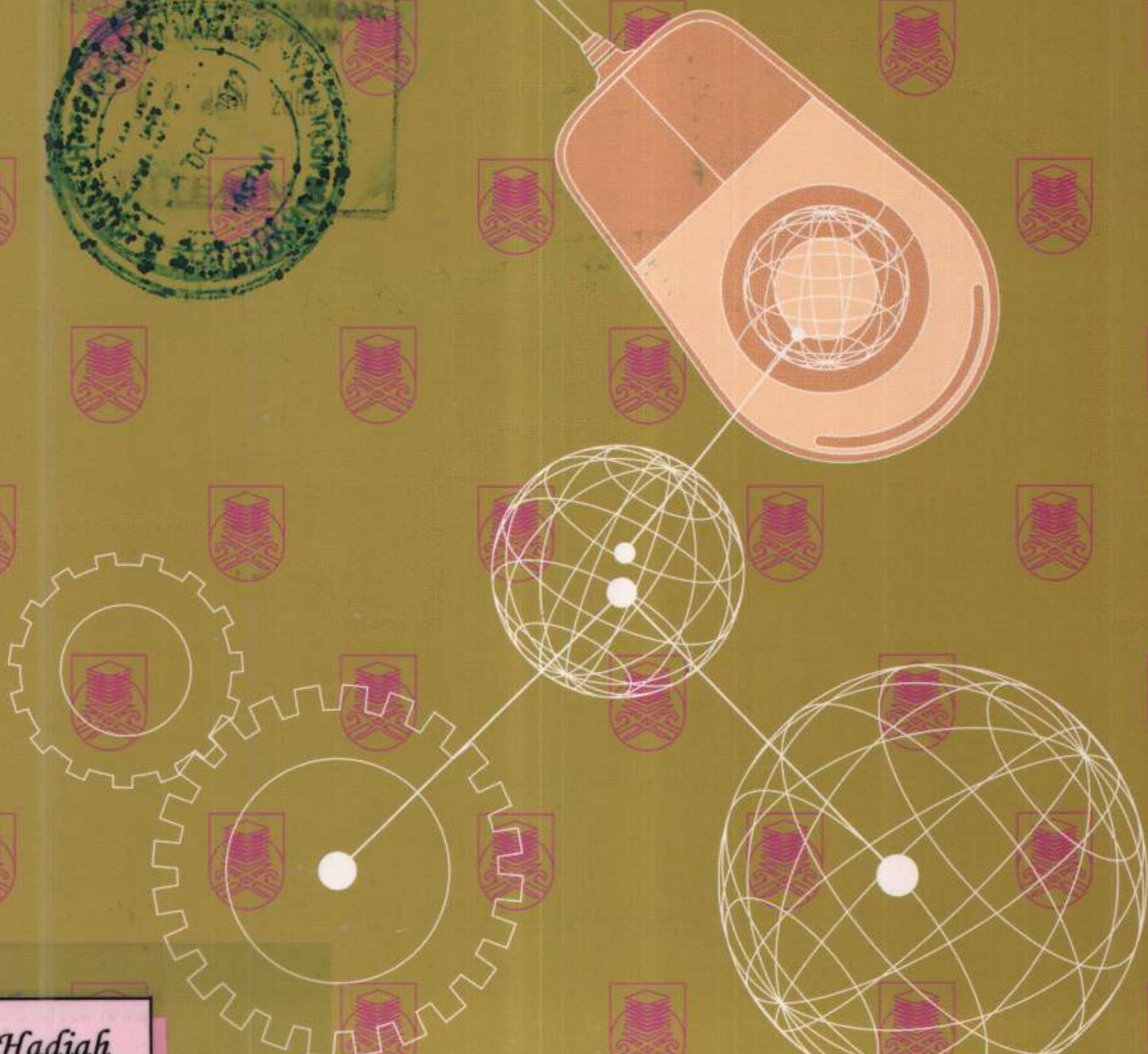
ESTEEM

ACADEMIC JOURNAL VOLUME 1. 2003 • ISSN: 1675-7939



Universiti Teknologi MARA Pulau Pinang

ESTEEM

Volume 1, December 2003

CONTENTS

The Prediction of Diesel Engine NO_x Emissions using Artificial Neural Network

Mohd. Mahadzir Mohammud
Jabatan Kejuruteraan Mekanikal, UiTM Cawangan Pulau Pinang,
Email: *mohdmahadzir@hotmail.com*,

Khairil Faizi Mustafa
Sekolah Kejuruteraan Mekanikal, Kampus Kejuruteraan USM, Pulau Pinang.
Email: *khairilfaizi@hotmail.com*

Abstract

This paper describes an experimental and computer simulation studies used to develop a suitable algorithm to predict and control the oxides of nitrogen (NO_x) emitted from the Yanmar L60AE-D single cylinder direct injection diesel engine, fitted in a Cusson's Engine Test Bed Model P8160. NO_x contained in the exhaust gases of diesel engines have been identified as elements responsible for polluting our atmosphere. In order to reduce or to control diesel engine polluting emissions, the formation mechanism of NO_x can be predicted. A neural network model is developed to obtain the NO_x emission concentration under various operating condition. The neural network, well suited for non-linear phenomena modelization, is able to deal with high uncertainly input level and able to operate outside of their range of training experience. A feedforward neural network structure has been selected with a backpropagation training procedure. Four operating parameters (engine speed, engine load, exhaust temperature and air fuel ratio) have been used as an input data in the modelling process. The modelling algorithm implemented, takes a large set of measurements to learn how to predict the NO_x emission from four operating parameters. The predicted values obtained using neural network model are compared with the experimental values. The studies show that the predicted results are in good agreement with experimental values, within less 9 % relative error.

Keywords: NO_x prediction, NO_x emission simulation, NOx data collection and modelling, Diesel engine modelling, Neural networks

Introduction

Diesel engine is the most efficient power plant among all known types of internal combustion engines. It has long been the workhorse of industry because of their high torque output, durability, exceptional fuel economy and ability to provide power under the wide range of conditions. However, the exhaust emissions from the diesel engines have the potential to cause a range of health problems and pollute the environments.

Oxides of Nitrogen (NO_x), one of the exhaust gases of diesel engines have been identified as elements responsible for polluting the atmosphere (Heywood, 1988). According to German (1995), NO_x production is a function of peak bulk gas temperature and the oxygen availability. It is primarily formed in the post-flame region where the temperatures are high enough about 1723-3000 K (Dales and Thiessen, 1982 and Bacha et al., 1998). NO_x release in the atmosphere reacts with other chemicals especially in strong sunlight to form ozone and it is one of the major causes of photochemical smog (Pulkrabek, 1997).

An alarming increase in the NO_x pollutions in our environments and the increasing demands from government to the engine manufactures to lower and optimise the NOx emissions of diesel engines have lead to an intensive research (Matsui et.al, 1997 and Krijnsen et.al, 2001) in the combustion process. Over the pass few years, many efforts have been addressed to the design of new engines (Itoyama et.al, 1997 and Kawashima et.al, 1999) and to develop innovative control system (Arsie et.al, 1998) in order to achieve the targets imposed by government on controlling NO_x emissions. Many approaches have been made toward the assessment of reliable methodologies for the optimal engine control strategies. These methodologies are based on the development of easy-to-handle fast engine computer models able to synthesize the information derived from experimental data. A model based on computer engine control allows the opportunity to associate engine NO_x emissions with those engine operation parameters that give rise to variations in the NO_x emissions. Through these methodologies, the development of virtual sensors is needed to provide the model based control systems with useful feedback signal. Recent work (Atkinson et.al, 1998; Hanzevack et.al, 1997; Traver et.al, 1999; Brace, 1998 and Deacon et.al, 1994) has described the use of neural networks for emissions prediction based on parameters commonly associated with monitoring and engine control. Significant success was demonstrated in predicting emissions levels from various engine types using a feedforward network. The feedforward architecture associated with back propagation based prediction algorithm, has been known as an algorithm with a very fast convergence rate (Wilamowski et. al, 2001).

The present work describes an experimental and computer simulation studies used to develop a suitable algorithm to predict and control the NO_x emissions of single cylinder diesel engine capable of producing 4.5 kW. A neural network model is developed to obtain the NO_x emission concentration under various operating condition. Four operating parameters (engine speed, engine load, exhaust temperature and air fuel ratio) have been used as an input data in the modelling process. The modelling algorithm that was used, takes a large set of measurements to learn how to predict the NO_x emission from four operating parameters. Three processes such as train, test and verify have been done to examine whether the develop network can give a good accurate prediction.

Experiment Set up

The engine used for the experiments was a Yanmar L60AE-D single cylinder direct injection engine, fitted in a Cusson's Engine Test Bed Model P8160 capable of producing 4.5 kW. The engine was coupled to an electric dynamometer to provide brake load and it was equipped with the appropriate instrumentation for control and measurement of the operating conditions. The schematic diagram of the experiment set up is presented in Figure 1 and its main specifications are shown in Table 1.

The Yanmar L60AE-D engine used diesel fuel during the experiments. The fuel consumption was measured with the aid of a fuel switching, a burette and a stopwatch while the air consumption was measured by means of an air plenum chamber, a venturi meter and a monometer. Two thermocouplers fitted in the exhaust pipe and in the air plenum chamber, were used to measure various exhaust emission temperatures and air intake temperatures. The strain gauge load cell was used to measure engine load. All these measurements are shown on the display board. The engine exhaust stream was also diverted to a MSI compact multiple gas analyser capable of measuring oxides of nitrogen, NO_x. Before entering the analyser, the exhaust gas was pre-treated by passing it through a filter (particle trap) and silicon gel, to reduce both the particles and the water vapour content in order to protect the sensitivity and durability of the analyser.

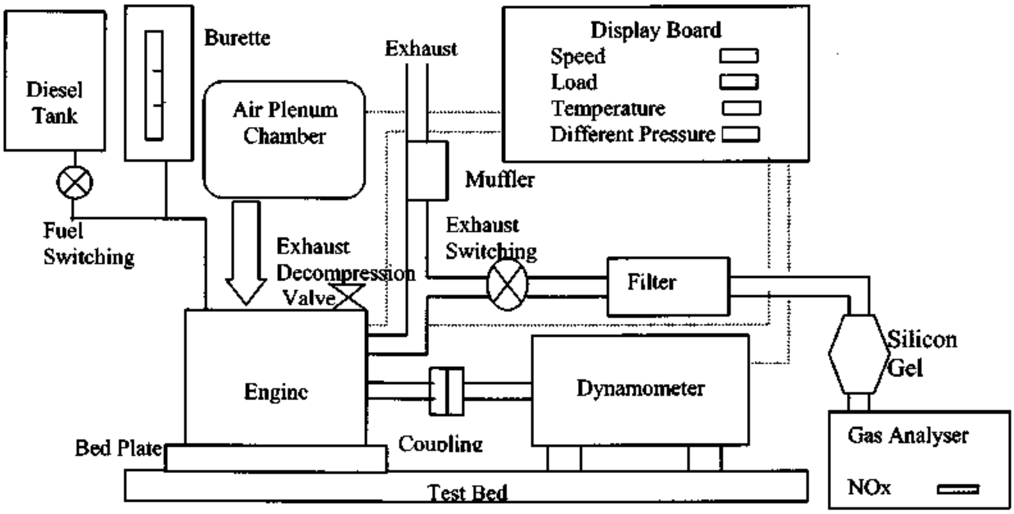


Figure 1: Block diagram of engine test facility

Model	: Yanmar L60AE-DTM
No Engine	: 64208
Fuel	: Diesel
Type	: One cylinder, 4 stroke, direct injection
Capacity	: 273 cc
Bore and stroke	: 75mm x 62mm
Maximum power	: 4.5kW at 3600 rpm
Compression ratio	: 19.5 :1
Fuel injection timing	: 14° ± 1°
Fuel injection pressure	: 19.6 Mpa
Intake valve timing	: Open at 25° BTDC
	Close at 59° ABDC
Exhaust valve timing	: Open at 59° BBDC
	Close at 25° ATDC
Cooling System	: Air System

Table 1: Engine Specifications

A test of 153 and 10 random separate load and speed settings were chosen to provide a range of engine performance test. Figure 2 represented the torque-speed data points of 153 and 10 random separate torque and speed settings. At each set of point, the engine was brought to the appropriate speed and load and allowed to settle into a steady state condition in order to prevent in-stability in operating conditions and to provide steady NO_x gaseous exhaust emissions. Once the engine had achieved a steady state condition, four inputs parameters (engine speed, engine torque, exhaust temperature, air fuel ratio) as well as a response parameter (exhaust NO_x concentration) measured by MSI compact multiple gas analyser were recorded. Finally at the end of the test, the engine was kept running on light load for a while before shut down

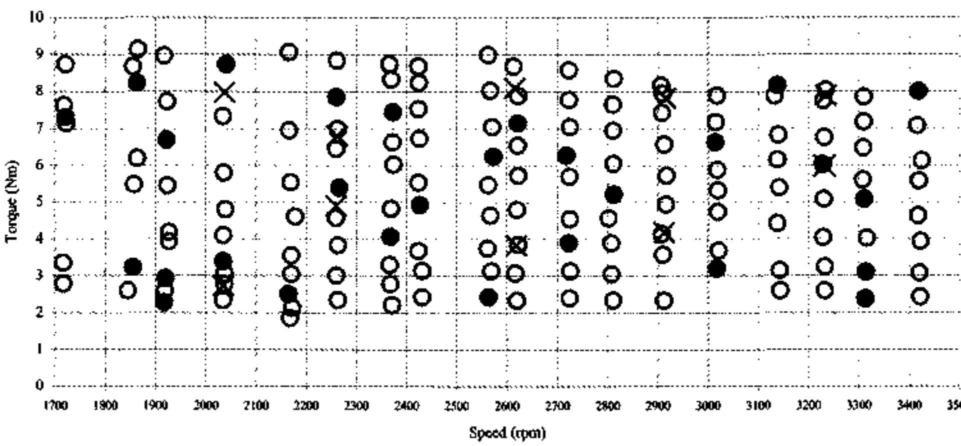


Figure 2: 153 and 10 random torque-speed data points
(o = training set, • = test set, x = verification set)

Data Manipulation

Once all the data had been collected for each of 153 points and 10 random points by setting load and speed, the free mapping technique for prediction which can readily cope with the large multi input, multi output data set in a rapid and accurate manner is needed. One of the techniques that widely used for such tasks is the artificial neural network (Berry et.al, 2001; Traver et.al, 1999; Brace, 1998 and Deacon et.al, 1994).

Artificial Neural Networks

An artificial neural network is an electronic model consisting of interconnected large simple artificial cells called nodes that works in a parallel way and produced an output based on the neural structure of the brain. From the analogy with human brain behaviour, artificial neural networks are able to produce a process from training examples rather than from a coded algorithm which simulate the process base on mathematic model. In other words, they are capable of modelling complex and non-linear problems simply by being presented with examples and sets of input output patterns. That is why they had been used for many applications such as control problem, diagnostics, mapping and modelization problem, optimisation and pattern recognition (Arsie et.al, 1998).

Artificial neural network operates by accepting input into a set of input nodes, processing the input through neural connections and then producing a set of output as output nodes as shown in Figure 3. The output is obtained by processing the weighted sum of the inputs with a transfer function called activation function. The number and strength of weight connections between input and output nodes will determine the final output. The weights of the connections between the nodes cannot be pre-determined for a large scale so the learning ability is necessary for an artificial neural network to adjust the weight during the learning process in which all the examples are presented to artificial neural network repeatedly. After the learning process, the artificial neural network can be used to obtain the answer to an input pattern.

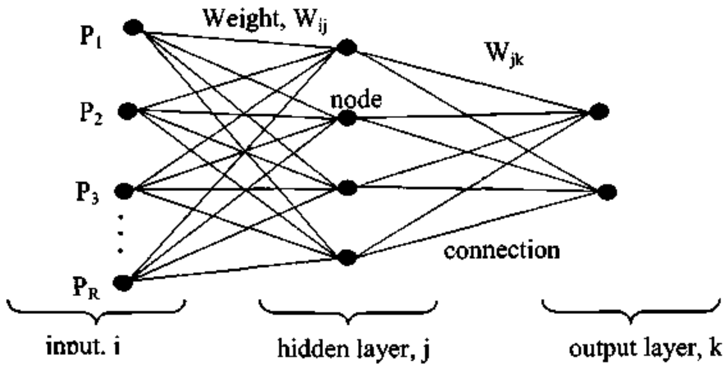


Figure 3: Basic structure of an artificial neural network

Artificial Neural Networks Application

The software used for artificial neural network application was MATLAB version 6.1. The architecture of the network used in this project was a feedforward network. It used a backpropagation training algorithm. In fact, this is a common device for representing non-linear continuous functions.

The feedforward backpropagation consists of four input nodes, six hidden nodes and one output node were used to model the oxides of nitrogen, NO_x emissions of Yanmar diesel engine. Engine speed N, torque T, exhaust emission temperature T_e and air fuel ratio A/F are employed as the input to evaluate the correlation and effect to NO_x, as an output. Figure 5 shows the network structure used for the engine model.

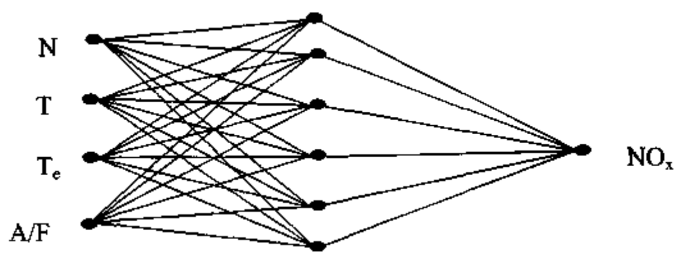


Figure 5: Neural Network representation of Yanmar engine

The feedforward backpropagation network used, had two layers of node with the first layer being tan-sigmoid functions and second layer comprised of linear functions. The experimental data composed of more than 1000 set of data of 153 and 10 torque- speed condition points. Referring to Figure 2 the data corresponding to the points with mark – o, mark – and mark – x. The operating parameter data sets were divided into three sections. The first was to train the network, the second to test the trained network and the third to verify the trained network. For the train network, only 125 (mark-o) of the 153 points were used. To analyse the productivity level of the artificial neural network, the other 28 points (mark -) were used to test the network on unseen data in order to improve the accuracy of the network and to ensure sufficient training had been performed. After analysing the effects on the test data, another 10 random points (mark - x) were used to verify the structure model of the network whether could perform a good accuracy in prediction. Finally, the post training analysis method was used to provide a relative measure of the accuracy of the predictive network of NO_x exhaust emissions. A correlation coefficient, R between the prediction and actual values was determined for training, testing and verifying process.

Results and Discussion

The parameters that contributed to NO_x emission of the Yanmar diesel engine were engine torque, speed, air fuel ratio and exhaust temperatures. These parameters were presented into the artificial neural network model for training, testing and verification. As the results, the comparison between computed and measured of the training, testing and verification network for NO_x concentration emissions models were presented in Figure 6, 7 and 8. The method of the post training analysis was used to describe these results. The vertical axis represents the prediction amounts of NO_x pollutant produced by the computer and the horizontal axis represents the actual values of NO_x pollutant from the experimental.

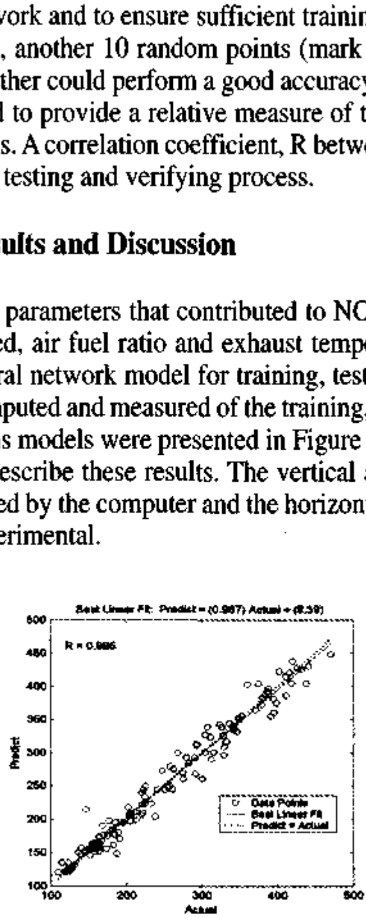


Figure 6: Comparison between computed and measured NO_x emission, training process.

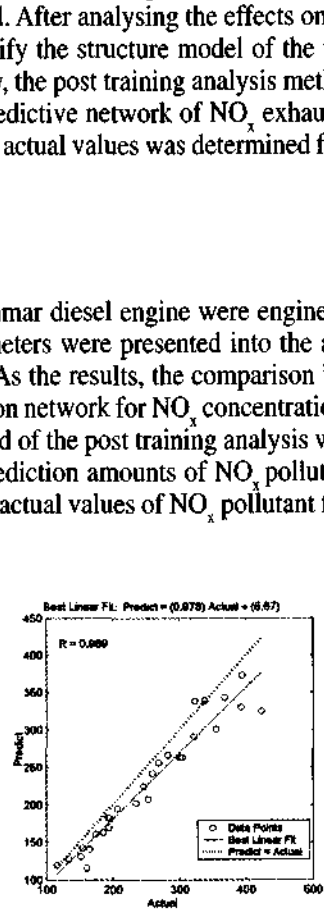


Figure 7: Comparison between computed and measured NO_x emission, testing process.

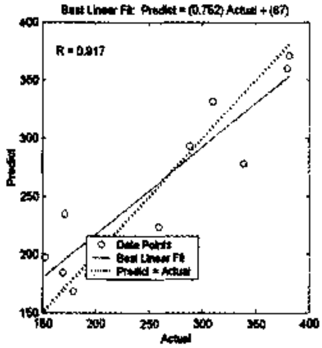


Figure 8: Comparison between computed and measured NO_x emission, verification process.

In the simulation process of the trained network, the training process stopped when the maximum epoch reached at 1500 epochs and the sum square error of the network was 1.0472. Although the sum square error obtained was higher than the optimum value 0.001 (Matthews, 2000) it was sufficient to show that the trained network was in the perfect training process. Table 2 shows the results of trained, tested and verified network in term of the correlation coefficient R, the best linear regression, m and relative error in percentage.

Network	R	m	relative error (%)
Train	0.985	0.967	1.5
Test	0.969	0.878	3.1
Verify	0.917	0.752	8.3

Table 2: Computational analysis of train, test and verify network

It can be seen that the trained network is relatively good for prediction application because of two reasons. First, the values of the correlation coefficient, R and the slope of the best linear regression m, where they are very close to one. According to Demuth and Beale (1998) when the perfect fit of the network achieved (predictions exactly equal to actual), the R and m values were equal to one. This means that the correlation between the prediction and the actual values of NO_x are in a good fit. The second reason is the relative error between NO_x prediction and actual values. The relative error was 1.5% and this percentage was found to give a very good fitting on the trained network.

After the trained network models were precisely established, the testing and the verification process were used to determine whether the network has learned from the training process and predict successfully by itself. Referring to Table 1, the R and m values of testing and verify network are also close to one. It means that the developed network for prediction is in a good fit. Despite increase to the m values for both testing and verification network there was considerable success because these values tend to give a good fit.

Figure 9, 10 and 11 represent the simulation results of the NO_x concentration emissions between the prediction and actual values of trained, tested and verified network. They show the predicted values are exactly at a same spot as for the actual data. The relative error of 1.5%, 3.1% and 8.3% for trained, tested and verified network are achieved. According to Duran et.al (2001), Lucas et.al (2001), Turunen et.al (2000) and Traver et.al (1999), the relative error below than 20% has capability to give a good prediction or forecast. It can therefore be concluded that the artificial neural network with a single hidden layer based on the standard backpropagation algorithm using eventually only the simple sigmoid as activation function, resulted as a very efficient model to predict NO_x exhaust emissions from diesel engine.

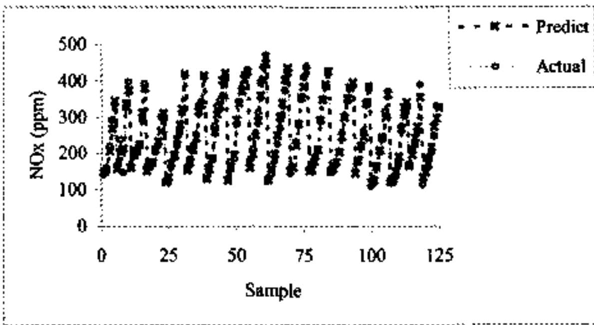


Figure 9: Predicted vs. actual values of NOx emissions, training network.

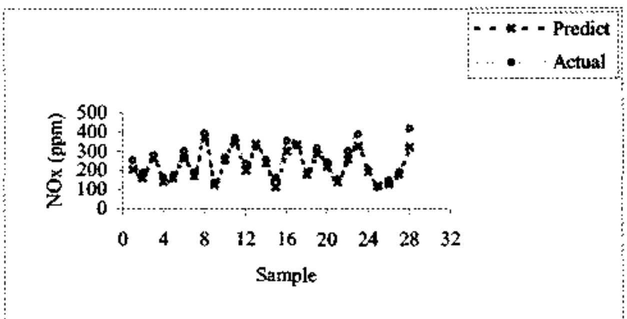


Figure 10: Predicted vs. actual values of NOx emissions, testing network

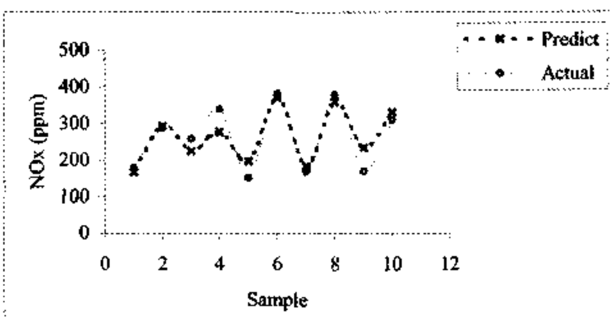


Figure 11: Predicted vs. actual values of NOx emissions, verify network

Conclusion

The application of an artificial neural network to predict the oxides of nitrogen, NO_x concentrations emitted from single cylinder direct injection diesel engine for preliminary design of control strategies has been developed and used successfully.

The feedforward architecture with a backpropagation training algorithm was found to be very suitable for prediction purpose. The three processes (train, test, verify) results shown that the correlation coefficient, R obtained was very close to one. The simulation results of NO_x concentrations between prediction and actual values also shown the relative error of 1.5%, 3.1% and 8.3% were obtained. These results were less than 9% and were found to give a very good fitting on the neural network model.

It can therefore be concluded that the developed artificial neural network model from feedforward architecture with a backpropagation training algorithm proved to be a very accurate and efficient model to predict NO_x concentration emissions for Yanmar diesel engine. Further work is in progress to implement the artificial neural network models in the complete computational procedure for the optimal engine control strategies. For this purpose, the areas of a model reference control based on neural network will be studies.

References

Arsie, I., Pianese, C. and Rizzo, G. (1998). Enhancement of Control Oriented Engine Models Using Neural Network. In: Proceedings of The 6th IEE Mediterranean Conference on "Control System", *9-11 June, Alghero, Italy. pp. 465-471.*

Atkinson, C., Long, T. and Hanzevack, E. (1998). Virtual Sensing: An Emissions Prediction System for ON-Board Diagnostics and Engine Control, SAE Paper 980516.

Bacha, J., et al. (1998). Diesel Fuels. *Technical Review. USA: Chevron Products Company, Inc.*

Berry, E., Wright, J., Kukla, P., Gu, F. and Ball, A. D. (2001). *The Prediction of Diesel Engine Smoke Emission from Routine Engine Operating Parameters, and its Implications for Engine Health Monitoring. In:* Proceedings of Marcon 2001 Conference, *Gatlinburg Tennessee, USA.*

Brace, C. (1998). *Prediction of Diesel Engine Exhaust Emissions using Artificial Neural Networks. Presented at 'Neural Networks in System Design'* IMechE Seminar Lucas Electrical and Electronic Systems. *10 June, Solihull.*

Dales, D.N. and Thiessen, F.J. (1982). Diesel Fundamental: Principles and Service. *New Jersey: Prentice-Hall, Inc.*

Deacon, M., Vaughan, N. D., Brace, C. J. and Charlton, S. J. (1994). *Prediction of Emissions from a Turbocharged Passenger Car Diesel Engine using a Neural Network. In:* ImechE International Conference "Turbocharging and Turbocharges", *7-9 June.*

Demuth, H. and Beale, M. (1998). Neural Network Toolbox for Use with MATLAB. *User's Guide Version 3. The MathWorks, Inc.*

Duran, A., Ballesteros, R., Carmona, M. and Lucas, D. A. (2001). *Simulation of Atmospheric PAH Emissions from Diesel Engines.* Chemosphere, *44, pp. 921-924.*

German, J. (1995). *Observation Concerning Current Motor Vehicle Emissions.* SAE *Paper 950812.*

Hanzevack, E., Long, T. and Atkinson, C. (1997). *Virtual Sensing for Spark Ignition Engines Using Neural Networks. In:* Proceedings of The American Controls Conference, *Albuquerque, June.*

Heywood, J. B. (1988). Internal Combustion Engine Fundamentals. *New York: McGraw-Hill, Inc.*

Itoyama, H., et al. (1997). *A Study of An EGR Control System for Diesel Engine Based On The Intake Exhaust Control System Model.* SAE *Paper 970621.*

Kawashima, J., Muranaka, S. and Aiyoshizawa, E. (1999). *Development of New 4-Valve / Cylinder Small DI Diesel Engine.* Trans. JSAE, ***20****, pp. 183-190.*

Krinjsen, H. C., Leeven, J. C. M., Bakker, R., Bleek, C. M. and Calis, H. P. (2001). *Optimum NO_x Abatement in Diesel Exhaust Using Inferential Feed forward Reductant Control.* Fuel, ***80****, pp. 1001-1008.*

Lucas, D. A., Carmona, M., Duran, A. and Lapuerta, M. (2001). *Modeling Diesel Particulate Emissions with Neural Networks.* Fuel, ***80****, pp. 539-548.*

Matsui, Y., et al. (1997). *A New Combustion Concept for Small DI Diesel Engines, (1st Reports).* Trans. JSAE, *28 (1), pp.41.*

Matthews, J. (2002). *Generation 5: At the Forefront of Artificial Intelligence.* Web Magazine *[Internet]. Available from:* http://www.generation5.org/nn_bp.shtml *[Accessed Sept. 6th, 2002].*

Pulkrabek, W. W. (1997). Engineering Fundamentals of the Internal Combustion Engine. *New Jersey: Prentice- Hall, Inc.*

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 1999-01-1532, 3-6 May.*

Turunen, R., Kallio, A. and Rantanen, P. (2000). Performance Development of a Medium Speed Diesel Engine. *Final Report. Finntech Oy: Kyto M. Tekes Pro Motor, pp. 173-186.*

Wilamowski, B. M., Kaynak, O., Iplikci, S. and Efe, M. O. (2001). *An Algorithm for Fast Convergence in Training Neural Networks.* IEEE Trans. on Neural Networks, *1, pp. 1778-1782.*