An Intelligent Neural Network Based Gas Detection System using Metal Oxide Gas Sensor

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Abstract: Probabilistic Neural Network (PNN) has been used to ensure the reliable evaluation of responses from Zinc Oxide (ZnO) based sensors comprising of as deposited ZnO nanoflakes. Nanoflakes were deposited on a SiO2 coated p-Si substrate by a low cost chemical deposition technique. One type of sensor structure, to investigate the effect of catalytic metal alloy electrode (Pd-Ag) was fabricated in a standard laboratory. This paper reports the development of an artificial neural network based model and a special types of neural network i.e. PNN is used for successfully recognizing different concentrations of methane with two different metal contacts. The data obtained from the sensors have been analyzed using MATLAB. PNN is based on Radial Basis function. PNN classifier has been able to detect the toxic gas with 95.2 % sensitivity.

Keywords: Zinc Oxide; gas sensor; probabilistic neural network; radial basis function; MATLAB.

1 INTRODUCTION

Methane is a biologically inert gas but it becomes toxic when its presence reduces the oxygen in the environment. The word, 'Fire damp,' particularly applicable for underground coal mines, is a combination of CH_4 (5-14%) and air, has a tendency to explode. Moreover it may cause breathing trouble by producing CO_2 while eliminating oxygen from air [1-2]. Therefore the development of an efficient methane sensor for the detection of low concentration of methane is essential.

Quantitative detection of combustible and toxic gases are of great importance for the safely of common people, to avoid health hazards and also to shun the risk of accidental explosion. Recently, several nanoforms of semiconducting metal oxides have taken market at relatively low temperature range ~100–200°C [3, 4] to detect the combustible

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gases. But these metal oxide based sensors suffer from poor selectivity [5]. Also, cross sensitivity may hamper the output. Moreover, it is unable to detect specific concentration of gases very precisely. Another major drawback of these sensors is drift at the sensor output when it is subjected to variation in ambient temperature as well as relative humidity.

As suggested by different researchers this problem can be overcome by incorporating noble metal catalytic contact, surface modification or by making hybrid sensors [6-8]. Though the cross sensitivity and selectivity issues have been taken care of but still drift is a serious issue which can be professionally overcome by pattern classification system [9-11]. PNN is one of the superior methods to quantify precisely the presence of various components of gases from a gas mixture.

Neural network are composed of simple elements operating in parallel. These elements are inspired by biological nervous system. We can train a neural network to perform a particular function by adjusting the values of the connection between elements.Neural network have been trained to perform complex functions in various fields of application including pattern recognition, identification, classification, speech, vision and control system.

The basic attributes of neural network may be divided into the architecture and the functional properties or neurodynamics. Architecture defines the network structure, that is, the artificial neurons in the network and their interconnectivity. Neural network consists of many interconnected neurons, or processing elements, with familiar characteristics, such as inputs, synaptic strengths, activation, outputs and bias. The neurodynamics of neural networks defines their properties, that is, how the neural network learns recall associates and continuously compares new information with existing knowledge, how it classifies new information, and how it develops new classification if necessary.

The sensor was based on as deposited ZnO nanoflakes by a low cost chemical deposition technique. The sensors were exposed to CH_4 with different concentration (100 ppm -10000 ppm). The data generated from the sensors were used to train a multilayer neural network, which can logically produce output to undetected input data.

2 SENSOR FABRICATIONS

Nanostructure ZnO nanoflakes were deposited by chemical deposition method on SiO_2/Si substrate using Sodium Zincate solution (Na_2ZnO_2). The details of deposition technique for nanostructure ZnO is reported in our earlier publication [12]. Pd-Ag (70%) catalytic electrodes were deposited on the ZnO sensing layer by an e-beam evaporation method (10^{-6} mbar) using Al metal masks.

3 MEASUREMENT TECHNIQUES

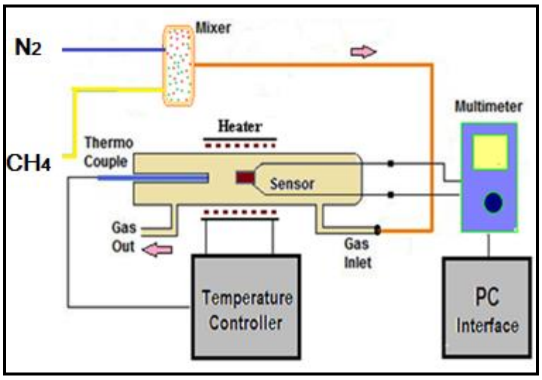

Fig. 1. Gas measurement set up.

Only one resistive type sensor was used for the test purpose for the collection of data generated from the sensors when exposed to methane. The sensor was exposed to test gas with five different methane concentrations (100 ppm, 500 ppm, 1000 ppm, 5000 ppm, 10000 ppm) consecutively. The sensor was as deposited ZnO with Pd-Ag (76%) contact and the operating temperature was 200°C. The schematic of gas measurement set up with detailed discussions are reported elsewhere [12]. The sensor was placed inside a closed test chamber with gas inlet and outlet. IOLAR grade N_2 was used as the carrier gas forultra pure methane which was mixed in proportion in the chamber followed by a mixing coil. The gas flow and mixing ratio were precisely monitored and controlled with the help of mass flow controller (MFC) (Alicat scientific, M-50SCCM-D) for methane and a needle valve and mass flow meter (MFM) (Alicat scientific, M-1000SCCM-D) for N_2. The sensors were designed to operate in a resistive mode and Fig. 1 shows a model of the sensor measuring circuit. Pd-Ag contact electrodes were made on the top of the sensing layer by e-beam evaporation technique in order to provide electrical connection. A Data Logger (Agilent U1252A) was used to monitor the variation of sensor resistance.

4 PROBABILISTIC NEURAL NET-WORK

A useful interpretation of the network outputs under certain circumstances is to estimate the probability of class membership, in which case the network is actually learning to estimate a probability density function (PDF). This is the case of the probabilistic neural network (PNN), a special type of neural network using a kernel-based approximation to form an estimate of the p.d.f. of categories in a classification problem. This particular type of ANN provides a general solution to pattern classification problems by following the probabilistic approach based on the Bayes decision theory. PNN uses a supervised training set to develop probability density functions within a pattern layer. The PNN model is extremely fast and accurate, making it suitable for fault diagnosis and signal classification problems in real time. It is guaranteed to converge to a Bayesian classifier provided that it is given enough training data. The PNN requires no learning process and there is no need for setting the initial weights of the network.

Fig. 2 shows the basic architecture of PNN. P is the input vector comprising of 3 sets of input vector. Each set of input vector (R) contains 250 elements. C represents the no. of classes; in this case it is three. The 1st and 2nd layer of weights are represented by IW and LW respectively. The bias weight for the hidden layer is being represented by b. ‖dist‖ is the norm of input vector with distance metric. The neurons in the hidden layer is denoted by x. Structure of PNN consists of two basic layers, like input layer and output layer and one hidden layer i.e. feature layer. When the sensor is exposed to test gas in three different temperatures like 150ºC, 200ºC and 250ºC among which 200ºC is the optimum temperature, resistance of the sensor changed in a random manner. Those resistance values are taken as input variables to the Input layer. At the output layer corresponding gases are identified.

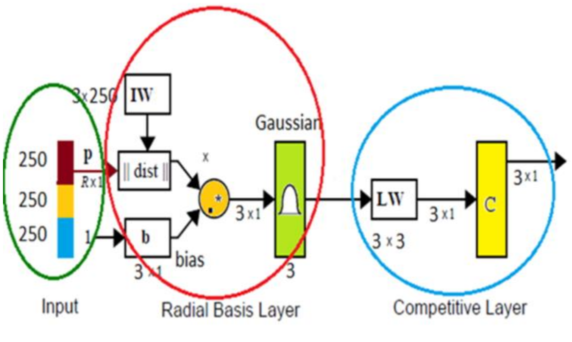

Fig. 2. PNN architechture.

DATA GENERATED FROM THE SENSORS (as shown in table 1) are classified into three classes depending upon the range and resolution of the resistance values of different gases. Class1 consists of resistances of 500.0 M and 100k resolution, class 2 consists of resistances of 50.00 M and 10.00 k resolution and so on.

Table1. Classification of data generated from sensor.

Sl. No.	Function (resistance)	Range	Resolution	Class
1.	7.55E+07	500.0 M	10.00 k	1
2.	7.48E+07	500.0 M	10.00 k	1
3.	7.45E+07	500.0 M	10.00 k	1
4.	7.59E+07	500.0 M	10.00 k	1
5.	7.59E+07	500.0 M	10.00 k	1
6.	7.65E+07	500.0 M	10.00 k	1
7.	7.62E+07	500.0 M	10.00 k	1
8.	7.62E+07	500.0 M	10.00 k	1
9.	7.62E+07	500.0 M	10.00 k	1
10.	7.78E+07	500.0 M	10.00 k	1
11.	1.28E+07	50.00 M	1.000 k	2
12.	1.26E+07	50.00 M	1.000 k	2
13.	1.25E+07	50.00 M	1.000 k	2
14.	1.23E+07	50.00 M	1.000 k	2
15.	1.19E+07	50.00 M	1.000 k	2
16.	1.18E+07	50.00 M	1.000 k	2
17.	1.15E+07	50.00 M	1.000 k	2
18.	1.13E+07	50.00 M	1.000 k	2
19.	1.12E+07	50.00 M	1.000 k	2
20.	1.10E+07	50.00 M	1.000 k	2
21.	4.13E+06	5.000 M	100	3
22.	4.09E+06	5.000 M	100	3
23.	4.03E+06	5.000 M	100	3
24.	3.98E+06	5.000 M	100	3
25.	3.98E+06	5.000 M	100	3
26.	3.94E+06	5.000 M	100	3
27.	3.89E+06	5.000 M	100	3
28.	3.85E+06	5.000 M	100	3
29.	3.82E+06	5. 000 M	100	3
30.	3.78E+06	5.000 M	100	3

5 RESULTS

The PNN based evaluation of the toxicity of the various combustible gases has been presented in this paper. The output from the metal oxide gas sensor (in the form of resistance values) has been fed into the PNN architecture. It has been observed that the PNN network has been able to distinguish the different levels of toxicity with 95.2% accuracy. The misclassifications are shown in Fig. 3.

In Fig. 3 blue lines is the actual class. Each class has 250 training Tuples. PNN has been indicated by green circles. Correctly classified classes overlap with the actual class of the toxic gas i.e. the blue line overlap with the green circles.

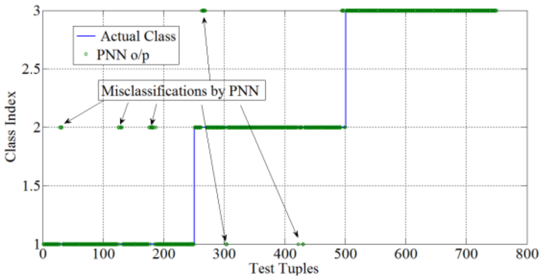

Fig. 3. Validation and testing.

6 CONCLUSIONS

Nanocrystalline ZnO (n type) based sensor was fabricated. The proposed pattern recognition methods used here to construct the simple pattern classifier, which is able to recognize and classify methane with different concentrations with good consistency and precision. Multilayer perception was used for gas recognition architecture output neurons. There are three layers in the architecture. The network is fed with 750 experimentally obtained data sets out of which 56% of the data were used for training, 44% for testing. The network gave an overall accuracy of 95.2% when trained with PNN algorithm.

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