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Combustion Analysis of a CI Engine Performance Using Waste Cooking Biodiesel Fuel with an Artificial Neural Network Aid

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Abstract: A comprehensive combustion analysis has been conducted to evaluate the performance of a commercial DI engine, water cooled two cylinders, in-line, naturally aspirated, RD270 Ruggerini diesel engine using waste vegetable cooking oil as an alternative fuel. In order to compare the brake power and the torques values of the engine, it has been tested under same operating conditions with diesel fuel and waste cooking biodiesel fuel blends. The results were found to be very comparable. The properties of biodiesel produced from waste vegetable oil was measured based on ASTM standards. The total sulfur content of the produced biodiesel fuel was 18 ppm which is 28 times lesser than the existing diesel fuel sulfur content used in the diesel vehicles operating in Tehran city (500 ppm). The maximum power and torque produced using diesel fuel was 18.2 kW and 64.2 Nm at 3200 and 2400 rpm respectively. By adding 20% of waste vegetable oil methyl ester, it was noticed that the maximum power and torque increased by 2.7 and 2.9% respectively, also the concentration of the CO and HC emissions have significantly decreased when biodiesel was used. An artificial neural network (ANN) was developed based on the collected data of this work. Multi layer perceptron network (MLP) was used for nonlinear mapping between the input and the output parameters. Different activation functions and several rules were used to assess the percentage error between the desired and the predicted values. The results showed that the training algorithm of Back Propagation was sufficient enough in predicting the engine torque, specific fuel consumption and exhaust gas components for different engine speeds and different fuel blends ratios. It was found that the R^2 (R: the coefficient of determination) values are 0.99994, 1, 1 and 0.99998 for the engine torque, specific fuel consumption, CO and HC emissions, respectively.

Key words: Alternative fuel, Biodiesel-diesel blends, Artificial Neural Network

INTRODUCTION

One hundred years ago, Rudolf Diesel tested vegetable oil as fuel for his engine. In 1930s and 1940s vegetable oils were used as diesel fuels, but only in emergency situations[1, 2]. Alternative fuels for diesel engines are becoming increasingly important due to diminishing petroleum reserves and the environmental consequences of exhaust gases from petroleum fuelled engines[3, 4]. A number of studies have shown that triglycerides hold promise as alternative diesel engine fuels. So, many countries are interested in that. For example, evaluation of the production of biodiesel in Europe since 1992 shows an increasing trend [5]. Waste vegetable oil methyl ester is a biodiesel. Biodiesel is defined as the mono alkyl esters of long chain fatty acids derived from renewable lipid sources. Biodiesel, as defined, is widely recognized in the alternative fuel industry. Biodiesel is typically produced through the reaction of a vegetable oil or animal fat with methanol in the presence of a catalyst to yield glycerine and methyl esters [6, 7]. The blend of 75:25 ester/diesel (B25) gave the best performance [8, 9]. The high viscosity, acid composition, and free fatty acid content of such oils, as well as gum formation due to oxidation and polymerization during storage and combustion, carbon deposits, and lubricating oil thickening are some of the more obvious problems. Consequently, considerable effort has gone into developing vegetable oil derivatives that approximate the properties and performance of hydrocarbon-based diesel fuels. Problems encountered in substituting triglycerides for diesel fuels are mostly associated with their high viscosity, low volatility, and polyunsaturated

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character[4]. Lee and his colleagues recently reported that using B20 in diesel engine reduced SO2 emissions which were 19.7 ± 2.5% lower than No. 2 fuel, while NOx emissions were similar[4]. Dorad and his co-workers results showed that using biodiesel resulted in lower emissions of CO up to 58.9%, CO2 up to 86%, excepting a case which presented a 7.4% increase, NO up to 37.5%, and SO2 up to 57.7%, with increase in emission of NO2 up to 81%, excepting a case which presented a slight reduction[4]. Among the attractive features of biodiesel fuel are: (i) it is plant-, not petroleum-derived, and as such its combustion does not increase current net atmospheric levels of CO2 a "greenhouse" gas; (ii) it can be domestically produced, offering the possibility of reducing petroleum imports; (iii) it is biodegradable; and (iv) relative to conventional diesel fuel, its combustion products have reduced levels of particulates, carbon monoxide, and, under some conditions, nitrogen oxides. It is well established that biodiesel affords a substantial reduction in SOx emissions and considerable reductions in CO, hydrocarbons, soot, and particulate matter (PM). There is a slight increase in NOx emissions, which can be positively influenced by delaying the injection timing in engines [4, 10, 11]. From the available literature regarding the use of biofuel blends in IC engines, it is obvious that one has to overcome the obstacles encountered in actual operating conditions. Understanding and implementing these technical know how and reaching to the solid conclusions was the main objective of the present investigation, the results of which is depicted in the present paper. The actual engine performance is the core objective while using biofuel blends. Artificial neural networks (ANN) are used to solve a wide variety of problems in science and engineering, particularly for some areas where the conventional modeling methods fail. A well-trained ANN can be used as a predictive model for a specific application, which is a data-processing system inspired by biological neural system. The predictive ability of an ANN results from the training on experimental data and then validation by independent data. An ANN has the ability to re-learn to improve its performance if new data are available[12]. An ANN model can accommodate multiple input variables to predict multiple output variables. It differs from conventional modeling approaches in its ability to learn about the system that can be modeled without prior knowledge of the process relationships. The prediction by a well-trained ANN is normally much faster than the conventional simulation programs or mathematical models as no lengthy iterative calculations are needed to solve differential equations using numerical methods but the selection of an appropriate neural network topology is important in terms of model accuracy and model simplicity. In addition, it is possible to add or remove input and output variables in the ANN if it is needed. The objective of this study was to develop a neural network model for predicting engine parameters like emission, fuel consumption and torque in relation to input variables such as engine speed and biofuel blends. This model is of a great importance due to its ability to predict engine performance under varying conditions.

MATERIALS AND METHODS

In the present investigation, biodiesel was produced from waste vegetable oil of MEGA Motors Co. restaurant. 1.8 gr KOH (as Alkali catalyst) and 33.5cc methanol (as an alcohol) was applied for 120 gr waste vegetable oil in this reaction. Biodiesel production reaction time was 1 hour with stirring and no heat. Up to one week time needs for separation and washing process. The Waste vegetable oil methyl ester was added to diesel fuel in 10 to 50 percent ratios and then used as fuel for 2 cylinder diesel engine. The experimental setup consists of a diesel engine, an engine test bed and a gas analyzer. The schematic of the experimental setup is shown in fig. 1.

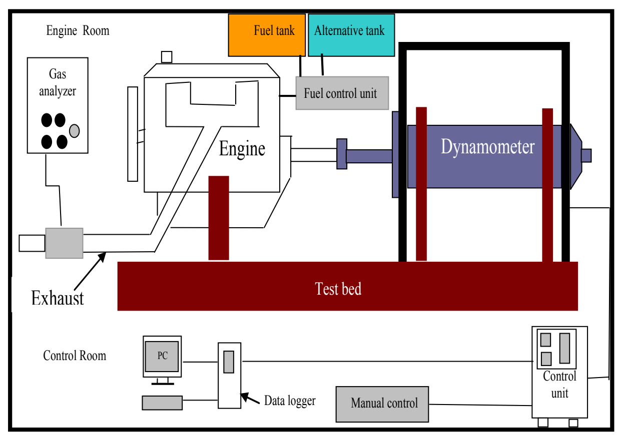


Fig. 1: Engine test setup

There are two fuel tanks, one is for diesel fuel and the other for fuel blends. The engine under study is a commercial DI, water cooled two cylinders, in-line, naturally aspirated, RD270 Ruggerini diesel engine whose major specifications are shown in Table 1. The test engine was coupled to a Schenck W130 electric eddy current dynamometer. A Horiba gas analyzer model MEXA-324GB was used for measuring CO and HC emissions. Engine was run at several speeds at full load and power, torque, fuel consumption and emissions was measured. The matrix of experimentation is shown in Table 2.

Table 1: Engine Specification

No. of cylinder	2
Cooling system	Air cooled
Bore (mm)	95
Stroke (mm)	85
Volume (cc)	1205
Power (hp)	23.4
Rated speed (rpm)	3000
Torque (Nm/rpm)	67/2300
Compression ratio	18:1

Table 2: The matrix of experimentation

Parameter	Levels 1	2	3	4	5	6	7
Speed (rpm)	1200	1600	2000	2400	2800	3200	3600
Load (%)	100	-	-	-	-	-	-
Bio diesel* (%)	0	10	20	30	40	50	-
Diesel fuel (%)	100	90	80	70	60	50	-

* The symbol used for Waste vegetable oil methyl ester is B

NEURAL NETWORK DESIGN

Artificial intelligence (AI) Systems are widely accepted as a technology offering an alternative way to tackle complex and ill-defined problems[13]. They can learn from examples, are fault tolerant in the sense that they are able to handle noisy and incomplete data, are able to deal with nonlinear problems, and once trained can perform prediction and generalization at high speed, They have been used in diverse applications in control, robotics, pattern recognition, forecasting, medicine, power systems, manufacturing, optimization, signal processing, and social/psychological sciences AI systems comprise areas like, expert systems, artificial neural networks, genetic algorithms, fuzzy logic and various hybrid systems, which combine two or more techniques[13]. Artificial Neural Network is a system loosely modeled on the human brain. A biological neuron is shown in (Fig. 2). In brain, there is a flow of coded information from the synapses towards the axon. The axon of each neuron transmits information to a number of other neurons. .According to Haykin a neural network is a massively parallel distributed processor that has a natural propensity for storing experiential knowledge and making it useful. It resembles the human brain in two respects: the knowledge is acquired by the network through a learning process, and inter neuron connection strengths known as synaptic weights are used to store the knowledge[13].

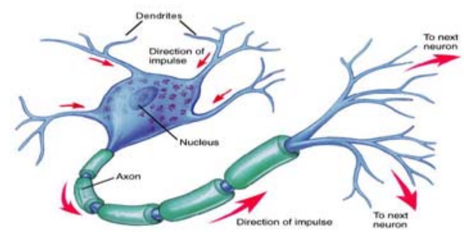


Fig. 2 :A simplified model of a biological neuron

A learning algorithm is defined as a procedure that consists of adjusting the weights and biases of a network, to minimize an error function between the network outputs, for a given set of inputs, and the correct outputs. ANNs have been widely used for many areas, such as control, data compression, forecasting, optimization, pattern recognition, classification, speech, vision, etc. Nowadays, ANNs have been trained to overcome the limitations of the conventional approaches to solve complex problems. ANNs can be trained to solve problems that are difficult for conventional computers or human beings. ANNs, on the other hand, succeed the limitations of the conventional approach by extracting the desired information directly from the data. The fundamental processing element of a neural network is a neuron. Basically, a biological neuron receives inputs from other sources, combines them in someway, performs generally a nonlinear operation on the result, and then outputs the final result. The network usually consists of an input layer, some hidden layers, and an output layer. Each input is multiplied by a connection weight. In the simplest case, products and biases are simply summed, then transformed through a transfer function to generate a result, and finally obtained output. Networks with biases can represent relationships between inputs and outputs more easily than networks without biases. A transfer function consisted generally of algebraic equations is linear or nonlinear. An important subject of a neural network is the training step. There are essentially two types of ANN learning models supervised learning and unsupervised learning. With supervised one, input is presented to the network along with the desired output and the weights are adjusted so that the network attempts to produce the desired output. The weights, after training, contain meaningful information whereas before training they are random and have no meaning. Neural networks that do not rely on the use of target data are trained using unsupervised learning. Instead of trying to map the data input–output relationship, the goal is to find an underlying structure of the data. There are different learning algorithms. A popular algorithm is the back-propagation algorithm, which have different variants. Back-propagation training algorithms gradient descent and gradient descent with momentum are often too slow for practical problems because they require small learning rates for stable learning. In addition, success in the algorithms depends on the user dependent parameters learning rate and momentum constant. Faster algorithms such as conjugate gradient, quasi-Newton, and Levenberg–Marquardt (LM) use standard numerical optimization techniques. These algorithms eliminate some of the disadvantages above mentioned. ANN with back-propagation algorithm learns by changing the weights, these changes are stored as knowledge. LM method is in fact an approximation of the Newton'smethod. The algorithm uses the second-order derivatives of the cost function so that a better convergence behavior can be obtained. In the ordinary gradient descent search, only the first order derivatives are evaluated and the parameter change information contains solely the direction along which the cost is minimized, whereas the Levenberg–Marquardt technique extracts a biter parameter change vector. Suppose that we have a function E(X) which needs to be minimized with respect to the parameter vector x. The error during the learning is called as root-mean squared (RMS) and defined as follows:

$$RMS = \left(\left(\frac{1}{p} \right) \sum_j \left| t_j - o_j \right|^2 \right)^{1/2} \qquad (1)$$

In addition, absolute fraction of variance (R^2) and mean absolute percentage error (MAPE) are defined as follows respectively:

$$R^2 = 1 - \left(\frac{\sum_j \left(t_j - o_j \right)^2}{\sum_j \left(o_j \right)^2} \right) \qquad (2)$$

$$MAPE = \frac{o - t}{o} \times 100 \qquad (3)$$

Where t is target value, o is output value, and p is pattern. Input and output layer are normalized in the (-1,1) or (0,1) range. To get the best prediction by the network, several architectures were evaluated and trained using the experimental data. The back-propagation algorithm was utilized in training of all ANN models. This algorithm uses the supervised training technique where the network weights and biases are initialized randomly at the beginning of the training phase. The error minimization process is achieved using gradient descent rule. There were two input and four output parameters in the experimental tests. The two input variables are engine speed in rpm and the percentage of biodiesel blending with the conventional diesel fuel. The four outputs for evaluating engine performance are engine torque in Nm, Brake Specific Fuel Consumption (bsfc) in lit/KW hr, and emissions including HC and CO in ppm. Therefore the input layer consisted of 2 neurons which corresponded to engine speed and levels of biofuel blends and the output layer had 4 neurons (Fig. 3).

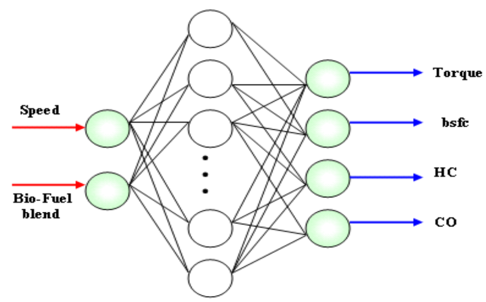


Fig. 3: Configuration of multilayer neural network for predicting engine parameters

The number of hidden layers and neurons within each layer can be designed by the complexity of the problem and data set. In this study, the number of hidden layers varied from one to two. To ensure that each input variable provides an equal contribution in the ANN, the inputs of the model were preprocessed and scaled into a common numeric range (-1,1). The activation function for hidden layer was selected to be logic. Linear function suited best for the output layer. This arrangement of functions in function approximation problems or modeling is common and yields to better results. However many other networks with several functions and topologies were examined which is shown in table1 briefly. Three criteria were selected to evaluate the networks and as a result to find the optimum one among them. The training and testing performance (MSE) was chosen to be .00001 for all

ANNs. The complexity and size of the network was also important, so the smaller ANNs had the priority to be selected. Finally, a regression analysis between the network response and the corresponding targets was performed to investigate the network response in more detail. Different training algorithms were also tested and finally Levenberg-Marquardt (trainlm) was selected. The computer program MATLAB 7.2, neural network toolbox was used for ANN design.

RESULTS AND DISCUSSIONS

Fuels Properties: Transesterification of the waste vegetable oil reduced the viscosity from 31.8 mm^2/s to 4.15 mm^2/s. This achievement paved the way to use the produced biofuel to be used as diesel engine fuel without any engine modifications. The biodiesel high flash point makes it possible for its easy storage and transportation. It should be noted that the diesel fuel flashpoint is 64°C. The biodiesel sulfur content is another interesting advantage of the produced fuel which is 18 ppm only. Comparing the 18 ppm sulfur content of the produced biodiesel with the 500 ppm sulfur content of the diesel fuel used in Tehran operating diesel vehicles, the advantage of the biodiesel over the diesel fuel in terms of the environmental benefits can be justified. This comparison indicates that the sulfur content of biodiesel produced from the waste vegetable oil in Iran is 28 times lesser than the diesel fuels used in Tehran diesel vehicles. An easy way of reducing the diesel fuel sulfur content is the biodiesel blend which is the subject matter of an ongoing research work; its result may be published in near future. Fuel properties are mentioned in Table 3.

Torque and Power: First of all, fuel rack is placed in maximum fuel injection position for full load conditions. Then, the engine is loaded slowly. The engine speed is reduced in this way with increasing load. The trend of performance curves (power and torque) are very common like those mentioned in valid concerned literature. Range of speed was selected between 1200 – 3600 rpm. Engine test results with net diesel fuel showed that maximum torque was 64.2 Nm which occurred at 2400 rpm. The maximum power was 18.12 kW at 3200 rpm. Power and torque for fuel blends at full load is shown in figs. 4 and 5. Considering power and torque performance with fuel blends, one can say that the trend of these parameters versus speed is perfectly similar to net diesel fuel. Fig. 4 and Table 4 show engine speed and engine power relationship at full load condition using net diesel fuel and fuel blends. The net diesel fuel is used as a base for comparison. The fuel blend behavior is similar to that of net diesel fuel in developing power.

Table 3: Fuel properties

Property	Method	Units	Diesel	Biodiesel
Flash point, closed cup	D 93	°C	64	182
Pour point	D 97	°C	0	-3
Kinematical viscosity, 40 ° C	D 445	mm^2/s	4.03	4.15
Sulfated ash	D 874	wt. %		0.00
Total Sulfur	D 5453	wt. %	0.0500	0.0018
Copper strip corrosion	D 130	-	1a	1a
Cloud point	D 2500	°C	2	0
Color	D 1500	-	-	L 1.5

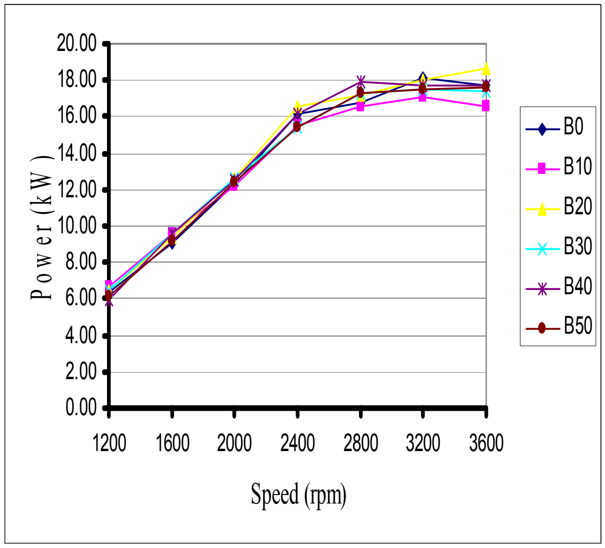


Fig. 4: Relationship between engine speed and engine power for different fuel blends

Fig. 5 and Table 5 show engine torque for all fuels used at full load condition.

Table 4: Engine power at full load using diesel and fuel blends

	B0	B10	B20	B30	B40	B50
1200	6.31	6.67	6.43	6.43	5.92	6.17
1600	9.06	9.59	9.39	9.61	9.56	9.19
2000	12.31	12.23	12.58	12.64	12.48	12.37
2400	16.13	15.47	16.60	15.37	16.10	15.42
2800	16.73	16.59	17.20	17.32	17.94	17.32
3200	18.12	17.05	18.05	17.45	17.75	17.45
3600	17.75	16.59	18.61	17.37	17.71	17.63
average	13.77	13.46	14.12	13.74	13.92	13.65

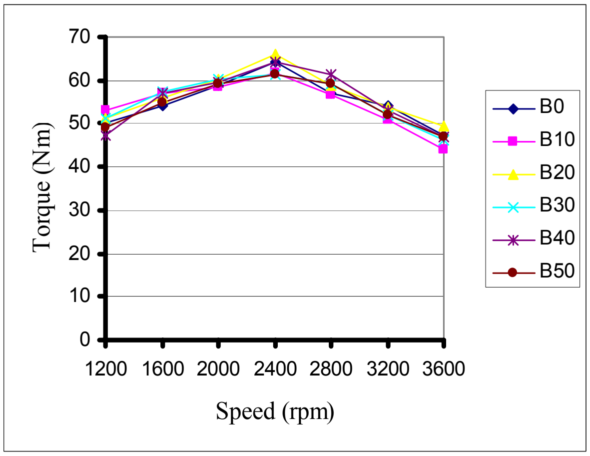


Fig. 5: Relationship between engine speed and torque for different fuel blends

Table 5: Engine torque at full load using diesel and fuel blends

B0	B10	B20	B30	B40	B50
50.2	53.1	51.2	51.2	47.1	49.1
54.1	57.1	56.1	57.4	57.1	54.9
58.8	58.4	60.1	60.4	59.6	59.1
64.2	61.6	66.1	61.2	64.1	61.4
57.1	56.6	58.7	59.1	61.2	59.1
54.1	50.9	53.9	52.1	53	52.1
47.1	43.9	49.4	46.1	47	46.8
55.086	54.514	56.500	55.357	55.586	54.643

Fuel consumption: Fuel consumption curves of net diesel fuel at full load are shown in fig. 6. The curves show that fuel consumption at full load condition and low speeds is high. Fuel consumption first decreases and then increases with increasing speed. The reason is that, the produced power in low speeds is low and the main part of fuel is consumed to overcome the engine friction. Irrespective of fuel consumption at low speed (1200 rpm), fuel consumption is increased with increasing speed. The reason probably is that, friction power increases with increasing speed. Fig. 6 and Table 6 show brake specific fuel consumption with various fuels blend percentage. The curves show that brake specific fuel consumption of fuel blends trends is very similar to net diesel fuel. Brake specific fuel consumption of fuel blends is higher than net diesel fuel. In other words, increasing fuel blend percentage, a mild increase in brake specific fuel consumption is observed.

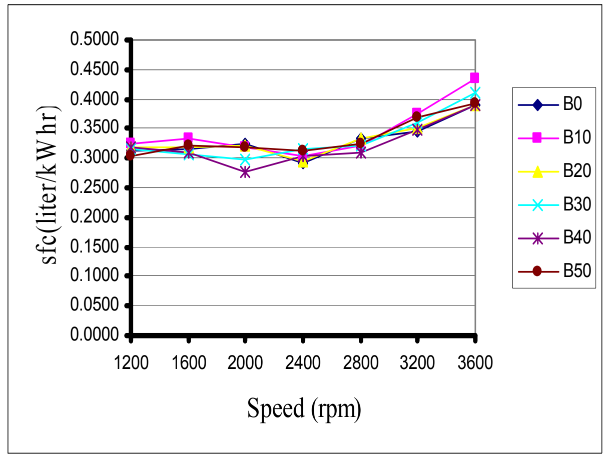


Fig. 6: Effect of fuel blends on bsfc at full load and different speeds

Table 6 shows increased engine brake specific fuel consumption in comparison with net diesel fuel at full load condition and various speeds. This table shows that mean value of engine specific fuel consumption of 10, 20, 30, 40 and 50% blends for various engine speeds is 4.0, 0.8, 0.6, -2.2 and 1.4 percent respectively higher than net diesel fuel.

Exhaust emission: Biodiesel contains oxygen in its structure. When biodiesel is added to diesel fuel, the oxygen content of fuel blend is increased and thus smaller oxygen is needed for combustion. However oxygen content of fuel is main reason for better combustion and CO and HC emission reduction, (figs. 7 and 8).

Table 6: Variation of bsfc using fuel blends with respect to diesel fuel

	B0	B10	B20	B30	B40	B50
1200	0	3.6868	2.359	1.503	2.015	-2.54
1600	0	5.2771	0.902	-3.11	-1.612	1.477
2000	0	-1.90	-0.72	-8.53	-14.72	-2.12
2400	0	4.4496	1.245	8.203	4.702	7.795
2800	0	-3.46	-0.62	-3.63	-7.254	-2.73
3200	0	8.568	2.299	4.669	1.306	7.412
3600	0	11.54	0.160	5.229	0.042	0.766
average	0	4.022	0.802	0.617	-2.218	1.435

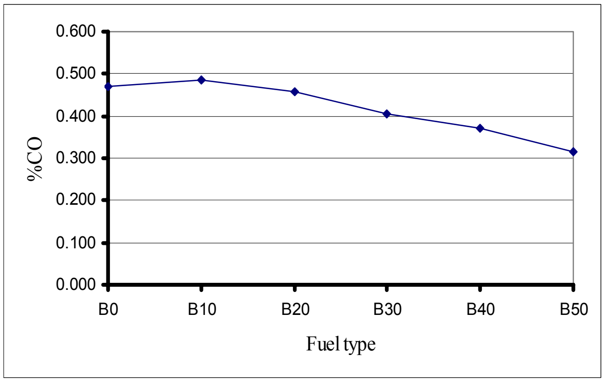


Fig. 7: Effect of fuel blends on average CO emission at full load

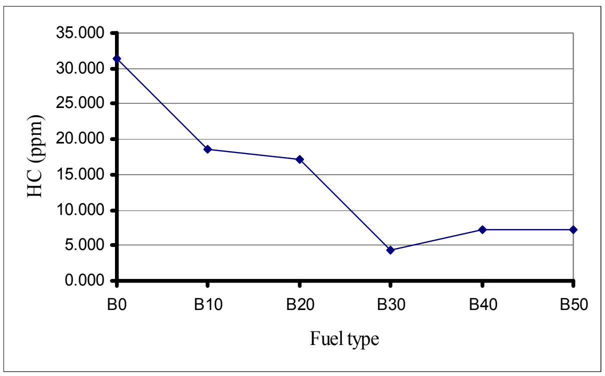


Fig. 8: Effect of fuel blends on average HC emission at full load

A network with one hidden layer and 25 neurons proved to be an optimum ANN as shown in Table 7. R in Table 7 represents the correlation coefficient (R-value) between the outputs and targets. The R-value didn't increase beyond 25 neurons in the hidden layer. Consequently the network with 25 neurons in the hidden layer would be considered satisfactory. The initial weights and bias were 1.3562, -3.7591 and 19.433, respectively in the first layer. The performance of the network in training is shown in fig. 9. The goal for the training was set to 10^{-5}. This ensured a satisfactory response. From all the networks trained, few ones could provide this condition, from which the simplest network was chosen. To have a more precise investigation into the model, a regression analysis of outputs and desired targets was performed as shown in (figs. 9 to 13). There is a high correlation between the predicted values by the ANN model and the measured values resulted from experimental tests. The correlation coefficient was 0.99994 in the analysis of the whole network (Fig. 11), which implies that the model succeeded in prediction of the engine performance.

Table 7: Summary of different networks evaluated to yield the criteria of network performance

Activation function	Training rule	Neurons in hidden layer	Training error	R
sig/lin	trainlm	25	9.996×10^{-6}	**.99997**
tan/lin	trainlm	25	4.6×10^{-4}	.99929
sig/lin	traingdx	25	.0137	-
sig/lin	trainscg	25	8.5×10^{-3}	.99106
sig/lin	trainrp	25	6×10^{-3}	.99221
sig/lin	trainlm	24	6.09×10^{-5}	.9993
sig/lin	trainlm	23	2.1×10^{-4}	.9992
sig/lin	trainlm	22	2.7×10^{-4}	.9995
sig/lin	trainlm	26	9.7×10^{-6}	.99997
sig/lin	trainlm	27	9.39×10^{-6}	.99995
sig/lin	trainlm	28	8.27×10^{-6}	.99997

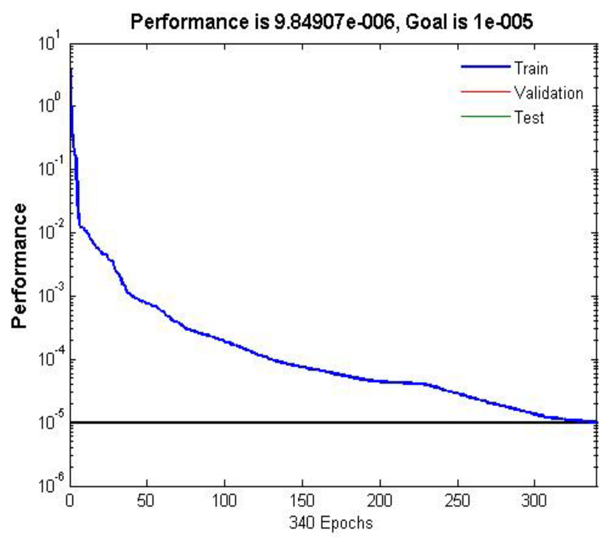


Fig. 9: Training error (MSE) curve

There is a strong correlation in modeling engine torque as depicted in (fig. 11). It is derived from the figs. 11 and 12 that one can definitely predict engine torque and bsfc separately using the designed network. It is also observed in Fig. 13 that the ANN provided the best accuracy in modeling the emission indices (HC and CO). Generally, the artificial neural network offers the advantage of being fast, accurate and reliable in the prediction or approximation affairs, especially when numerical and mathematical methods fail. There is also a significant simplicity in using ANN due to its power to deal with multivariate and complicated problems.

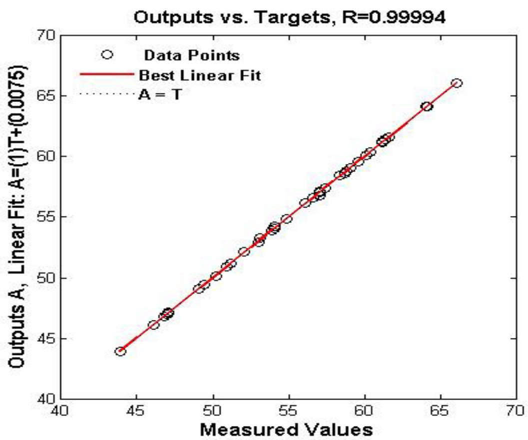


Fig. 10: regression analysis between the network response and the corresponding outputs

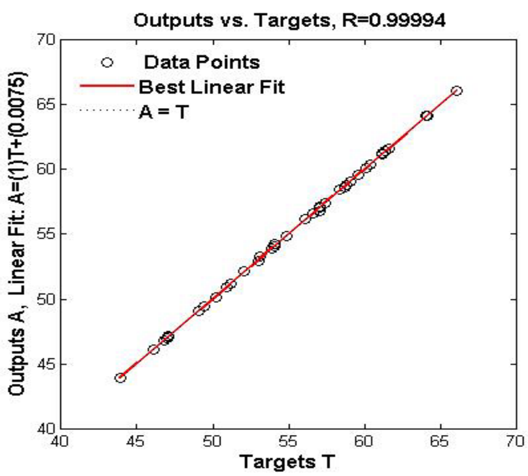


Fig. 11: The predicted outputs vs. the measured values of engine torque

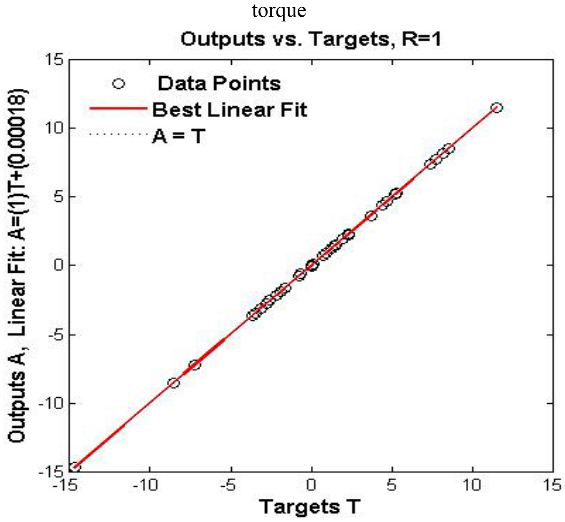
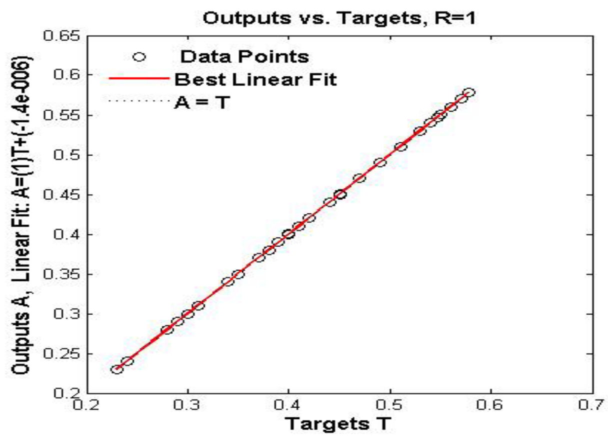
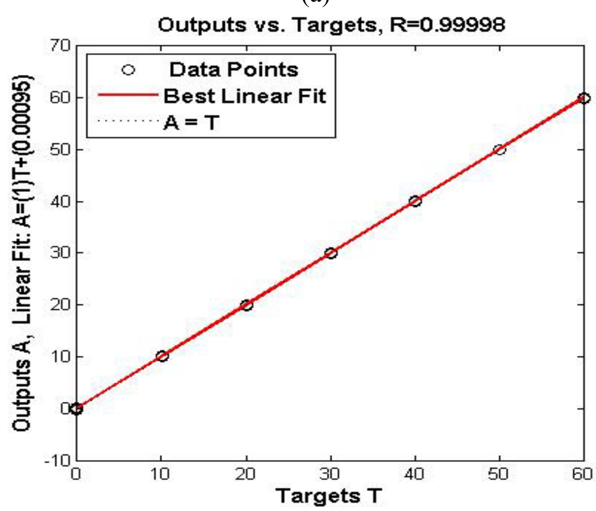


Fig. 12: The predicted outputs vs. the measured values of bsfc



(a)



(b)

Fig. 13: The predicted outputs vs. the measured values, (a) CO (b) HC

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