Neural Network Calibration of a Semiconductor Metal Oxide Micro Smell Sensor

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***Abstract*-A Design of a micro smell sensor based on semiconductor metal oxide method is presented. This sensor is able to recognize two different kinds of gas (CO and H_2) and will estimate the amount of dominate gas in the environment. The SnO_2 is employed as the key module of the sensor. A neural network calibration is applied to the sensor in order to identification of one of the two gases in an environment with complex combination of gases. The results vividly show that the sensor is able to approximate the amount of these two gases in the pool of gases.**

Keywords: Micro smell sensor, Neural Network, error Backpropagation training, gas sensing

I. INTRODUCTION

The ability of gas detection has greatly attracted scientists' attentions in last decade. Gas sensors have many applications in various fields. Monitoring and control of the emissions in internal combustion motors and automobiles, measuring the amount of dangerous gases in laboratories and industries and controlling the amount of gases in domestic environments in order to assuring the safety of people are some of its application[1,2].

The experimental studies on surface of solids leaded the gas sensors to convert the chemical absorption of gas to some response signals [1-3]. The working principle of SnO_2 sensors is the chemical oxidation and reductions, by which some electrons will transport between the surface and the gas. It's would be note that micro scale heat transfer has a key role in this process. The process will cause generation of the response signals. [1-5]

One of the important tasks that gas sensors should accomplish is recognition of one specific kind of gas in an environment consisting of combination of gases. There are many ways by which the sensor could provide this ability. In this paper the Neural Network calibration is employed to learn the system how to identify one kind of gas.

The backpropagation training algorithm is applied to the sensor using 1000 predetermined data. After learning process the smell sensor demonstrated good response to the learned gases, and a showed the undefined mode for the environment without those gases.

II. WORKING PRINCIPLE

The network is a Perceptron network with 18 input layer, 54 latent layer and 5 out put layers. Based on this network the matrix of **V** has 54 rows and 18 columns (54×18) and **W** has 5 rows and 54 columns (5×54). Figure1 shows a schematic of the artificial network.

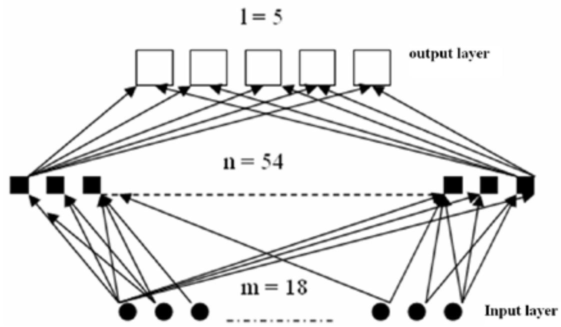

Figure 1-the schematic of the employed network

The input of network is feed by the output of smell sensor. For this purpose the output electrical signal of smell sensor is digitalized to an array of 18 discrete. The output of neural network is a 5 digit array in which the 3 left bits of array are related to the number of layer of the gas, and the other 2 bits indicate a code for the gas (analyte). For example if the output array is (0 0 1 0 1) it means that the gas of A is recognized by the sensing element 1.

The entries of matrices **V** and **W** will change by applying the train algorithm till the error became converge to an amount smaller than E_{max}. Figure 2 shows the E_{rms} _ the error in training of neural network, with respect to the number of trainings on the entries of matrices **V** and **W**.

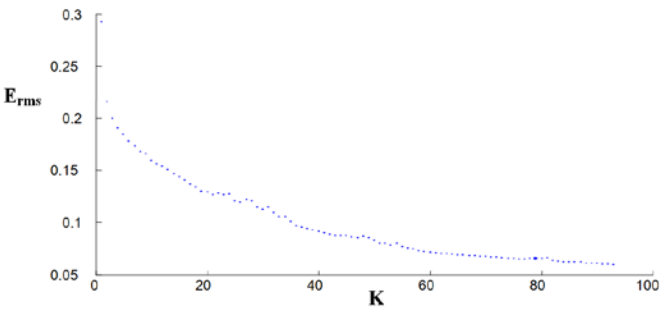

Figure 2- the vaiation of E_{rms} with respect to the number of trainings (K)

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III. TRAINING AND THE RESULTS

A. The behavior of network while sensing analyte A

In training process about 1000 prerecognized input signals was employed. Then the behavior of network under various kinds of inputs was studied. First, by applying the error backpropagation algorithm the best inputs for analyte A is determined. Figure 3 and table 4 show the best output signals of sensing element 1 and the real amount of analyte as the real.

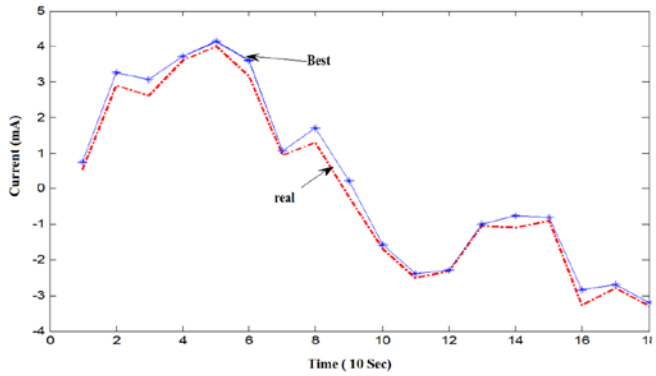

Figure 3- the sensed amount of analyte A (best) and the real amount of the analyte in environment (real). Voltage is fixed and equal to 10 Volt.

Table I- The numerical compare between sensed amount of analyte 1 in sensing element 1 and it's real amount in the environment

The Sensed amount of analyte 1	[0.7564 3.2708 3.0642 3.7243 4.1386 3.6137 1.0665 1.7163 0.2174 -1.5639 -2.3752 -2.2915 -1.0041 -0.7643 -0.8030 -2.8495 -2.6973 -3.2063]
The Sensed amount of analyte 1	[0.5269 2.9133 2.6271 3.5924 4.0060 3.1786 0.9481 1.3116 -0.2412 -1.6790 -2.4951 -2.3117 -1.0432 -1.0866 -.8990 -3.2670 -2.7867 -3.2944]

In the same way the sensing behavior of sensing element 2 to analyte A is studied.

B. the behavior of network while sensing analyte B

The error backpropagation is implemented to the smell sensor, and the sensing quality is studied in both sensing elements 1 and 2. The quality of sensing in element 1 is shown in figure 4.

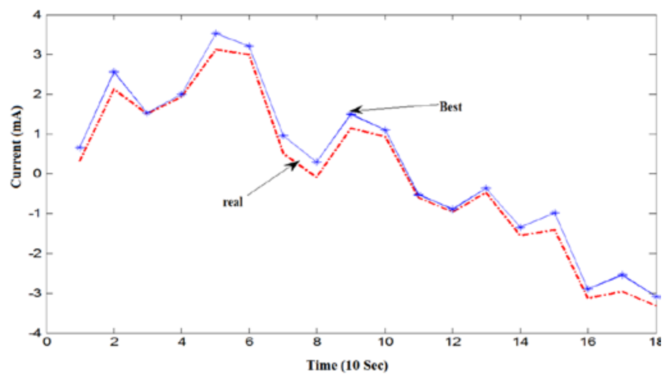

Figure 4- the sensed amount of analyte B (best) and the real amount of the analyte in environment (real). Voltage is fixed and equal to 10 Volt.

E. The behavior of network while sensing analyte C (untrained analyte)

To study the behavior of network to an untrained analyte, the system is feed by gas C. As the matrices of network are not trained for this gas, the network will identify the gas in its range of ability. The result of identification for gas C is z=[0.0028 0.0016 0.9968 0.6743 0.3283] but according to our database the correct output for this gas was d=[1 0 1 1].

It can be seen that the system has tried to identify the input analyte but couldn't identify it correctly.

IV. CONCLUSION

A micro smell sensor is supposed and the neural network calibration is implemented on the sensor. By applying the error backpropagation training algorithm, the micro smell sensor is able to recognize two different kinds of gases in an environment with a good estimation of their amount.

According to the results, the sensor has good adaptation with the analytes that has trained by them and for untrained gases the sensor has no good identification in the environment. In the case that analytes A and B are CO and H_2 in environments which need to control the pollution in certain amounts.

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