Application of an artificial neural network model for prediction of diesel engine heat using nano-additives in diesel-biodiesel blends

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Abstract: Biodiesel is a renewable clean bioenergy produced from vegetable oils, animal fats, and micro-algal oil. It can be applied to instead of diesel fuel without any special modifications to the engines. In recent years, nano-catalysts or nano-additives was added to fuels to improve the thermo-physical properties of them. In this study, the carbon nanotubes (CNTs) as additives were mixed with the B5 and B10 fuel blends to evaluate the temperature of the cylinder head and cylinder block of a CI single-cylinder engine through artificial neural network (ANN). The CNTs with concentrations of 30, 60, and 90 ppm were used for each fuel blends, and engine was running at three speeds of 1800, 2300, and 2800 rpm under full load. The results of optimum ANN model showed that the training algorithm of Back-Propagation with 24 neurons in a hidden layer was enough to predict temperature of engine's cylinder head and cylinder block for different modes. The mean square error (MSE) for training, validation and testing of optimum ANN model were 0.00095, 10.40, and 9.71, respectively. The corresponding R-values were 0.9999, 0.9487 and 0.9726, respectively. It can be concluded that neural network is a powerful tool to predict the temperature of diesel engines' cylinder head and cylinder block with a reasonable accuracy.

Keywords: cylinder head and block, ANN, temperature, carbon nanotubes

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1 Introduction

Today, more than 80% of produced energy is from oil, coal and natural gas. About 98% of carbon emissions are from fossil fuel combustion. Reducing the use of fossil fuels can significantly decrease the emissions. This can be achieved by replacing fossil fuels by renewable fuels. Sustainable sources of renewable energy will play an important role in the future global energy (Najafi et al., 2011). Biodiesel is one renewable sustainable bioenergy as it can be produced from vegetable oils, animal fats and micro-algal oil, and also it can be applied to instead of diesel fuel without any special modifications to the engines (Taghizadeh-alisaraei et al., 2012; Tan et al., 2014). Recently, nano-additives in fuels improve the thermo-physical properties such as high surface area-to-volume ratio, thermal conductivity, and mass diffusivity. Many studies have been showed that nano-additives along with diesel, biodiesel, and their blends could enhance the flash point, fire point, kinematic viscosity, and other properties (Shaafi et al., 2015). Moy et al. (2002) reported that the carbon nanotube (CNT) could act as a potential nano-additive for the fuels to enhance the burning rate of the fuel, and improve the cetane number; it also acts as an anti-knock additive to promote the clean burning, and suppress the smoke formation.

In the case of temperature of engine block, the

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increasing of the liner temperature can have the multiple advantage of reducing the specific fuel consumption, however, lower head temperature reduces the thermal stress of the top portion of engine, decreases the knocking and pre-ignition, and increases the volumetric efficiency (Choudhary et al., 2014). The importance of engine heat transfer is clear, due to its role in engine efficiency, emission, endurance, friction, and lubrication (Ahmadi et al., 2012).

Many studies have been conducted in the case of biofuel and their effect on the engine combustion, performance, and emission characteristics with an artificial neural network. Ghobadian et al. (2009) investigated the diesel engine performance and exhaust emission analysis using waste cooking biodiesel fuel with an artificial neural network. They observed that the ANN model can predict the engine performance and exhaust emissions quite well with correlation coefficient (R) of 0.9487, 0.999, 0.929 and 0.999 for the engine torque, SFC, CO and HC emissions, respectively. The prediction MSE of desired outputs between the measured values and the simulated values were obtained as 0.0004 by the model (Ghobadian et al., 2009). Ismail et al. (2012) developed an artificial neural networks (ANN) modelling program for a light-duty diesel engine which was using blends of various biodiesel fuels with conventional fossil diesel as its power. The results were indicated that back-propagation feed-forward neural network which was combination of tansig/pureline transfer functions, TRAINLM training algorithm, and NoN value of 10, were the optimum ANN model. In another study, Javed et al. (2015) investigated the use of ANN modeling for prediction of performance and emission characteristics of a four stroke single cylinder diesel engine with Jatropha Methyl Ester biodiesel blends along with hydrogen in dual fuel mode. The results showed that the Levenberg-Marquardt back-propagation training algorithm with logarithmic sigmoid and hyperbolic tangent sigmoid transfer function was best model for prediction of performance and emissions characteristics. The overall regression coefficient, MSE, and MAPE for the developed model were 0.99360%, 0.0011% and 4.863001%, respectively. Kiani et al. (2010) developed the application of ANN for the prediction of performance and exhaust emissions in SI engine which was using ethanol-gasoline blends. Results showed the ANN provided the best accuracy in modeling the emission indices with correlation coefficient equal to 0.98, 0.96, 0.90, 0.71, 0.99 and 0.96 for CO, CO_2 (carbon dioxide), HC, NO_x, torque and brake power, respectively. In another study, Sharma et al. (2015) investigated the use of ANN for predicts the performance and exhaust parameters of a single cylinder 4-stroke diesel engine at different injection pressures using blended mixture of Polanga biodiesel. The result showed that the ANN model can predict the engine performance and exhaust emissions quite well with high correlation coefficient (R) for performance and exhaust parameters of a diesel engine.

Oğuz et al. (2010) performed the prediction of diesel engine performance using biofuels with ANN. Diesel, biodiesel, and bioethanol were mixed together to be used in developed artificial neural network. Power, moment, fuel consumption and specific fuel consumption (SFC) were estimated by using the artificial neural network which was developed by input values. As a result, through performed statistical analyses, it seems that realized artificial intelligence model is an appropriate model to estimate the performance of the engine used in the experiments.

Available data indicate that ANN is a powerful modeling tool which has the ability to identify complex relationships from input–output data. Therefore, the objective of this study is to develop a neural network model for predicting the cylinder head and cylinder block temperature of the engine in relation to input variables including engine speed and fuel blends. Due to the potential properties of CNTs and the lack of studies of diesel-biodiesel blend fuels, the present work is aimed to establish the effects on cylinder head and cylinder block temperature of a single cylinder diesel engine with artificial neural networks (ANN).

2 Materials and Methods

In this research, the biodiesel produced from waste cooking oil, using trans-esterification reaction based on

ASTM D6751 standard. Then, the carbon Nanotubes (CNTs) with dosage of 30, 60, and 90 ppm were mixed with B5 (5% biodiesel and 95% diesel) and B10 fuel blends. When CNTs added to any fuel blend, the mixed fuel should mix for 15 minutes in the ultrasonic device (manufacturer: Hielscher UP400S, Germany) in order to provide a homogenous emulsion fuel. The experiments were performed on three levels of engine speeds of 1800, 2300, and 2800 rpm under full load with three repetitions.

2.1 Experimental Set-up

The experiments were conducted on a four-stroke, single cylinder, air cooled diesel engine, and its main parameters are presented in Table 1. The engine was running under ambient temperature of 22°C and atmospheric pressure of 878 mbar. In order to determine and measure the engine load and torque, eddy current dynamometer model WE400, was employed with a round speed of 10000 rpm and maximum measuring torque of 80 N m. Details of the measurement and devices for experiments are given in Table 3. The block diagram of temperature setup is shown in Figure 1. To measure the temperature at different points the engine block, the PT100 type-A temperature sensors were used. The measurement and recording of temperature data were done in LabVIEW-2013 software.

Table 1 Specifications of all equipment and devices used in the experiments

Device	Specifications
Test Engine	Lombardini Model 3LD510, single-cylinder, four-stroke, direct injection, air-cooled, cylinder volume of 510 cm^3, 9 kW power at 3000 rpm, rated speed 3000 rpm, 32.8 Nm peak torque at 1800 rpm
Dynamometer	Model WE400, Eddy current dynamometer, Maximum torque of 80Nm, Maximum speed of 10000 rpm
Other Devices and Sensors	-Ultrasonic homogenizer: Hielscher UP400S, Germany. -Fuel flow meter: volumetric type, brand OVAL, made in Japan. -Exhaust temperature sensor: thermocouple type K (0 to 1000°C), -Humidity measurement sensor: (3% to 99%). -Ambient pressure: (700 to 1100 mbar). -Temperature sensor: PT100 (–75 to 400°C).

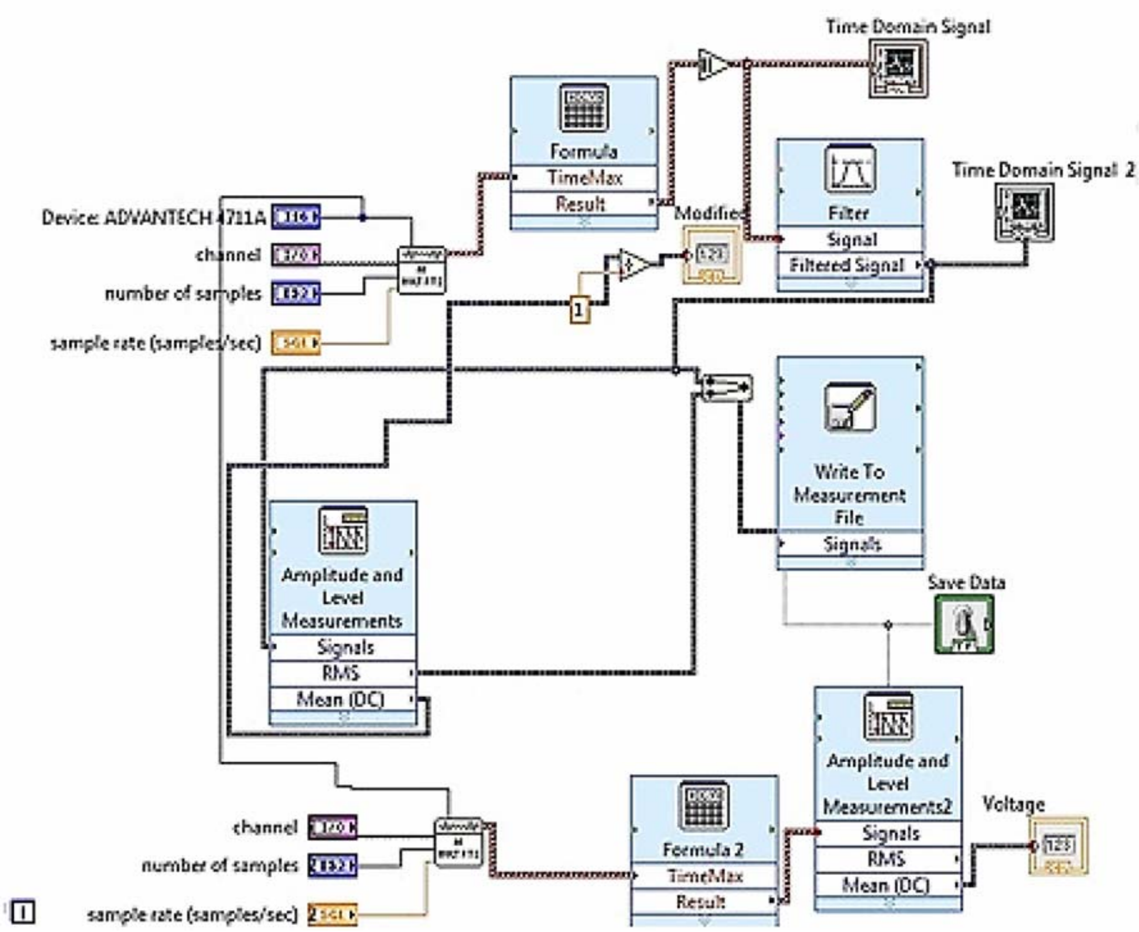


Figure 1 Block Diagram of temperature measurement set up

2.2 Neural network modelling

The development and the training of the network model were carried out, using Neural Network Toolbox of MATLAB software version 8.3. Figure 2 shows the neural network architecture with back propagation neural network model (BPNN) employed in this study. The saved data by LabVIEW-2013 were used for neural networks modeling. The network had three layers: input layer, hidden layer and output layer. There was two input data series (Engine speed: 1800, 2300, 2800 rpm and fueled blends: B0, B5, B10, B5CNT30, B5CNT60, B5CNT90, B10CNT30, B10CNT60, B10CNT90) and two outputs data series (cylinder head and cylinder block temperature), the numbers of neurons in the input and output layer were set on 2 and 2, respectively. In many ANN applications, the back propagation architecture with one hidden layer is enough. Different training algorithms were tested and Levenberg–Marquardt (trainlm) was selected. The activation function for hidden layer was selected to be the tan-sigmoid transfer function which is shown in Table 4 as ‘‘sig’’. The output of this function will fall into (–1, +1) range. Linear function suited best for the output layer which is shown as ‘‘lin’’ in Table 4. Therefore, taking sig/lin as an example, it is meant tan-sigmoid transfer function for hidden layer and linear transfer function for the output layer. This arrangement of functions in function approximation problems or modeling is common and could yield better results. In order to find an optimal architecture, different numbers of neurons in the hidden layer were considered, and prediction error R-value for each network was calculated.

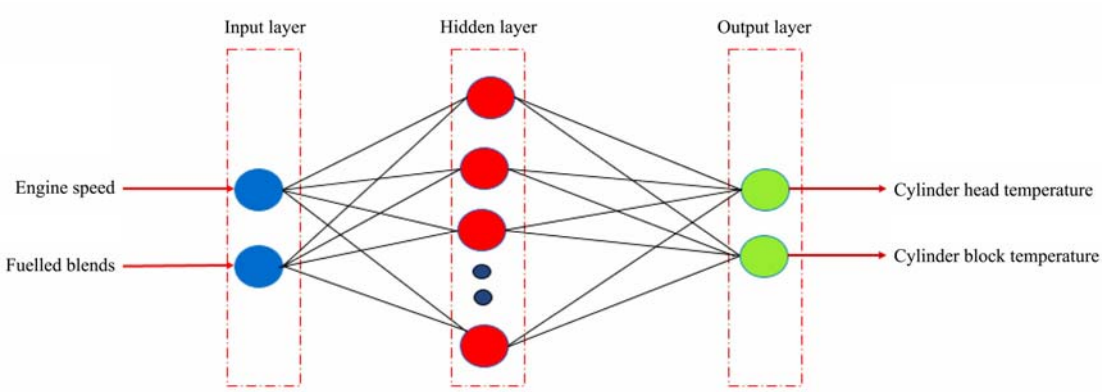


Figure 2 Neural network architecture diagram

3 Results and Discussion

First, the analysis is carried out for temperature of engine’s cylinder block and cylinder head at speeds of 1800, 2300, and 2800 rpm. Then, results for artificial neural network is discussed.

3.1 Fuel properties

Table 2 shows the specifications of the pure diesel and biodiesel fuel, which measured was based on ASTM standard. Moreover, the optimum range for produced biodiesel in ASTM D6751 standard is provided in this table. The cetane numbers of employed fuel blends vary from 58.2 (pure diesel) to 62.5 (biodiesel). Table 3 presents the all fuel blends properties which was measured according to ASTM standard guidelines.

3.2 Experimental results

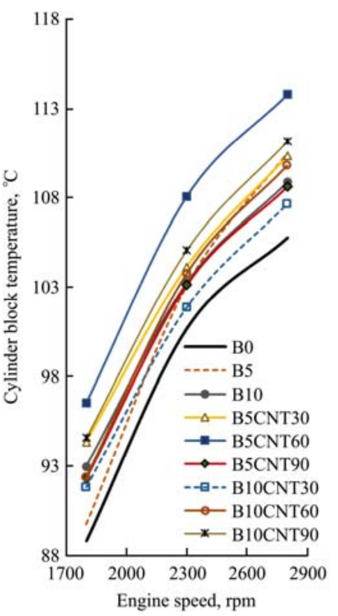
Figure 3a shows the effect of carbon nanotubes that was added to biodiesel on the engine cylinder block temperature. It is seen that the maximum cylinder block temperature for all fuels occurs in speed of 2800 rpm, and with the engine speed increasing, the cylinder block temperature increases. With enhancing the engine speed from 1800 to 2300 and then to 2800 rpm, cylinder block temperature increases by 11.98% and 18.39%, respectively. Overall, the cylinder block temperature rises with increasing the share of CNTs in the fuel blends, which reflects that the improved combustion and the effective energy conversion of fuel has turned to useful work. The cause of this increase can be attributed to the produced energy inside the cylinder that has increased the surface to volume ratio of nanoparticles and the heat transfer coefficient (Ichinose et al., 1992). Figure. 3b shows the effect of CNTs added to B5 and B10 on the cylinder head temperature. Fuel blends of B5CNT60 and B10CNT30 have the highest cylinder head temperature, whereas the B5 and B10 have the lowest value. By increasing the engine speed from 1800 to 2300 and then to 2800 rpm, the cylinder head temperature increases 10.91% and 17.44%, respectively. On the other hand, by adding the CNTs to diesel fuel, the average temperature of cylinder head increases 4.80% for all fuel blends. This can be attributed to that the CNTs is reduced the ignition delay and combustion duration of fuel which lead to higher peak cylinder pressure and faster heat release rate (Kannan et al., 2011; Zhu et al., 2012).

Table 2 The specifications measured based on ASTM standard for diesel and biodiesel fuels

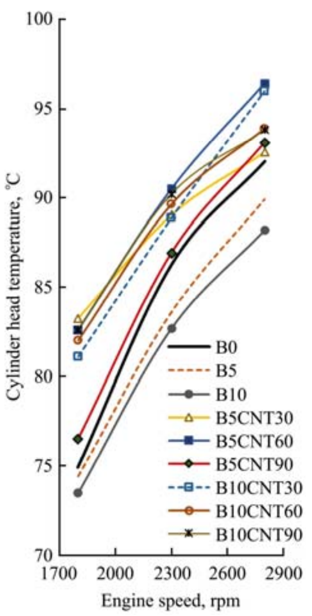
Properties	ASTM	Diesel	Biodiesel (tested)	biodiesel (Standard)	Units
Flashpoint	D-92	64	176	130 min	˚C
Cetane number	D-613	58.2	62.5	47 min	-
Kinematic viscosity at 40˚C	D-445	3.28	4.73	1.9-6.0	$mm^2 s^{-1}$
Water and sediment	D-2709	0.05	0.05	0.05 max	% vol.
Density	-	0.827	0.880		$g cm^{-3}$
Cloud point	D-2500	2	–1	-	˚C
Pour point	D-97	–2	–4	-	˚C
Free Glycerol	D-6584	0.01	0.016	0.02 max	mass%
Copper corrosion	D-130	1a	1a	No.3 max	-

Table 3 The characteristics measured based on ASTM standard for tested fuels (at 15˚C)

Fuel	Density, $g cm^{-3}$	Kinematic viscosity, $mm^2 s^{-1}$	Dynamic viscosity, mPa s	HHV, $mJ kg^{-1}$	LHV, $mJ kg^{-1}$
B5	0.8296	5.5761	4.6261	45.56	42.76
B10	0.8348	5.8481	4.8819	45.46	42.69
B5CNT30 ppm	0.8296	5.6441	4.6821	45.56	42.76
B5CNT60 ppm	0.8295	5.5871	4.6346	45.56	42.76
B5CNT90 ppm	0.8295	5.4241	4.4992	45.56	42.76
B10CNT30 ppm	0.8317	5.6449	4.6949	45.52	42.73
B10CNT60 ppm	0.8319	5.6894	4.7331	45.52	42.73
B10CNT90 ppm	0.8319	5.6694	4.7163	45.52	42.73



a. Engine cylinder block temperature



b. Cylinder head temperature

Figure 3 Diagram of engine block and head temperature at engine speeds of 1800, 2300 and 2800 rpm for different fuel blends

3.3 ANN prediction results

In this study, an ANN model was developed for prediction of the temperature in different points on a diesel engine's block using mentioned fuel blends at three engine speeds. The prediction of engine body temperature was carried out by back-propagation model with Levenberg-Marquardt training algorithm which has previously described. In this model, 70% of the data set was randomly assigned as the training set, while the remaining 30% of data are put aside, 15% for testing and 15% for validation. Therefore, the number of neurons was chosen from 2 to 30 neurons in a hidden layer. The accuracy of the network was evaluated by the mean squared error (MSE) and correlation coefficient (*R*-value). The criterion of MSE and *R* was selected to evaluate networks with optimum solution. A network with one hidden layer and 24 neurons was proved to be an optimum ANN as shown in Table 4. The performance of the network is shown in Figure 4. However, when the increasing number of neurons beyond 24, it has no-significant improvement to the performance of the networks. It can be concluded that the network with 24 neurons in hidden layer give better results of minimum MSE and higher R-value.

A regression analysis between the network output and the corresponding targets was performed in order to investigate the network response in more detail. The results showed the constructed model was sufficient in predicting diesel engine heat at various engine speeds. The ANN predicted outputs versus measured values for the cylinder head temperature (a) and cylinder block temperature (b) are showed in Figure 5. The correlation coefficient (R-value) between the output and target data set for two cases of (a) and (b) are 0.9218, and 0.9301, respectively. So, this indicated that there is a high correlation between predicted model and experimental data.

A Comparison of experimental results and the ANN predictions of model is shown in Figure 6. It was observed that the ANN model can predict engine heat accurately close to actual experiment data.

Table 4 Summary of different networks evaluated to yield the criteria of network performance

Activation function	Training rule	Neurons in Hidden layer	MSE			*R*		
			Training	Validation	Testing	Training	Validation	Testing
Sig/lin	Trainlm	2	2.50	6.04	5.83	0.9869	0.9736	0.9610
Sig/lin	Trainlm	3	2.00	3.49	2.44	0.9885	0.9902	0.9919
Sig/lin	Trainlm	4	1.40	6.94	6.79	0.9932	0.9376	0.9624
Sig/lin	Trainlm	5	0.6288	2.85	3.74	0.9968	0.9917	0.9780
Sig/lin	Trainlm	6	0.4630	2.14	0.3459	0.9973	0.9924	0.9990
Sig/lin	Trainlm	7	0.7786	1.88	5.63	0.9955	0.9927	0.9822
Sig/lin	Trainlm	8	15.20	8.32	48.68	0.9576	0.9806	0.9244
Sig/lin	Trainlm	9	0.5652	7.04	78.82	0.9973	0.9580	0.8971
Sig/lin	Trainlm	10	1.39	29.50	53.25	0.9932	0.9248	0.9048
Sig/lin	Trainlm	11	0.3853	2.40	0.9065	0.9982	0.9891	0.9975
Sig/lin	Trainlm	12	1.31	2.83	5.45	0.9936	0.9900	0.9673
Sig/lin	Trainlm	15	0.1049	6.62	14.10	0.9995	0.9817	0.9953
Sig/lin	Trainlm	18	0.4663	16.13	125.08	0.9976	0.9423	0.6376
Sig/lin	Trainlm	20	1.69	1.60	11.02	0.9915	0.9948	0.9381
Sig/lin	Trainlm	22	1.39	8.44	5.34	0.9961	0.9681	0.9787
Sig/lin	Trainlm	24	0.00095	10.40	9.71	0.9999	0.9487	0.9726
Sig/lin	Trainlm	26	1.80	40.36	60.20	0.9914	0.8597	0.8616
Sig/lin	Trainlm	28	13.49	122.12	13.32	0.9431	0.6429	0.9661
Sig/lin	Trainlm	30	0.0339	12.34	43.50	0.9998	0.9662	0.9458

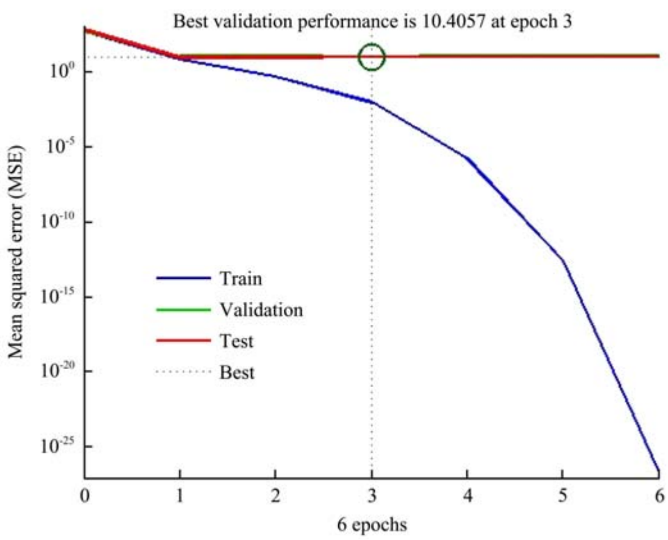


Figure 4 The performance of the optimum ANN model.

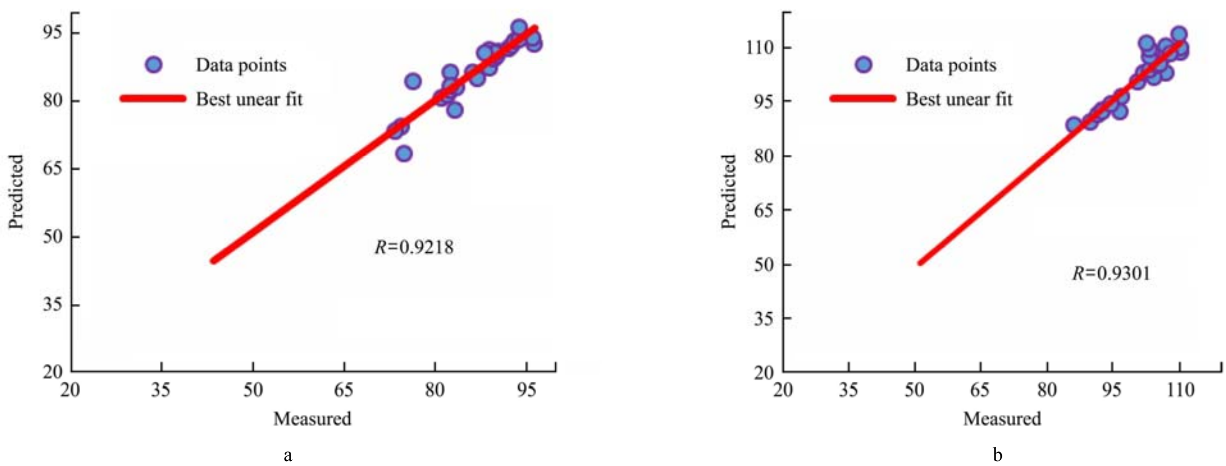
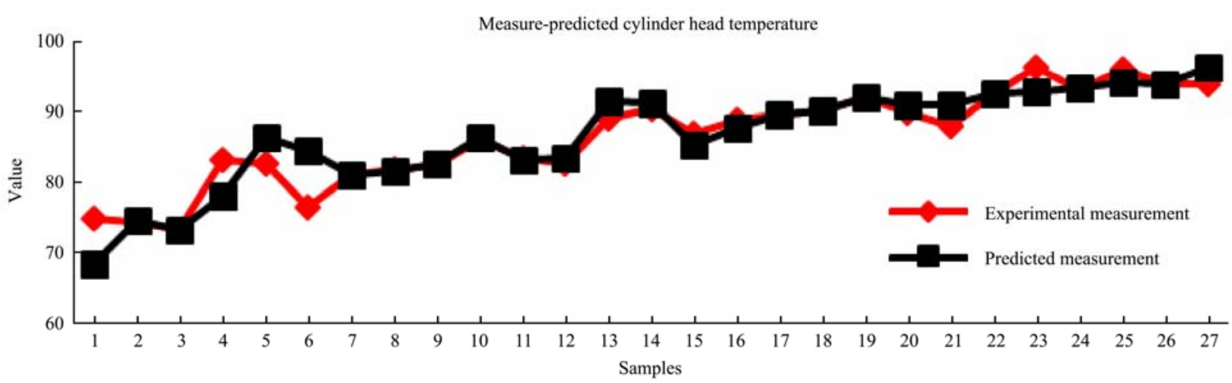
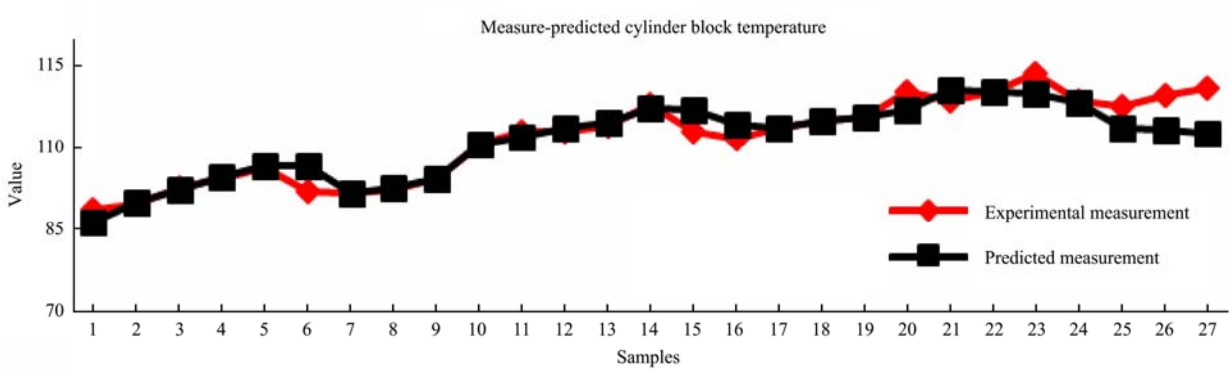


Figure 5 The ANN prediction for the cylinder head temperature (a) and cylinder block temperature (b) versus experimental values



a



b

Figure 6 Comparisons of experimental results and the ANN predictions for the cylinder head temperature (a) and cylinder block temperature (b) for various test patterns

4 Conclusion

In the present study, an artificial neural network (ANN) was developed and tested by the collected temperature data from a single cylinder engine's body using diesel-biodiesel blend with adding of CNTs. From the experiment results, with enhancing the engine speed from 1800 to 2300 and then to 2800 rpm, cylinder block temperature increases by 11.98% and 18.39%, respectively. Also, the cylinder block temperature rises by increasing the share of CNTs in the fuel blends, which reflects that the improved combustion and the effective energy conversion of fuel has turned to useful work. Fuel blends of B5CNT60 and B10CNT30 have the highest cylinder head temperature, whereas the B5 and B10 have the lowest value. The results of ANN analysis showed that the training algorithm of Back-Propagation can predict the temperature of engine cylinder head and cylinder block for different engine speeds and fuel blends. It concluded that for optimum ANN model, the lowest MSE and highest R-value as a criterion for training, validation and testing evaluation were 0.00095, 10.40, 9.71 (MSE), and 0.9999, 0.9487 and 0.9726 (*R*-value), respectively. Analysis of the experimental data by the ANN revealed that there is a good correlation between the predicted data resulted from the ANN and measured ones. Therefore, the ANN proved to be a desirable prediction method to predict the temperature of diesel engine cylinder head and cylinder block with reasonable accuracy. In the case of future studies, it is recommended to measure the body temperature of engine's body simultaneous with the changing of the pressure inside the cylinder for CNTs mixed with diesel-biodiesel blends and the results are modelled by artificial neural network.

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