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Experimental and Modeling of Efficiency and Emissions of a Diesel Engine Operated by Diesel-Waste fish oil biodiesel mixtures Containing Nano-additives Using Artificial Neural Networks

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Abstract
In this study, waste fish oil biodiesel and pure diesel fuel were mixed containing Fe_2O_3 nanoparticles as a catalyst. The Fe_2O_3 nanoparticles were evaluated at 50 and 100 ppm added to B10 at different engine speed under full load condition. Results show that adding nanoparticles could improve the combustion and efficiency of diesel engine as well as emissions. Then,multi-layer networks with feed-forward back diffusion neural network model, the algorithm of levenberg-marquardt (trainlm) as the algorithm of training, and thetan-sig, log-sig and purelintransmission function as an activation function were employed in the present research. The input or independent parameters included fuel mixture, engine speed, and fuel consumption, while, the target parameters individually included engine power, UHC, CO_2, CO, NO_X and , torque. The result shows that in the optimal network, there are two hidden layer with 15-15 neurons and transmission function of logsig- logsig, for hidden layer one and two, respectively. This study implies that ANNcan bea robust toolfor predicting efficiency, and emission of diesel engines with high correlation between experimental data and predicted model.
Keywords:ANN model, Biodiesel, efficiency, Emissions, Nano-additives.

1. Introduction

Nowadays, more than 80% of all of energy requirements, and near 98% of carbon emissions are due to fossil fuel and its combustion [1,2]. Due to most widely use of diesel engines, it has been reported that diesel engines exhaust emissions are the essential source of air pollution [3]. Therefore, Nowadays, the researchers' focus is on clean and renewable fuels due to growing energy demand,harmful ecological impacts of using fossil fuel and also in order to decrease the emissions [1,4,5]. It has been reported thatit is possible to use biofuels (biodiesel and bioethanol) as a supplement or alternative to gasoline/diesel fuel derived from fossil fuels [1,6,7]. Biodiesel as an alternative to diesel fuel is one of the most used renewable fuel for diesel engines. It is an oxygenated, non-toxic, sulfur-free, biodegradable and mixable fuel in

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any proportion mixture with diesel fuel [8]. Based on various researches that has been done, it is obvious, addition of nanoparticles additives could enhance the efficiency and emissions characteristics of the biodiesel/diesel fuel mixture in diesel engine [9]. Therefore, in this research the metal base nanoparticles selected to add in diesel-waste fish oil biodiesel mixed in order to measure the efficiency, and emissions characteristic of a single-cylinder diesel engine.Latterly, because of flexibility, precision and quick response properties of Artificial neural network (ANN), it was opted as a positive and attractive techniques in the literature for modeling and solving the complicated problems [10].

Artificial neural networks (ANNs) are computer systems which are able to produce, form and explore modern knowledge automatically and with no aid such as the human brain [11]. They have been utilized for solving those types of problems in science and engineering, specifically when the conventional modeling techniques fail to solve them [11]. ANN as a robust tool can apply multiple input variables to predict multiple output variables [12]. In the following, some researcheson applyingANNsin the case of the efficiency and emission of the engines with various biofuels are reviewed.

Rao et al.analyzed the diesel engine efficiency and exhaust emission employing biodiesel with ANN. They identifiedthe standard back diffusion algorithm as the most appropriate choice for training the model. They also used a multi-layer perception (MLP) network for non-linear mapping between the input and output parameters[13]. In another research, predicting the diesel engine efficiencyapplying biofuels with ANNwas studied. Thediscovered artificial intelligence model was identified as aproper model forevaluating the efficiency of the engine applied in the experiments [11]. Ghobadian et al.analyzed the diesel engine efficiency and exhaust emission applying waste cooking biodiesel fuel withANN. Their result showed that the ANN model predicted the engine efficiency and exhaust emissions well enough[14]. Karonis et al.employed the neural network technique for studying the correlation of exhaust emissions from a diesel engine. They showed that very good predictions were achievedfor anykindof emissions[15].

Karthickeyan et al. Developed the ANN model for predictingefficiency and emission features of Variable compression ratio (VCR) engine with orange oil biodiesel mixtures. The ANN model showed that the Levenberg–Marquardt with log and tan sigmoidal transmission function could give the optimaloutcomes[16]. Parlak et al. examined the employment of artificial neural network for predicting specific fuel consumption and exhaust temperature for a Diesel engine. The result showed that a back diffusion neural network model with a 3–7–2 (number of input layer–hidden layer–output layer nodes) configuration was the best model to predictcertain fuel consumption and exhaust temperature in a diesel engine[17]. Deh Kiani et al. employed the ANN model for predicting the output torque, engine brake power and exhaust emissions of the spark ignition engine by mixture of ethanol-gasoline. They reported that the ANN model based on algorithm of standard back- diffusionsupplies the finest result in the emission modeling [18]. Rezaei et al. employed ANN for predictingefficiency of homogeneous charge compression ignition engines (HCCI) with ethanol and butanol fuels. The results of validating indicated that by both FF and RBF models, HCCI engine efficiency metrics can be predictedwith an error of less than 4% for ethanol and butanol fueled engines [19].

According to the literature review, no research has been done in the field of experimental analysis of using diesel-waste fish oil biodiesel mixed containing Fe_2O_3 nanoparticles at different peed under full load condition on single-cylinder diesel engine and also applyingANNsfor prediction of the efficiency, and emissions of diesel engine. Hence, because of lackingthe studies on applying diesel-waste fish oil biodiesel mixture containing Fe_2O_3 nanoparticles, this study aims to evaluate experimental analysis of diesel engine by this fuel and present a neural network model to predict engine efficiency, and emissions of a single-cylinder diesel engine.

2. MaterialsandTest Methods

In order to conduct experiments, a four-stroke single-cylinder diesel engine was employed. In this engine, a governor controls and stabilizesthe rotational speed. A dynamometer was implemented to apply the load to the engine. An eddy current dynamometer was applied to assess the brake power and the torque of the engine under rotational speeds and applied engine loads.In this research, waste fish oil biodiesel and standard diesel fuel were mixed then Fe_2O_3 nanoparticles as an additive were added to the mixture. Tow fuel mixtures of D100, B10 (90% pure diesel and 10% waste fish oil biodiesel) were provided. After it, Fe_2O_3 nanoparticles as an additive were added to B10 mixture by dosage of 50 and 100 ppm. An ultrasonic homogenizer(HielscherUP400S, Germany) device was employed to prepare and homogenize the fuel mixtures. Totally, four fuels ie., D100 (Pure diesel), B10 (90% pure diesel and 10% waste fish oil biodiesel), B10-50 ppm NP (90% pure diesel and 10% waste

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fish oil biodiesel containing 50 ppm Fe_2O_3 nanoparticles) and, B10-100 ppm NP (90% pure diesel and 10% waste fish oil biodiesel containing 100 ppm Fe_2O_3 nanoparticles) were tested.

Here, the experiments were conducted on full-load engine condition and three engine speeds of 1700, 2300, and 2900 rpm.The Torque, power, and BSFC as a efficiency parametersand CO, CO_2, UHC and NOx as an emissions parameters were recorded and transferred to a computer during each test.

3. ANN Modeling

Predictingthe efficiencyand emissions of a single-cylinder diesel engineby ANN is the major focus of this research. For this purpose, a program in Matlab software was developed for predictingthe efficiency, and emissions of a diseleengine at variuoseconditions.Here,engine speed, kind of fueland fuel consumption wereutilized as input layer. The outputparameters included engine power, BTE, UHC, CO,$CO_2$and NOxemissions. Figure 1 depicts neural network architecture diagram. The input-output parameters in data sets areordered and normalized in the range of 0 and 1before training the model. Due to the output layer activation function being linear in allarchitectures; just the input parameters were normalized.

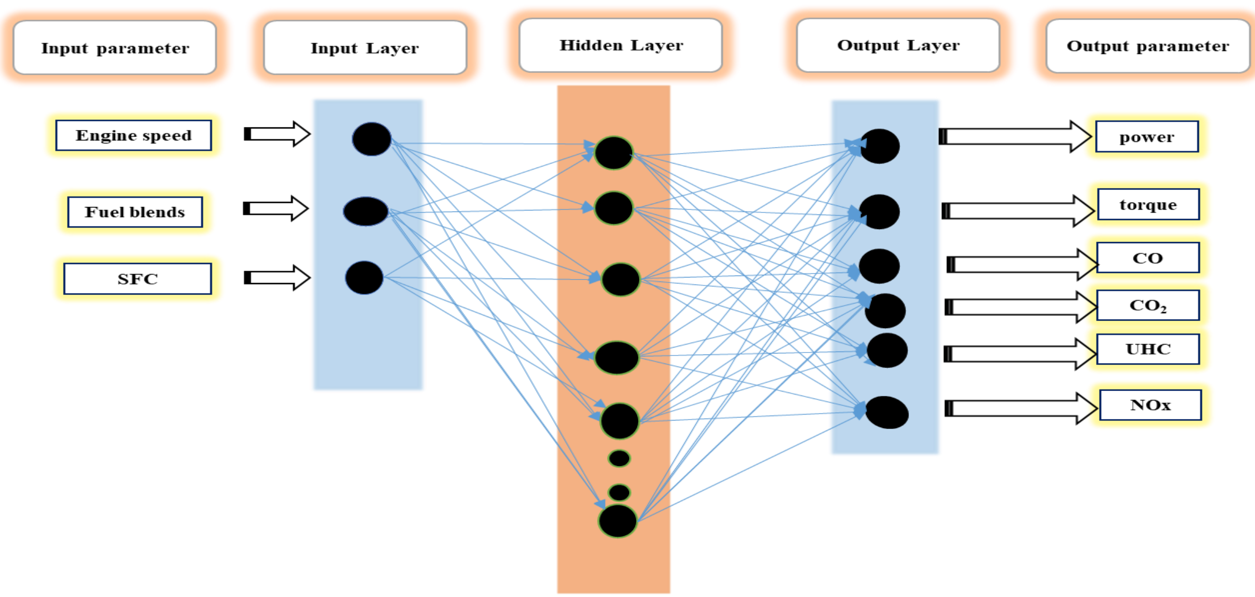

Fig. 1. Neural network architecture diagram.

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In the presentmodel, 70% of the whole datasets hasbeenfreelychosen for training the model, whilst the remainingdata was partitioned uniformly, 15% for validating and 15% for testing. MLP with feed-forward back diffusion neural network model has beenimplemented. The algorithm of levenberg-marquardt (trainlm) was applied as the algorithm of training. The tan-sig, log-sig and purelintransmission function have beenapplied as an activation function in the presentstudy, governed by Eqs. (1) and (2).

$$logarithmicsigmoid = \frac{1}{1+e^{-x}}, (1)$$

$$tangentsigmoid = \frac{2}{1+e^{-2x}} - 1, (2)$$

where x is the input data.

In this study, the network training was conducted with differentnumbers of hidden layers and neurons in order to choose the optimal network model. The statistical techniques of MSE and correlation coefficientwereutilized for comparing. The optimal network model was driven byminimumquantity ofMSE and maximum quantity of (R)calculated by Eqs. (3) and (4), respectively.

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(T_i - O_i)^2 \ (3)$$

$$R = 1 - \left(\frac{\sum_{i=1}^{n}(T_i - O_i)^2}{\sum_{i=1}^{n}(T_i - \bar{O})^2} \right) (4)$$

In Eq. (3) and (4), and'n' is the number of tests, 'T_i' is the evaluatedquantities, 'O_i' is the predicted quantitiesand '$\bar{O}$' is the mean of predicted quantities.

4. Results and Discussion

In this section, power, torque, and BSFC at speed of 1700, 2300, and 2900 rpm are analyzed. Also, the results for emissions of CO, CO_2, UHC, and NOxareargued. Then, the ANN model used performed for efficiency and emissions of diesel engine that used in the present researchto find the optimal model.

4.1. Efficiency

4.1.1.Torque and Power

In Figure 2 the trend of Fe_2O_3Nano-additives added to B10 (diesel-Waste fish oil biodiesel mixtures)on the engine torque is presented. As shown in figure 2, the maximum torque occurs in 1700 rpm for all fuel mixtures. As a result, the torquereducesby 11.75%and21.14%,respectively, by enhancement ofthe engine speedfrom 1700to 2300and 2900 rpm. In the all engine speed, B10 mixtures create the minimum torque. It could be because of the lower biodiesel heating

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quantitycompared to the all fuel mixtures that tested [5,20].Also, the result shows that nanoparticles added to B10 leading to increase the torque of diesel engine.It could be due to that nanoparticles as an additives in fuel mixture leading to enhance the engine combustion qualityandimproved the combustion[5,7]

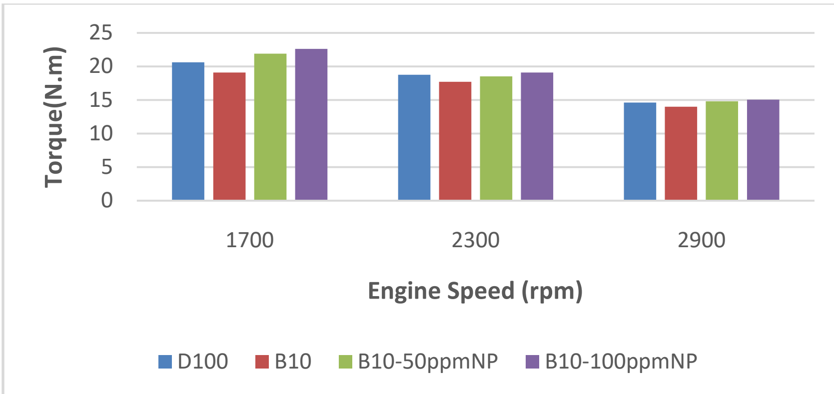

Fig.2.Diagram of an engine torque at speed of 1700, 2300 and 2900 rpm for several fuel mixtures.

In Figure3, the impact of Fe_2O_3nanoparticles added to B10on the engine power is shown. Results showthe power increases from speeds of 1700 to 2900 rpm. Overall, the trendof brake power is analogous to that of engine torque for tested fuel mixtures. The fuel mixtures of B10-100 NP have the maximum power, whilst B10 have the lowest power in all of engine speed tested. In view of nanoparticles added to fuelmixture, it could be conclude that the Fe_2O_3nanoparticles added in the fuel mixture (B10), leading toimprove combustion quality. It can be attributed to the nanoparticles added to fuel leading to produced more energy inside the cylinder[5,21].

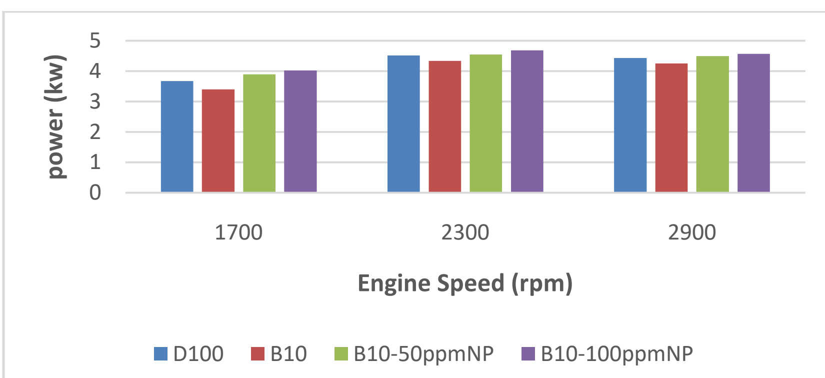

Fig.3.Diagram of an engine power at speed of 1700, 2300 and 2900 rpm for several fuel mixtures.

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4.1.3. BSFC

The impact of Fe_2O_3 nanoparticles added to B10on the BSFC of engine is shown in Figure 4. As a results shows, the BSFCincreases by 8.33%and14.58%,respectively, by enhancingthespeed of theengine from 1700to 2300and 2900 rpm. In the all engine speed, B10 mixtures create the maximum BSFC. This can be caused by the lower heating quantityof biodiesel and subsequentlythe quantityofheating of the diesel-biodiesel mixture is decreased compared to the all fuel mixtures that tested [20,22]. Also, the results show that nanoparticles added to B10 leading to decrease the BSFC of diesel engine. It could be due to that nanoparticles as an additives in fuel mixture leading to enhance the engine combustion quality and improved the combustion[5,7]

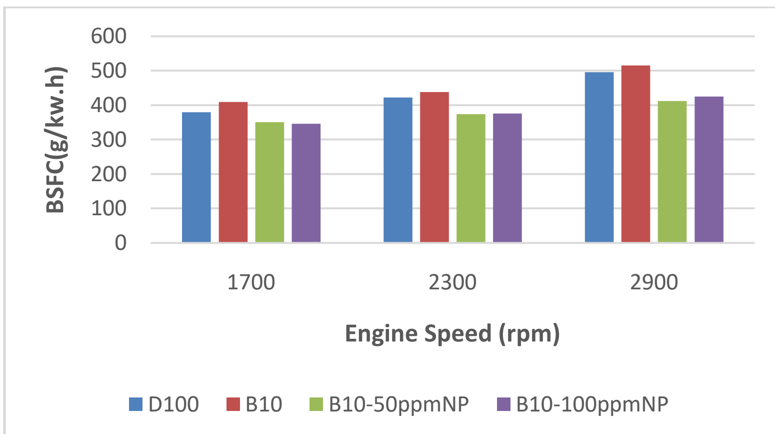

Fig.4.Diagram of an engine SFC at speed of 1700, 2300 and 2900 rpm for several fuel mixtures.

4.2. Emissions

4.2.1. CO and CO_2

Figure 5.shows theCOemissionsforallfuelmixturesunder several enginespeeds. It is perceived thatin all engine speeds,theamount ofCO emission indiesel fuel is maximum. The lowest amount ofCO emission is for the cases of B10, and B10-100 ppm NP.It can be funded that the combination of B10 and 100 ppm Fe_2O_3 nanoparticles has created the lowest of CO at the 1700 and 2300 rpm.This can be lead to the best conditions of reaction is provides cause of the temperature of the exhaust gases[5,7].

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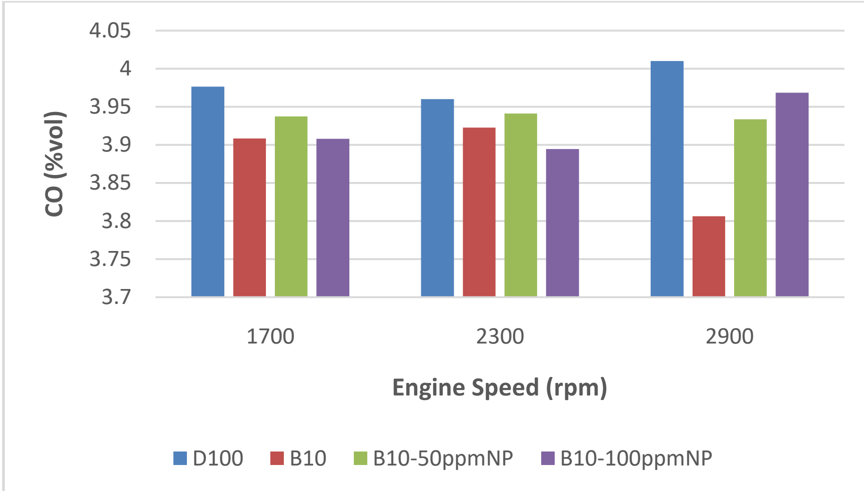

Fig. 5. Diagram of CO emission at engine speed of 1700, 2300 and 2900 for several fuel mixtures.

Figure 6, displays theCO_2emissionsforallfuelmixtures under various enginespeeds. According to this figure, in all engine speeds,theamount ofCO_2emission increasing by added Fe_2O_3 nanoparticles to B10 fuel mixture. The lowest amount ofCO_2emission is for the cases of pure diesel, and B10mixture. Also, the highest amount ofCO_2 emission is for the cases of B10-100 ppm NP. It can be funded that the combination of B10 and Fe_2O_3 nanoparticles has created the highest of CO_2at all enginespeed.This can be attributed to the conditions of reaction is provides from of the temperature of the exhaust gases [5,7].

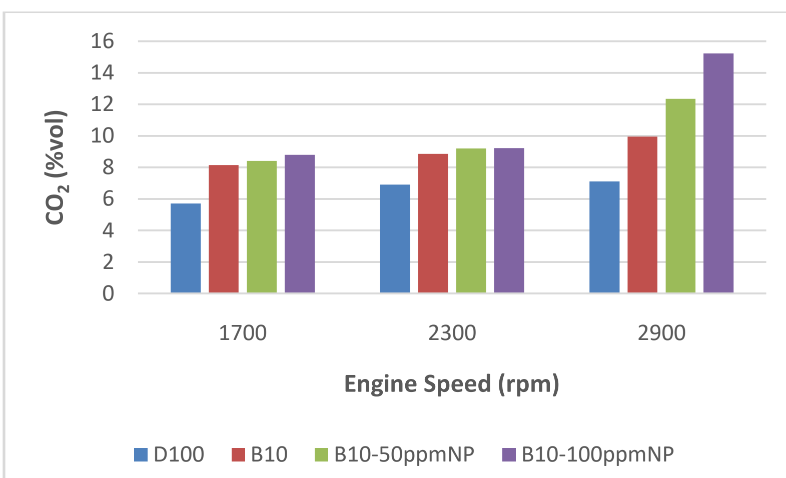

Fig. 6. Diagram of CO_2 emission at engine speed of 1700, 2300 and 2900 for several fuel mixtures.

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4.2.2. UHC and NOx

The impact of Fe_2O_3 nanoparticles added to B10on the UHC emission of diesel engine tested is shown in Figure 7. As a result it shows that generally, the minimum UHC emissions are produced in speed of 1700 rpm and the maximum amount of UHC emissions are crated in 2300 rpm wherein the engine functionsclose to the rated speed. This can be attributed that is possibly a greatincrement in exhaust temperature[5,7]. Also, the results show that nanoparticles added to B10 lead to decrease the UHC of diesel enginein comparison with diesel fuel. This can be due to that nanoparticles as an additives in fuel mixture lead to enhance the engine combustion quality and improved the combustion [5,7].

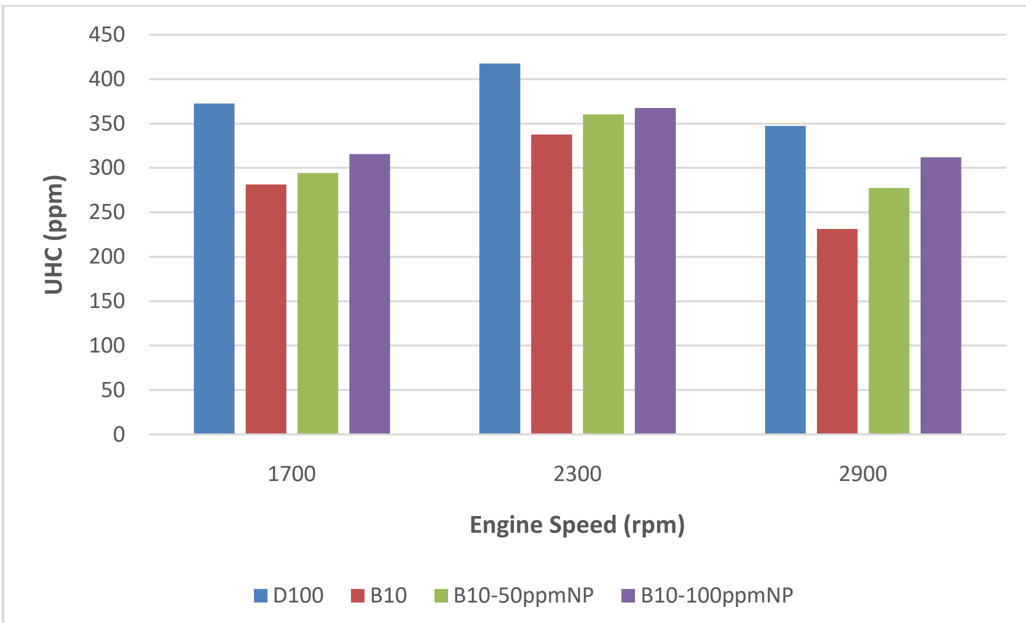

Fig. 7. Diagram of UHC emission at engine speed of 1700, 2300 and 2900 for several fuel mixtures.

Figure 8, depicts the impact of Fe_2O_3 nanoparticles added to B10on theNOx emission of diesel engine tested.As a result, B10mixture crated the more NOx in comparison with diesel fuel. It could be contributed that exhausttemperature isincreased by added biodiesel to diesel because of O_2 in the biodiesel structure. Also, in view of nanoparticle added to fuel mixture, the NOx emission increased. It could be due to that nanoparticles as an additives in fuel mixture leading to enhance the engine combustion

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quality and improved the combustion as a catalyst that leading to increases the exhaust temperature[5,7].

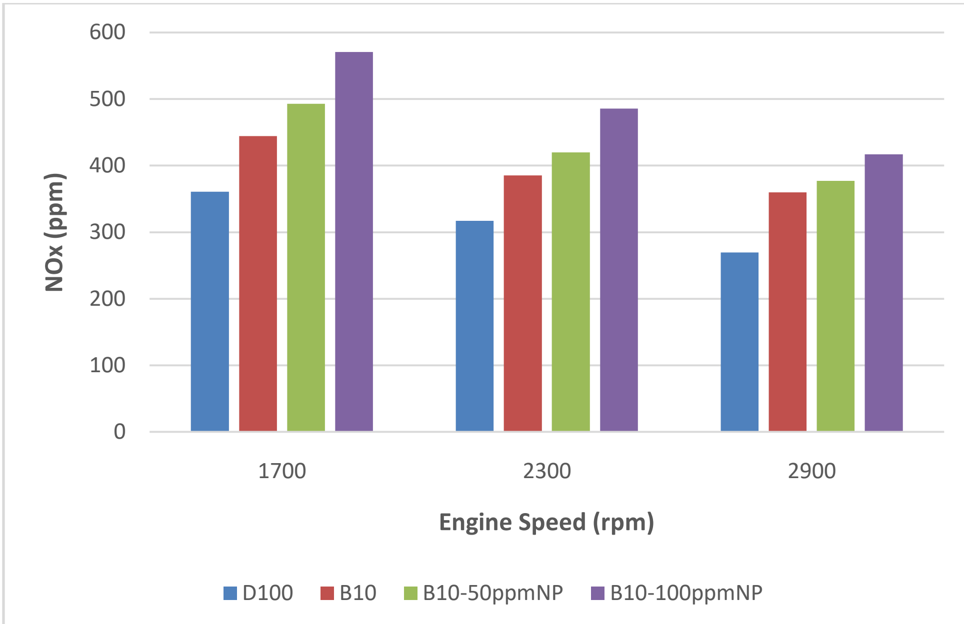

Fig. 8. Diagram of NOx emission at engine speed of 1700, 2300 and 2900 for several fuel mixtures.

4.3. ANN model results

ANN model was carried out for efficiency, anddiesel engineemissionwith diesel-biodiesel including Fe_2O_3 nanoparticles fuelmixtures under different engine speeds.

Severalnetworkmodelswere appliedto discover the most appropriate prediction by the ANN model. In Table 1, a summary of variousnetwork models estimated to give the criteria of network efficiencyare presented. The algorithm of trainlm, purelin transmission function for output layer and the transmission function of log-sig, tan-sig with 2 hidden layers are chosen in this table. There are two hidden layer in the optimal network with 15-15 neurons and transfer function of logsig- logsig, for hidden layer one and two, respectively.In Figure9, the efficiency and overall R quantities of optimal ANN model is shown. The optimal topologycorrelation coefficient for training, validating and testingare 0.99985, 0.99904 and 0.99791, respectively. Besides, the MSE quantities of optimal topologymodel for training, validating and testingare acquired as 0, 2.0624, and 2.4481, respectively.

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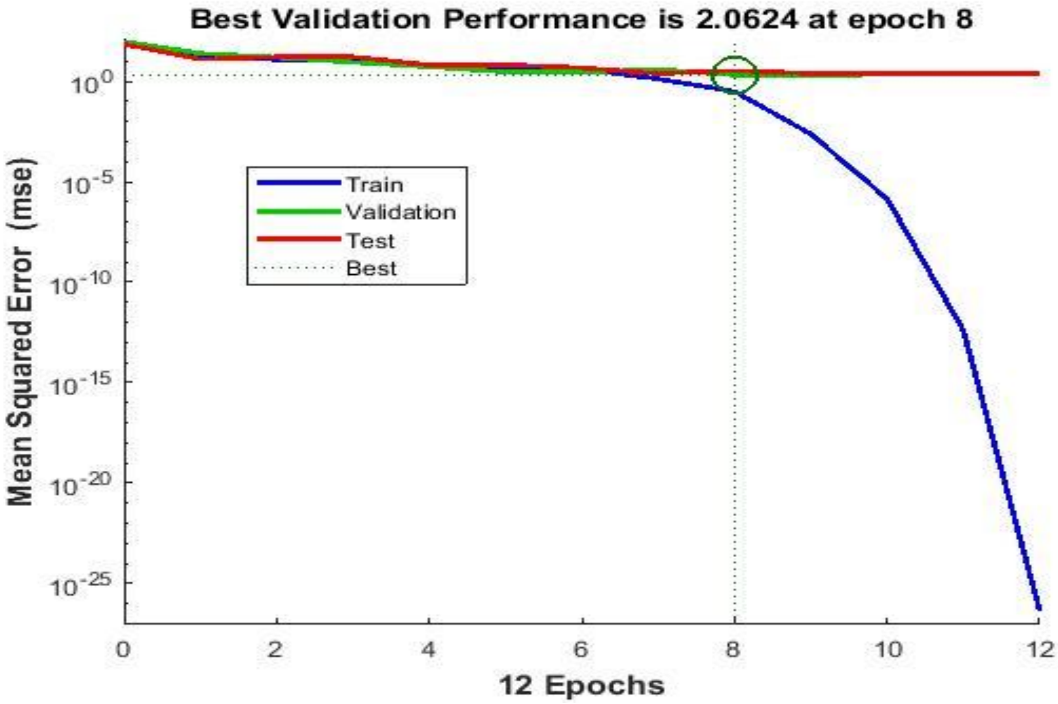

Fig.9. Efficiencyof the optimal network.

In order to study the network response in more detail a regression analysis between the corresponding targets and the network output was carried out. The result shows that the developed model adequatelypredict the efficiency, and diesel engineemission. In Figures10and 11, the predicted outputs by ANN versus measured quantities for efficiency, and emissions are demonstrated. Quantitiesof efficiencyregression coefficientobtained from ANN are0.97349 and0.991663for torque and power, respectively. Additionally, quantities of emissionsregression coefficientobtained from ANN are 0.98921, 0.992678, 0.994744, and 0.903677forCO, CO_2, UHC, andNOx, respectively. This shows that predicted model and experimental datahave high correlation with each other in optimal ANN model.

As a conclusion, it can be said that ANN is a robust application for predicting efficiency and emission parameters of engines with acceptable precision.

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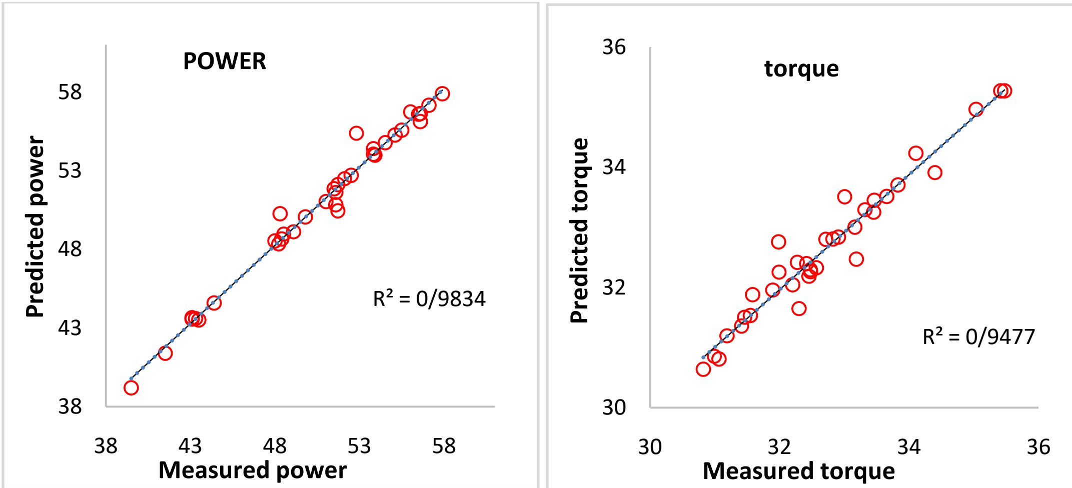

Fig. 10.Predicting quantities of ANN and experimental for efficiency parameters.

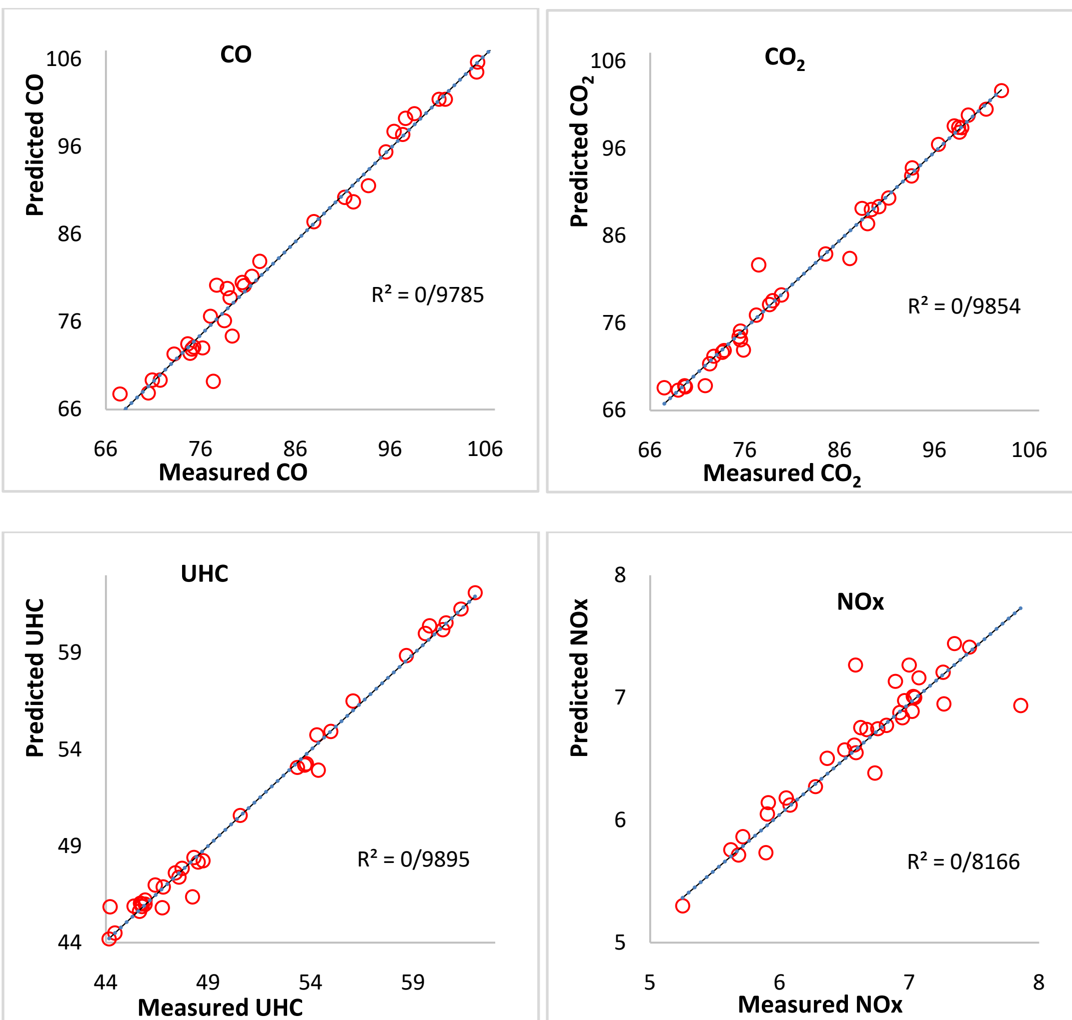

Fig. 11. Predictingquantities of ANN and experimental fordiesel engineemissions.

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Table 1. Summary of various network models estimated to give the criteria of network efficiency.

Networks number	**Activation function**	**Training rule**	**Neurons in hidden layers**		**MSE**			**R**			**Epoch**	Time (s)
			Layer 1	**Layer 2**	**Training**	**Validating**	**Testing**	**Training**	**Validating**	**Testing**		
1	Tan/Pur	trainlm	5	-	0.5551	2.6503	3.3427	0.99969	0.99866	0.99759	17	0
2	Tan/Pur	trainlm	10	-	0.1229	8.2202	5.1181	0.99962	0.99702	0.99752	7	0
3	Tan/Pur	trainlm	20	-	0.0029	6.8496	3.0467	0.99963	0.999777	0.99895	5	0
4	Tan/Pur	trainlm	30	-	0.0004	2.4587	4.9500	0.99996	0.99912	0.99767	4	0
5	Log/Pur	trainlm	5	-	0.4286	5.3832	4.3969	0.99926	0.99721	0.99727	1	2
6	Log/Pur	trainlm	10	-	0.0996	5.1054	8.9605	0.9999	0.99768	0.99476	13	0
7	Log/Pur	trainlm	20	-	0.0098	7.8996	9.6203	0.99984	0.99602	0.99606	4	0
8	Log/Pur	trainlm	30	-	0.0000	7.0798	8.3383	0.9996	0.99596	0.99626	4	0
9	Log/Log/Pur	trainlm	10	10	0.0926	8.2989	2.8820	0.9994	0.99652	0.99775	7	0
10	**Log/Log/Pur**	**trainlm**	**15**	**15**	**0.0000**	**2.0624**	**2.4481**	**0.99985**	**0.99904**	**0.99791**	**8**	**0**
11	Log/Log/Pur	trainlm	20	20	0.0000	8.0083	7.0152	0.99963	0.99547	0.99631	7	0
12	Log/Log/Pur	trainlm	20	25	0.0044	8.3046	6.6949	0.99858	0.99492	0.99609	3	0
13	Log/Log/Pur	trainlm	25	20	0.0000	9.2814	4.9946	0.99979	0.99551	0.99721	8	0
14	Log/Log/Pur	trainlm	25	25	0.0000	13.1199	10.7911	0.99956	0.99396	0.99505	3	0
15	Tan/Tan/Pur	trainlm	10	10	0.0317	4.8273	9.9892	0.99985	0.99737	0.99463	7	0
16	Tan/Tan/Pur	trainlm	15	15	0.0118	11.7747	7.7339	0.99717	0.99685	0.99593	5	0

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17	Tan/Tan/Pur	trainlm	20	20		0.0000	13.3989	7.4388		0.99992	0.99375	0.99641	5	0
18	Tan/Tan/Pur	trainlm	25	25		0.0000	10.6364	12.8336		0.99693	0.99027	0.98548	5	0
19	Tan/log/Pur	trainlm	10	10		0.1351	9.0990	7.0104		0.9981	0.996	0.99596	5	0
20	Tan/log/Pur	trainlm	15	15		0.0039	15.9094	4.0175		0.99229	0.99668	0.99296	7	0
21	Tan/log/Pur	trainlm	20	20		0.0000	14.3756	12.4895		0.99699	0.99313	0.99399	3	0
22	Tan/log/Pur	trainlm	20	25		0.0016	5.8147	19.6947		0.99692	0.9964	0.9863	2	0
23	Tan/log/Pur	trainlm	25	20		0.0000	11.9491	8.0112		1	0.99494	0.99611	8	0
24	Tan/log/Pur	trainlm	25	25		0.0000	5.9878	6.9302		0.99959	0.99728	0.99625	5	1
25	Log/Tan/Pur	trainlm	10	10		0.1194	4.5388	8.3300		0.99871	0.99841	0.99641	4	0
26	Log/Tan/Pur	trainlm	15	15		0.0021	9.4714	8.9846		0.9998	0.99545	0.99507	6	0
27	Log/Tan/Pur	trainlm	20	20		0.0000	7.7820	13.0252		1	0.99683	0.97407	8	0
28	Log/Tan/Pur	trainlm	20	25		0.0000	3.6960	8.1147		1	0.99762	0.9954	9	0
29	Log/Tan/Pur	trainlm	25	20		0.0000	10.1197	6.3902		0.99998	0.99496	0.997	5	0
30	Log/Tan/Pur	trainlm	25	25		0.0000	3.2329	6.9756		1	0.99817	0.99806	9	0

In the suggested ANN model,just restricted amounts of obtained data is needed for training,whilein the usual look-up table technique in the ECU of internal combustion engine, lots of experimental data is requiredfor predicting or calibrating the engine efficiency, control emissions, and reducing the engine knocking utilizing vibration signal [19]. Here, it is possible to use the suggested ANN model fordecreasing ECU calibration cost and computationtime.

5. Conclusion

The objective of this study was to evaluate the Fe_2O_3 nanoparticles added to B10 at different engine speed under full load condition. Then, a model of neural network for prediction of the engine efficiency, and emissions of a single-cylinder diesel engineusing diesel-biodieselmixturescontaining differ dosage of Fe_2O_3 nanoparticles as a catalyst.Results show that adding nanoparticles could improvethe combustion and efficiencyof diesel engine as well as emissions. Then, in next section of this study, 70% of the whole datasets has beenfreelychosen for training the ANN model, whilst the remaining data has been partitioned uniformly, 15% forvalidating and 15% for testing. MLP with feed-forward back diffusion neural network model, the algorithm of levenberg-marquardt (trainlm) as the algorithm of training, and thetan-sig, log-sig and purelintransmission function were implementedas an activation function. The result showsthat in the optimal network, there aretwo hidden layer with 15-15 neurons and transmission function of logsig- logsig, for the hidden layersone and two, respectively. The optimal topology correlation coefficient for training, validating and testingare 0.99985, 0.99904 and 0.99791, respectively. Also, the MSE quantitiesrelated tomodel of optimal topologyfortraining, validating and testingwerederived as 0, 2.0624, and 2.4481, respectively. From this study,it is concluded that the ANN is a robust toolforpredictingefficiency, and diesel engines emission with high correlation between experimental data andpredicted model.

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