according to the models and network structures.

MODEL NUMBER	Network structure	Learning Algorithm	Md			P			SFC			Efficiency			HC			CO			NOx		
			R^2	MAPE	RMSE	R^2	MAPE	RMSE	R^2	MAPE	RMSE	R^2	MAPE	RMSE	R^2	MAPE	RMSE	R^2	MAPE	RMSE	R^2	MAPE	RMSE
MODEL 1	4-2-1	LM				0.9993	0.5958	0.0666				0.9945	0.3657	0.1353	0.8978	9.6694	28.6271						
	4-3-1	LM	0.9999	0.0129	0.0148	0.9808	2.0239	0.1280	0.9972	0.4021	0.5547	0.9657	0.8407	0.2918	0.9078	6.8314	16.3580						
	4-5-1	LM				0.9148	6.199	0.7037				0.9782	0.7305	0.2826	0.5978	10.685	30.8196						
	4-3-5-1	SCG													0.9471	7.3072	19.4978						
	4-3-1	OSS													0.9828	1.9652	5.2237	0.8921	3.7703	0.0221			
	4-4-1	OSS																0.9354	2.7499	0.0407			
	4-5-1	OSS																0.9495	2.5427	0.0374			
	4-5-1	BFG																			0.9103	4.9246	43.3627
MODEL 2	4-3-4 or 3	LM	R^2 : 0.9999 MAPE: 1.0652 RMSE: 0.5387												R^2 : 0.9977 MAPE: 4.2817 RMSE: 54.1213								
			0.9969	0.4005	0.1529	0.9956	3.2866	0.2631	0.9971	0.2909	1.0284	0.9965	0.2827	0.1019	0.9532	5.1010	16.4996	0.9163	3.0500	0.0448	0.9603	20.927	226.0325
	4-4-4 or 3	LM	R^2: 0.9999 MAPE: 0.8791 RMSE: 1.2066												R^2 : 0.9680 MAPE: 13.3161 RMSE: 254.6819								
			0.9793	0.5864	0.2220	0.9992	1.6474	0.2220	0.9944	0.6457	2.3862	0.9933	0.6366	0.2469	0.8850	10.429	26.8327	0.7182	8.2941	0.1112	0.5092	29.669	1078.523
	4-5-4 or3	LM	R^2 : 0.9997 MAPE: 2.1619 RMSE: 2.5481												R^2 : 0.9776 MAPE: 15.6193 RMSE: 207.6903								
			0.9290	1.0497	0.4056	0.9915	4.5514	0.3724	0.9644	1.5300	5.0411	0.9613	1.5167	0.5053	0.8818	17.094	51.8978	0.7469	11.47	0.1461	0.5412	26.223	871.9371
	4-6-3	LM													R^2 : 0.9741 MAPE: 8.3334 RMSE: 129.0713								
															0.5574	8.4655	24.5299	0.8078	6.1981	0.0839	0.4250	26.775	544.2967
	4-7-3	LM													R^2 : 0.9983 MAPE: 4.8060 RMSE: 55.5568								
															0.9669	4.8888	11.3300	0.9544	4.6678	0.0570	0.9653	21.300	234.0682
MODEL 3	4-5-7	LM	R^2 : 0.9682 MAPE: 11.7377 RMSE: 187.2169																				
			0.9525	2.1302	0.7941	0.9626	5.5889	0.5639	0.9886	1.1582	3.9366	0.9862	1.2207	0.4199	0.9050	30.734	48.5604	0.1036	18.396	0.2109	0.1989	22.936	492.9263
	4-6-7	LM	R^2 : 0.9726 MAPE: 9.9470 RMSE: 180.4781																				
			0.9898	0.8827	0.2938	0.7978	15.347	1.6503	0.9812	1.2950	4.9529	0.9828	1.1785	0.4174	0.8794	21.869	32.0117	0.7576	6.2633	0.0867	0.4676	22.793	476.3970
	4-7-7	LM	R^2 : 0.9835 MAPE: 7.3955 RMSE: 142.3715																				
			0.9913	1.1731	0.4007	0.9858	4.3179	0.4062	0.9918	0.8164	3.0469	0.9903	0.7922	0.2741	0.8928	20.149	40.1841	0.9107	6.7179	0.0849	0.6231	17.802	374.5171
	4-8-7	LM	R^2 : 0.9667 MAPE: 15.0045 RMSE: 164.6900																				
			0.9394	2.2835	0.8451	0.8922	9.9778	0.9118	0.9726	3.6338	11.541	0.9285	1.6693	0.6419	0.7421	51.425	52.6891	0.8671	17.143	0.1995	0.1755	18.898	432.3751
	4-3-7	BFG	R^2 : 0.9843 MAPE: 3.9372 RMSE: 75.6059																				
			0.9903	0.5381	0.2131	0.9955	7.1497	0.5298	0.9967	0.4262	1.3995	0.9959	0.4382	0.1495	0.9376	4.8746	9.4932	0.9494	4.2592	0.0566	0.5424	9.8744	199.8031

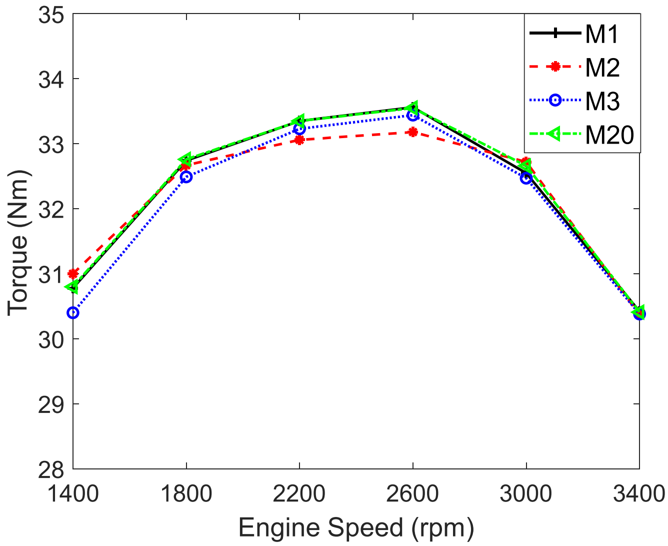

Fig. 13. Torque.

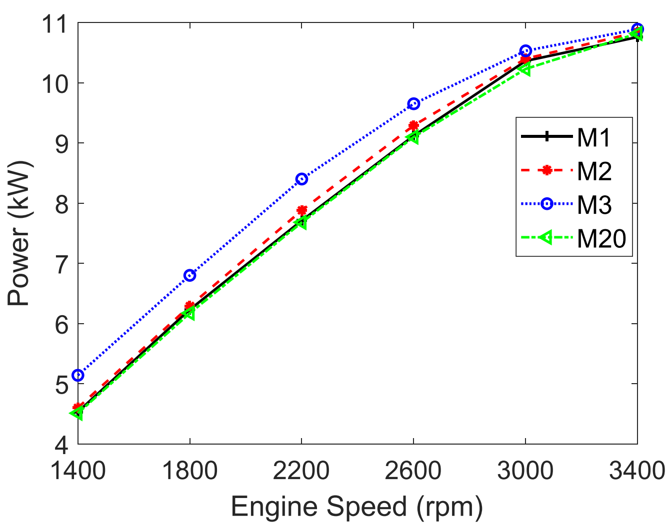

Fig. 14. Power.

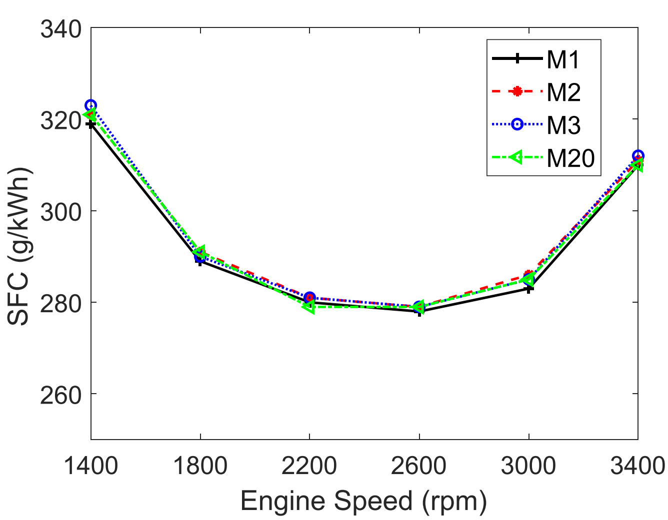

Fig. 15. Specific fuel consumption.

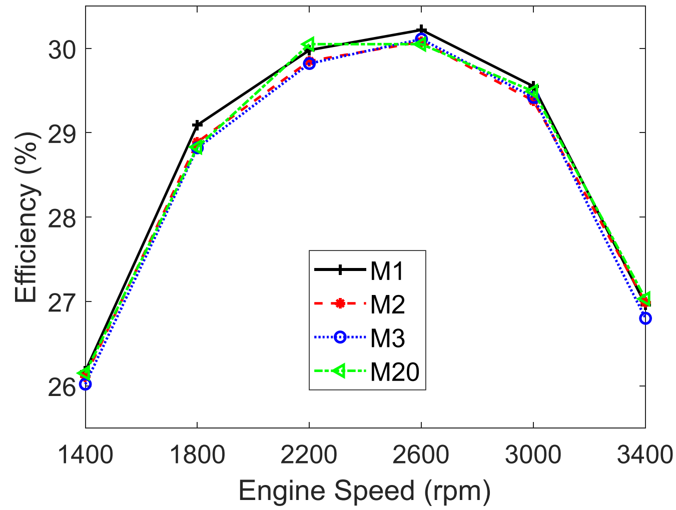

Fig. 16. Efficiency.

between revolution transitions are very high. Therefore, sharp corners are seen on the curve. It is seen in Fig. 17 that M2 estimated NOx values the best with ANN. Revolution-related errors in M2 estimations were 2.868–0.618–3.939-1.284–6.775–12.685 %. It is seen that as revolution increased, errors increased as well. The high rate of errors in M1 shows that estimation is difficult [64] in the model where NOx is evaluated as an output by itself. This situation indicates the weak relationship of NOx with the inputs in this model. Error rates reaching up to 25 % in M3 shows that estimation got worser with the engine performance parameters included in the model.

The breaking point [13,22] at 2200–2600 rpm makes the estimation of HC values with ANN difficult [49]. Therefore, more trials were made for the estimation of HC and CO values compared to the other values. The best estimation in M1 was made with 0.25 % error at 1400 rpm, while the worst estimation was made with 4.4 % error at 1800 rpm; the best estimation in M2 was made with 3.29 % error at 3000 rpm, while the worst estimation was made 14.16 % error at 1400 rpm; and, the best estimation in M3 was made with 0.005 % error at 3000 rpm, while the worst estimation was made 8.347 % error at 2600 rpm. The breaking point in HC curve was estimated only in BP network trained with OSS in M1 [66,67]. Other estimations displayed inclining-declining curves (Fig. 18).

The break in CO curve, which is similar to HC curve, occurred between 1800–2200 rpm. This breaking point was spotted in M1 by OSS5

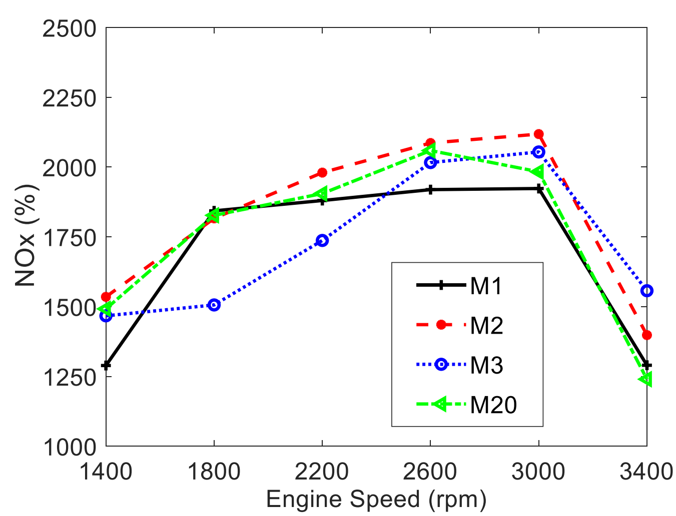

Fig. 17. NOx emissions.

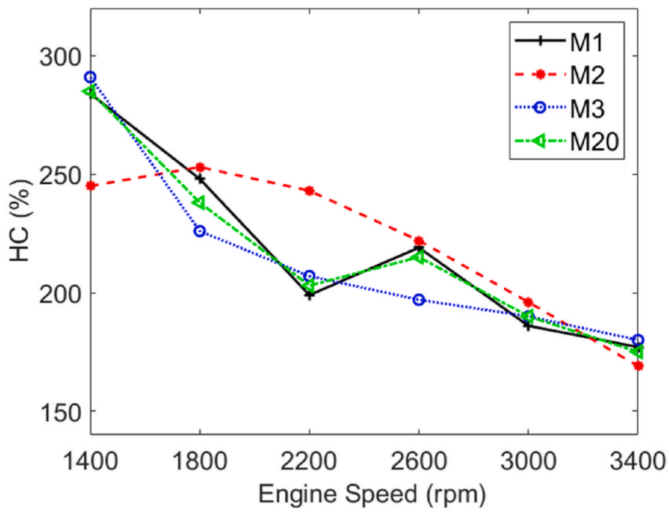

Fig. 18. HC emissions.

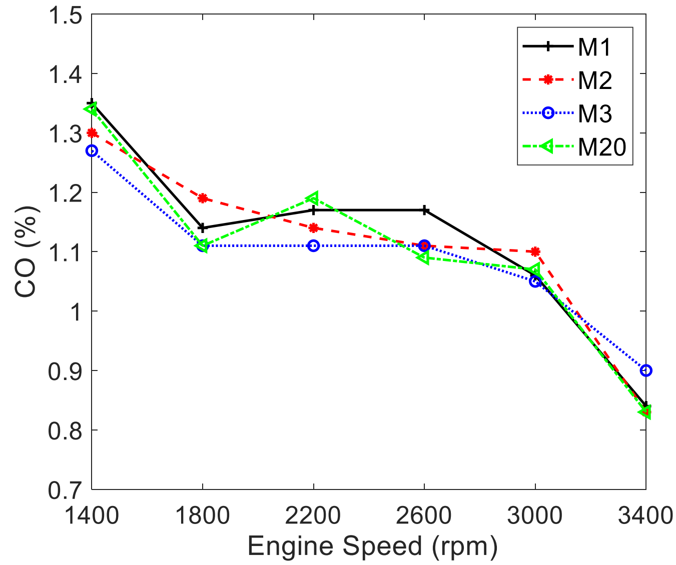

Fig. 19. CO emissions.

network. This situation shows that OSS-trained BP networks can spot breaking points [13,25]. However, although the number of inputs and outputs is the same, the number of hidden neurons may vary. Another interesting point in CO estimation is that the experimental data given as 0.83 at 3400 rpm in M2 was estimated with zero error. While the estimations of M1 model, where only CO was estimated, yielded good results, the estimations made by M2 are at a useable level with 7.23 % error rate. It can be stated that with the 8.83 % error rate, the use of engine performance parameters in the estimation of CO in M3 worsened the results (Fig. 19). Still, the estimation results were at a useable level.

4. Conclusions

In the first phase of the study, the changes in engine performance and exhaust emissions as a result of coating the upper surface of the piston with ceramic material were examined. In the second phase, changes in performance and emission values when the gasoline was blended with 10 % and 20 % methanol were analyzed. In the final phase of the study, the effect of M20 fuel on the changes in both performance and exhaust emission values were estimated with ANN in MATLAB-nntool. The results of the experimental study and prediction with ANN are summarized below.

- Engine performance parameters and HC emissions showed improvements with the application of ceramic coating.
- However, NOx emissions increased as a result of the coating.
- The combination of ceramic coating and M10/M20 fuels resulted in overall improvements in engine performance parameters and exhaust emissions.
- The partial coating method led to an increase in effective power, effective efficiency, and NOx emissions, while HC emissions decreased.
- The use of M10 and M20 fuels in the engine contributed to a reduction in NOx emissions without adversely affecting engine performance parameters.
- The comprehensive approach of both engine coating and alternative fuel usage resulted in a 3.7 % increase in effective power compared to the standard situation.
- Notably, there were decreases of 19 % and 18 % in NOx and HC emissions, respectively, showcasing the potential for achieving a balance between enhanced engine performance and reduced emissions.
- Engine performance parameters were estimated with over 99 % accuracy using ANN with three different structures.
- ANN trained with LM yielded good results in cases where the mathematical relationship between predicted values and engine performance was high.
- ANN trained with BFG performed better in situations where this relationship was reduced, particularly in predicting exhaust emission values.
- Input values such as speed, load, coating type, and fuel type had a direct impact on engine performance values, allowing for easy predictions with LM.
- However, these input values were not directly correlated with exhaust emission values, revealing the difficulty in predicting emissions accurately.
- In ANNs with multiple outputs, a step-by-step statistical evaluation of criteria used to determine prediction results in sensitive data increased the reliability of predictions.
- The study suggests that utilizing different models for predicting and evaluating systems with multiple outputs may offer a more accurate approach.

CRediT authorship contribution statement

Idris Cesur: Investigation, Methodology, Validation, Visualization, Writing – original draft, Writing – review & editing, Resources. **Fatih Uysal:** Methodology, Software, Writing – original draft, Writing – review & editing, Validation.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

No data was used for the research described in the article.

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