International Journal of Automotive Technology, Vol. 6, No. 2, pp. 95−105 (2005)

1229−9138/2005/020−03

PREDICTION OF EMISSIONS USING COMBUSTION PARAMETERS IN A DIESEL ENGINE FITTED WITH CERAMIC FOAM DIESEL PARTICULATE FILTER THROUGH ARTIFICIAL NEURAL NETWORK TECHNIQUES

N. BOSE* and I. RAGHAVAN

Department of Mechanical Engineering, Mepco Schlenk Engineering College, Sivakasi-626005, Tamilnadu, India

(Received 4 March 2004; Revised 3 August 2004)

Abstract–Diesel engines have low specific fuel consumption, but high particulate emissions, mainly soot. Diesel soot is suspected to have significant effects on the health of living beings and might also affect global warming. Hence stringent measures have been put in place in a number of countries and will be even stronger in the near future. Diesel engines require either advanced integrated exhaust after treatment systems or modified engine models to meet the statutory norms. Experimental analysis to study the emission characteristics is a time consuming affair. In such situations, the real picture of engine control can be obtained by the modeling of trend prediction. In this article, an effort has been made to predict emissions smoke and NOx using cylinder combustion derived parameters and diesel particulate filter data, with artificial neural network techniques in MATLAB environment. The model is based on three layer neural network with a back propagation learning algorithm. The training and test data of emissions were collected from experimental set up in the laboratory for different loads. The network is trained to predict the values of emission with training values. Regression analysis between test and predicted value from neural network shows least error. This approach helps in the reduction of the experimentation required to determine the smoke and NOx for the catalyst coated filters.

KEY WORDS : In-cylinder parameters, Diesel particulate filter (DPF), Catalyst coating, Artificial neural network techniques (ANN), Back propagation method, Emission prediction

1. INTRODUCTION

Diesel engines are used as prime movers for heavy duty vehicles due to their high efficiency and low specific fuel consumption. Their application in the light duty vehicles has also increased over the recent years. Considering the stringent emission control legislations, the statutory limits have become even more severe. The main pollutants are smoke, HC, NO_x and Particulate matter (Heywood, 1988). But Diesel engines have become more popular than other engines, because of the better torque characteristics exhibited and the fuel economy. Neural network (NN) models have been studied in recent years, with an objective of achieving human like performance in many fields of knowledge engineering. NN applications are growing rapidly as artificial intelligence tools in the area of pattern recognition. The feasibility of using the in-cylinder pressure – based variables in a diesel engine, has been explored to predict gaseous exhaust emissions through the use of artificial neural networks (Traver *et al.*, 1999).

A mathematical model of a catalytic converter, for predicting exhaust emissions with in-cylinder parameters for an engine has been developed (Bhagavantrarao *et al.*, 1989).

As the soot has to be removed periodically, when a Diesel particulate filter (DPF) is used, some method is to be found to burn the soot. The regeneration behaviour and transient thermal response of diesel particulate filters were studied and temperature was considered to be a very important parameter as it influences emissions (Rumminger *et al.*, 2001). Pressure drop across the DPF is measured by a manometer which shows the pressure difference between the inlet and the outlet. Pressure drop implies the extent and effectiveness of combustion of accumulated soot particles within the DPF. Many researchers have worked on the pressure drop of diesel particulate filters and it is widely considered for prediction of emissions (Athanasios *et al.*, 2001; Pontikakis *et al.*, 2001; Versaevel *et al.*, 2000; Sathish *et al.*, 1999; Athanasios and Konstandopoulos, 1999; Athanasios and Evangelos, 1999; Julian *et al.*, 1996; Athanasios and John

**Corresponding author.* e-mail: nbose@mepcoeng.ac.in

Table 1. The specifications of the engine and test equipments.

Sl. No	Item	Description
1.	Engine type	Four Stroke, Single cylinder, Diesel, Constant Speed, Water cooled
2.	Make/Model	Kirloskar TV1
3.	BHP	7.0 at 1500 rpm (5.15 kW)
4.	Bore × Stroke (mm)	87.5 × 110.0
5.	Cyclic capacity	0.6615lit (0.6615×10^{-3} m^3)
6.	Normal Compression ratio	17.5:1
7.	Dynamometer type	Eddy current
8.	Lever arm at load cell	Load measurement by load cell.
9.	Speed measurement	Sensor with digital indicator
10.	Fuel flow measurement	Fuel measuring unit and flow transmitter
11.	Air flow measurement orifice diameter	Orifice meter with manometer and DP transmitter
12.	Air flow measurement	Rota meter
13.	Temperature measurement	RTD PT-100 sensors and transmitters
14.	Cylinder pressure measurement	Piezo sensor
15.	Crank position/speed	Rotary encoders
16.	Analysis	Through computer
17.	Interfacing	ADC/DAC card engine indicator-AX104
18.	Power consumption	1 kW max.
19.	Overall dimension	4000 × 2500 × 1500(Ht) mm.

1989). It has been found from literature that copper is a good catalyst for smoke reduction and iron is good catalyst for NOx reduction (Saravanan *et al.*, 1999).

In this article, the Diesel particulate filter parameters have also been taken into account along with the in-cylinder combustion derived parameters for prediction of emissions. These parameters are used in a MATLAB software program for the prediction of Smoke and NO_X at the DPF exit, through the use of artificial neural network techniques.

2. EXPERIMENTAL SETUP

A Kirloskar-make single cylinder four stroke diesel engine served as the test facility.

All the signals from the sensors have been interfaced to the computer. The computer can also display Pressure-crank angle diagrams. The software enables real time logging and off-line data analysis. The schematic diagram of the test set up is shown in Figure 1.

The specifications of the engine and test equipments are given in Table 1.

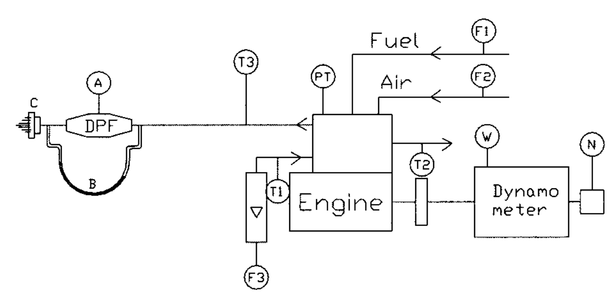
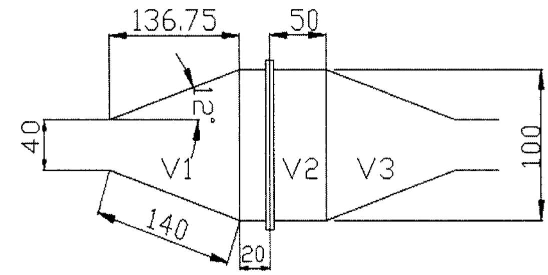


Figure 1. Schematic diagram of test set-up.
A – Thermometer to measure trap inlet temperature.
B – Exhaust pipe.
C – Manometer
DPF – Diesel Particulate Filter
F_1 – Fuel flow rate in Kg/hr.
F_2 – Air flow rate in Kg/hr.
F_3 – Jacket water flow rate in Kg/hr.
N – Engine speed in rpm.
T_1 – Jacket water inlet temperature in K.
T_2 – Jacket water outlet temperature in K.
T_3 – Exhaust gas temperature in K.

3. DESIGN OF DPF

A catalyst coated ceramic foam trap has been used in this investigation. Diesel Particulate Filter cover volume is equal to three times the volume of engine cylinder as shown in Figure 2. As noted from literature, ceramic foam trap length has been made equal to trap diameter and DPF cover volume equal to engine displacement (Athanasios *et al.*, 1989).

Space velocity is an important factor in the design of DPF.



All dimensions are in mm

Figure 2. Diesel particulate filter cover.

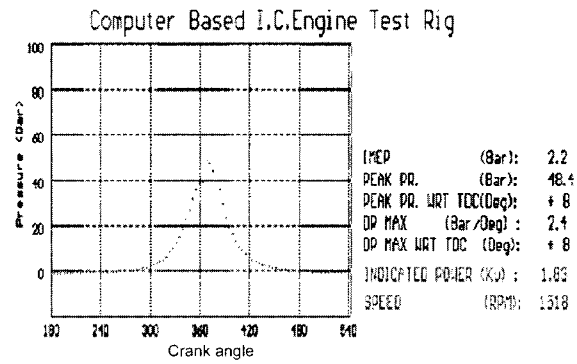


Figure 3. Typical pressure-crank angle diagram.

$$\text{Space Velocity} = \frac{\text{Exhaust gas flow rate m}^3\text{h}}{\text{DPF Volume in m}^3}$$

According to the Federal test procedure, the oxidizer is designed for space velocities in the range of 1,00,000 to 1,50,000 h^{-1} at rated engine conditions. By conducting the test at maximum load conditions and considering the amount of exhaust gases, space velocity at the rate of 1,13,000 h^{-1} has been considered for designing the DPF.

Figure 2 represents the diesel particulate filter cover. The catalytically coated ceramic foam trap 10 pores per inch approximately of 100 mm × 100 mm × 66 mm is fitted inside the DPF cover. A digital temperature indicator located at the center of DPF in the wall is used for measuring the wall temperature. Pressure drop across the DPF is measured with a mercury manometer.

4. COLLECTION OF DATA

NAVCO make Kane-May International 9106 (Quintox) gas analyzer is used to measure NOx. A Bosch smoke meter is used to measure smoke. To provide a wide range of performance and emissions, 50 readings have been taken for different load conditions from no load to full load. Every time, the load was changed and the speed was brought to rated value to provide steady exhaust emissions.

The combustion derived parameters (Traver *et al.*, 1999) for the in cylinder conditions were displayed along with pressure-crank angle diagram (Figure 3) and also calculated by empirical correlations. Tables 2 and 3 show the various combustion derived parameters from the cylinder pressure data and DPF respectively.

The parameters representative of combustion measured for the DPF are wall temperature and pressure drop.

Table 2. Combustion derived parameters from cylinder pressure data.

Shorthand Abbreviation	Explanation	Definition and contribution
pp	Peak pressure	Maximum pressure encountered in individual cycle (kPa)
ppl	Location of peak pressure	Location of the maximum pressure encountered (CA°)
imep	Indicated mean effective pressure	Integrated work for the compression and expansion cycles, divided by the displacement of a single cylinder (kPa).
id	Ignition delay	Time in crank angle degrees from fuel injected to the measured start of combustion (CA°).
cd	Combustion duration	Time in crank angle degrees from 10% to 90% of the mass fraction burned curve (CA°).
maxq	Maximum heat release	Maximum value of the instantaneous heat release used to calculate the mass fraction burned (kJ/deg.).
mql	Maximum heat release location	Location of the maximum heat release (CA°).
lmf b50	Location of mass fraction burned – 50%	Location of 50% of the integrated mass fraction burned curve (CA°).

Table 3. Combustion derived parameters from DPF.

Shorthand Abbreviation	Explanation	Definition and contribution
prdr	Pressure drop	Pressure drop across the DPF, measured with a mercury manometer.
wt	Wall temperature	Temperature depends on the reaction inside the DPF, measured with a digital temperature indicator.

Irrespective of catalytic coating in the ceramic foam filter, the pressure drop and wall temperature obtained by measurement, will bring to light, the extent of combustion inside the DPF.

5. ARTIFICIAL NEURAL NETWORK (ANN) TECHNIQUES

Artificial neural networks are composed of elements that perform in a manner that is analogous to the biological neuron. Given a set of inputs, perhaps with desired outputs, they self adjust to produce consistent responses. The Neural Networks are used in universal approximation i.e., mapping input to the output. They are capable of learning from their environment. They are used as a tool for finding non-evident, non-linear dependencies between data. The artificial neuron will have many inputs and output. The structure of a single neuron is given in Figure 4.

The neuron has a set of nodes that connects it to inputs, output, or other neurons, also called synapses. A Linear combiner is a function that takes all inputs and produces a single value. A simple way of doing it is by adding together the inputs multiplied by the synaptic Weight. The sum of the weights is then given to the activation function.

The input should not be linear. Applying the activation function takes any input from minus infinity to plus infinity and squeezes it into -1 to 1 or 0 to 1 interval. The threshold then acts on the activation function to give the output value.

The number of neurons in the inner layers also called hidden layers is not specific. When the number becomes too few, the quality of prediction will drop and the network doesn't behave as the brains do. If it is made too many – it will have a tendency to "remember" the right answers, rather than predicting them. Then the neural network will work very well on the familiar data, but will fail on the data that had never been presented before. Finding the compromise is more of an art, than science.

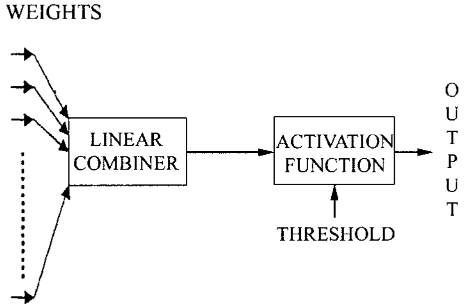


Figure 4. Structure of a neuron.

The neural network receives inputs, which can be of different kinds. When the neuron in the first layer receives its input, it will apply the Linear Combiner and the activation function to the inputs and produce the output. This output will become the input for the neurons in the next layer. Thus the next layer will feed forward the data, to the next layer until the last layer is reached.

The predicted output is then compared with the target value and the error is then calculated as

Error = (Desired output – Predicted output)

The weights and biases are then calculated according to the error obtained. Epoch is the presentation of the set of training (input and/or target) vectors to a network and the calculation of new weights and biases. The training vectors can be presented one at a time or all together in a batch.

Back propagation is a technique used to train multi-layer feed-forward neural networks. It is used to calculate previous layer weight and bias corrections by using the learning rate and the layer error predictions as

Net Weight =
(Old Weight × Adjustment × Learning Rate)

The learning rate is an important factor. For example, when it is set to 0.01, it will take 100 patterns to make a 10% adjustment. Momentum is something that can speed up calculations significantly.

To train the neural network, the inputs are presented to determine the values of the hidden layer and of the output layer. The results of the output layer are compared with the correct results. Then the weights in W and V are adjusted so that they are closer to produce that output. The rule used for modifying the weights is known as the delta rule, because it changes each weight according to how much it had in the final outcome (the delta, or partial derivative of the output with respect to the weight). This rule is applied to all the weights at the same time and the

W weights are not changed and those new weights are used in the V equation.

Adoption of Neural Network Techniques

The emission pattern with respect to load in a diesel engine is found to be non linear since it depends on a number of factors such as combustion conditions, load temperature and pressure. Statistical methods having linear regression are limited in their ability to predict the process outcome. Although large amounts of data for combustion conditions can be determined, there is an appreciable scatter in these data and organizing them suitably is a great task. It may be possible to use a number of alternative input permutations for a given set of loading conditions.

The above considerations have led to the identification of neural network techniques as being particularly suitable for modeling the emission characteristics under the various loading conditions. When employed in a neural network approach, it is relatively easy to incorporate a large number of system inputs to accommodate these effects. As the modeling is directly incorporated within the weights of the neural network connections, any non linearity or interdependence within the relationships is necessarily incorporated within the output predictions. Supervised training or unsupervised training techniques can be used for an investigation. The supervised learning requires the pairing of each input vector with a target vector representing the desired output, input vector together with desired output is called as training pair. Usually a network is trained over a number of such training pairs. If an input vector is applied, the corresponding output vector is calculated and it is compared with the corresponding target vector. The error difference is then fed back through the network and the weights are changed according to an algorithm which tends to minimize the error. The vectors of the training set are applied sequentially and errors are calculated and the weight is adjusted for each vector, until the error for the entire training set is at the lowest level. Unsupervised training requires no target vector for the outputs, and hence no comparisons to predetermined ideal responses. In this work, back propagation neural network with supervised training has been used.

The main objective of the present work is to study the ability of neural networks in predicting the values of emissions such as NOx and smoke using Back Propagation network. Statistical correlation of emission with in-cylinder and DPF derived information has been obtained. Each emission parameter is dependent on some input variables which rank top in correlation. More number of readings are required for training in ANN. Using 40 out of 50 experimental readings, corresponding combustion derived parameters are obtained from their

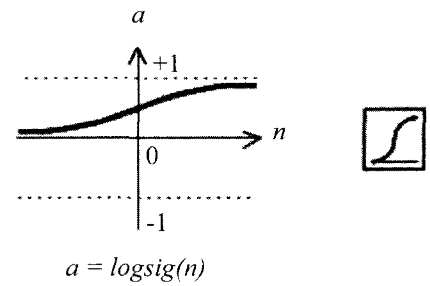


Figure 5. Log-Sigmoid transfer function.

pressure-crank angle diagrams. With these 40 set of combustion derived parameters as input variables, training of network is done NN tool in the MATLAB environment giving the corresponding emission values as targets to obtain the trained network. Predicted emission values and errors are obtained from the network. Validation of this trained network is tested by the reserve randomly chosen 10 values.

Poly line shows the curve for the ten predicted values ($y = ax^2 + bx + c$ form). For this poly line non linear curve, regression analysis has been done and the correlation coefficient (R^2) values have been obtained. R^2 value nearer to 1 has the least error. R^2 value equal to 1 gives perfect fit. (Traver *et al.*, 1999).

Figure 5 shows the Log-sigmoid transfer function. This function acts as a kind of "smoothed" form of the step functions. The algorithm used is logsig(n) = 1/(1 + exp(−n)). Traingda training function has been selected which give the minimum variations and used in the present investigation.

Figure 6 shows the typical 3 layer back-propagation neural network architecture.

Training of data (scaled values) has been carried out

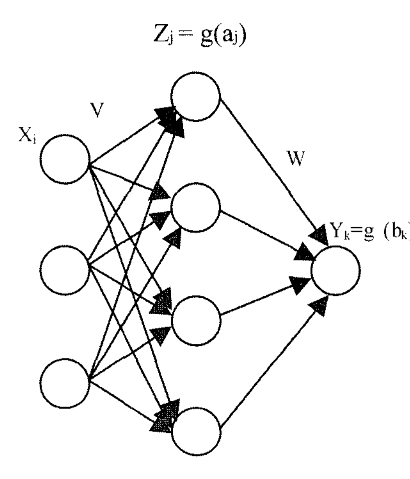


Figure 6. Typical 3 layer back-propagation neural network architecture.

using MATLAB functions by back propagation network method in supervised learning techniques. The trained values have been compared with experimental test values. Since they have a close proximity, for trend prediction, trained network can be used.

6. RESULTS AND DISCUSSION

Different combinations of input variables, number of layers and neurons have been tried and a trained network has been obtained for smoke and NOx.

6.1. Prediction for Smoke

Figure 7 shows the relationship between error and number of epochs for training smoke emission with copper catalyst coated DPF. It is seen that the goal is reached in 46555 epochs with 7 input variables, 18 neurons and 3 layer employing back propagation technique.

Using ANN program, out of the 50 readings taken, 40 values have been trained. The predicted network along with experimental values is seen in Figure 8. It is seen that the predicted and experimental values have a close proximity. In Figure 9, the reserve 10 values have been used for testing the predicted network from Figure 7. It is seen that, the R^2 is 0.9955 for the graph predicted smoke vs experimental smoke in Figure 10. Since it is close to 1, fitting is perfect. So the trained network could very well be used for smoke prediction.

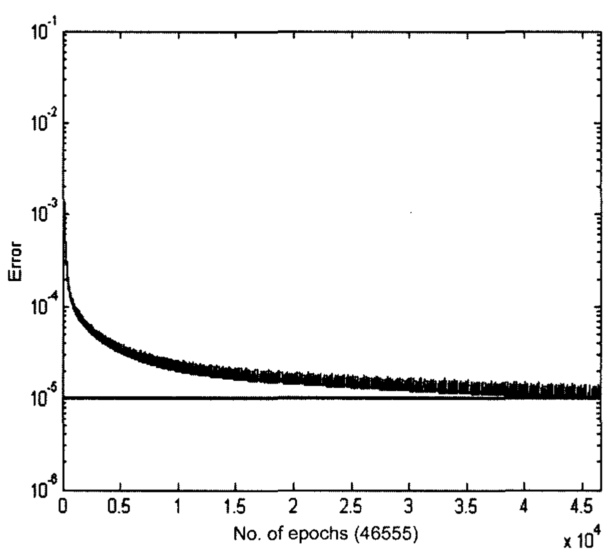


Figure 7. The relationship between error and no. of epochs for training smoke emission.

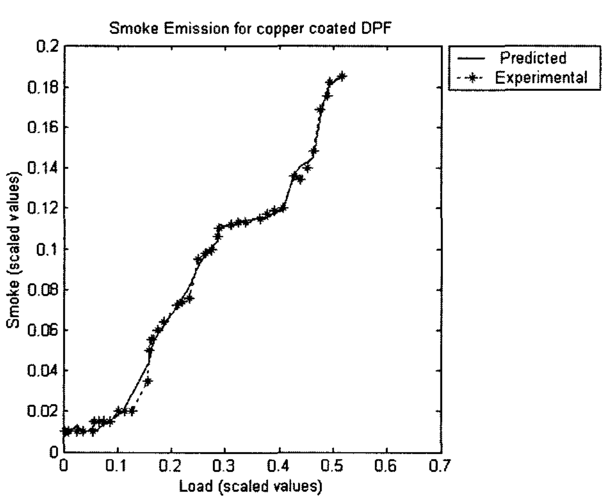


Figure 8. Variation of smoke with load for copper coated DPF.

6.2. Prediction for NOx

Figure 11 shows the relationship between error and number of epochs for training NOx emission with iron catalyst coated DPF. It is seen that the goal is reached in 56843 epochs with 8 input variables, 20 neurons and 3 layer employing back propagation technique.

Using ANN program, out of the 50 readings taken, 40 values have been trained. The predicted network along with experimental values is seen in Figure 12. It is seen that the predicted and experimental values have a close proximity. In Figure 13, the reserve 10 values have been

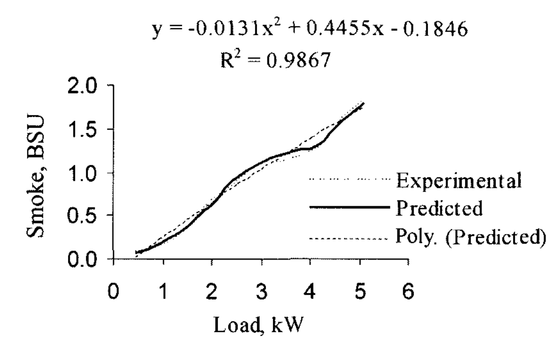


Figure 9. Testing the network for smoke Vs load.

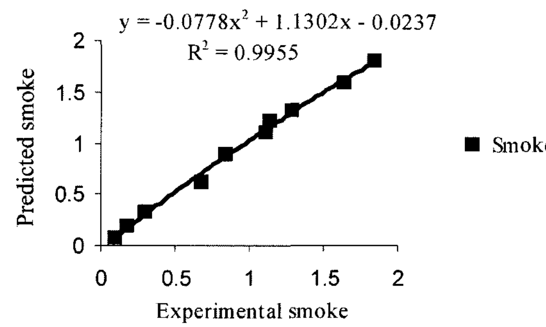


Figure 10. The relationship between experimental smoke and predicted smoke.

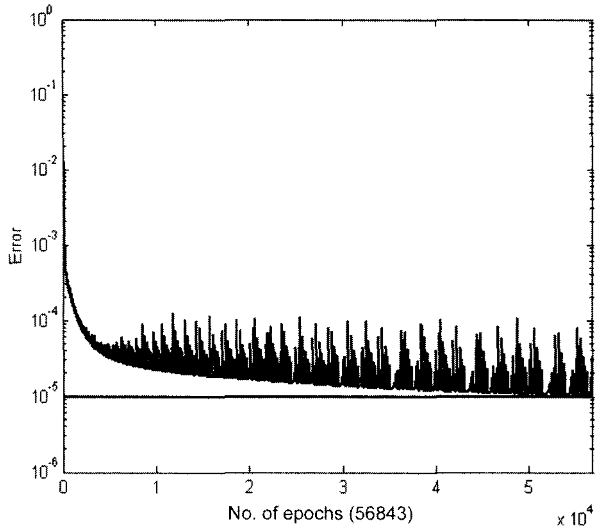


Figure 11. The relationship between error and no. of epochs for training NOx emission.

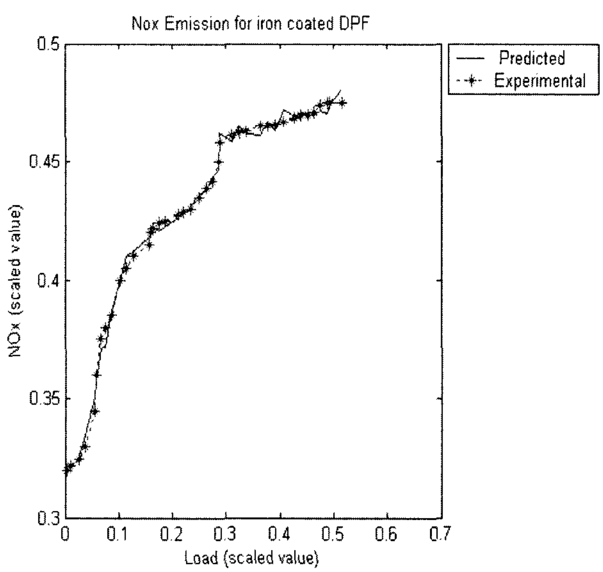


Figure 12. Variation of NOx with load for iron coated DPF.

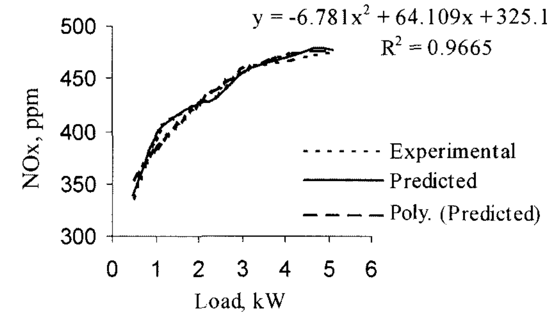


Figure 13. Testing the network for Nox Vs Load.

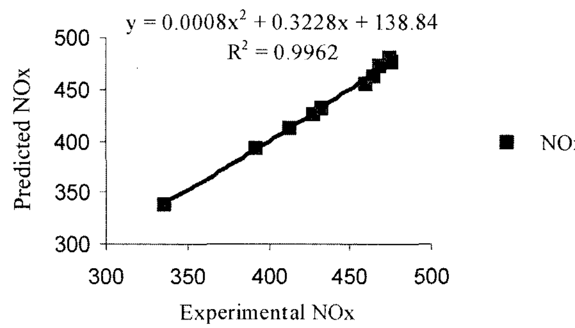


Figure 14. The relationship between experimental NOx and predicted NOx.

used for testing the predicted network from Figure 12. It is seen that, the R^2 is 0.9962 for the graph predicted NOx vs experimental NOx in Figure 14. Since it is close to 1, fitting is perfect. So the trained network could very well be used for NOx prediction.

7. CONCLUSIONS

The combustion parameters such as load, pp, ppl, imep, id, cd, lmfb50, maxq, prdr, wt have been considered as 10 input variables for the network. The network has been trained for 10 input variables; 9,8,7 and 6 input variables for different combinations under different number of layers (namely single, two and three hidden layers) and number of neurons (such as 100, 50, 25, 20, 18, 16, 15). The combination with minimum hidden layers and optimum input variables which gives the best regression values (R^2 values nearer to 1) have been obtained. For smoke the combination of the input variables such as load, pp, ppl, lmfb50, maxq, prdr and wt with single hidden layer and 18 neurons was found to give the best R^2 value of 0.9955 between experimental and predicted values. For NOx, the combination of the input variables such as load, pp, imep, lmfb50, id, maxq, prdr and wt with single hidden layer and 20 neurons was found to give the best R^2 value of 0.9962 between experimental and predicted values.

(1) An attempt has been made to use the Diesel particulate filter data also along with the in cylinder parameters for prediction of emissions after the DPF using the Neural Network Techniques.

(2) The networks can be used to predict the engine emissions in the absence of a gas analyzer.

ACKNOWLEDGEMENTS–The authors would like to acknowledge the principal and management of Mepco Schlenk Engineering College, Virudhunagar for giving permission to use the test facility.

REFERENCES

Athanasios, G. Konstandapoulos, Evangelos. S. and Mansour, M. (2001). Inertial contributions to the pressue drop of diesel particulate filters. *SAE Paper No.* 2001-01-0909.

Athanasios, G. Konstandopoulos, Evangelos. S., James, W. and Ronny, A. (1999). Optimized filter design and selection criteria for continuously regenerating diesel particulate traps. *SAE Paper No.* 1999-01-0468.

Athanasios, G. Konstandopoulos, and Margaritis, K. (1999). Periodically reversed flow regeneration of diesel particulate traps. *SAE Paper No.* 1999 01–0469.

Athanasios, G. Konstandopoulos and John, H. Johnson (1989). Wall-flow diesel particulate filter-their pressure drop and collection efficiency. *SAE Paper No.* 890405.

Bhagavantrarao, S., Mathur, H. B. and Babu, M. K. G. (1989). Some parametric studies from a mathematical model of a catalytic converter for predicting exhaust emissions conversion. *11th National Conference on IC Engines and Combustion, Dec 11-15.*

Heywood, J. B. (1988). *Internal Combustion Engine Fundamentals.* McGraw Hill, Inc.. New York. Julian. C. Tan., Cornelius. N. Opris., Kirby. J. Baumgard. and John. H. Johnson. (1996). A study of the regeneration process in diesel particulate trap using a copper fuel additive. *SAE Paper No.* 960136.

Matlab- Software Manual R12.

Pontikakis, G. N., Koltsakis, G. C. and Stamatelos, A. M. (2001). Dynamic filtration modeling in foam filters for diesel exhaust. *Chem. Eng. Comm.* 00: 1–26.

Rumminger, M. D., Zhou, X., Balakrishnan, K., Edgar, B. L. and Ezekoye, O. A. (2001). Regeneration behaviour and transient thermal response of diesel particulate filters. *SAE Paper No.* 2001-01-1342.

Saravanan, C. G. (1999). Experimental investigation on emission control from diesel engines using a catalytically coated ceramic foam filter. *Ph.D. Dissertation, Anna University,* Chennai.

Sathish, B. Gadde and John, H. Johnson (1999). A computational model describing the performance of ceramic diesel particulate trap in steady-state operation and over a transient cycle. *SAE Paper No.* 1999-01-0465.

Traver, M. L., Atkinson, R. J. and Atkinson, C. M. (1999). Neural network based diesel engine emissions prediction using in cylinder combustion pressure. *SAE Paper No.* 1999-01-1532, 1–15.

Versaevel, P., Colas, H., Koltsakis, G. C. and Stamatelos, A. M. (2000). Some empirical observations on diesel particulate filter modeling and comparison between simulation and experiments. *SAE Paper No.* 2000-01-477.

APPENDIX

Artificial Neural Network Program for Copper Catalyst coated DPF-Prediction of Smoke Emission

```
clc;
close all;
clear all;
load=[0.003   0.01    0.025   0.038   0.055
      0.057   0.067   0.076   0.088   0.102
      0.114   0.128   0.158   0.159   0.163
      0.174   0.186   0.21    0.221   0.233
      0.25    0.262   0.274   0.285   0.288
      0.31    0.324   0.338   0.364   0.378
      0.392   0.408   0.427   0.44    0.452
      0.463   0.475   0.489   0.493   0.515];
pp=[0.464     0.466   0.467   0.484   0.509
      0.513   0.516   0.518   0.532   0.553
      0.558   0.56    0.564   0.566   0.568
      0.57    0.572   0.574   0.575   0.578
      0.583   0.585   0.59    0.595   0.608
      0.634   0.646   0.65    0.655   0.655
      0.656   0.661   0.67    0.674   0.678
      0.683   0.691   0.6915  0.6924  0.693];
ppl=[0.372    0.372   0.372   0.368   0.368
      0.368   0.368   0.368   0.368   0.368
      0.368   0.368   0.368   0.368   0.368
      0.368   0.372   0.372   0.372   0.372
      0.372   0.372   0.368   0.372   0.372
      0.372   0.372   0.372   0.372   0.372
      0.372   0.372   0.372   0.372   0.372
      0.372   0.372   0.372   0.372   0.372];
lmfb50=[0.465 0.465   0.463   0.465   0.465
      0.465   0.465   0.465   0.465   0.465
      0.465   0.465   0.465   0.465   0.465
      0.465   0.465   0.465   0.465   0.465
      0.465   0.465   0.465   0.465   0.465
      0.471   0.471   0.471   0.465   0.465
      0.465   0.465   0.465   0.465   0.462
      0.462   0.465   0.465   0.465   0.465];
maxq=[0.1205  0.1262  0.1283  0.1074  0.1173
      0.1371  0.1321  0.1281  0.142   0.1684
      0.174   0.1621  0.1523  0.1511  0.1498
      0.1474  0.1578  0.1761  0.1826  0.1891
      0.1942  0.1907  0.1969  0.212   0.214
      0.2198  0.2231  0.2389  0.2564  0.261
      0.2623  0.272   0.2758  0.276   0.2762
      0.2851  0.305   0.312   0.318   0.3244];
prdr=[0.42 0.42 0.42  0.42    0.43    0.43
      0.43    0.435   0.435   0.44    0.44
      0.44    0.44    0.44    0.45    0.45
      0.45    0.455   0.455   0.455   0.455
      0.46    0.47    0.49    0.51    0.52
      0.53    0.53    0.54    0.54    0.54
```

```
        0.54    0.53    0.53    0.53    0.53
        0.525   0.52    0.52    0.52];
wt=[0.227 0.23  0.235   0.242   0.25    0.253
        0.265   0.269   0.272   0.285   0.289
        0.293   0.306   0.31    0.313   0.315
        0.318   0.324   0.326   0.327   0.336
        0.34    0.344   0.359   0.372   0.384
        0.39    0.394   0.401   0.406   0.408
        0.41    0.431   0.436   0.438   0.442
        0.458   0.465   0.471   0.496];
p=[ load;pp;ppl;lmfb50;maxq;prdr;wt];

smoke=[0.01     0.01    0.01    0.01    0.01
        0.015   0.015   0.015   0.015   0.02
        0.02    0.02    0.035   0.05    0.055
        0.06    0.064   0.072   0.074   0.076
        0.095   0.098   0.1     0.106   0.11
        0.112   0.113   0.113   0.115   0.117
        0.119   0.12    0.136   0.134   0.14
        0.148   0.169   0.176   0.182   0.185];

t=[smoke];

net=newff(minmax(p),[15,1],{'logsig','logsig'},'traingda')
;
net.trainParam.show = 100;
net.trainParam.lr_inc =1.05 ;
net.trainParam.lr_dec =0.7 ;
net.trainParam.max_fail =5 ;
net.trainParam.max_perf_inc =1.04 ;
net.trainParam.min_grad =1e-6 ;
net.trainParam.lr = 0.01;          %learning rate
net.trainParam.mc = 0.9;           %momentum constant
net.trainParam.epochs = 100000;
net.trainParam.goal = 0.00001;
[net,tr]=train(net,p,t);
%p1=[0.15; 0.1231;0.3232];
a=sim(net,p);
fprintf('Traine smoke=%12.18d \n',a);
 fprintf('load=%f\n\n',load);
 fprintf('smoke=%f\n\n', smoke );
plot(load,a,load,smoke,'r:*');
xlabel('Load (scaled value)');
Ylabel('Smoke (scaled value)');
title('Smoke Emission for copper coated DPF');
legend('Predicted','Experimental');
     legend(' Predicted ','Experimental',-1)
```

Output Value from ANN
0.011074 0.011603 0.012325 0.0053714 0.0095556
0.0099965 0.011021 0.012372 0.015768 0.020468
0.022284 0.027764 0.041054 0.04406 0.052202
0.060283 0.05889 0.071606 0.076688 0.083365
0.092892 0.092968 0.09942 0.10683 0.10911
0.11271 0.11464 0.11079 0.11616 0.11619 0.11517
0.12106 0.13557 0.13781 0.1403 0.14793 0.1686
0.17475 0.17877 0.18674

Experimental Value from tabulation
0.1 0.1 0.1 0.1 0.1 0.1 0.15 0.15 0.15 0.15 0.17 0.2
0.2 0.2 0.3 0.35 0.5 0.55 0.6 0.64 0.68 0.72 0.74 0.76
0.84 0.95 0.98 1 1.06 1.1 1.11 1.12 1.13 1.13 1.14
1.15 1.17 1.19 1.2 1.28 1.36 1.34 1.4 1.48 1.64 1.69
1.76 1.82 1.84 1.85

Predicted Value from ANN

0.11	0.12	0.12	0.05	0.1	0.1
0.11	0.12	0.16	0.2	0.22	0.28
0.41	0.44	0.52	0.6	0.59	0.72
0.77	0.83	0.93	0.93	0.99	1.07
1.09	1.13	1.15	1.11	1.16	1.16
1.15	1.21	1.36	1.38	1.4	1.48
1.69	1.75	1.79	1.87		

Errors
-0.0010738 -0.0016026 -0.0023249 0.0046286
0.00044445 0.0050035 0.0039792 0.0026284
-0.00076833 -0.00046829 -0.0022843 -0.0077637
-0.0060537 0.0059397 0.0027981 -0.00028262
0.0051104 0.00039426 -0.0026876 -0.0073645
0.0021084 0.0050322 0.00057978 -0.00083366
0.00089075 -0.00071246 -0.0016437 0.0022139
-0.0011617 0.00080992 0.0038252 -0.0010625
0.00043079 -0.0038112 -0.00029855 7.1224e-005
0.00039756 0.0012544 0.0032345 -0.0017441

Output test Value from ANN
0.0073788 0.018806 0.032823 0.063095 0.090454
0.11048 0.12156 0.13202 0.15943 0.18035

Predicted Value from ANN
0.07 0.19 0.33 0.63 0.9 1.1 1.22 1.32 1.59 1.8

Experimental Value from tabulation
0.1 0.17 0.3 0.68 0.84 1.11 1.14 1.28 1.64 1.84

Artificial Neural Network Program for Iron Catalyst coated DPF - Prediction of NOx Emission

```
clc;
close all;
clear all;
load=[0.003     0.01    0.025   0.038   0.055
        0.057   0.067   0.076   0.088   0.102
        0.114   0.128   0.158   0.159   0.163
        0.174   0.186   0.21    0.221   0.233
        0.25    0.262   0.274   0.285   0.288
        0.31    0.324   0.338   0.364   0.378
        0.392   0.408   0.427   0.44    0.452
        0.463   0.475   0.489   0.493   0.515];
```

```
pp=[0.464    0.466   0.467   0.484   0.509
    0.513    0.516   0.518   0.532   0.553
    0.558    0.56    0.564   0.566   0.568
    0.57     0.572   0.574   0.575   0.578
    0.583    0.585   0.59    0.595   0.608
    0.634    0.646   0.65    0.655   0.655
    0.656    0.661   0.67    0.674   0.678
    0.683    0.691   0.6915  0.6924  0.693];
imep=[0.0388 0.03202 0.02673 0.03673 0.03973
    0.04025 0.041023         0.04166 0.0432
    0.055   0.06259 0.05642 0.054834
    0.05286 0.060832         0.05822
    0.064046         0.071034        0.07376
    0.075664         0.080032        0.08182
    0.05863 0.08011 0.086026         0.09023
    0.092834         0.096456        0.1
    0.105   0.1093  0.1146  0.124   0.118
    0.113   0.1152  0.126   0.126342
    0.126654         0.1272];
lmfb50=[0.465 0.465  0.463   0.465   0.465
    0.465   0.465   0.465   0.465   0.465
    0.465   0.465   0.465   0.465   0.465
    0.465   0.465   0.465   0.465   0.465
    0.465   0.465   0.465   0.465   0.465
    0.471   0.471   0.471   0.465   0.465
    0.465   0.465   0.465   0.465   0.462
    0.462   0.465   0.465   0.465   0.465];
id=[0.287       0.288   0.288   0.288   0.288
    0.288   0.288   0.288   0.287   0.289
    0.289   0.288   0.288   0.288   0.289
    0.289   0.288   0.288   0.288   0.289
    0.289   0.29    0.288   0.289   0.289
    0.289   0.289   0.288   0.288   0.291
    0.291   0.288   0.291   0.291   0.291
    0.289   0.29    0.289   0.289   0.289];
maxq=[0.1205    0.1262  0.1283  0.1074  0.1173
    0.1371  0.1321  0.1281  0.142   0.1684
    0.174   0.1621  0.1523  0.1511  0.1498
    0.1474  0.1578  0.1761  0.1826  0.1891
    0.1942  0.1907  0.1969  0.212   0.214
    0.2198  0.2231  0.2389  0.2564  0.261
    0.2623  0.272   0.2758  0.276   0.2762
    0.2851  0.305   0.312   0.318   0.3244];
prdr=[0.42      0.42    0.42    0.43    0.43
    0.435   0.44    0.44    0.44    0.45
    0.45    0.455   0.46    0.47    0.47
    0.47    0.475   0.475   0.48    0.48
    0.49    0.49    0.5     0.52    0.53
    0.535   0.54    0.54    0.56    0.56
    0.565   0.565   0.555   0.555   0.55
    0.55    0.545   0.54    0.54    0.54];
wt=[0.215       0.217   0.22    0.232   0.241
    0.243   0.256   0.258   0.261   0.272
    0.276   0.28    0.292   0.294   0.298
    0.3     0.304   0.308   0.31    0.311
    0.3205  0.326   0.332   0.3455  0.36
    0.37    0.374   0.379   0.3865  0.388
    0.392   0.395   0.415   0.42    0.424
    0.4305  0.441   0.45    0.458   0.478];
p=[ load;pp;imep;lmfb50;id;maxq;prdr;wt];
nox=[0.32       0.322   0.325   0.33    0.345
    0.36    0.375   0.38    0.385   0.4
    0.405   0.41    0.415   0.42    0.422
    0.424   0.425   0.428   0.429   0.43
    0.435   0.439   0.442   0.45    0.458
    0.461   0.462   0.463   0.465   0.465
    0.466   0.467   0.469   0.47    0.47
    0.471   0.474   0.475   0.475   0.475];
t=[nox];
net=newff(minmax(p),[20,1],{'logsig','logsig'},'traingda')
;
net.trainParam.show = 100;
net.trainParam.lr_inc =1.05 ;
net.trainParam.lr_dec =0.7 ;
net.trainParam.max_fail =5 ;
net.trainParam.max_perf_inc =1.04 ;
net.trainParam.min_grad =1e-6 ;
net.trainParam.lr = 0.01;        %learning rate
net.trainParam.mc = 0.9;         %momentum constant
net.trainParam.epochs = 100000;
net.trainParam.goal = 0.00001;
[net,tr]=train(net,p,t);
%p1=[0.15; 0.1231;0.3232];
a=sim(net,p);
fprintf('Traine NOx=%12.18d \n',a);
fprintf('load=%f\n\n',load);
fprintf('NOx=%f\n\n',nox);
plot(load,a,load,nox,'r:*');
xlabel('Load (scaled value)');
Ylabel('NOx (scaled value)');
title('Nox Emission for iron coated DPF');
 legend('Predicted', 'Experimental');
     legend(' Predicted','Experimental',-1)
```

Output Value from ANN

0.32095 0.32342 0.32419 0.32271 0.35452 0.36822
0.37206 0.37222 0.38495 0.40165 0.3989 0.40711
0.41451 0.41776 0.42406 0.42851 0.42312 0.4292
0.43177 0.42805 0.43496 0.43871 0.44141 0.45099
0.4559 0.45928 0.46361 0.46255 0.46561 0.46475
0.46557 0.46763 0.46879 0.46955 0.47083 0.46966
0.4755 0.47319 0.47497 0.47475

Experimental Value from tabulation

320 322 325 330 336 345 360 375 380 385 392 400
405 410 413 415 420 422 424 425 427 428 429 430
433 435 439 442 450 458 460 461 462 463 464 465

465 466 467 468 469 470 470 471 474 474 475 475 475 475

Predicted Value from ANN
321 323 324 323 355 368 372 372 385 402 399 407 415 418 424 429 423 429 432 428 435 439 441 451 456 459 464 463 466 465 466 468 469 470 471 470 476 473 475 475

Errors
-0.00094534 -0.0014206 0.00080879 0.0072948 -0.0095171 -0.0082198 0.0029412 0.0077788 4.9606e-005 -0.0016491 0.0061046 0.0028917 0.00049048 0.0022351 -0.0020562 -0.0045101 0.0018814 -0.0012017 -0.0027743 0.0019529 4.2167e-005 0.00029146 0.0005936 -0.00098565 0.0021033 0.0017239 -0.0016148 0.00044553 -0.00061037 0.00024597 0.00042601 -0.00063002 0.00021105 0.0004519 -0.00083151 0.0013382 -0.0015003 0.0018069 3.3184e-005 0.00024769

Output test Value from ANN
0.33866 0.39361 0.41205 0.42579 0.43157 0.45516 0.4626 0.47183 0.47995 0.47671

Predicted test value from ANN
339 394 412 426 432 455 463 472 480 477

Experimental test value from tabulation
336 392 413 427 433 460 464 468 474 475