CA9700824

# Determining the Confidence Levels of Sensor Outputs using Neural Networks

**Gregory S. Broten and H.C. Wood**

Department of Electrical Engineering, University of Saskatchwan,
Saskatoon, Sask. S7N 0W0, Canada
E-mail:gsb132@dvinci.usask.ca or Broten_Greg/support@sask.aecl.ca

**Abstract**

This paper describes an approach for determining the confidence level of a sensor output using multi-sensor arrays, sensor fusion and artificial neural networks. The authors have shown in previous work that sensor fusion and artificial neural networks can be used to learn the relationships between the outputs of an array of simulated partially selective sensors and the individual analyte concentrations in a mixture of analytes [1]. Other researchers have shown that an array of partially selective sensors can be used to determine the individual gas concentrations in a gaseous mixture [2] [3] [4] [5] [6]. The research reported in this paper shows that it is possible to extract confidence level information from an array of partially selective sensors using artificial neural networks. The confidence level of a sensor output is defined as a numeric value, ranging from 0% to 100%, that indicates the confidence associated with a output of a given sensor. A three layer back-propagation neural network was trained on a subset of the sensor confidence level space, and was tested for its ability to generalize, where the confidence level space is defined as all possible deviations from the correct sensor output. A learning rate of 0.1 was used and no momentum terms were used in the neural network. This research has shown that an artificial neural network can accurately estimate the confidence level of individual sensors in an array of partially selective sensors. This research has also shown that the neural network's ability to determine the confidence level is influenced by the complexity of the sensor's response and that the neural network is able to estimate the confidence levels even if more than one sensor is in error. The fundamentals behind this research could be applied to other configurations besides arrays of partially selective sensors, such as an array of sensors separated spatially. An example of such a configuration could be an array of temperature sensors in a tank that is not in equilibrium. Hence each sensor represents a sample which contributes information about the process in the tank.

# 1 Introduction

The reliability of sensors and the information being given by sensors is important to the nuclear industry. A shutdown or a system failure due to the failure of a sensor(s) can be expensive. As a result it is important to be able to estimate the confidence level of the output of a sensor installed in a nuclear plant.

This paper discusses the use of artificial neural networks and sensor arrays using partially selective sensors to determine the confidence level of the output from a given sensor. Previous research has shown that neural networks can be used to accurately determine input analyte concentrations for the outputs of an array of partially selective sensors [7]. This research shows that the information available from a sensor array can also be used to estimate the confidence level of each sensor output in an array of partially selective sensors.

# 2 Modelling Partially Selective Sensors

A partially selective sensor is simply a transducer that responds to more than one analyte. When modelling a partially selective sensor, it can be modelled at various levels of complexity.

## 2.1 Complex Sensors

At a high degree of complexity the sensor model could include the following properties: the time dependence of the sensor's output, the dependence on temperature and the effects of *interference* between analytes. Analytes are said to *interfere* when the sensor output from the combined analytes does not equal the summed sensor outputs when the sensor is exposed to each analyte separately. This interference effect is the result of several of the analytes affecting the same physical property that the transducer employs to measure analyte concentrations. A sensor that has interference shall be referred to as a complex or nonlinear sensor.

At a lower level of complexity, the sensor could be modelled without any dependence on time or temperature. Hence the output of the sensor would be static and would not vary with time or temperature. The output of an analyte sensor that responds to two analytes that are time and temperature independent can mathematically be represented as:

$$O_2(x, y) = f(x + i_1(y)) + g(i_2(x) + y) \tag{1}$$

where, in the term $f(x + i_1(y))$, $x$ is the primary analyte and $i_1(y)$ is the interference due to analyte $y$, and, in the term $g(i_2(x) + y)$, $y$ is the primary analyte and $i_2(x)$ is the interference due to analyte $x$. In the function $O_2(x, y)$ there are two variables, $x$ and $y$, and the variables may interact with each other through the terms $i_1(y)$ and $i_2(x)$. Figure 1 shows the response of a hypothetical complex sensor to two analytes.

## 2.2 Simple Sensors

At the lowest level, a sensor could be modelled without any time or temperature dependencies, or effects of interferences.

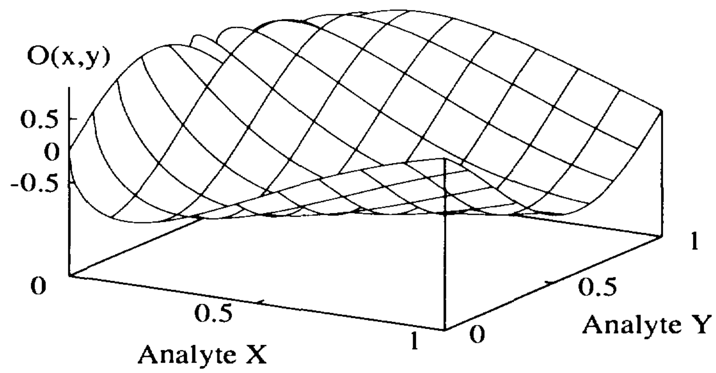


Figure 1: Response of a complex sensor to two analytes

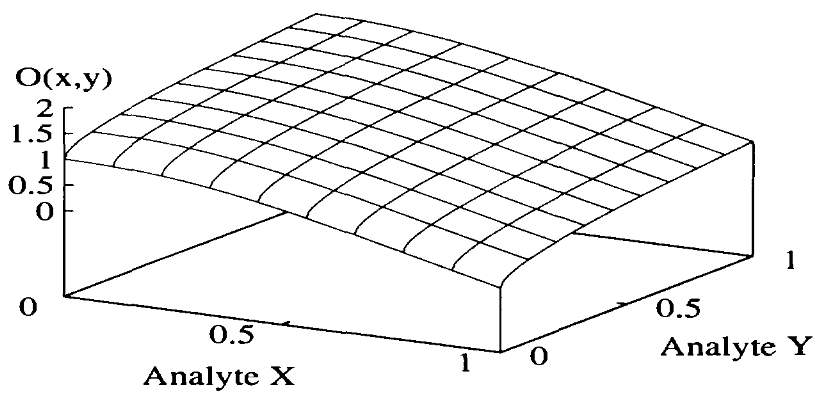


Figure 2: Response of a simple sensor to two analytes

This type of sensor will be referred to as a simple or non-complex sensor. At this level of modelling, the output of a sensor that responds to two analytes could mathematically be represented by the following equation:

$$O_4(x, y) = f(x) + g(y) \tag{2}$$

In the above equation the sensor output, $O_4(x, y)$, is simply the sum of the two functions $f(x)$ and $g(y)$.

The response of a hypothetical simple sensor to two analytes is shown in Figure 2.

# 3 Modelling Partially Selective Sensor Arrays

When partially selective sensors are used for analyte sensing, multiple sensors are necessary in order to determine the individual analyte concentrations. The minimum number of sensors required in the sensor array must be equal to the number of analytes in the mixture. If the sensor responses are nonlinear, then the number of required sensors may be greater than the number of analytes in the mixture.

For multiple-analyte sensors, arranged in an array with each sensor responding to three different analytes, the format for the output responses would be:

$$\begin{aligned} O_1(x, y, z) &= f_1(x + i_{11}(y) + i_{12}(z)) + g_1(i_{13}(x) + y + i_{14}(z)) + \\ &\quad h_1(i_{15}(x) + i_{16}(y) + z) \\ &\vdots \\ O_n(x, y, z) &= f_n(x + i_{n1}(y) + i_{n2}(z)) + g_n(i_{n3}(x) + y + i_{n4}(z)) + \\ &\quad h_n(i_{n5}(x) + i_{n6}(y) + z) \end{aligned} \tag{3}$$

Since there are three different analytes in this example and for each analyte there is an interference term from each of the other analytes, the result is six different interference terms for each sensor response. This is represented in Equation 3 by the interference term $i_{kl}[x, y, z]$, where the subscript $k$ is the sensor number and $l$ is the index of the interference term.

## 3.1 Sensor Confidence Level Data

The sensor confidence level data is determined by randomly adding noise to the true output of a given sensor in a sensor array, with the noise have a magnitude ranging between 0% and 100% of the sensor's output magnitude. Hence the data from the sensor array consists of a single sensor's output with noise added and the remainder of the sensors in the array have true confidence level outputs.

# 4 Neural Network Solution

A feedforward artificial neural network was used to learn the relationships between the sensor outputs and the confidence level of the selected sensor in the sensor array. The neural network is trained on a subset of the confidence level space, and in the process it is able to learn to generalize to all confidence level space. The term generalize is defined as the ability to produce correct output responses, when the neural network is presented with data that it has not previously seen.

The type of artificial neural network used was a feedforward network with a sigmoidal activation function for each neuron. There were $N$ inputs, corresponding to the $N$ sensors, and $1$ output, corresponding to the sensor confidence level. The two hidden layers each contained 24 neurons (arbitrary number), and the inputs and outputs of the neural network were continuous variables that ranged from 0 to 1. Given that both the number of sensors in the sensor array and the sensor responses were continuously being varied, no attempt was made to optimize the neural network configuration. It should also be noted that at this time no literature exists that describes how to determine the optimum neural network size. If the neural network size is too small the network may fail to learn. If the neural network size is too large the network may become over-trained on the training data and begin to memorize it. Over-training or memorization is defined as the ability to produce correct results for the training data, but for the neural network being unable to generalize to data that it has not seen before. Figure 3 illustrates the neural network architecture used for these investigations.

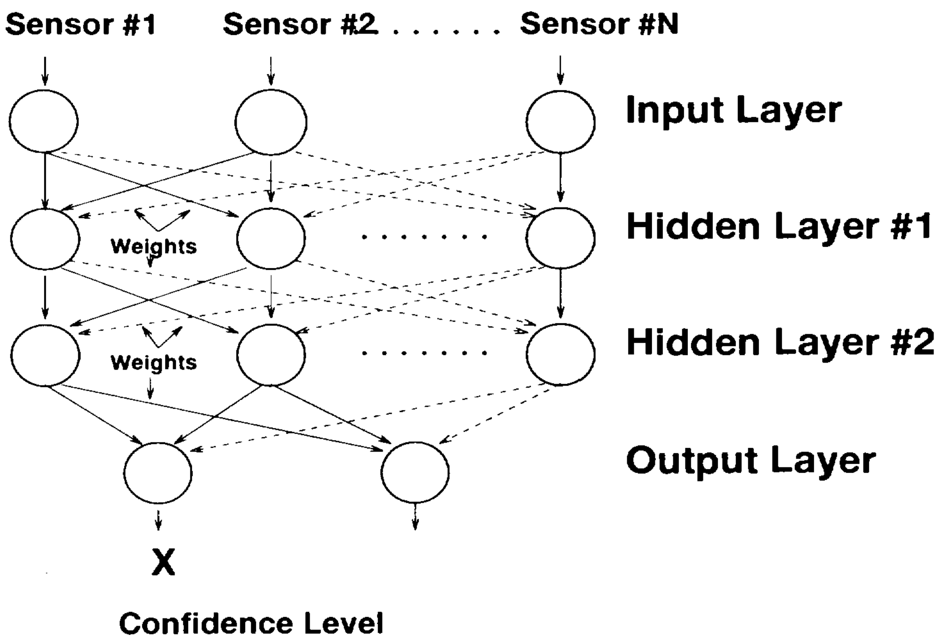


Figure 3: Architecture of a feedforward perceptron network.

When using the artificial neural network technique the number of sensors used must not be less than the number of analytes in the mixture.

# 5 Affects of Sensor Complexity

The affects of the sensor complexity on the ability of the neural network to determine the sensor confidence level were investigated. Two factors related to the sensor complexity were investigated, sensors with monotonic versus non-monotonic responses and sensor with and without interferences. All simulations performed in this section used the same neural network configuration; a three layer network with 24 neurons in the input and hidden layers and a learning rate of 0.1. No attempts were made to optimize the neural network size or the learning rate. If the neural network failed to reach the specified training goal of a summed squared error of 0.05, after 10,000 training epochs, the training was terminated. The training goal of 0.05 corresponds to an average deviation of 5.66% from the true sensor confidence level. This means that on average, for the 250 testing vectors presented to the neural network, it was able to determine the sensor confidence level within 5.66% of the correct sensor confidence level.

## 5.1 Sensors with Monotonic Responses

This research found that the neural network was better able to determine the confidence level for each sensor in the sensor array of simple sensors with no interferences. Figures 4 and 6 show the neural networks ability to determine the the confidence level for sensors in a sensor array without interferences. Figures 5 and 7 show the neural networks ability to determine the the confidence level for sensors in a sensor array with interferences. As can be seen in the following figures, the neural network was better able to determine the sensor confidence levels for sensors without interferences.

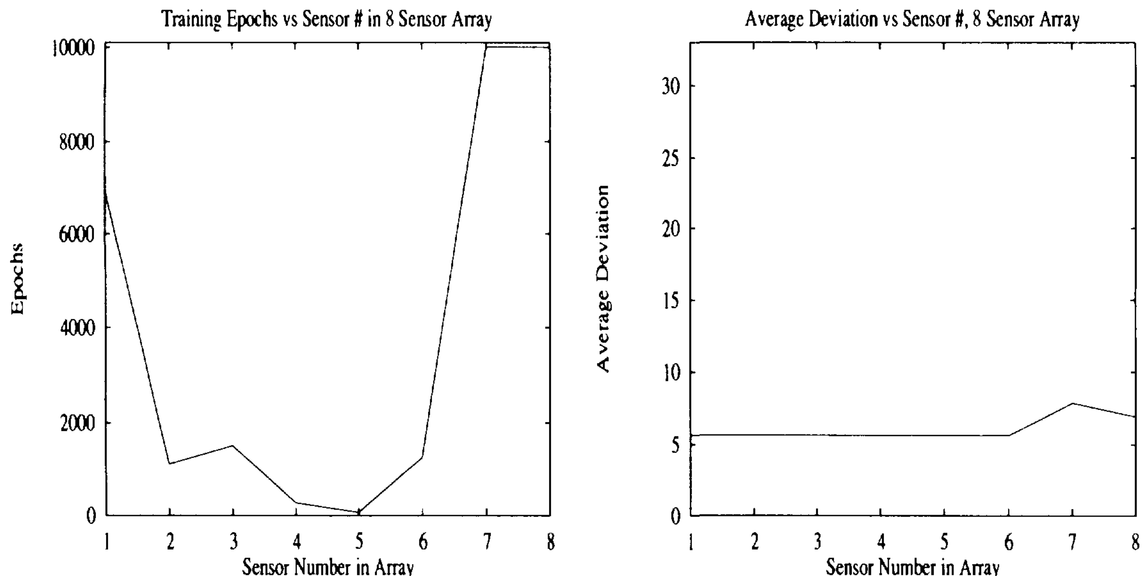


Figure 4: Training epochs and Average deviation vs sensor number, two analytes, no interference.

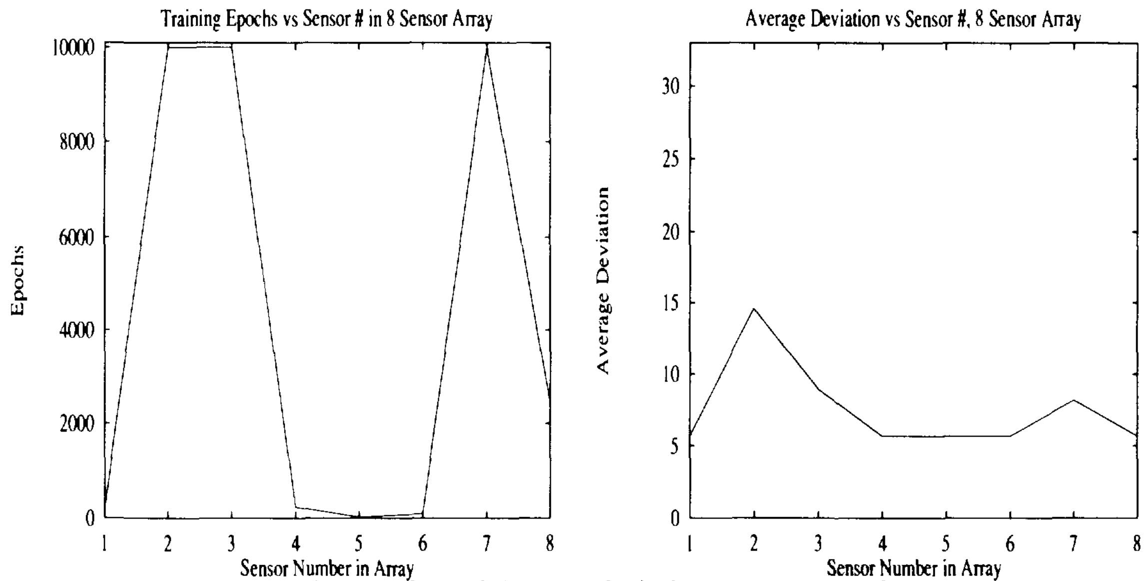


Figure 5: Training epochs and Average deviation vs sensor number, two analytes, interference.

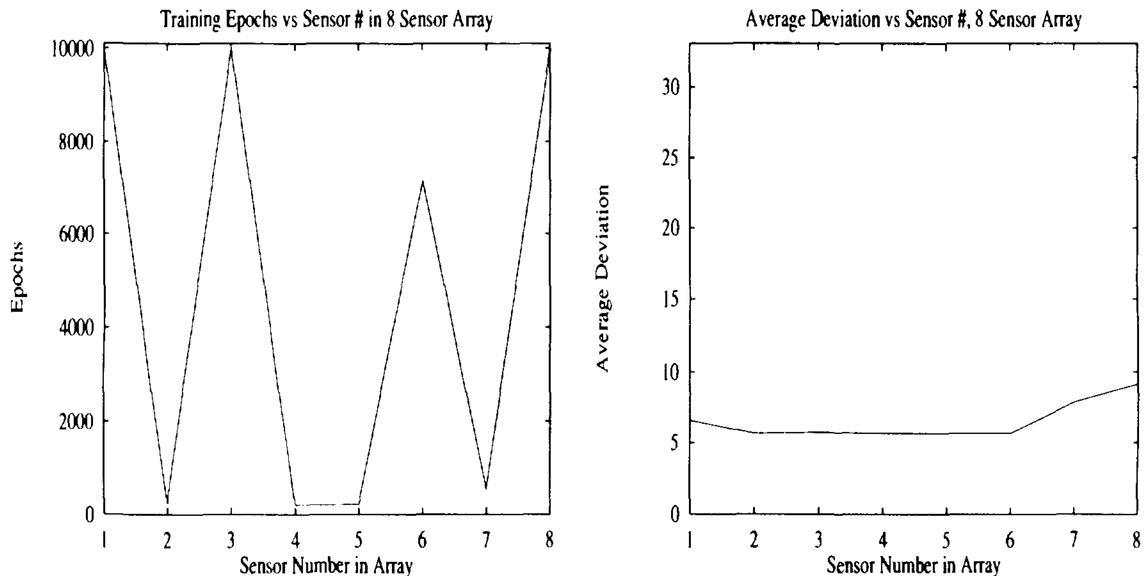


Figure 6: Training epochs and Average deviation vs sensor number, three analytes, no interference.

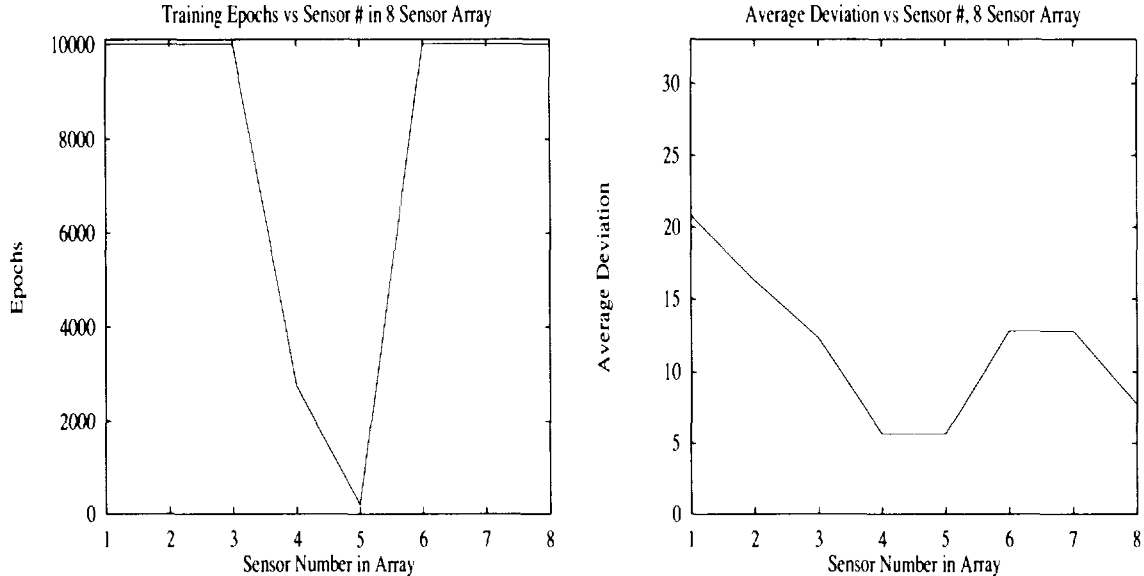


Figure 7: Training epochs and Average deviation vs sensor number, three analytes, interference.

The above figures show both the number of training epochs and the average deviation from the correct sensor confidence level for the neural network. When the number of training epochs required was 10,000, the neural network was unable to achieve the specified training goal of a summed squared error of 0.05 over the testing data vectors presented. The average deviation figure shows the corresponding average deviation of the neural network from the correct sensor confidence level, for the neural network at its best trained configuration. It should be noted that if a given sensor did not achieve the specified training goal, that this does not mean that it was not possible to achieve that level of certainty in determining the sensor's confidence level. It only indicates that the given neural network configuration, in conjunction with the specified training and testing data was unable to achieve the specified training goal. By increasing the training data set size or optimizing the neural network configuration, it may be possible to achieve the specified training goal.

## 5.2 Sensors with Non-Monotonic Responses

This research found that the neural network had more difficulty in determining the sensor confidence levels when the sensor responses were non-monotonic in nature than it had for sensor responses that were monotonic in nature. Figures 8 and 10 show the neural networks ability to determine the the confidence level for sensors in a sensor array without interferences. Figures 9 and 11 show the neural networks ability to determine the the confidence level for sensors in a sensor array with interferences. As can be seen in the following figures, the neural network was better able to determine the sensor confidence levels for sensors without interferences.

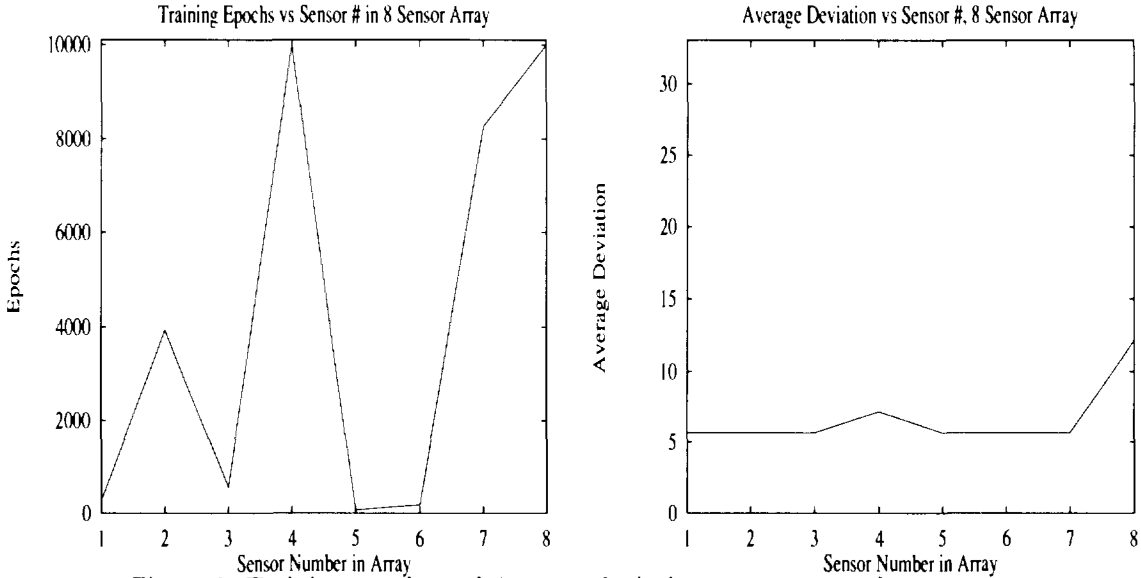


Figure 8: Training epochs and Average deviation vs sensor number, two analytes, no interference.

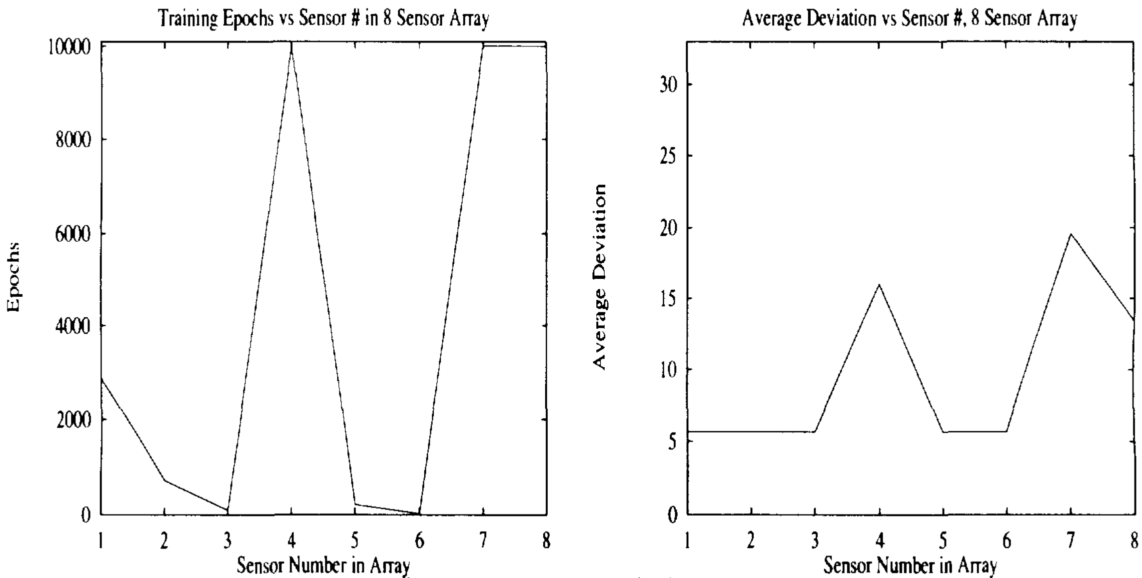


Figure 9: Training epochs and Average deviation vs sensor number, two analytes, interference.

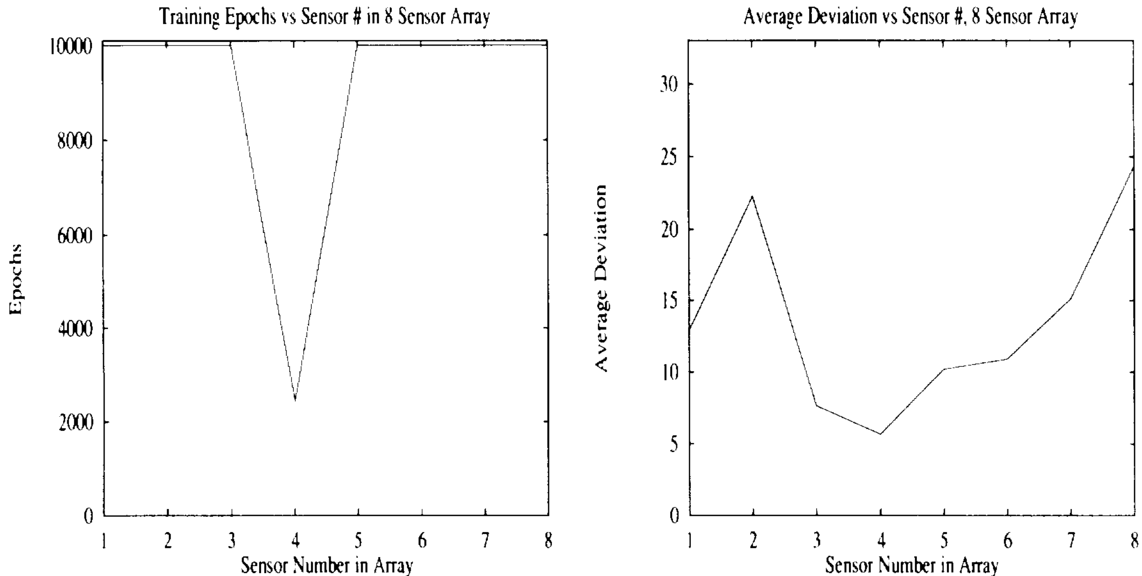


Figure 10: Training epochs and Average deviation vs sensor number, three analytes, no interference.

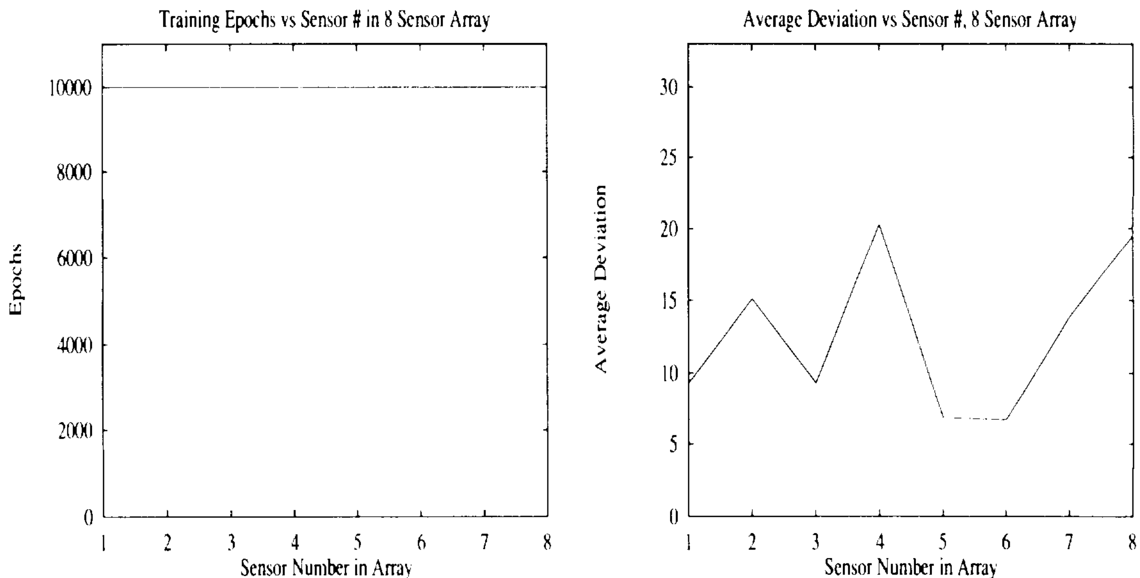


Figure 11: Training epochs and Average deviation vs sensor number, three analytes, interference.

# 6 Testing Results

The ability of the neural network to estimate the sensor confidence level when another sensor was in error, was also tested. First the neural network was trained to determine the sensor confidence level for a given sensor in the sensor array. The neural network was then tested to investigate the affects of having an additional sensor with added noise.

## 6.1 Training

The following Figures 12 and 13 show the results of training the artificial neural network. The neural network was trained to estimate the confidence level, for a given sensor in the array, using the information supplied by all sensors in the sensor array. The training and testing data, used by the neural network, was created by using simulated partially selective sensors. Each sensor's true output was determined for the given analyte inputs, then, a specified sensor's output was randomly corrupted by noise, with the noise value have a magnitude of up to 100% of the sensor output. The neural network was then trained to estimate this confidence level of the sensor output.

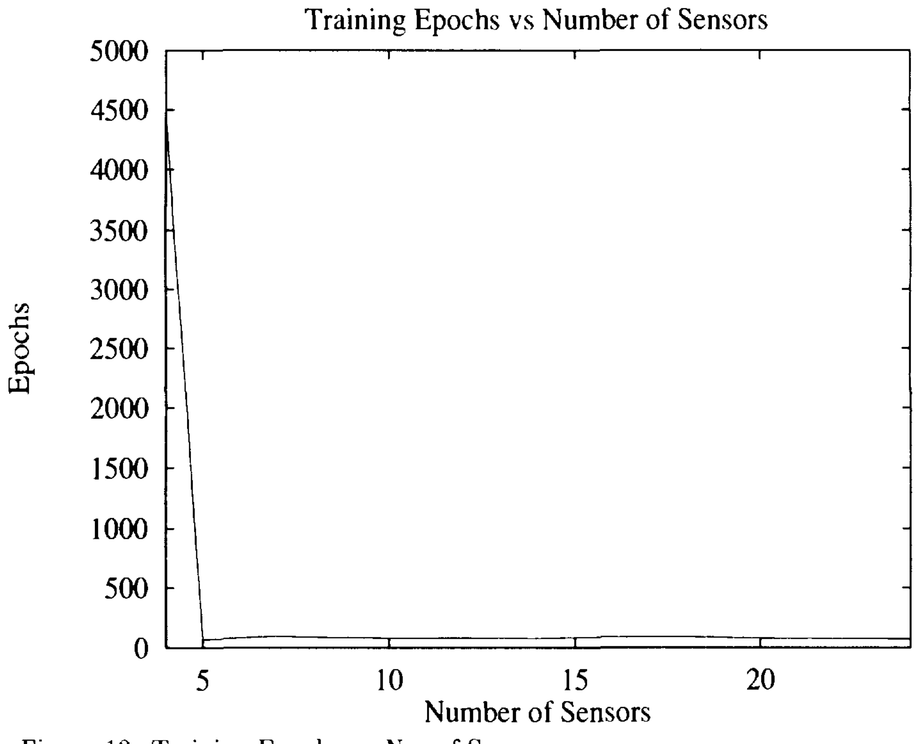


Figure 12: Training Epochs vs No. of Sensors

Figure 12 shows the training results for sensor number 1, as the number of sensors in the sensor array is varied from 4 sensors to 24 sensors. The neural network was trained to a summed square error of 0.05 and the sample size was 250 input/output vectors. This corresponds to an average deviation of 5.66% from the true confidence level. It should be noted that the confidence level is simply one minus the corruption level.

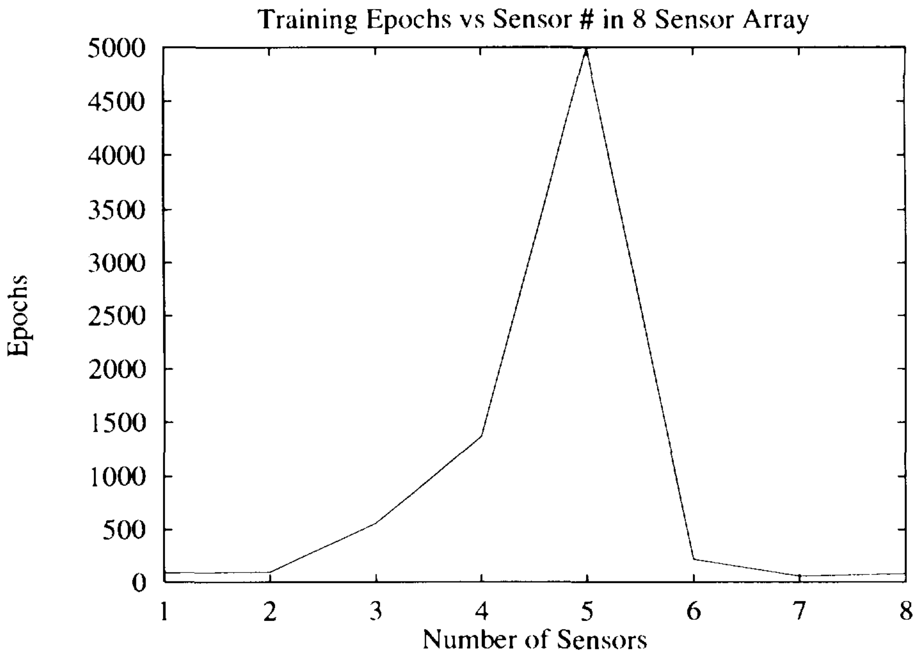


Figure 13: Training Epochs vs Sensor No., 8 Sensor Array

Figure 13 shows the training results for an array of eight sensors, where the neural network was trained to estimate the corruption level of each sensor in the sensor array. The neural was trained on 250 training vector and tested on 250 testing vectors. The summed square error was set at 0.05, which corresponds to an 5.66% deviation, on average, from the true confidence level.

## 6.2 Testing with an additional Sensor in Error

The following Figures 14 and 15 show the results using a trained neural network is used to estimate the confidence level for a given sensor when another sensor is also in error.

Figure 14 shows the testing results for sensor number 1, as the number of sensors in the sensor array is varied from 4 sensors to 24 sensors. In this test another sensor was also randomly in error, with a maximum error magnitude of 25% of the sensor's output. The figure shows the average deviation from the true confidence level, with the maximum deviation having a value of 23%. As can be seen, the addition of another sensor in error did not adversely affect the neural networks ability to estimate the confidence level for sensor number 1.

Figure 15 shows the testing results for an array of eight sensors, where an additional sensor was also in randomly in error. The range of the error mag-

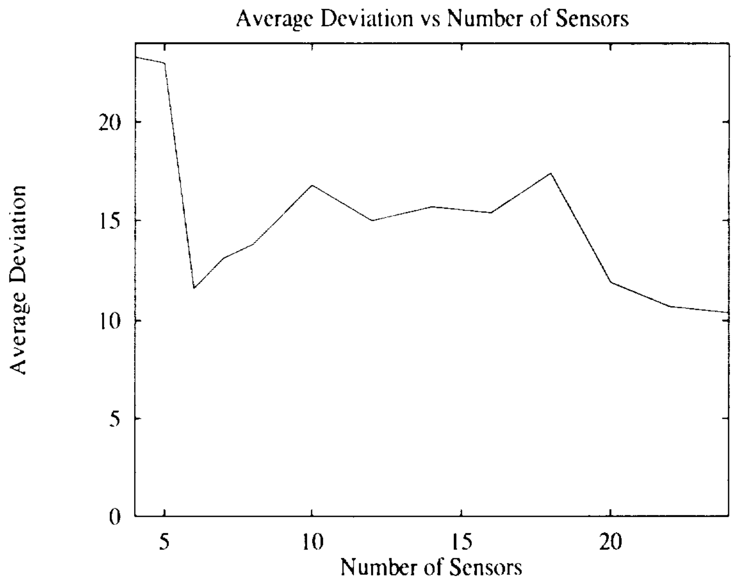

Figure 14: Average Deviation vs Number of Sensors, Two Sensors in Error

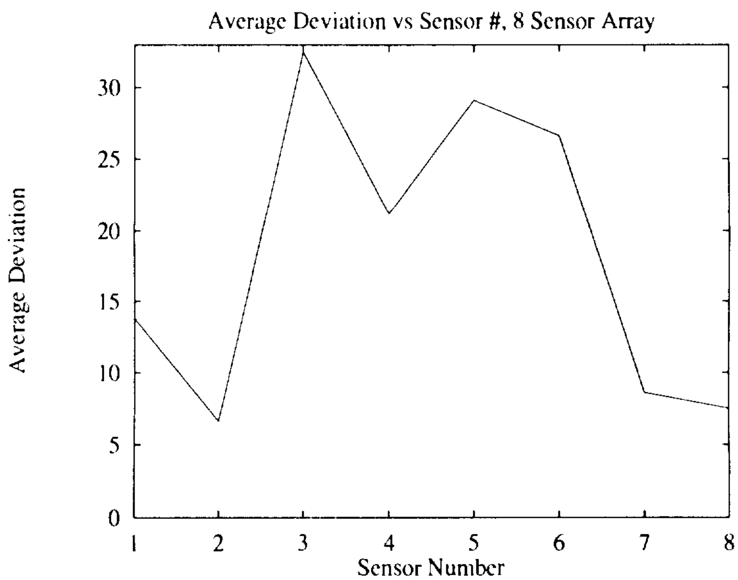

Figure 15: Average Deviation vs Sensor Number, 8 Sensor Array, Two Sensors in Error

nitude was 0% to 25% of the sensor's output magnitude. The figure shows the average deviation from the true confidence level, with the maximum deviation having a value of 33%. This figure shows that the neural network's ability to estimate the confidence level for each sensor in the sensor array, was not adversely affected by an additional sensor being in error.

### 6.3 Conclusions

The ability to estimate the confidence level of a sensor's output is powerful tool that could be use to enhance the overall reliability of a system, whether it be a simple system or a complex system. It would allow for the timely replacement of failed sensors as well as reducing system failures that are the result of sensor failures.

## References


[1] Broten, G., Wood, H., 'A neural network approach to analysing multi component nixtures', *Meas. Sci. Technol.*, **2**, 1993, pp. 1096-1105.

[2] Nakamoto, T., Fukunishi, K. and Moriizumi, T., 'Identification capability of odor sensor using quartz-resonator array and neural-network pattern recognition', *Sens. Actuators*, **B1**, 1990, pp. 473-476.

[3] Sundgren, H., Winquist, F., Lukkar, I. and Lundstrom, I., 'Artificial neural networks and gas sensor arrays: quantification of individual components in a gas mixture', *Meas. Sci. Technol.*, **2**, 1991, pp. 464-69.

[4] Zaromb, S, and Stetter, J. R., 'Theoretical basis for identification and measurement of air contaminants using an array of sensors having partly overlapping selectivities', *Sens. Actuators*, **6**, 1984, pp. 223-34.

[5] Carey, W. P., Beebe, K. R., Kowalski, B. R., Sanchez, E. and Geladi, P., 'Chemometric Analysis of Multisensor Arrays', *Sens. Actuators*, **9**, 1986, pp. 223-34.

[6] Gardner, J. W., Hines, E. L. and Wilkinson, M., 'Application of artifical neural networks of an electronic olfactory system', *Meas. Sci. Technol.*, **1**, 1990, pp. 446-51.

[7] Broten, G., 'A Neural Network approach to Analysing Multi-component Mixtures', *Master's Thesis, Univ. of Sask.*, 1992.