ARTIFICIAL NEURAL NETWORK MODELING OF JATROPHA OIL FUELED DIESEL ENGINE FOR EMISSION PREDICTIONS

by

Thirunavukkarasu GANAPATHY, Rakesh Parkash GAKKHAR, and Krishnan MURUGESAN

Original scientific paper
UDC: 621.43.041.6:662.756.3
DOI: 10.2298/TSCI0903091G

This paper deals with artificial neural network modeling of diesel engine fueled with jatropha oil to predict the unburned hydrocarbons, smoke, and NO_x emissions. The experimental data from the literature have been used as the data base for the proposed neural network model development. For training the networks, the injection timing, injector opening pressure, plunger diameter, and engine load are used as the input layer. The outputs are hydrocarbons, smoke, and NO_x emissions. The feed forward back propagation learning algorithms with two hidden layers are used in the networks. For each output a different network is developed with required topology. The artificial neural network models for hydrocarbons, smoke, and NO_x emissions gave R^2 values of 0.9976, 0.9976, and 0.9984 and mean percent errors of smaller than 2.7603, 4.9524, and 3.1136, respectively, for training data sets, while the R^2 values of 0.9904, 0.9904, and 0.9942, and mean percent errors of smaller than 6.5557, 6.1072, and 4.4682, respectively, for testing data sets. The best linear fit of regression to the artificial neural network models of hydrocarbons, smoke, and NO_x emissions gave the correlation coefficient values of 0.98, 0.995, and 0.997, respectively.

Keywords: *jatropha oil, injection timing, artificial neural network model, learning algorithm, emissions*

Introduction

Vegetable oils have been considered as one of the most versatile alternative fuel options for petroleum diesel in direct injection diesel engine applications because these oils have substantial prospect as a long-term substitute for diesel fuel [1]. In this context, many varieties of vegetable oils have been used by different countries, but only a very few and non-edible type such as jatropha oil, karanji oil, *etc*. can be considered to be economically affordable to some developing nations like India in particular [2-4].

In general the higher density of jatropha oil makes the fuel spray narrow and its penetration deeper. The higher viscosity of jatropha oil can lead to poor atomization and mixture formation with air. This may result in slower combustion, lower thermal efficiency, higher emissions of unburned hydrocarbons (HC), smoke, *etc*. The higher carbon residue of jatropha oil leads to injector coking which in turn results in poor fuel atomization and consequently high smoke levels [5]. However, with advanced injection timing there will be better combustion and improved performance and also reduction in emissions. Significant improvement in performance and emissions can also be evident with increased injection pressure because of enhanced

atomization at the nozzle outlet, more vapor distribution, and better mixing. At higher injection pressures mean diameter of fuel droplet reduces resulting in better mixing and distribution. However, very high injection pressures lead to fine droplets, which can adversely affect fuel distribution in air [6-8].

Therefore, in order to meet out the emissions norms and legislations, the fuel injection system parameters namely injector plunger diameter, injector nozzle opening pressure, number of nozzle holes and its size, and injection timing need to be modified and optimized in the case of jatropha oil fueled DI diesel engine. Experimental studies to measure the emissions from jatropha oil fueled diesel engine for various injection system design and operating conditions at different load and speed conditions and to optimize the injection system parameters are quite complex, time consuming, laborious, and expensive. The theoretical studies using mathematical models can predict the emissions from these engines, but the accuracy may not be sufficiently satisfactory [9, 10], on account of simplifying assumptions invoked for the calculation of various species of the exhaust gas components. Also developing an accurate mathematical model for the operation of a jatropha oil fueled diesel engine is too difficult due to the complexities involved. Hence the other alternative is to predict the emissions by experimental approach based on artificial neural networks (ANN) model. However, for producing good and reliable results, this approach itself is expensive and time consuming, because of the requirement of large volume of experimental data for precise and accurate training of the networks.

ANN have been applied to estimate desired output parameters when sufficient experimental data is provided. They allow the modeling of physical phenomena in complex systems without requiring explicit mathematical representations. It is evident from the literatures that many researchers have applied the ANN approach to predict the performance and exhaust emissions of gasoline, diesel, and biodiesel engines [9-13]. Neural networks have also been used successfully for analyzing the effect of cetane number on exhaust emissions from engine [14]. Korres *et al*. [15] have applied ANN to evaluate the relationships between lubricity and other diesel fuel properties.

The present paper deals with the development and applicability of an ANN model for the prediction of exhaust emissions of jatropha oil fueled direct injection diesel engine. Experimental results from the literature [5] has been used as the data base for training and testing the present ANN models for predicting the emissions of unburned HC, smoke, and NO_x of the diesel engine fueled with jatropha oil.

ANN model

Artificial neural networks are computational models composed of processing units called neurons connected together to form a network. They are used to solve complex functions. The computation that each neuron performs, along with the way they are interconnected, decides a particular type of neural network. While there are numerous different artificial neural network architectures that have been studied by researchers, the most successful one for the engine emission prediction applications have been multilayer feed forward networks. These are networks in which there is an input layer consisting of nodes that simply accept the input values and successive layers of nodes that are neurons. The outputs of neurons in a layer are inputs to neurons in the next layer. The last layer is called the output layer. Layers between the input and output layers are known as hidden layers.

The development of the ANN model consists of two stages. In the first stage called training, about 2/3 to 3/4 of the total data volume of the input-output set is used to train the network. The intention is to tune the independent parameters of the network, so that it can "learn" the under-

lying relationship between inputs and outputs. In this the weights and bias values are initially chosen randomly and the weights are adjusted, so that the network attempts to predict the desired output. In the second stage called testing, about 1/4 to 1/3 of the total volume of input data sets is employed in the network simulation to validate the network predictions. The typical architecture of feed forward neural network is shown in fig. 1.

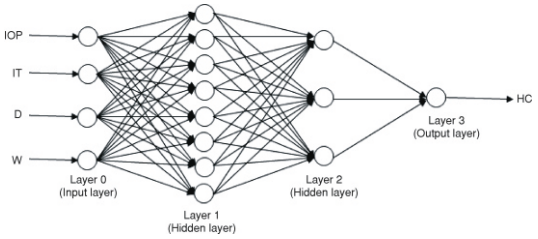

Figure 1. Feed forward back propagation neural network (topology 4-8-3-1)

The networks are trained to perform a particular function by adjusting the values of the connection-strengths between the adjacent elements. For this purpose several learning algorithms are used. All of these algorithms use the gradient of the performance function to determine how to adjust the weights to minimize performance. The gradient is determined using a technique called back propagation, which involves performing calculations backwards through the network. The back propagation computation is derived using the chain rule of calculus. In this back propagation training algorithm, the weights are moved in the direction of the negative gradient to get convergence. After training the ANN model, the network can be simulated for the test input data sets and then they can also be validated for adoption with minimum error rate. Neural networks contain no preconceptions of what the model shape will be, so they are ideal for cases with low system knowledge. They are useful for functional prediction and system modeling where the physical processes are not understood or are highly complex. However, they require a lot of data to give good confidence in the results and hence neural networks are not suitable for small data sets. However, with large number of inputs, the number of connections and hence the complexity increases rapidly.

Methodology

Unfortunately there is no clear theory to guide us on choosing the number of nodes (neurons) in each hidden layer or indeed the number of layers. The common practice is to use trial and error, although there are schemes for combining optimization methods such as genetic algorithms with network training for these parameters. Since trial and error is a necessary part of neural network applications it is important to have an understanding of the standard method used to train a multilayered network. The common method used to train the network is back propagation. While it is possible to consider many activation functions, in practice it has been found that the logistic sigmoid function works best. The training of all sets of a training data group is named an epoch [16].

In the present study the experimentally measured emissions values for different design and operating conditions of the injection system of the jatropha oil fueled diesel engine at several load conditions were used to train and test an artificial neural network. Injector opening pressure (IOP, bar), injection timing (IT, degree CA), and plunger diameter (D, mm) which represents the injection system design and operating parameters and percentage of engine load (W, %) were used as the input layer, while unburned hydro-carbons (HC, ppm), smoke density (S, BSU) and nitrogen oxides (NO_x, ppm) emissions were used as the output layer. The multi-layer feed forward networks of different topology have been used in the model and the back propagation learning algorithm has been applied to the hidden layers. Scaled conjugate gradient (SCG) and Levenberg-Marquardt (LM) algorithms have been used for the variants. Neurons in the input layer have no transfer function while that in the hidden layers have logistic sigmoid (logsig) transfer

function. A linear activation function called purelin transfer function, has been used for the neurons in the output layer. All the input and output data sets have been normalized between 0 and 1 before they are fed to the ANN model.

A computer code has been developed in MATLAB 7.0 and the networks have been trained and tested. In order to have more accuracy of training the networks and to have minimum errors in output prediction, an increased number of neurons in the hidden layers were tried. Initially the network topology with one hidden layer was tried and subsequently number of hidden layers was increased. The ANN architecture, as shown in fig. 1, has been used with different topology for different outputs. It was found that two hidden layers with 8 or 9 neurons in the first hidden layer and three neurons in the second hidden layer give optimum results. First, the networks were trained successfully, and then the test data was used to test the network. With help of results obtained by the network, the outputs are compared using statistical methods. Errors at the learning stage and testing stage are described as the mean square error (*MSE*), R^2, maximum percentage error, and mean percentage error (*MPE*) values. The equations by which these errors are computed are:

$$MSE \quad \frac{1}{p} \sum_{j} \left| t_j \quad o_j \right|^2 \tag{1}$$

$$R^2 \quad 1 \quad \frac{\sum_{j} (t_j \quad o_j)^2}{\sum_{j} o_j^2} \tag{2}$$

$$MPE \quad \frac{1}{p} \sum_{j} \frac{t_j \quad o_j}{t_j} 100 \tag{3}$$

where t_j is the target value for the j^{th} data set, o_j is the output value for the j^{th} data set, and p is the pattern (total number of data sets used).

Results and discussion

The total patterns consisting of 108 input-output data sets have been divided into two samples, one sample consisting of 83 data sets were used as training data (tab. 1) and the other

Table 1. Input-output data sets for training

Plunger diameter [mm]	Injector opening presure [bar]	Injection timing [deg CA]	Engine load [%]	HC [ppm]	Smoke [BSU]	NO_x [ppm]
7	220	33.5	20	404	0.3	142
7	220	33.5	25	403	0.3	200
7	220	33.5	50	419	0.4	247
7	220	33.5	40	435	0.4	386
7	220	33.5	60	498	0.9	326
7	220	33.5	70	603	1.2	1001
7	220	33.5	75	635	1.3	1024
7	220	33.5	90	910	2	1303
7	220	33.5	100	1298	2.4	1431
8	205	32	15	365	0.5	200

Table 1. (continuation)

Plunger diameter [mm]	Injector opening presure [bar]	Injection timing [deg CA]	Engine load [%]	HC [ppm]	Smoke [BSU]	NO_x [ppm]
8	205	32	25	663	0.6	326
8	205	32	30	741	0.7	401
8	205	32	40	852	0.9	636
8	205	32	50	908	1.2	895
8	205	32	70	1185	1.8	1279
8	205	32	75	1307	1.9	1366
8	205	32	80	1583	2.1	1441
8	205	32	100	2290	3.6	1753
8	220	32	15	383	0.3	134
8	220	32	20	481	0.3	228
8	220	32	30	512	0.4	404
8	220	32	40	543	0.5	647
8	220	32	50	618	0.6	903
8	220	32	60	715	0.7	1119
8	220	32	75	878	1.1	1403
8	220	32	80	953	1.3	1551
8	220	32	90	1150	1.7	1930
8	240	32	15	292	0.1	115
8	240	32	20	303	0.2	224
8	240	32	25	304	0.3	333
8	240	32	40	383	0.4	688
8	240	32	50	507	0.5	961
8	240	32	60	609	0.6	1206
8	240	32	70	721	0.7	1560
8	240	32	80	744	1	1819
8	240	32	90	868	1.4	2091
8	240	32	100	1115	1.8	2538
8	260	32	20	385	0.2	284
8	260	32	25	451	0.2	375
8	260	32	30	484	0.3	427
8	260	32	50	604	0.4	1056
8	260	32	60	724	0.5	1306
8	260	32	70	789	0.5	1727
8	260	32	75	855	0.7	1871
8	260	32	90	1031	1.3	2438
8	260	32	100	1417	1.6	2659
8	205	30.5	15	469	0.6	170

Table 1. (continuation)

Plunger diameter [mm]	Injector opening presure [bar]	Injection timing [deg CA]	Engine load [%]	HC [ppm]	Smoke [BSU]	NO_x [ppm]
8	205	30.5	25	725	0.7	220
8	205	30.5	30	871	0.7	257
8	205	30.5	40	915	1.2	484
8	205	30.5	60	1083	1.7	902
8	205	30.5	70	1317	2.1	1107
8	205	30.5	75	1496	2.4	1179
8	205	30.5	80	1752	2.6	1215
8	205	30.5	100	2377	3.9	1540
8	205	33.5	15	413	0.4	196
8	205	33.5	20	469	0.5	324
8	205	33.5	30	592	0.7	463
8	205	33.5	40	692	0.8	707
8	205	33.5	50	792	1	987
8	205	33.5	70	993	1.5	1452
8	205	33.5	75	1049	1.8	1534
8	205	33.5	80	1172	1.9	1626
8	205	33.5	90	1496	2.5	1753
8	205	34.5	20	491	0.5	289
8	205	34.5	25	569	0.5	400
8	205	34.5	40	703	0.6	734
8	205	34.5	50	826	0.8	1053
8	205	34.5	60	926	1	1336
8	205	34.5	75	1250	1.6	1622
8	205	34.5	80	1395	1.8	1745
8	205	34.5	90	1741	2.2	1932
8	205	34.5	100	2210	2.6	2070
9	220	23	15	266	0.1	101
9	220	23	20	283	0.1	135
9	220	23	25	299	0.2	203
9	220	23	30	299	0.2	225
9	220	23	50	315	0.4	473
9	220	23	60	347	0.5	586
9	220	23	70	387	0.5	743
9	220	23	80	428	0.8	890
9	220	23	90	468	1.2	1047
9	220	23	100	517	1.9	1137

Table 2 Input-output data sets for testing

Plunger diameter [mm]	Injector opening pressure [bar]	Injection timing [deg. CA]	Engine load [%]	HC [ppm]	Smoke [BSU]	NO_x [ppm]
7	220	33.5	15	380	0.3	94
8	205	32	20	564	0.6	276
8	220	32	25	491	0.3	309
8	240	32	30	315	0.3	442
8	260	32	40	527	0.3	688
8	205	30.5	50	982	1.4	711
8	205	33.5	60	882	1.2	1290
8	205	34.5	70	1127	1.4	1535
9	220	23	75	412	0.6	822
7	220	33.5	80	691	1.5	1174
8	205	32	90	2002	2.6	1615
8	220	32	100	1555	2.1	2200
8	260	32	15	352	0.1	140
8	205	30.5	20	658	0.7	207
8	205	33.5	25	547	0.6	370
8	205	34.5	30	603	0.6	487
9	220	23	40	307	0.3	338
7	220	33.5	50	458	0.6	641
8	205	32	60	986	1.3	1093
8	220	32	70	812	0.9	1268
8	240	32	75	744	0.8	1682
8	260	32	80	877	0.8	2082
8	205	30.5	90	2165	3.2	1348
8	205	33.5	100	2038	3.4	1868
8	205	34.5	15	413	0.5	190

sample of randomly selected 25 data sets were used as test data (tab. 2). Experimentally measured unburned HC, smoke, and NO_x emission results of neat jatropha oil fueled direct injection diesel engine for different operating conditions were used as the data sets for the present ANN modeling study. The different experimental test conditions were obtained with different combinations of injector opening pressures, injection timing, plunger diameter, and engine loads. The feed forward back propagation networks with topology of 4-8-3-1, 4-9-2-1, and 4-8-3-1 were found to give best predictions of HC, smoke, and NO_x emissions respectively. The *MSE*, R^2, and the *MPE* values were used for comparison. The ANN model emissions results have been shown for both training and testing data in tab. 3. For each output separate network was used.

Table 3. Predicted results of the ANN model

Outputs	ANN topology	Algorithm	*MSE* (Training)	R^2 (Training)	*MPE* (Training)	*MSE* (Testing)	R^2 (Testing)	*MPE* (Testing)
HC	4-8-3-1	LM	9.72E-05	0.9976	2.7603	7.55E-04	0.9904	6.5557
NO_x	4-8-3-1	SCG	1.05E-04	0.9984	3.1136	3.39E-04	0.9942	4.4682
Smoke	4-9-2-1	SCG	9.96E-05	0.9976	4.9524	4.95E-04	0.9904	6.1072

The training plots of the different ANN networks used in the study are shown in fig. 2 for HC, smoke and NO_x emission networks. It can be seen that the goal selected for all the outputs is same (0.0001). Also it is found that the training performance *MSE* value of HC network

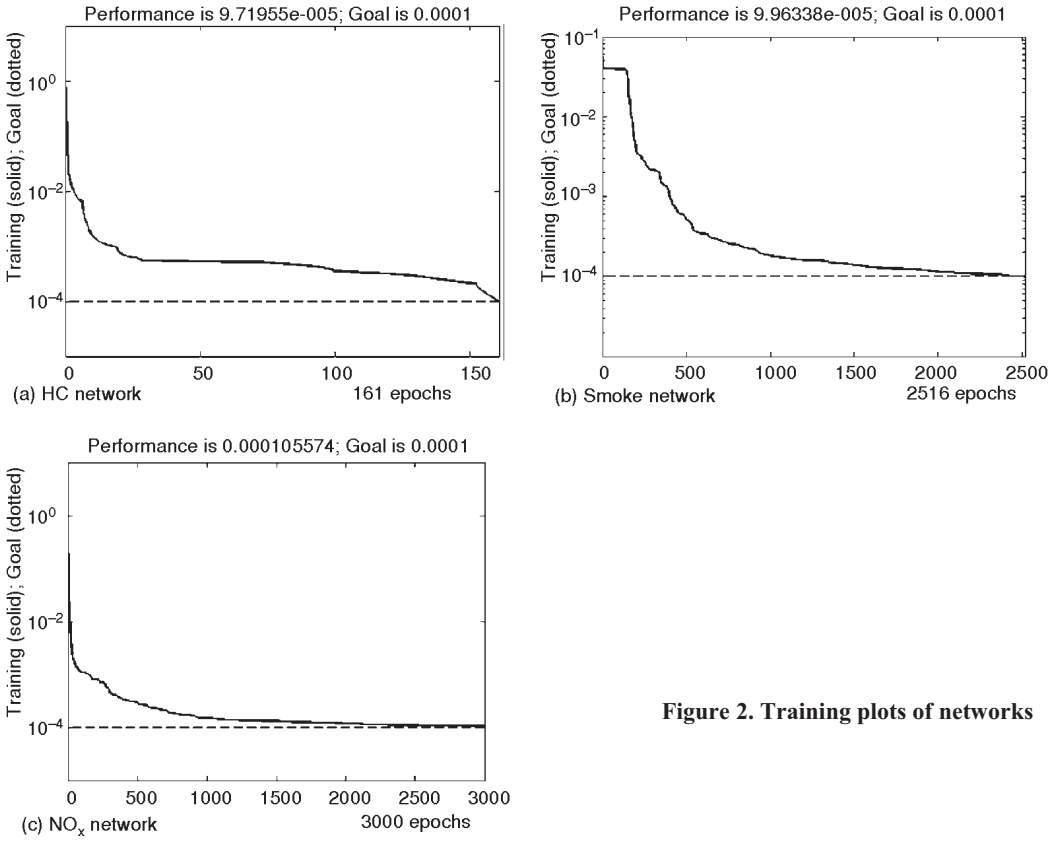

Figure 2. Training plots of networks

as shown in fig. 3(a) and smoke network as shown in fig. 3(b) is less than that of NO_x network model, fig. 3(c). The training number (epochs) used for HC, smoke and NO_x models are 161, 2516, and 3000, respectively. With these training numbers the goal is reached in all the networks. Figure 3 shows the histograms of number of output sets falling on the different range of error percentage values. It is shown in fig. 3(a) that 80% of the output sets fall on the lower error range of ±10% in the case of HC network simulation. Figure 3(b) shows the histogram for the case of smoke and it is about 80% of the output sets falling on the error range of –5 to 10%. Histogram for NO_x shown in fig. 3(c) reveals that 40% and 50% of outputs fall on 0 to –5% and

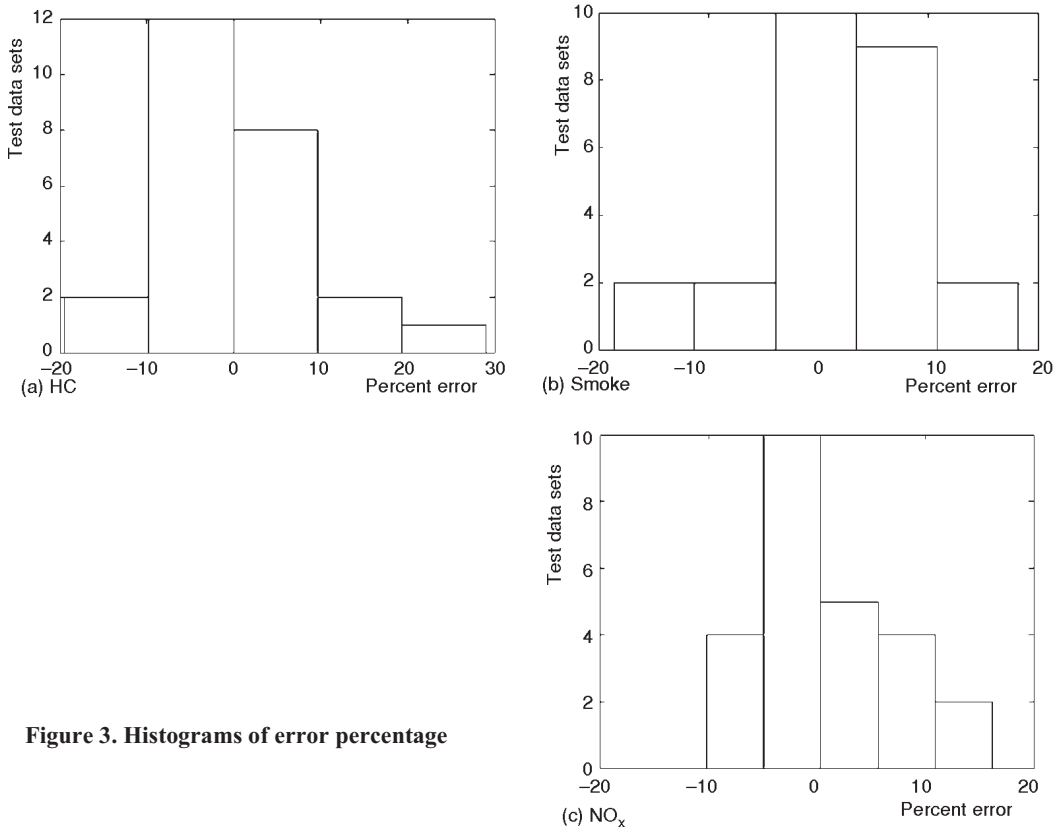

Figure 3. Histograms of error percentage

±10% error range, respectively. It can be observed that small amount of output sets have error range of ±20% while 80 to 90% of the outputs have low error ranges.

The comparison of results predicted by ANN model with experimental results for different emission parameters are given in figs. 4 to 6. It can be noted from the fig. 4 that the model predictions are very close to the experimental values of HC emissions. The R^2 value obtained for the HC model was 0.9904 with *MSE* of 0.0007 and *MPE* of 6.5557. Figure 5 shows that the predicted results of the model very well fit to the characteristic curve of experimental results of

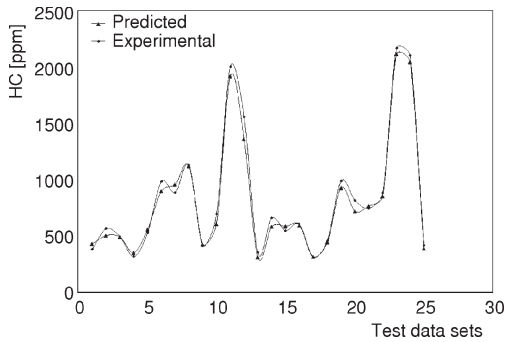

Figure 4. Comparison of experimental and ANN predicted results for HC

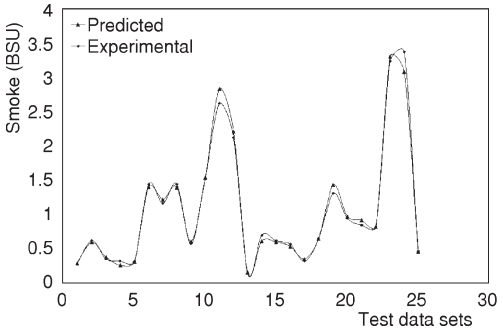

Figure 5. Comparison of experimental and ANN predicted results for smoke

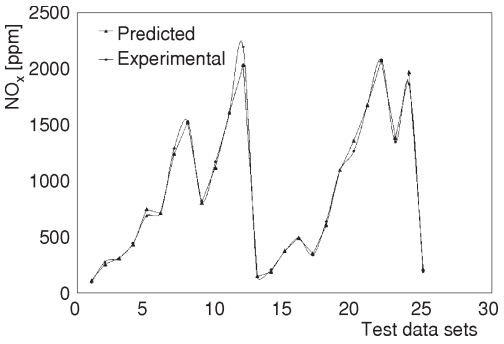

Figure 6. Comparison of experimental and ANN predicted results for NO_x

smoke emissions. The R^2 value obtained for the smoke model was 0.9904 with *MSE* of 0.0005 and *MPE* of 6.1072.

The comparison of results of prediction for the NO_x emissions with their experimental values is given in fig. 6. It can be observed that the two curves are very close to each other. This reveals that predictions of the NO_x model are very well in agreement with the actual values of emission. The R^2 obtained for the model was 0.9942 with *MSE* of 0.0003 and *MPE* of 4.4682. Hence the ANN model can be applied to predict the HC, smoke, and NO_x emissions of jatropha oil fueled diesel engine for a given injection timing, injector opening pressure, plunger diameter, and engine load conditions.

The performance of a trained network can be measured to some extent by the errors on the training, validation, and test sets, but it is often useful to investigate the network response in more detail. One option is to perform a regression analysis between the network response and the corresponding targets. The regression analysis is performed on these three ANN models to confirm the suitability of the networks. Figures 7 shows the results of regression analysis performed on HC, smoke, and NO_x networks. It can be noted from fig. 7(a) that the best linear fit of the HC model has a slope of 0.989 and y intercept of 0.00249 which are, respectively, very near to 1 (the slope of the case where the response *A* is exactly equal to target *T* and zero (the y intercept of the case where the response is

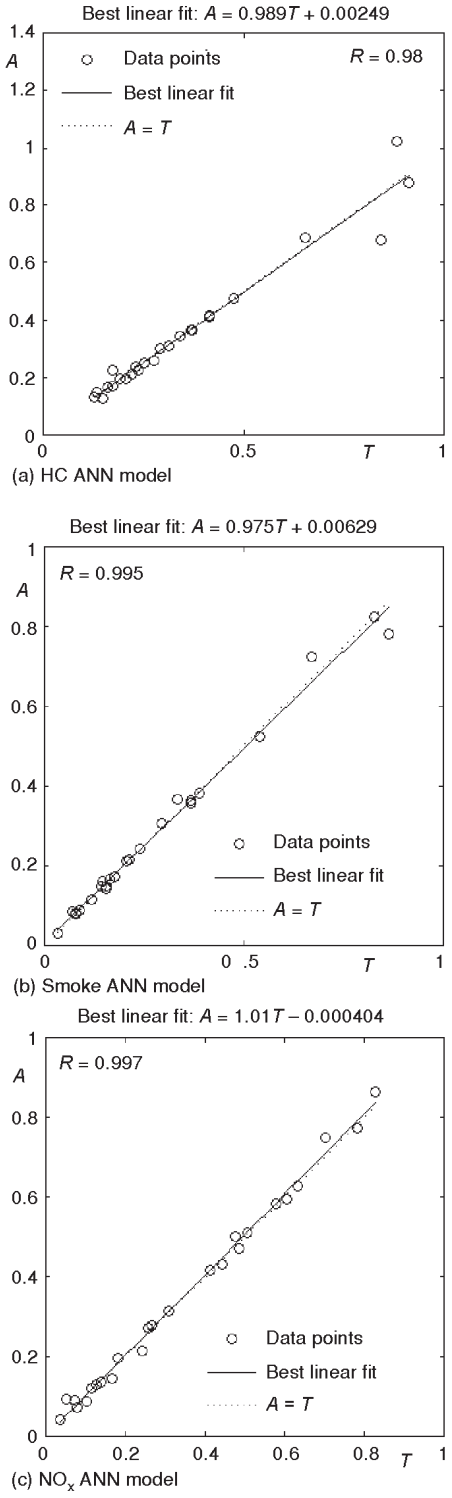

Figure 7. Linear fits of ANN models

exactly equal to target), and figs. 7(b) and 7(c) show that the slopes of best fits of smoke and NO_x network models are also very near to 1 while their y intercepts are very near zero. However the slope of the best linear fit of the NO_x emission model is higher than that of others.

The correlation coefficient (R value) between the outputs and targets provides the measure of how well the variation in the outputs A is explained by targets T. The R value of very close to 1 indicates a good fit. The fig. 7 indicates that the correlation coefficient values of all the networks are very near to 1 and thus give good fits.

Conclusions

The ANN models have been developed for predicting the HC, smoke and NO_x emissions of jatropha oil fueled direct injection diesel engine. Four inputs namely, injection timing, injector opening pressure, plunger diameter and engine load are used as the input layer while the output is either HC, or smoke, or NO_x emissions. Feed forward back propagation learning algorithms with two hidden layers with 8 or 9 neurons in the first hidden layer and 2 or 3 neurons in the second hidden layer are used. About 77% of the total data sets have been used for training and 23% have been used for testing. The ANN models for HC, smoke and NO_x emissions yielded R^2 values of 0.9976, 0.9976 and 0.9984 and mean percent errors are smaller than 2.7603, 4.9524, and 3.1136, respectively, for training data sets, while the R^2 values are 0.9904, 0.9904, and 0.9942 and mean percent errors are smaller than 6.5557, 6.1072, and 4.4682, respectively, for testing data sets. The best linear fit of regression to the ANN models of HC, smoke, and NO_x emissions have yielded the correlation coefficient values of 0.98, 0.995, and 0.997, respectively. The results may easily be well thought-out to be within the acceptable limits. Hence these ANN models may be considered for predicting the emissions in jatropha oil fueled diesel engines.

References

[1] Forson, F. K., Oduro, E. K., Hammaond Donkoh, E. Performance of Jatropha-Oil Blends in a Diesel Engine, *Renewable Energy, 29* (2004), 7, pp. 1135-1145

[2] Joshi, H. C., Biodiesel from Jatropha an Alternative Fuel for the Future, *Invention Intelligence*, Scientific Research Magazine, National Research Development Corporation New Delhi, Sep.-Oct. 2003, pp. 205-216

[3] Senthil Kumar, M., Ramesh, A., Nagalingam, B., An Experimental Comparison of Methods to Use Methanol and Jatropha-Oil in a Compression Ignition Engine, *Biomass and Bioenergy, 25* (2003), 3, pp. 309-318

[4] Pramanik, K. Properties and use of Jatropha Curcas Oil and Diesel Blends In Compression Ignition Engine, *Renewable Energy, 28* (2003), 2, pp. 239-248

[5] Narayana Reddy, J., Ramesh, A., Parametric Studies for Improving the Performance of a Jatropha-Oil Fueled Compression Ignition Engine, *Renewable Energy, 31* (2006), 12, pp. 1994-2016

[6] Yamane, K., Ueta, A., Shimamoto, Y., Influence of Physical and Chemical Properties of Bio-Diesel Fuels on Injection, Combustion and Exhaust Emission Characteristics in a Direct Injection Compression Ignition Engine, *Int J Engine Res, 2* (2001), 4, pp. 249-261

[7] Celikten, I., An Experimental Investigation of the Effect of Injection Pressure on the Engine Performance and Exhaust Emission in Indirect Injection Diesel Engines, *Applied Thermal Engineering, 23* (2003), 16, pp. 2051-2060

[8] Icingur, Y., Altiparmak, D., Effect of Cetane Number and Injection Pressure on a DI Diesel Engine Performance and Emissions, *Energy Convers Manage, 44* (2003), 3, pp. 389-97

[9] Arcaklioglu, E., Celikten, I., A Diesel Engine's Performance and Exhaust Emissions, *Applied Energy, 80* (2005), 1, pp. 11-22

[10] Canakci, M., Erdil, A., Arcaklioglu, E., Performance and Exhaust Emissions of a Biodiesel Engine, *Applied Energy, 83* (2005), 6, pp. 594-605

[11] Cenk Sayin, H. *et al.*, Performance and Exhaust Emissions of a Gasoline Engine Using Artificial Neural Network, *Applied Thermal Engineering, 27* (2007), 1, pp. 46-54
[12] Golcu, M., *et al*., Artificial Neural Network Based Modeling of Variable Valve-Timing in a Spark-Ignition Engine, *Applied Energy, 81* (2005), 2, pp. 187-197
[13] Celik, V., Arcaklioglu, E., Performance Maps of a Diesel Engine, *Applied Energy, 81* (2005), 3, pp. 247-259
[14] Deng Yuanwang, *et al*., An Analysis for Effect of Cetane Number on Exhaust Emissions from Engine with Neural Network, *Fuel, 81* (2002), 15, pp. 1963-1970
[15] Korres, D. M., *et al*., A Neural Network Approach to the Prediction of Diesel Fuel Lubricity, *Fuel, 81* (2002), 10, pp. 1243-1250
[16] Haykin, S., Neural Networks: a Comprehensive Foundation, MacMillan Publishing Company, New York, USA, 1994

Authors' affiliations:

T. Ganapathy (**corresponding author**)
Internal Combustion Engines Laboratory,
Mechanical and Industrial Engineering Department,
Indian Institute of Technology Roorkee,
Roorkee 247667, India
E-mail: tganappathi@yahoo.co.in

R. P. Gakkhar, K. Murugesan
Internal Combustion Engines Laboratory,
Mechanical and Industrial Engineering Department,
Indian Institute of Technology Roorkee,
Roorkee, India

Paper submitted: September 29, 2008
Paper revised: March 23, 2009
Paper accepted: April 18, 2009