Prediction Of Diesel Engine NO_x Emissions Using ANN Technique

[1]P. Vijaya Raghavan, [2] Dr.Sunder Selwyn.T , [3] T.Punitha
[1]Assistant Professor, Department of Mechanical Engineering,
[2] Professor, Department of Mechanical Engineering,
[1]Prince Shri Venkateshwara Padmavathy Engineering College.
[2]Prince Dr.K.Vasudevan College of Engineering & Technology, Chennai.
[3]Faculty, Prince Shri Venkateshwara Arts and Science College, Gowriwakkam.

Abstract

Diesel motor is getting expanding mainstream because of its high proficiency and solidness. Thinking about the main ozone harming substance, carbon dioxide (CO2), the diesel motor is better than fuel motor. Sadly, the diesel motor transmits significant degree of oxides of nitrogen (NOx). Close control of ignition in the motor will be fundamental to accomplish consistently expanding effectiveness upgrades while fulfilling progressively rigid outflows guidelines. As new levels of opportunity are made, because of advances in innovation, the confounded cycles of emanation arrangement are trouble to survey. Counterfeit neural organization (ANN)- based motor displaying offers the potential for a multidimensional, versatile, learning control framework which doesn't need information on the overseeing conditions for motor execution or the burning energy of discharges arrangement that an ordinary guide based motor model require. This paper assesses the capacities of ANN as a prescient instrument for multi-chamber diesel motor NOx discharges. The trials were completed with a fixed light-obligation Nissan diesel motor test-rig planned and amassed to permit testing of the motor in a lab climate. Standard research center methodology were utilized to gauge the motor working boundaries and its tailpipe emanations. ANNs were prepared on trial information and used to anticipate the oxides of nitrogen (NOx) discharges under different working factors. Part of fluctuation (R2) and mean outright rate blunder (□) were utilized for correlation in the affectability examination. The Levenberg-Marquardt (LM) calculation with 11 neurons delivered the best outcomes. Among the inspected blends of learning standards in various models of backpropagation (BP) plans, a bunch of 0.05, 0.05 and 0.3 for learning rate, energy and weight separately, gave the best-found the middle value of precision. For pre-determined motor rates and loads with LM calculation, □ were discovered to be somewhere in the range of 0.68 and 3.34%.

Keywords: Artificial Neural Networks, Capabilities, Multi-cylinder Diesel Engine, NO_x Emissions

1. Introduction

Future will require significantly more complex control than existing map- based control strategies, having more degrees of freedom than those of today. Standard classical “one- dimensional” or map-based diesel engine control will prove woefully inadequate in dealing with the multiple independent degrees of freedom presented by fuel injection rate shaping, EGR, boost and valve control in future diesel engines. Moreover, the costs, time required, and complexity associated with engine development, performance mapping, and control system development and calibration are increasing significantly. What is required is a multidimensional, adaptive, learning control system that does not require the laborious development of an engine model while having excellent performance and emissions prediction capabilities across the fuel life of the engine, for all engine-operating conditions. Artificial neural network (ANN) – based virtual sensing offers all of these capabilities (Howlett et al., 2005; He and Rutland, 2004).

ANN models may be used as alternative way in engineering analysis and predictions. They are recently used also in engine optimization regarding engine operating parameters and emissions (Alonso et al., 2007; Wu et al., 2006; Hafner et al., 2017; Desantes et al., 2005; Kesgin, 2004; Diagrammatical and Assanis, 2014). ANN models mimic somewhat the learning process of a human brain. They operate like a “black box” model, requiring no detailed information about the system. Instead, they learn the relationship between the inputs parameters and the controlled and uncontrolled variables by studying previously recorded data, similar to the way a nonlinear regression might perform (Hashemi and Clark, 2017; Clark et al., 2018; Sekemen et al., 2006). Another advantage of using ANNs is their ability to handle large and complex systems with many interrelated parameters. They seem simply to ignore excess data that are of minimal significance and concentrate instead on the more important inputs (Wu et al., 2006). The excellent generalization capabilities that are achieved through online learning means the engine control system designer need make no assumptions about the governing equations dictating the engine performance and combustion characteristics. The ANN-based engine model is able to automatically develop the engine behaviour over time, allowing a truly optimized and adaptive engine control system to be developed with minimum effort (Alonso et al., 2007; Hafner et al., 2018).

2. Research Method

The ANN modelling used NO_x data that were obtained from a test-rig designed and assembled to allow testing of the engine in a laboratory environment. The test engine is a four-cylinder direct-injection diesel engine. The specifications of the engine and fuel used are as shown in Tables 1 and 2 respectively.

Table 1: Engine specifications

Make and Model	LD 20-D, Nissan diesel
Type	4-stroke cycle, in-line
Number of cylinder	4
Bore	95mm
Stroke	105mm
Displacement	$2.0 \times 10^{-3}\ m^3$
Compression ratio	21:1
Air induction	Naturally aspirated, water cooled
Valves per cylinder	4
Number of nozzles	4
Fuel injection type	Bosch-type injection pump
Maximum power	80 kW at 3600 rpm
Maximum torque	196 Nm at 2200 rpm
Maximum speed	5000 rpm
Rotating inertia	$0.148\ kg\ m^2$

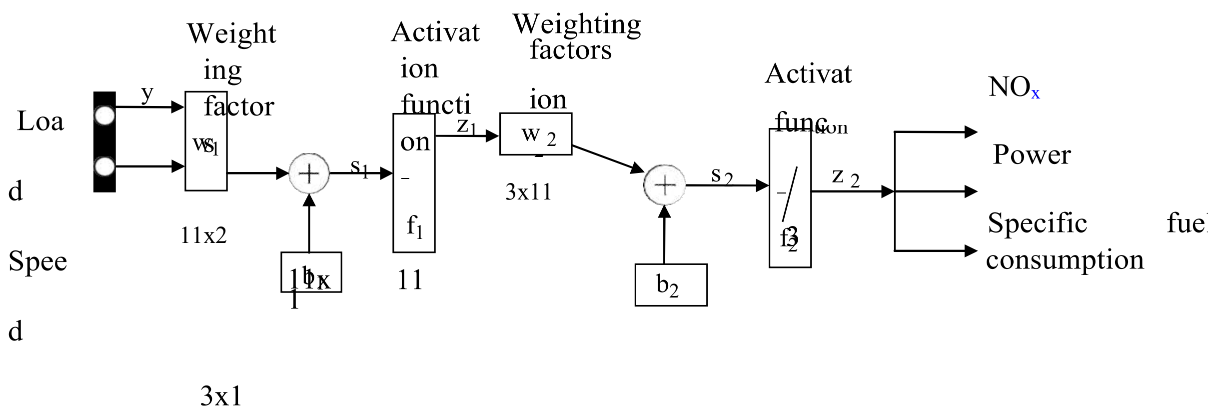
The engine was run naturally aspirated in order to obtain repeatable inlet pressure shortly after start. The speed and the load of the research engine were controlled independently by a dynamometer and a fuel control system. Air flowrate was measured using a laminar flow element and fuel flowrate was measured using a positive displacement meter. Digital tachometer was used in engine speed measurements. Manifold temperatures and pressures were measured using thermocouples and strain- based pressure transducers respectively. Gaseous exhaust emissions were measured with the aid of pocket gas^{TM} -portable gas analyzer.
Engine emission tests were performed at 1000 to 5000 rpm in steps of 500 rpm with various loading conditions of 25%, 50%, 75% and 100% of the load, where 504N load corresponds to 100%. Among the various kinds of ANN approaches that exist, the BP learning algorithm, which has become the most popular in engineering applications, was used in this study.

Artificial Neural Networks Modelling

The ANN was trained by adjusting the values of connections (weights). The objective was to obtain a specific output from a particular input. Standard BP is a gradient descent algorithm in which the gradient is computed for nonlinear multilayer networks (He and Rutland, 2004). The ANN parameters (weights and biases) were adjusted to minimize the sum of the squares of the differences between the actual values and network output values. The ANN was trained in a batch mode where its parameters were only updated after all the input-output pairs were presented. The Levenberg-Marquardt (L-M) algorithm was employed for the training and the target performance goal (mean square difference between ANN output and target output) was set at 0.001. The maximum number of epochs (representation of the input/output pairs and the adjustment of ANN parameters) was set at 100.

The ANN used to predict the emission was trained with neural network toolbox in MATLAB 6.5. The BP network with various activation functions was selected. The hidden layer was discretized to three different parts with dissimilar transfer functions to identify different features in each pattern.

Figure 1: Selected ANN model

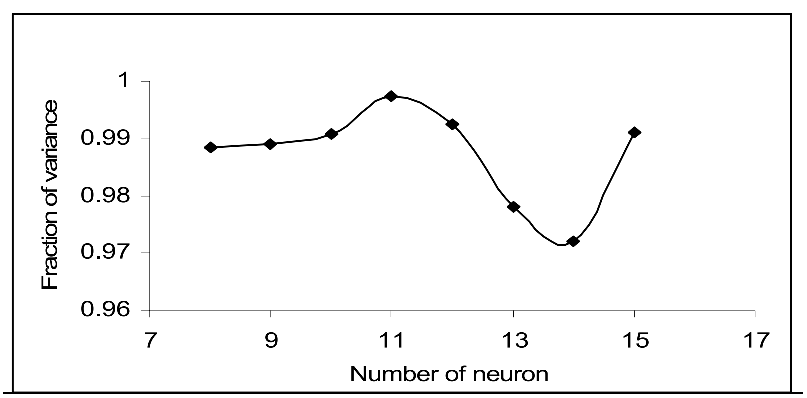


Considering the known relationship (Sekemen et al., 2006) between engine emissions and power, two variables of engine speed and load were chosen as major inputs for training the ANN. To obtain the best prediction of values, the number of neurons was increased step-by step from 8 to 15 in a single hidden layer. All experimental results at 33 different engine operating conditions were partitioned into two independent datasets: 23 cases for training, the other 10 for testing. The 23 cases were randomly chosen to form the training dataset, leaving the remaining 10 cases as the test dataset. Learning datasets were used to train the neural network to recognize patterns.

3. Results and Discussion

Effects of the number of neurons in the hidden layer in NO_x ANN performance is shown in Fig.2.

Figure 2: Effects of neuron numbers in the hidden layer on fraction of variance for NO_x ANN



The performance was measured in terms of the R^2 and the mean absolute percentage error (ξ). An initial improvement when increasing the number of neurons was obtained in the ANN performance. This behaviour can be explained because, as the number of neurons increases, the ANN ability to deal with more complex problems also increases. After the first rise, the trend is not maintained and small oscillations are produced because when more neurons are used, more weights need to be adjusted with the same training information (Alonso et al., 2007). At a certain point, a balance between complexity of the problem and limited number of data available for the training is reached. The most adequate architecture was selected among MLP with 3 hidden layers and a number of neurons ranging from 3 to 15; smaller structures were too simple to provide good results in the problems studied. The upper limit was taken at 15 neurons because much more experimental tests were needed in order to obtain a proper adjustment of the higher number of weights (Alonso et al., 2007). The criteria followed for the architecture choice was the highest averaged R^2 obtained. The resulting ANN architectures selected for NO_x was 11 neurons and 0.997 averaged R^2.

Figs. 3 and 4 showed the network prediction for NO_x and their deviations from measured values at 25% load condition as wireframe surfaces respectively, to provide easier visual evaluation of brake power and sfc influences on NO_x emissions. The mean absolute percentage error (□) in the predicted values of NO_x were found to be in the range of 1.6% to 3.34%. This good predictive ability can be observed from Fig 4, indicating that the network was able to accurately learn the training data sets.

Figure 3: Specific NO_x emissions at steady operation at 25% load condition

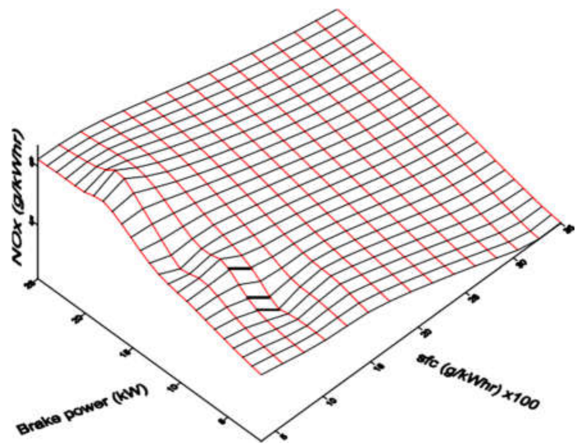
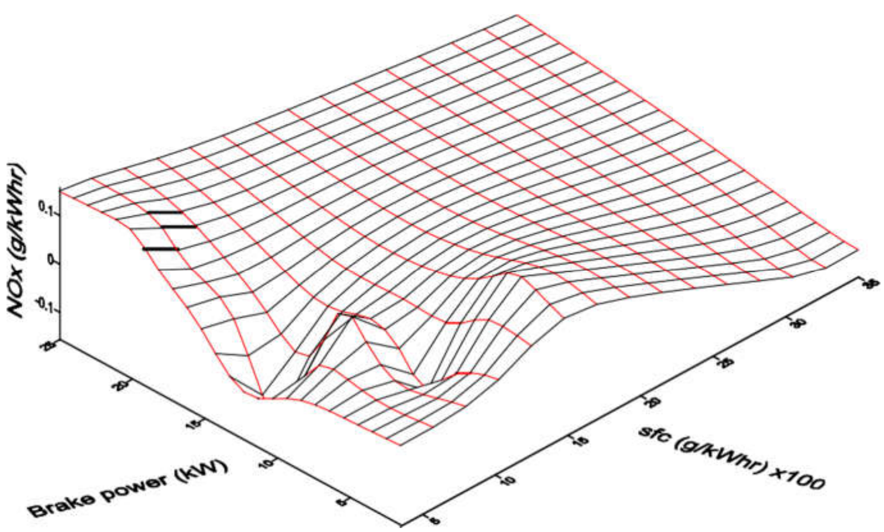


Figure 4: Standard deviation distribution of NO_x emissions map at 25% load condition



Deviations from measured values at 50% load condition are as shown in Figs. 5 and 6 respectively. The □ in the predicted values of NO_x were in the range of 1.4% to 3.27%. The predictive ability of the network for 50% load condition was found to be satisfactory.

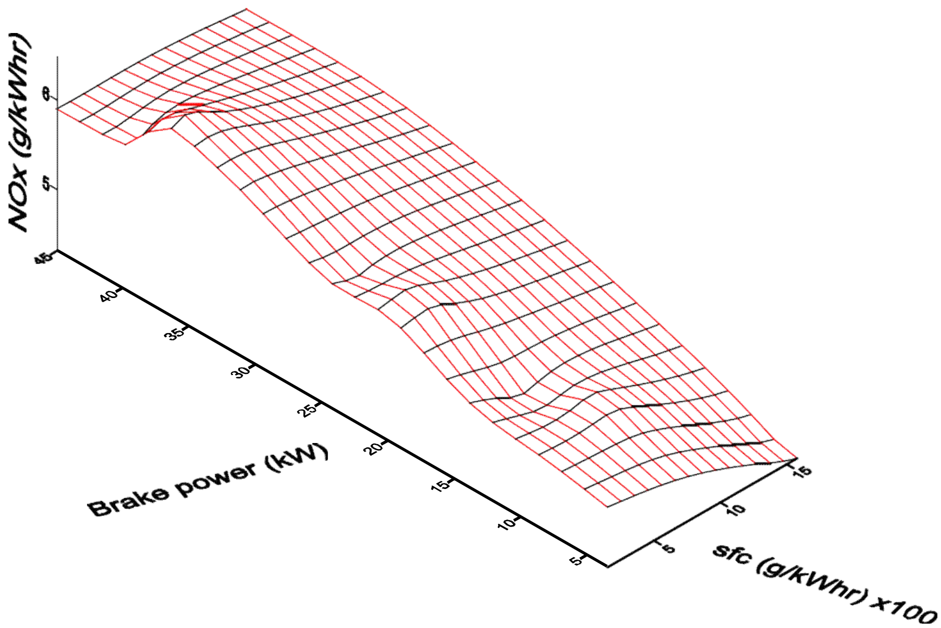
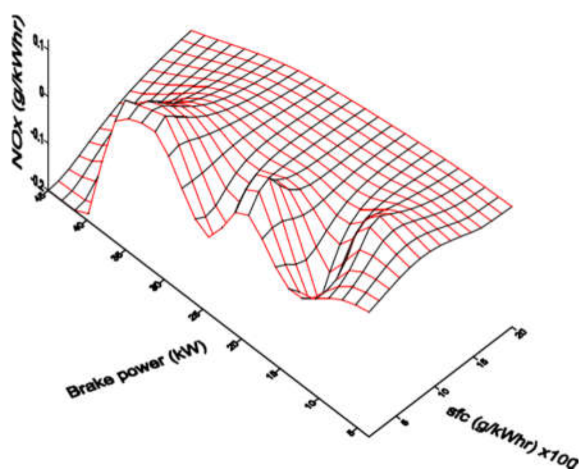


Figure 5: Standard deviation distribution of NO_x emissions map at 50% load condition



Figs.6 and 7 illustrate the 3-D plots of the network prediction for NO_x and their deviations from measured values at 75% load condition respectively. The □ in the predicted values were in the range of 0.68% to 2.88%. Fig.8 depicts the good predictive ability of the network.

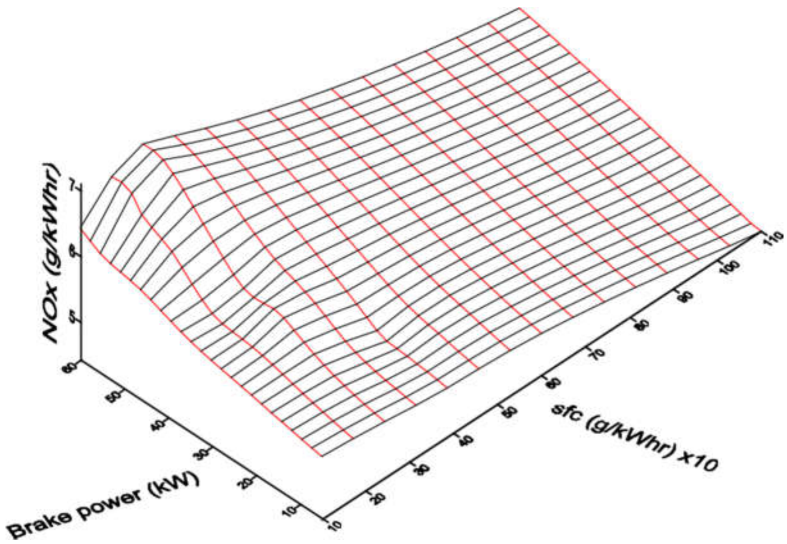
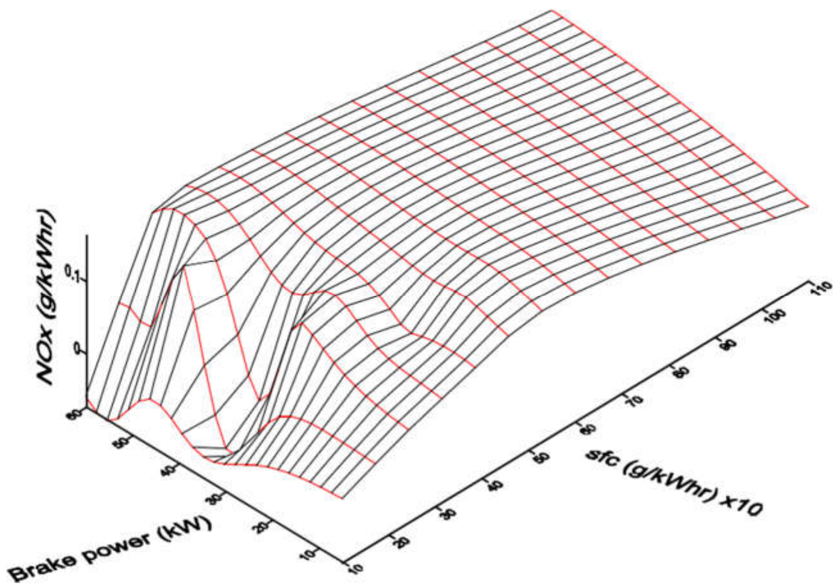


Figure 7: Standard deviation distribution of NO_x emissions map at 75% load condition



The results for the prediction of NO_x and their deviations from measured values at 100% load condition are presented as surface plots in Figs.9 and 10 respectively. The □ in the predicted values were in the range of 0.7% to 2.8%. The predictions were in good agreement with the actual values. Fig. 11 presents the NO_x emission results of eight testing cases predicted by the trained MLP and experimental data.

4. Conclusion

ANN models of a multi-cylinder direct injection diesel engine have been developed and validated. The neural network model of the engine was able to make highly complex, nonlinear and multidimensional associations between selected input parameters and outputs to allow acceptable degree of accuracy in the predictions of the engine torque, fuel consumption and NO_x across the full range of the engine operation. For a pre-specified engine speed and load, the models were shown to produce mean absolute percentage error (□) in the predicted values of NO_x in the range of 0.68 to 3.34%. However, there was an appreciable error in the predicted NO_x level at lower load condition, which was reduced slightly over time as the measured level increased slowly. This was due to thermal effects not considered in the models such as warming of combustion chamber at lower load condition. The networks had only air and coolant temperatures available as input, both of which are only weakly related to combustion chamber temperature.

The emission prediction of NO_x matched the measurement with high overall accuracy as evidence from the error analyses. Among the examined combinations of learning criteria in different architectures of BP designs, a set of 0.05, 0.05 and 0.3 for learning rate momentum and initial weight respectively gave the best-averaged accuracy. ANN modelling has proved to be an excellent tool to predict NO_x emissions from diesel engines.

References

[1] Alonso, J. M., Alvarruiz, F., Desantes, J. M., Hernández, L., Hernández, V. and Moltó, G. (2007); Combining Neural Networks and Genetic Algorithms to Predict and Reduce Diesel Engine Emissions, IEEE Transactions on Evolutionary Computation, Vol. 11, No. 1, pp. 46-55.

[2] Clark, N. N.; Tehranian, A.; Jarrett, R. P. and Nine, R. D. (2007); Translation of Distance Specific Emissions Rates between Different Heavy Duty Vehicle Chassis Test Schedules, SAE Technical Paper No. 2007-01-1754.

[3] Clark, N. N.; Gajendran, P. and Kern, J. M. (2008); A predictive Tool for Emissions from Diesel Vehicles, Environmental Science Technology, Vol. 37, pp. 7-15.

[4] Delagrammatikas, G. J. and Assanis, D. N. (2014); Development of a Neural Network Model of an Advanced, Turbocharged Diesel Engine for use in Vehicle – Level Optimization Studies, Journal of Automobile Engineering, Vol. 218, pp. 521 – 523.

[5] Desantes, J, Lopez, J.; Garcia, J. and Hernandez, L. (2011); Application of Neural Networks for Prediction and Optimization of Exhaust Emissions in a HD Diesel Engine, SAE Technical Paper No. 2011-01-1144.

[6] Desantes, J. M., Lopez, J. J., Garcia, J. M. and Hernandez, L. (2015); Multi-Objective Optimization of Heavy-Duty Diesel Engines under Stationary Conditions, Journal of Automobile Engineering, Vol. 219, pp. 77-87.

[7] Hafner, M., Schuler, m. and Nelles, O. (2012); Neural Net Models for Diesel Engines- Simulation and Exhaust Optimization, Control Engineering Practice, Vol. 30, No. 2, pp. 402- 412.

[8] Hashemi, N. and Clark, N. N. (2012); Artificial Neural Network as a Predictive Tool for Emissions from Heavy Duty Diesel Vehicles in Southern California, International Journal of Engine Research, Vol. 8, pp. 321-336. Evaluation of Artificial Neural Network Performance in Predicting Diesel Engine NO_x Emissions 653

[9] He, Y. and Rutland, C. J. (2014); Application of Artificial Neural networks in Engine Modelling, International Journal of Engine Research, Vol. 5, No. 4, pp. 281 – 296.

[10] Howlett, R. J., Howson, P. A. and Walters, S. D. (2015); Determination of Air-Fuel Ratio in Automotive Ignition System using Neural networks, IEEE Transactions on Neural Networks, Vol. 41, No. 1, pp. 60-67.

[11] Kalogirou, S. A. (2014); Artificial Intelligence for the Modelling and Control of Combustion Processes: A Review, Progress in Energy and Combustion Science, Vol. 29, pp. 515-566.

[12] Kesgin, U. (2014); Genetic Algorithm and Artificial Neural Networks for Engine Optimization of Efficiency and NO_x Emission, Fuel, Vol. 83, pp. 885 – 895.

[13] Krijnsen, H. C.; Van Kooten, W. J.; Calis, H. A.; Verbeek, R. P. and Van den Bleek, C. M. (2012); Prediction of NO_x Emissions from a Transiently Operating Diesel Engine using an Artificial Neural Network, Chemical Engineering and Technology, Vol. 22, pp. 601-607.

[14] NNPC (2009); Kaduna Refining and Petrochemical Co. LTD Technical Report, No. 4, p. 87.

[15] Rakopoulos, C. D., Rakopoulos, D. and Kyristsis, C. (2009); Development and Validation of a Comprehensive Two-Zone Model for Combustion and Emissions Formation in a Diesel Engine, International Journal of Energy Research, Vol. 27, pp. 1221-1249.

[16] Rice, M., Kramer, J., Mueller, R., and Mueller-Haas, K. (2008); Development of an Integrated NO_x and PM reduction Aftertreatment System: SCRi™ for Advanced Diesel Engines, SAE Technical Paper No. 2008-01-1321.

[17] Sekemen, Y.; Cinar, C.; Erduranli, P. and Boran, E. (2008); The Investigation of the Effect of Injection Pressure and Maximum Fuel Quantity on Engine Performance and Smoke Emissions in Diesel Engines, Journal of Polytechnic, Vol. 7, pp. 321-326. using In-cylinder Combustion Pressure, SAE Technical Paper No. 2009-01-1532.