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Prediction of emissions and exhaust temperature for direct injection diesel engine with emulsified fuel using ANN

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Abstract: Exhaust gases have many effects on human beings and the environment. Therefore, they must be kept under control. The International Convention for the Prevention of Pollution from Ships (MARPOL), which is concerned with the prevention of marine pollution, limits the emissions according to the regulations. In Emission Control Area (ECA) regions, which are determined by MARPOL as ECAs, the emission rates should be controlled. Direct injection (DI) diesel engines are commonly used as a propulsion system on ships. The prediction and control of diesel engine emission rates is not an easy task in real time. Therefore, in this study, an artificial neural network (ANN) structure using the back propagation (BP) learning algorithm and radial basis function (RBF) has been developed to predict the emissions and exhaust temperature for DI diesel engines with emulsified fuel. In order to show the ANN performance, the network outputs and experimental results of the BP and RBF have been compared in this paper. The experimental results were obtained from a real diesel engine. The results showed that the emissions and exhaust temperature were estimated with a very high accuracy by means of the designed neural network structures and the RBF is more reliable than the BP.

Key words: Neural networks, emulsified fuel, diesel engine emissions, back propagation, radial basis function

1. Introduction

It is obvious that exhaust gases have many effects on human beings and the environment. For these life-sustaining reasons, the emissions from diesel engines used in land and sea vehicles are gradually limited. The International Convention for the Prevention of Pollution from Ships (MARPOL) regulations determine Emission Control Areas (ECAs). Emissions have to be kept under control in these ECA regions. Owing to the limitation of the emissions, particularly NO_x emissions, internal combustion engines use the 'optimum emulsified fuel composition' to improve the emissions' quality. It is therefore important to note that the estimation and the prediction of emissions from diesel engines have great significance in this context. Moreover, it is not an easy task to predict emissions from diesel engines in real time. If a powerful, accurate, and fast prediction algorithm is developed, the emissions of a diesel engine can be kept under control in real time.

To predict these emissions from diesel engines, Rakopoulos et al. used a comprehensive, 2-zone, transient, diesel combustion model and found that both the NO and the soot emissions were higher in the exhaust

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values during transient than in steady-state conditions [1]. Pawar and Kulkarni studied a numerical method to predict the NO_x emissions by considering the parameter equivalence ratio and the study showed that when the equivalence ratio increases, the NO_x increases [2]. Maass et al. built a parallel network structure consisting of 3 nonlinear autoregressive exogenous inputs to predict the smoke emissions of diesel engines [3].

In the cases of numerical and mathematical methods' inadequacy, the artificial neural network (ANN) is commonly used to generate fast, accurate, and reliable predictive results [4].

To predict the performance, emissions (CO, CO_2, NO, NO_x, hydrocarbons (HCs), and smoke), and exhaust temperature (T_{exh}) of internal combustion engines, fueled with diesel, biodiesel blends, gasoline, and dual fuel, the ANN approach, particularly with the back propagation (BP) algorithm, was used by some researchers. Kiani et al. predicted the performance and exhaust emissions in a spark ignition engine fueled with ethanol–gasoline blends with the application of an ANN [4]. Parlak et al. predicted the specific fuel consumption (SFC) and the T_{exh} for a diesel engine with the ANN application [5]. Canakci et al. studied a diesel engine fueled with biodiesel produced from waste frying palm oil to predict the performance and exhaust emissions [6]. Ganapathy et al. investigated the artificial neural modeling of a *Jatropha* oil fueled diesel engine for emission predictions [7]. Sayin et al. compared the experimental results of the performance and exhaust emissions of a gasoline engine using an ANN [8]. Ghobadian et al. analyzed the diesel engine performance and exhaust emission analysis using waste cooking biodiesel fuel with an ANN and could predict the engine performance and exhaust emissions [9]. Yusaf et al. studied the compressed natural gas (CNG)-diesel engine performance and exhaust emission with the aid of the ANN [10]. Yucesu et al. analyzed the mathematical model and experimental results of a spark ignition engine's performance that used an ethanol–gasoline blend of fuel [11]. Obodeh and Ajuwa predicted the NO, power, and SFC of diesel in a diesel engine using an ANN BP algorithm [12]. Hashemi and Clark studied a diesel engine and predicted the NO_x, CO, CO_2, and HC emissions by means of BP [13]. Çelik and Arcaklioğlu predicted the T_{exh}, brake specific fuel consumption (BSFC), and fuel/air equivalence ratio in a diesel engine using an ANN BP algorithm [14]. Zweiri and Lakmal studied a diesel engine to predict the indicated torque by means of a BP neural network (NN) [15]. Shivakumar et al. predicted the brake thermal efficiency (BTE), brake specific energy consumption (BSEC), T_{exh}, NO_x, smoke, and HC of a diesel engine fueled with a biodiesel blend using an ANN BP algorithm [16].

To predict the same parameters in internal combustion engines fueled with diesel, biodiesel, and dual fuel, the radial basis function (RBF) was used by some researchers, as well. Liu and Fei studied a dual fuel engine that was fueled with CNG and predicted the CO and NO_x emissions by means of the RBF [17]. Zhang and Tian predicted the CO, NO_x, and smoke emissions in a dual fuel engine, fueled with coal water slurry (CWS)-diesel, using a RBF NN [18]. Wang et al. analyzed a marine 2-stroke diesel engine's emissions based on the modeling of a RBF NN [19]. Wang et al. predicted the NO_x emissions using cylinder pressure based on the RBF and BP NN in the diesel engine [20]. Manjunatha et al. studied a diesel engine, fueled with a biodiesel blend, and predicted the NO_x, CO_2, CO, HC, and smoke emissions by means of the RBF and BP NN [21].

The previous studies are summarized in Table 1. Studies about diesel and gasoline engines that work with different kinds of fuels (diesel, gasoline, biodiesel blends, and dual fuels) estimate different parameters (engine performance, emissions, and T_{exh}) and learning algorithms, such as NNs, BP, and RBF.

However, it can be seen from Table 1 that there have been no studies to predict the emissions and T_{exh} for direct injection (DI) diesel engines with emulsified fuel using an ANN application and a comparison with the BP and RBF learning algorithms. Therefore, an ANN structure with BP and RBF was developed to predict emissions and T_{exh} for DI diesel engines with emulsified fuel and RBF-BP NN structures were compared for prediction in this study. In order to detect network performances, the network outputs were compared with a real diesel engine's data.

Table 1. Comparison of the previous studies.

Authors	Fuel type	Inputs	Outputs	Learning algorithm
Parlak et al. [5]	Diesel	Engine speed, mean effective pressure, injection timing	SFC, T_{exh}	BP
Obodeh and Ajuwa [12]	Diesel	Load, speed	NO, Power, SFC	BP
Hashemi and Clark [13]	Diesel	Speed, torque	NO_x, CO_2, HC, CO	BP
Çelik and Arcaklioğlu [14]	Diesel	Cooling water temperature, speed, power	T_{exh}, BSFC, fuel/air equivalence ratio	BP
Zweiri and Lakmal [15]	Diesel	Crankshaft speed, crankshaft position	Indicated torque	BP
Wang et al. [19]	Diesel	Speed, load, fuel flow rate, air-mass flow rate, scavenge air pressure, max. injection pressure	NO_x, CO, CO_2, HC, filter smoke number	RBF
Wang et al. [20]	Diesel	Speed, max. pressure diff. and angle, angle difference of fixed pressure	NO_x	RBF + BP
Canakci et al. [6]	Biodiesel	Fuel properties, speed, environmental conditions	Flow rates, max. injection pressure, emissions, engine load, max. cylinder gas pressure, thermal efficiency	BP
Ganapathy et al. [7]	Biodiesel	Injection timing, injector opening pressure, plunger diameter, load	HC, smoke, NO_x	BP
Ghobadian et al. [9]	Biodiesel	Engine speed, biodiesel blend	Torque, BSFC, HC, CO	BP
Shivakumar et al. [23]	Biodiesel	Load, compression ratio, blend percentage	BTE, BSEC, T_{exh}, NO_x, CO, smoke, HC	BP
Manjunatha et al. [21]	Biodiesel	Density, kinematic viscosity, blend, brake power, T_{exh}	NO_x, CO_2, CO, HC, smoke	RBF + BP
Shivakumar et al. [16]	Biodiesel	Compression ratio, injection timing, blend percentage, load	BTE, BSEC, T_{exh}, NO_x, smoke, HC	BP
Yusaf et al. [10]	Compressed natural gas (CNG)/diesel	Engine speed, dual fuel engine (CNG-diesel)	Brake power torque, BSFC, BTE, NO_x, CO, CO_2, O_2, T_{exh}	BP
Liu and Fei [17]	(CNG)/diesel	Rotation speed, quantity of natural gas, pilot, injection timing	CO, NO_x	RBF
Zhang and Tian [18]	Water coal slurry (CWS)/diesel	Rotation speed, quantity of coal, pilot, injection timing	CO, NO_x, smoke	RBF
Sayin et al. [8]	Gasoline	Lower heating value, torque, speed, air inlet temperature	BSFC, BTE, CO, HC, T_{exh}	BP
Golcu et al. [29]	Gasoline	Speed, valve timing	Torque, fuel consumption	BP
Kiani et al. [4]	Ethanol gasoline blend	Blend, engine load, engine speed	Torque, power, CO, CO_2, HC, NO_x	BP
Yucesu et al. [11]	Ethanol gasoline blend	Density, ignition timing, relative air-fuel ratio, compression ratio	Engine torque, SFC	BP
This study	Emulsified fuel	Engine speed, emulsified fuel percentage, operating load	CO, CO_2, NO, NO_x, HC, T_{exh}	BP + RBF

2. Materials and methods

2.1. Experimental setup

In this study, a single cylinder, naturally aspirated, 4-stroke, and water-cooled real DI diesel engine with a bowl in the piston combustion chamber was used. The schematic diagram and experimental test setup are shown in Figures 1a and 1b, respectively, and the specifications of the engine are given in Table 2. To measure the brake torque, the engine is coupled to a hydraulic dynamometer with 50 kW absorbing capability. Full load tests were conducted at the engine speeds of 1200, 1400, 1600, 1800, 2000, 2200, and 2400 rpm.

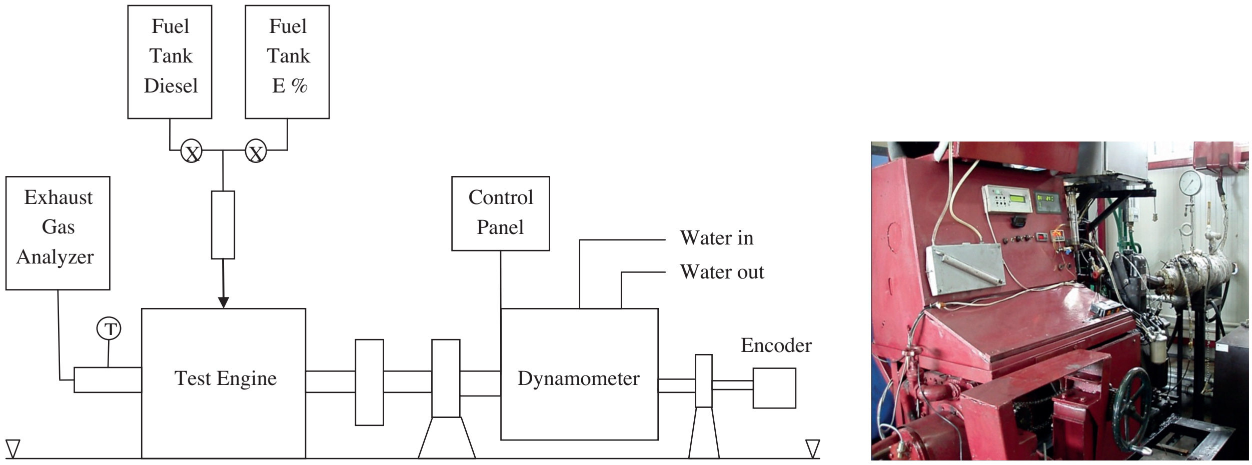

Figure 1. Experimental setup.

Table 2. Specification of the test engine.

Engine type	Super star
Bore [mm]	108
Stroke [mm]	100
Cylinder number	1
Stroke volume [l]	0.92
Power - 1500 rpm [kW]	14.7
Injection pressure [bar]	175
Injection advance [CA bTDC]	35
Maximum speed [rpm]	2500
Cooling type	Water
Injection type	DI

The dynamometer load, engine speed, fuel, and airflow rates were recorded after allowing adequate time for the engine to stabilize at each operating condition. The engine was run for a period of 2 min to obtain 10 readings for each concerned parameter at stabilized condition. After the load tests were conducted for the standard engine with injection timing of a 35° crank angle (CA), the same procedure was conducted for engine tests with emulsified fuels.

The water-in-diesel emulsified fuel, which consists of diesel fuel, surfactant, and ordinary tap water, was prepared in an electrical blender at a speed of about 1600 rpm. To stabilize the emulsified fuels, 2% of mass surfactant mixture, which consists of Span 80 and Tween 80, was used. The weight of the diesel, water, and surfactant was measured at 0.01 g of sensitivity. Six blends were tested: pure diesel and diesel fuel + surfactant

+ 5%, 10%, 15%, and 20% water by mass. The engine was started with pure diesel for each running and then switched to the test blend.

The emissions were measured with a MRU Spectra 1600 L gas analyzer, and for the smoke emissions, a Bilsa Mode 5000 opacimeter was used. Special emphasis has been given to the measurement error for the pollutant emissions. To ensure the accuracy of the measured values, the gas analyzer was calibrated before measurements were taken using reference gases. The smoke meter was also allowed to adjust to its zero point before each measurement.

2.2. Neural network structure

ANNs can be used as an algorithm offering an alternative method to predict an internal combustion engine's performance, emissions, and T_{exh} values for comparison with experimental results. Neurons, inspired by the human brain, are used to determine the output values using input values. Neurons are able to learn from examples that are fault-tolerant and can deal with nonlinear problems, and once trained, they can perform prediction and generalization at high speeds [22]. An ANN has the ability to relearn to improve its performance if there are new available data. It is able to accommodate multiple input variables to predict multiple output values [23]. In ANN models, the activation functions, which form its output depending on its inputs, play an important role [24]. ANN applications are powerful modeling tools that can identify the complex relationships with the input-output data [5] and an ANN model's success is subject to appropriately selected parameters, which are the number of neurons and layers, the learning algorithms, the number of epochs for which the model is iterated, the nonlinear function used in the neurons, and the initial weights of the inputs and layers [25].

BP is a kind of learning method in ANN that has emerged as the standard algorithm for the training of multilayer perceptrons, against which other learning algorithms are often benchmarked [22]. The error between the output of the network and the desired output is minimized by altering the weights and biases in the BP learning algorithm [9]. On the other hand, the BP algorithm is an extension of the least mean square (LMS) algorithm, which can be used to train multilayer networks. Both BP and LMS are approximate steepest descent algorithms that minimize the squared error. The BP algorithm uses the chain rule so as to compute the derivatives of the squared error with regards to the weights and biases in the hidden layer [26]. From another point of view, one of the major problems with the basic BP algorithm has been its long training times. The techniques for speeding up convergence have been classified into 2 main categories, which are heuristic methods and standard numerical optimization methods. The Levenberg–Marquardt BP (LMBP) algorithm is the fastest algorithm within the heuristic methods and standard numerical optimization methods that we have tested for training multilayer networks of moderate size, even though it requires a matrix inversion at each iteration [26]. The data are spread out from the input layer to the hidden layer(s) in the LMBP algorithm. After that, it reaches the ?nal output layer, and in the output layer, the error signals spread out to the hidden layers and the input layers [27].

RBF is another kind of learning algorithm method of ANNs, which has viewed the design of a NN as a curve-fitting problem in a high dimensional space [22]. Moreover, a RBF-based NN structure offers faster prediction than a conventional simulation program or mathematical technique [21]. A RBF-based NN structure includes 3 layers, the input, hidden, and output layers. The hidden layer consists of many RBF neurons and the hidden layer nodes are calculated from the Euclidean distance between the center and the network input vectors [17]. In spite of having a great many RBFs, the Gaussian function as a RBF is used as a RBF NN in applications. In the case where a Gaussian function is used as a hidden layer in the neuron activation function, the neuron's hidden layer value for each input data point is calculated as below [28]:

$$\emptyset_j = e^{\left[\frac{\left|x-c_j\right|}{\sigma_j^2}\right]}, \tag{1}$$

where $\emptyset_j$ is the Euclidean distance between x input data and the jth pattern of the hidden layer, c_j is the jth pattern of the RBF's center, and σ_j is the width of the j pattern of the RBF. The output parameter of the network is calculated as bellow:

$$y = \sum_{j=1}^{m} w_j \emptyset_j. \tag{2}$$

In this study, in order to predict the emission rates and T_{exh} for the emulsified fuel, the BP and RBF structures that are usually used for the parameter estimation are designed. Their performance is compared using the performance parameters. These networks have 3 inputs (engine speed, emulsified fuel percentage, and operating load) and 6 outputs (CO, CO_2, NO, NO_x, HC emissions, and T_{exh}). Thus, as can be seen in Figures 2 and 3, the input layer consists of 3 neurons, while the output layer has 6 neurons, both in BP and RBF. The data set is divided into 2 groups, the first to be used for training (80% of the data) and the second (20% of the data) for testing.

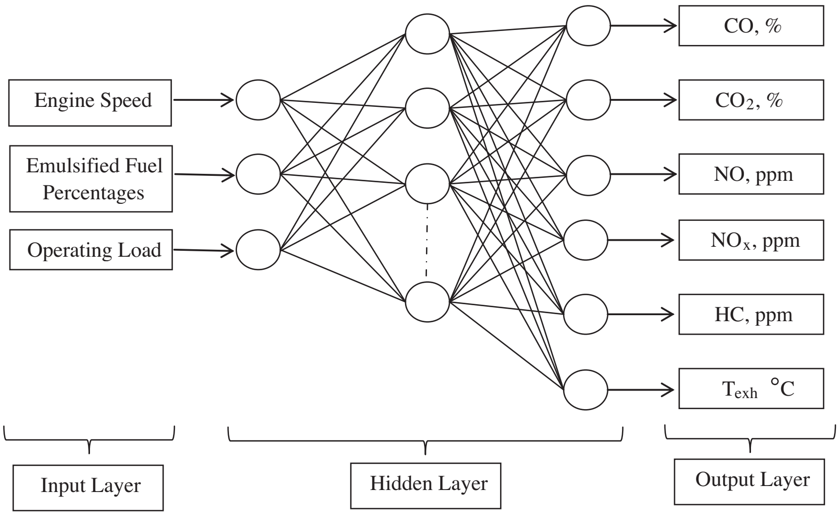

Figure 2. Multilayer NN structure of BP.

In order to show the 2 different NN structures' performances, the mean squared error (MSE), root mean squared error (RMSE), standard deviation (SD), and mean absolute percentage error (MAPE) are used. They are formulated as follows:

$$MSE(xy) = \frac{1}{n} \sum_{i=1}^{n} (x_i - y_i)^2, \tag{3}$$

$$RMSE = \sqrt{MSE}, \tag{4}$$

where n is the number of samples and x_i and y_i are the values of the ith samples in x and y, respectively.

$$SD = \sqrt{\frac{\sum (x-m)^2}{n-1}} \tag{5}$$

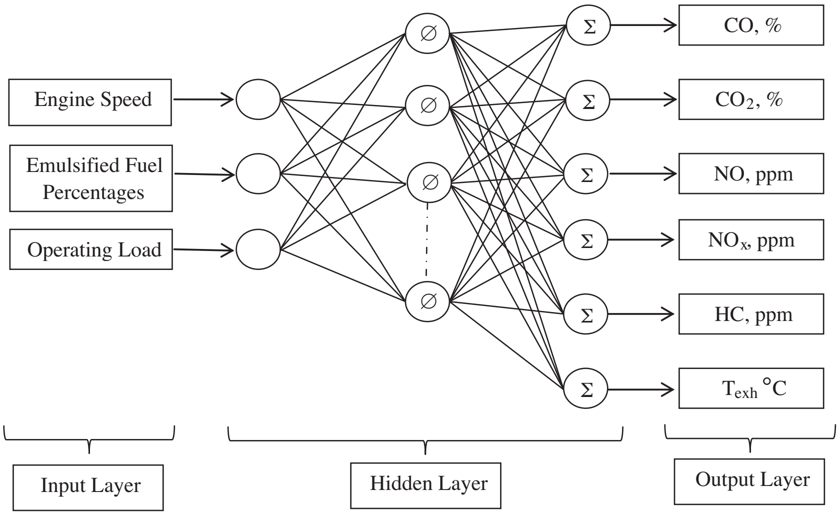

Figure 3. RBF structure.

Here, x is the individual value, m is the mean of all of the values, and n is the sample size (number of all of the values).

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{f_{i-}y_i}{f_i}\right| \tag{6}$$

Here, f_i is the predicted value, y_i is the actual value, and n is the number of patterns.

3. Results and discussion

In this study, the designed NN structures were used in order to predict the HC, CO, CO_2, NO, and NO_x amounts and the T_{exh} for a DI diesel engine with emulsified fuel. The numerical results that were obtained through the experiments were used for the learning phase of the NN [29]. The engine speed, emulsified fuel percentage, and operating load were used as the inputs of the structure, while the HC, CO, CO_2, NO, NO_x, and T_{exh} were used as the outputs.

First, a BP structure that has a single hidden layer was developed. Different neuron numbers were used in the hidden layer in order to decide the most reliable in the BP learning algorithm. In this regard, *tansig* for the input and *purelin* for the hidden layer, as a transfer function, were used in the network. Using a tangent transfer function, the experimental values were normalized between –1 to 1 with the formula:

$$\frac{\text{Actual value} - \text{Minimum}}{\text{Maximum} - \text{Minimum}} x\,(\text{High} - \text{Low}) + \text{Low}, \tag{7}$$

where *minimum* is the minimum value of the data, *maximum* is the maximum value of the data, and *high* is 1 and *low* is –1 for the normalization values. The BP structure's performance is shown in Figure 4 using the MSE.

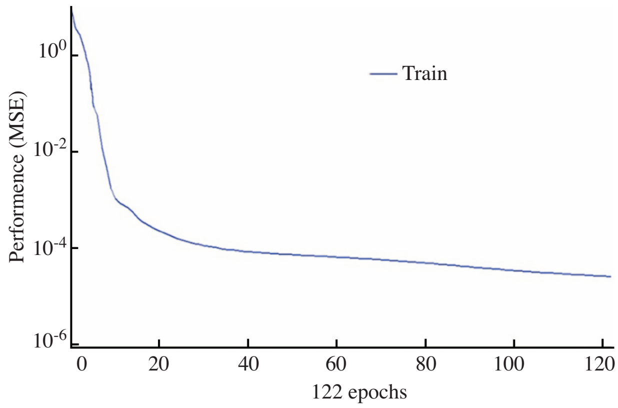

Figure 4. Performance of the proposed NN configuration of BP.

On the other hand, in order to detect the best suitable activation function, training algorithm, and neuron numbers in the hidden layer of the BP structure, a series of analyses were performed. The results are given in Table 3. According to this, the combination of tan/lin (tangent sigmoid/purelin) as an activation function, the LM algorithm as a training algorithm, and 26 neurons for the hidden layer produced the best results.

Next, in order to predict NO_x, NO, CO, CO_2, HC, and T_{exh}, a RBF NN structure with 2 hidden layers was used in this study. This RBF NN structure has 3 inputs, 2 hidden layers, and 6 outputs. The input and output layers are the same as those used in the BP NN structure.

Table 3. Summary of the different training algorithms evaluated to yield the criteria of the network performance of BP.

Activation function	Training algorithm	Hidden layer (neuron number)	Performance (MSE)	R (Training)	R (Test)
Sig/lin	Trainlm	20	2.52×10^{-4}	0.99951	0.92621
Tan/lin	Trainlm	20	2.04×10^{-4}	0.99959	0.92647
Tan/lin	Traingdx	20	1.87×10^{-1}	0.66267	0.61658
Tan/lin	Traingdx	12	8.78×10^{-2}	0.82207	0.72854
Tan/lin	Trainscg	20	4.63×10^{-3}	0.991	0.9206
Tan/lin	Traingd	22	4.54×10^{-3}	0.9917	0.92493
Tan/lin	Trainlm	19	7.71×10^{-5}	0.99984	0.92716
Tan/lin	Trainlm	21	1.55×10^{-5}	0.99994	0.92691
Tan/lin	Trainlm	22	3.18×10^{-6}	0.99996	0.92681
Tan/lin	Trainlm	23	4.75×10^{-5}	0.99991	0.92734
Tan/lin	Trainlm	24	1.23×10^{-5}	0.99997	0.92706
Tan/lin	Trainlm	25	5.39×10^{-5}	0.99989	0.9269
Tan/lin	Trainlm	26	1.23×10^{-6}	0.99999	0.92699

The experimental and predicted/simulated results of HC, NO, and NO_x in ppm; CO and CO_2 in %; and T_{exh} in $^\circ$C are given for both the BP and RBF in Figure 5, where it can be seen that the experimental and predicted/simulated values are very close. It is obvious that the prediction of the emissions and T_{exh} of a DI diesel engine with emulsified fuel can be accurately modeled using an ANN. In particular, the RBF structure outputs follow the experimental results better than BP.

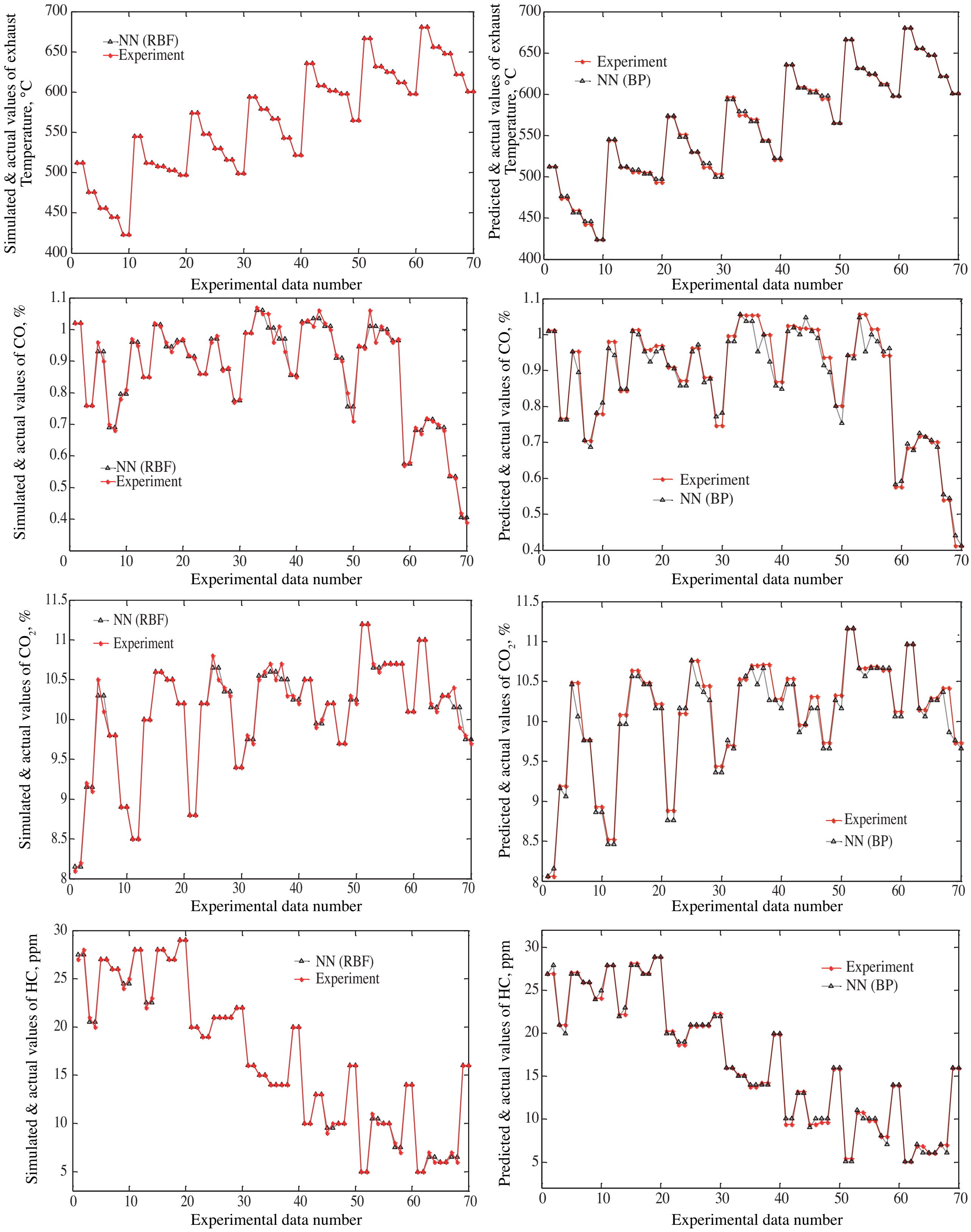

Figure 5. Comparison of predicted output and measured values with BP and RBF.

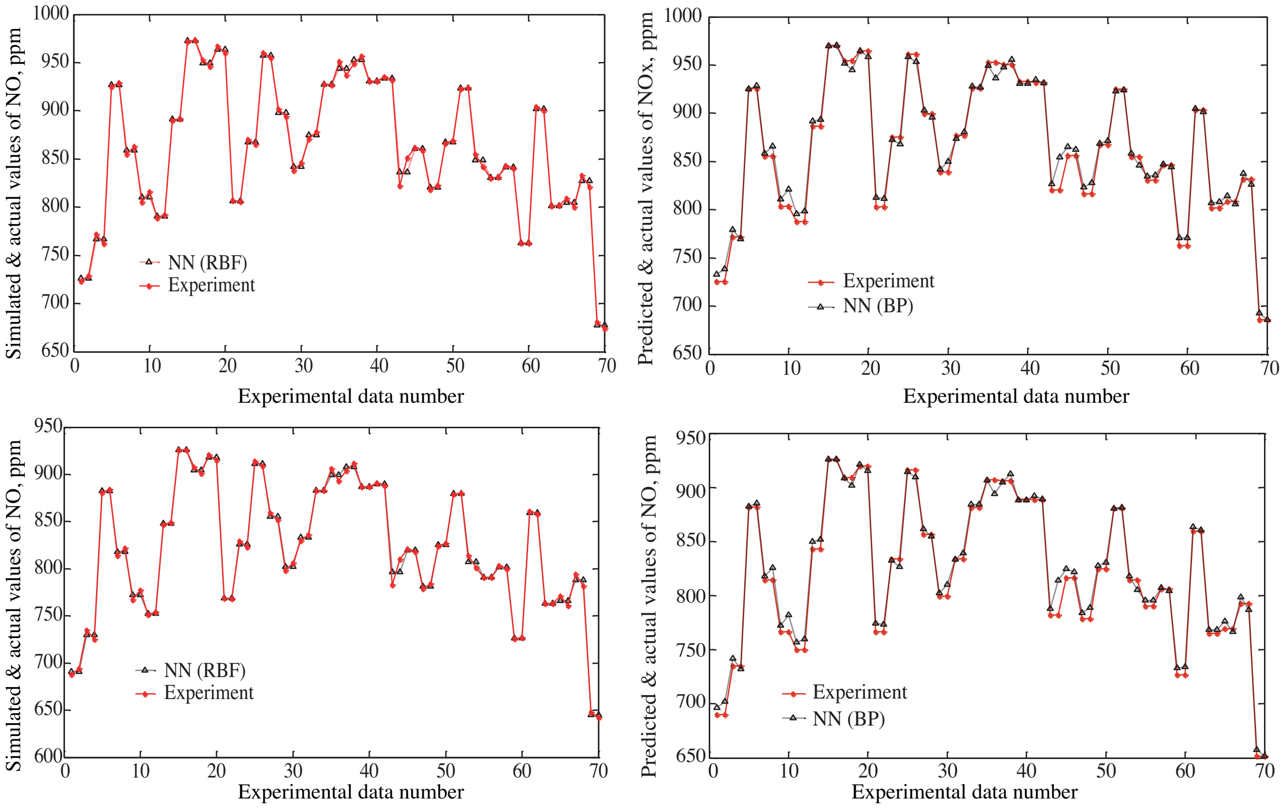

Figure 5. Continued.

On the other hand, in order to compare the network performance of BP and RBF, the MAPE, RMSE, and SD were used. The results are shown in Table 4, where it can be seen that the MAPE, RMSE, and SD values of the RBF network are smaller than those of the BP network for all values; in particular, the NO and NO_x emissions, which are very important for the new regulations on land and sea, are smaller. The RMSE, MAPE, and SD values of the RBF are more reliable and accurate than those of the BP NN. The T_{exh} estimation of the RBF NN achieved a very high accuracy.

Table 4. MAPE, RMSE, and SD for the output values of the network (BP and RBF).

	HC (5–28.8 ppm)		CO (1%–0.4%)		CO_2 (8%–11%)		NO (651–925 ppm)		NOx (686–970 ppm)		T_{exh} (423–680 °C)	
	BP	RBF	BP	RBF	BP	RBF	BP	RBF	BP	RBF	BP	RBF
MAPE	0.0215	0.0116	0.0198	0.0143	0.0083	0.0041	0.0065	0.0035	0.0066	0.0035	0.0030	0
RMSE	0.3712	0.2535	0.0269	0.0182	0.1306	0.0761	6.9793	3.9739	7.5102	4.0550	2.1458	0
SD	0.3739	0.2554	0.0252	0.0183	0.1100	0.0766	6.2714	3.9019	7.1136	4.0843	2.1609	0

4. Conclusion

The control of exhaust gases spreading from factories, machines, and vehicles has great importance for human health and the environment. According to new regulations on land and sea, the limitations of emissions, particularly NO_x and CO_2 emissions, have been considerable. Diesel engines that are used in ships generate exhaust gases. Therefore, their emissions must be kept under control according to regulations at sea. Due to the limitation of these emissions, particularly the NO_x emissions, internal combustion engines use an optimum emulsified fuel composition to improve the emissions' quality. Emission prediction and the control of it in real time is a complex and hard problem for a marine diesel engine. Emissions are predicted by numerical and mathematical methods; however, these methods are occasionally insufficient for prediction. An ANN is commonly used due to its accuracy, rapidity, and reliability.

Therefore, an ANN structure was developed to predict the HC, CO, CO_2, NO, and NO_x emissions and the T_{exh} for a DI diesel engine fueled with emulsified fuel. To this regard, 2 different ANN learning algorithms, the RBF and BP, were developed. Their performance was compared. The results show that the actual and predicted values of each output are very close to each other, either RBF or BP. However, RBF has a better performance than BP.

The exhaust emissions of marine diesel engines can be predicted with an ANN quickly and accurately [30]. Consequently, it is a useful method to predict the emissions while ships are sailing in ECA regions, therefore saving both engineering efforts and funds. In the next study, we would like to predict the real-time estimation of emissions and other parameters of a marine diesel engine.

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