A SENSOR ARRAY FOR CONTROL OF ENGINE EXHAUST AFTER-TREATMENT SYSTEMS

Ahmed Soliman*, Prabhu J.Jackson*,Giorgio Rizzoni*
and Prabir Dutta**

**Center for Automotive Research (CAR), The Ohio State Universit, USA.*
***Center for Industrial Sensors and Measurements (CISM), The Ohio State Universit, USA.*

Abstract: In the US majority of the trucks, buses and off-road vehicles are diesel powered. The advancement in technology and better designs have narrowed the differences between the diesel and gasoline engines making it a leading candidate for passenger cars. Due to this emergence the Department of Energy (DOE) and Environmental Protection Agency (EPA) have enforced strict emission regulations for diesel emissions. To attain a reduction in emissions, sensor development is needed for use in emission control systems for control and diagnostic purposes. The various ceramic-based gas sensors developed at the Center for Industrial Measurements and Sensors (CISM) have the capability for measuring exhaust gas concentrations. But unfortunately these sensors are subjected to interferences from other gas species. A methodology for predicting the gas concentrations from the sensor responses when there is interference from other gas species is proposed in this paper. The sensor array for gas concentration prediction is developed using Artificial Neural Networks (Back Propagation). The developed sensor array had the ability to predict gas concentration. A detailed description about the methodology is presented and discussed in detail as well as the future work about the extension and application of the sensor array is also mentioned in this paper.

Keywords: Neural Networks, Neural Nets, Sensors, Back Propagation, Algorithms, Pattern Recognition.

1. INTRODUCTION

In the US majority of the heavy trucks, buses and off-road vehicles are diesel powered. Only a small fraction of the passenger cars, pickups, light-duty trucks and Sports Utility Vehicles (SUV's) are diesel powered. Whereas in Europe, 50% of the cars are diesel powered. Although diesel engines are more durable and have better energy efficiency they are always under a common misconception that they are noisy, heavy and more polluting when compared to gasoline engines. Earlier diesel engines were not considered for passenger cars since they were heavier, slower to accelerate and more expensive than gasoline engines. In recent years the advancement and refinement of the Compression-Ignited-Direct-Injection (CIDI) engine (Diesel Engine) have made it a leading candidate for new generation vehicles in the US including passenger cars due to its high fuel efficiency and better performance characteristics. Better designs have narrowed the difference between the gasoline and diesel engines.

Diesel engines emissions have high NOx (oxides of nitrogen) and particulate matter (PM) when compared to the gasoline engines. The Department of Energy (DOE) and the Environmental Protection Agency (EPA) aware of the emergence and importance of diesel engines have enforced strict emission regulations for NOx and PM emissions. Thus controlling the emissions of oxides of nitrogen (NOx) is a key element for the successful implementation of the modern CIDI engine into future passenger vehicles.

The required emission reduction can be achieved by using both a sophisticated control of the combustion process and by an advanced exhaust emission control system. It is particularly important to both of these approaches to improve on board monitoring of the exhaust constituents NOx, PM, and oxygen (with emphasis on the first two). Furthermore, future emission regulations (i.e the EPA regulations 2007) require a drastic reduction in NOx emission from the present 2.5 g/bhp-hr to 0.2 g/bhp-hr by 2007. In order to attain such a reduction more sophisticated after-treatment systems are being developed.

Thus sensor development is needed for use with advanced emission control technologies and engine controls that will enable PNGV-candidate CIDI engines (operating on low-sulfur diesel fuel) to meet NOx and PM emissions targets (0.07 g/mi NOx and 0.01 g/mi PM) as well as other requirements (e.g., cost and efficiency). (Note that the NOx emission target eventually evolves to 0.03 g/mi in the 2007 time frame.) These sensors could save millions of dollars for the automotive industry since they would provide the best possible measure of the exhaust gas concentrations for an affordable price. The potential benefits are much larger than using emission maps for emission prediction. These sensors will enable the implementation of sophisticated control of combustion and the use of advanced exhaust emission control systems along with on-board diagnosis of these systems.

2. METHODOLOGY

Many gas sensors developed for exhaust gas measurement have some interference from other gases, noise and disturbances from the environment. A sensor that responds to a unique gas is highly desirable but unfortunately they deter from ideal behaviour. In order to get reliable measurement from these sensors special sensor arrays (i.e. multiple sensors with orthogonal responses) as described by Fulkerson, et al. (2002) using kernel regression are being developed to cancel out these interferences. A gas sensor array consists of two or more sensors that respond to different gas mixtures. Since most sensors (including the NOx Sensor) developed at The Center for Industrial Sensors and Measurements (CISM)(The Ohio State University) respond to more than one type of gas, a sensor array was needed to predict the gas concentration from the responses of each of the sensors in the array. A given sensor response could be modelled based on the response of that particular sensor to each of the gases as a function of concentration. Once the sensor array is modelled from the data obtained, the not so useful sensor response data could be translated into useful information about the composition of the mixture of gases. Different approaches could be used to develop these sensor arrays for accurate prediction. For developing the sensor array different methodologies like recursive least squares (Bay, 1999), kernel regression (Fulkerson, et al., 2002) and artificial neural networks could be used. But among the methodologies artificial neural networks was found to be the most suitable for developing the sensor array. The main emphasis is on the application of Neural Networks for developing the sensor array.

Artificial Neural Network has been a significant subject with vast amount of research for the search to achieve human-like performance. Neural nets are biologically inspired and organized to resemble the capability of the human brain. A neural network consists of simple elements operating in parallel. The simplest node sums several weighted inputs and passes the sum through a nonlinear element. It can be trained to perform a specific function by adjusting the values of the weights and biases between the elements. Neural networks are trained in such a way that a particular input leads to a specific target output. And the network is adjusted according to the comparison made on the output and input until the network output equals or approximately equals the target. Artificial Neural Networks when trained with sufficient and reliable data give good predictions. It is regarded as one of the robust tools for mapping highly nonlinear relations between multiple inputs and multiple outputs (Haykin, 1994). ANN's are used for complex pattern recognition problems. So as long as fair data is provided for training, good predictions can be expected unlike any other modelling tool. Neural network based modelling offers the possibility of multidimensional adaptive modelling which can give exact prediction for the given data even if the data is not orthogonal (Haykin, 1994).

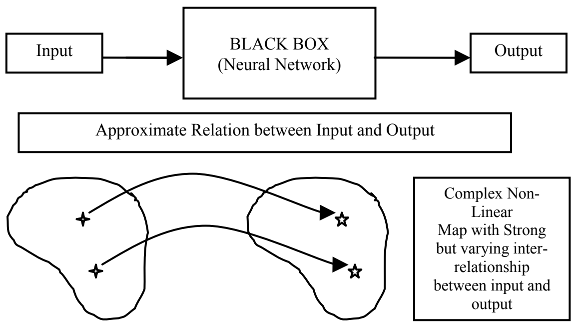


Figure 1 Neural Network: A Non-linear map between input and output

Figure 1 shows the schematic of the relationship between the input and output in a neural network. The most common approach to arrive at a mathematical model of the physical plant is to relate the input and output data available. A plant can be modelled as a mathematical relation only if all of the system parameters and the behaviour of the system are known. But in some systems it is very difficult to understand the behaviour and the uncertainties of the system (Muller and Schneider, 2000). For developing models for such complex systems various background neural approximation approaches like recurrent networks, regression backpropopagation, Radial Basis Functions, etc. could be used. Also, according to Wasserman (1993) most of the networks have some kind of backpropogation approach built in them. Therefore, modelling difficulties could be avoided by using neural networks.

Due to the complexity of chemical gas sensors, which are developed based on chemical reactions and the difficulty in understanding the uncertainties and interferences involved, the prediction of gas concentrations from the sensor response becomes complicated (i.e. the sensor might respond to other gases apart from the sensing gas). By having a sensor array for sensing multiple gases a pattern recognition approach (ANN) can be utilized to identify the gas concentrations in the mixture.

3. TWO SENSOR ARRAY

3.1 Experimental Setup

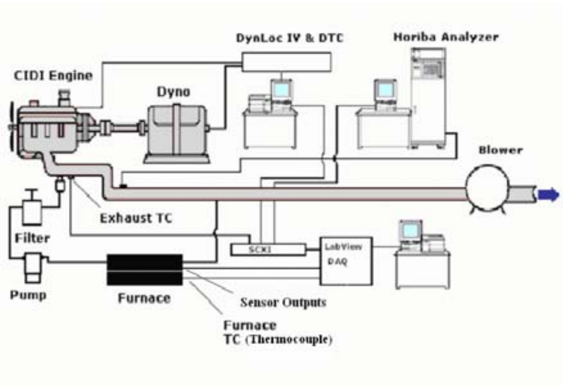


Figure 2 Experimental Setup used for Testing (CAR-OSU)

A 2.5 L Turbocharged CIDI (VM Motori Diesel) calibrated for a SUV was used for testing. The engine is equipped with a liquid cooled Exhaust Gas Recirculation (EGR) and an Air-cooled intercooler. As shown in Figure 2 the engine was coupled to a 200 HP Dynamometer controlled using a computer (PC). RS 232 cable was used for communication between the computer (PC) and Dyn-Loc IV & DTC (Dynamometer Controller).The data from tests were acquired using National Instruments SCXI- 1000, SCXI-1102C & SCXI-1303 connected to the PC through PCI-MIO-16E-4 Board. LabView 6.0 software was used to run the data acquisition system. Figure 3 shows a picture of the furnace used for this experiment.

Figure 3 High Temperature Furnace (Orton)

3.2 Sensors Used

CO Sensor

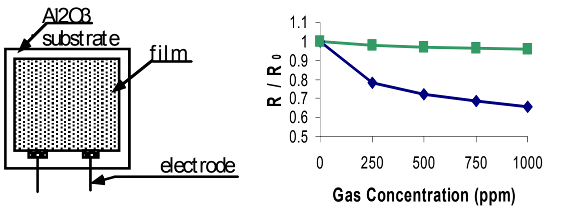


Figure 4 CO Sensor (75% rutile and anatase 25% TiO_2 composite sensor) (a) Thick Film CO Sensor Structure (b) Laboratory test result at 600^0C and 3% O_2 Ro - Resistance in the absence of sensing gas (Szabo, et al., 2003)

The CO sensor used for this experiment was developed at The Ohio State University Center for Industrial Sensors and Measurements (CISM) (Szabo, et al., 2003), (Azad, et al., 1995) and (Azad, et al., 1996). Researchers at CISM have developed a new type CO sensor based on (p-n) heterojunctions of anatase (n) and rutile (p) using TiO_2 as the base material as explained in (Savage, et al., 2001).These sensors have great potential because by changing the compositions of the rutile and anatase material the sensor response could be varied over a wide range for designing selective CO sensors. Figure 4 shows the structure of the CO sensor.

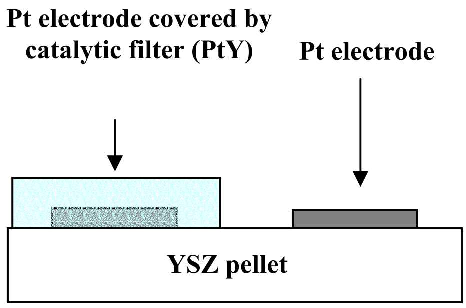


Figure 5 Planar Potentiometric NO_x Sensor with one Pt electrode covered with Zeolite (PtY) (Szabo and Dutta, 2003)

The NO_x Sensor used for this experiment was developed at CISM. It is a potentiometric sensor based on Yttria-Stabilized Zirconia with metal oxide sensing electrodes (Szabo and Dutta, 2003) & (Soliman, et al., 2002). Figure 5 shows the cross sectional view of the NO_x sensor used for this experiment. One of the Pt sensing electrodes was covered with a second PtY filter layer that keeps the electrode potential constant (close to the equilibrium potential determined by O_2) by creating an equilibrium NO_x mixture while the other uncovered Pt sensing electrode detects NO_x concentration changes. The Sensor needs to be maintained at 500^0C for it to detect the NO_x change. Slight CO interference was noted during laboratory testing in the presence of 3% O_2 (Szabo, et al., 2003).

3.3 Experimental Results

Data was acquired from engine testing at a constant engine speed of 1500 RPM while the torque was increased in steps till the desired range of CO and NO_x emission concentration were reached. Figure 6 shows the data acquired from the test. During the test the exhaust gas was sampled through the high temperature furnace where the CO and NO_x sensors were placed. The sensors were maintained at a constant temperature of around 500^0C. The signals from the sensors were measured using multimeters (HP 34401A Agilent Technology). The change in resistance was measured from the CO sensor and the potential difference was measured from the NO_x sensor. All the data were acquired on to a file by National Instrument Lab View software which runs the data acquisition system. Figure 7 shows the CO and NO_x responses.

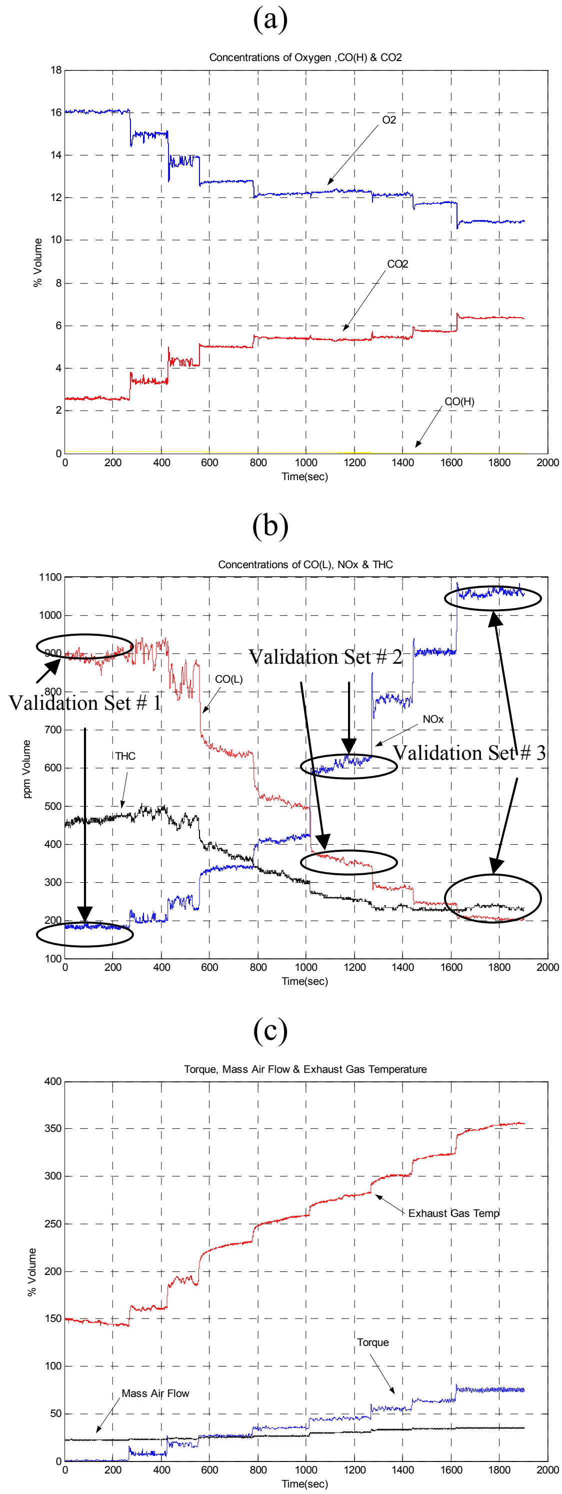
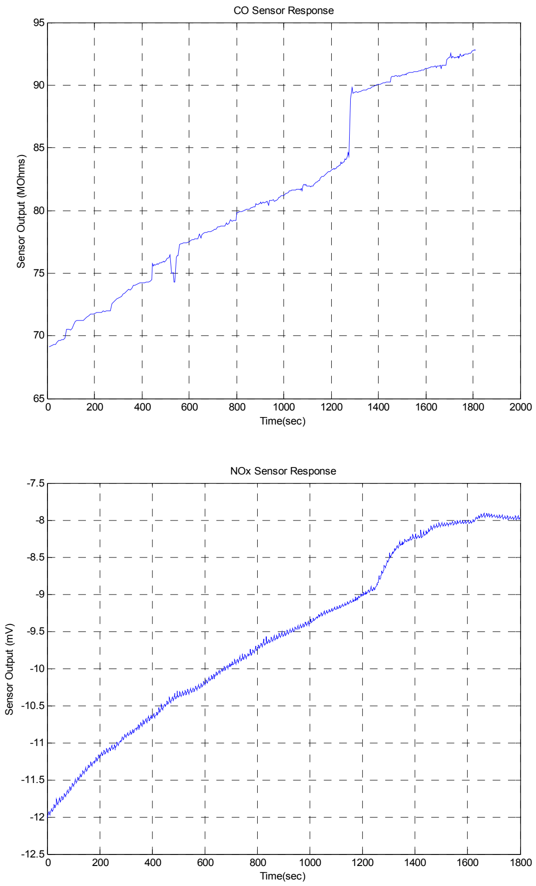


Figure 6 Experimental Results from engine testing (CAR) (a) Concentrations of Oxygen, CO (H) & CO_2 (b) Concentrations of CO (L), NO_x & THC (c) Torque, Mass Air flow & Exhaust Gas Temperature

(a)



(b)

Figure 7 (a) CO Sensor Response (b) NO_x Sensor Response (Both sensors were maintained at 500^0C)

3.4 Two Sensor Array (Neural Network)

Inputs (CO sensor & NO_x Sensor Output) $\rightarrow$ 2
Outputs (CO & NO_x Concentrations) $\rightarrow$ 2

The required number of hidden layers and neurons were adjusted accordingly to get the minimum Mean Percentage Error (MPE) during training. MPE could be actually called the error in prediction. One thousand data points were selected from the sensor response curves. From the selected data points 550 points were assigned for training and the remaining for validation. Before the data was used for training it was normalized between 0 and 1 by using the formula

$$x_N = \left(\frac{x - x_{\min}}{x_{\max} - x_{\min}} \right) factor + (y_1) \qquad (1)$$

where *factor* = $y_2 - y_1$ and y_1 & y_2 are the minimum and maximum values for the normalized data. The following network was chosen according to the data acquired for best results as shown in Figure 8.

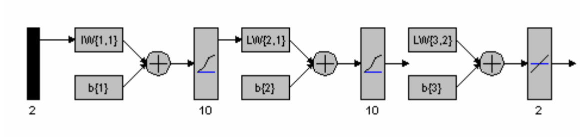


Figure 8 Two Sensor Array Neural Network [Matlab (NNTool)]

The developed neural network was trained with the training data set, where the output for each of the inputs was already known beforehand. The weights and biases were assigned random numbers to start with and adjusted to decrease error between the network output and the desirable output. The difference between network output and desirable output (error) is minimized after each epoch (each training cycle) till the minimal possible error is reached. The training data sets were used to train the system for several epochs till the desired MPE was reached. After each epoch the weights and biases of the network were adjusted accordingly. A performance of the order of 10^-6 was obtained while training the network. The goal of the network is to achieve 0 error between the actual target and the achieved target but training for a number of epochs a plateau in the error plot was reached.

After training the network till the lowest MPE, the network was validated. Three validation sets of 200, 150 and 100 data points with a total of 450 data points was used for simulation on the neural net which was already set to specific weights and biases from the training procedure. The validation sets were chosen from each region of the sensor response i.e. from the beginning, middle and end of the response curves to show both the interpolation and extrapolation capabilities of the network developed. Figure 9 shows the comparison between the actual gas concentrations and the predicted CO gas concentrations from the simulated neural network and also the prediction obtained from recursive least squares is also included just to illustrate the purpose of using neural networks for this application.

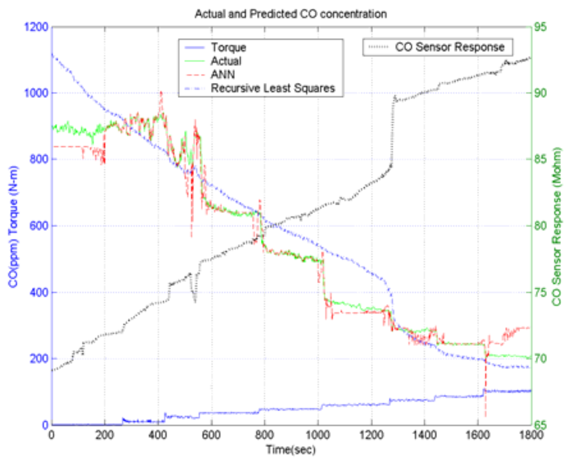


Figure 9 Actual CO and predicted CO concentration

Figure 10 shows the comparison between the actual and predicted NOx concentration from the simulated network. In addition to that the prediction obtained from recursive least square method is also presented to show the reason for using neural networks for this application.

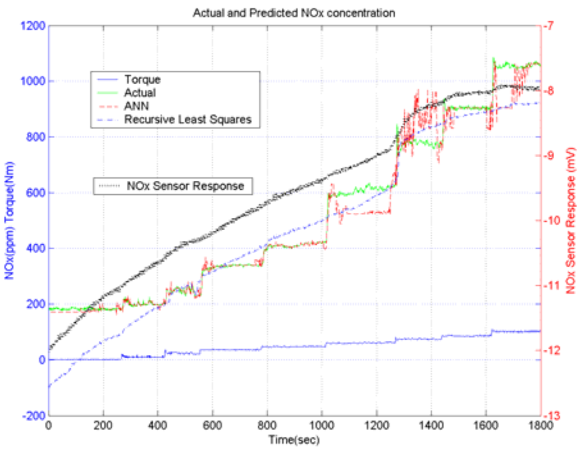


Figure 10 Actual NOx and predicted NOx concentration

From the results shown above it is clear that the neural network developed has the capability to extrapolate and interpolate producing reasonable results.

4. CONCLUSION AND FUTURE WORK

4.1 Conclusion

In this paper a sensor array was proposed to predict the exhaust gas concentrations from a diesel engine. Sensors developed by researchers at CISM namely CO and NO_x sensor were used for this application. Experiments were conducted at CAR on a diesel engine where the sensor responses along with operating conditions data were acquired. The acquired data was used to construct a two sensor array for CO and NO_x gas concentration prediction. A neural network model was developed with the sensor responses as input and CO & NO_x concentrations as output. It was demonstrated that the designed neural network when simulated after sufficient training gave reasonable predictions. However, these networks could be trained to negate the effect of noise and other disturbances that affect the sensor response.

4.2 Future Work

The present sensor array developed can be easily extended to a multiple sensor array which could incorporate different sensors to predict multiple gases. The work presented can be further extended to the development of a Neural Network model (multiple sensor array) for multiple gas concentration prediction. This array could be actually used in place of expensive gas analyzers for measuring multiple gas concentrations. For example the horiba analyzer measures CO, CO_2, O_2, NOx and THC so a combination of five sensors namely CO, CO_2, O_2, NOx and THC sensors along with a designed Artificial Neural Network (multiple sensor array) could be used for predicting the five gas species. Since the ceramic-based sensors are easy and cheap to fabricate a multi-sensor array would be easy to implement. Also, adaptive neural network could be used for developing the sensor array system that could compensate for changes in operating conditions like temperature, humidity, etc.

REFERENCES

Azad A., Younkman L., Akbar S., Soliman A. and Rizzoni G. (1995). Performance of a Ceramic CO Sensor in the Automotive Exhaust System. *SAE International Congress and Exposition*, SAE Technical paper 950478, Detroit, MI.

Azad. A.M, L.B. Younkman, S.A. Akbar, A. Soliman and G. Rizzoni (1996). Test Results of a Ceramic-Based Carbon Monoxide Sensor in the Automotive Exhaust Manifold - Role of Ceramics in Advanced Electrochemical Systems. *Ceramic Transactions,* **Vol. 65**, (P. Kumta, G. Rohrer and U. Balachandran (ed)), 343-354.

Bay.S John (1999). *Fundamentals of linear state space systems.* WCB/McGraw-Hill, Boston.

Fulkerson. M, P.Dutta, M.Frank and B.Patton. TiO2-based Sensor Arrays Modelled with Nonlinear Regression Analysis for determining CO and O2 Concentrations at High Temperatures (2002). *Sensors and Actuators B*, **Vol 87**, 471–479.

Haykin.S (1994). *Neural Networks: A comprehensive foundation*. Macmillan, New York.

Muller. R and Schneider. B (2000). Approximation and Control of the Engine Torque Using Neural Networks. *SAE Journal,* Paper 2000-01-0929.

Savage. N, B. Chwieroth, A. Ginwalla, B.R. Patton, S.A. Akbar and P.K. Dutta (2001), Composite n-p Semiconducting Titanium Oxides as Gas Sensors. *Sensors and Actuators B*, **Vol 79**, 17-27.

Soliman. A, Dutta. P and Szabo. N (2002). A NOx Sensor for Emission Reduction. *FISITA 2002 World Automotive Congress*, Helsinki.

Szabo. N, C. Lee, J. Trimboli, O. Figueroa, R. Ramamoorthy, S. Midlam-Mohler, A. Soliman, H. Verweij, P. Dutta and S. Akbar (2003). Ceramic-based chemical sensors, probes and field-tests in automobile engines. *Journal of Materials Science on "Chemical Sensors for Pollution Monitoring and Control",* **Vol 38**, Issue 21, pp. 4239-4245.

Szabo Nicholas F and Dutta. P (2003). Strategies for total NO_x measurement with minimal CO interference utilizing a microporous zeolite catalytic filter. *Sensors and Actuators B,* **Vol 88**, 168-177.

Wasserman P D (1993). *Advanced Methods in Neural Computing*. Van Nostrand Reinhold, New York.