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ANN Modeling of Electronic Nose Based on Co-doped SnO_2 Nanofiber Sensor

S. KHALDI and Z. DIBI

Advanced Electronic Laboratory, Electronic Department, Batna University
05 Avenue, Chahid Boukhlouf 05000 Batna, Algeria
Tel.: +213 33 80 54 94, fax: +213 33 80 54 94
E-mail: madji_samia@yahoo.fr

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Abstract: We present in this paper a novel neural network based technique to create a model incorporates intelligence for electronic nose. The idea is to create intelligent models; the first one, called selector, can select exactly the nature of gas detected. The second intelligent model is a corrector, which can automatically compensate the electronic nose's response characteristics and discriminating exactly the detected gas (nature and concentration), and make the response increases all time when the temperature increases. The electronic nose is based on Co-doped SnO_2 nanofiber sensor. The MATLAB environment is used during the design phase and optimization. The method discriminates qualitatively and quantitatively between six gases. The advantage of the method is that it uses a small representative database so we can easily implement the model in an electrical simulator. *Copyright © 2016 IFSA Publishing, S. L.*

Keywords: Electronic nose, EN, Gas sensor, ANN, Implementation, Selector, Corrector.

1. Introduction

The sensor technology of artificial olfaction had its beginnings with the creation of the first gas multi sensor array. Advances in aroma-sensor technology, electronics, biochemistry and artificial intelligence make it possible to develop devices capable of detecting and characterizing volatile aromas released from a multitude of sources for numerous applications. These devices, known as electronic noses (ENs), were engineered to mimic the 'human organ for smelling' within an instrument designed to obtain repeatable measurements, allowing identifications and classifications of aroma mixtures while eliminating operator fatigue. An electronic nose system typically consists of a multisensor array, an information-processing unit such as an artificial neural network (ANN), software with digital pattern-recognition algorithms, and reference-library databases.

Metal-oxide semiconductors such as SnO_2, ZnO, Fe_2O_3 and In_2O_3 are widely used as an element in electronic nose components for detecting small amount of target gas in air according to their electrical resistance changes. Accurate detection of toxic and dangerous gas is an important issue since both chemicals negatively affect human health and the environment [1]. It is well known that the high sensitivity, fast response and recovery, and selective detection are the three most important parameters in designing oxide semiconductor gas sensors [2]. Fast and high response characteristics, in particular, are required for real-time monitoring of harmful gases and avoiding possible disasters due to toxic gases [3-4]. Since the sensing mechanism is based on the surface reaction of these materials, their sensing performances are strongly dependent on the morphology and the structure of materials, grain size, crystal system, surface area, dimension, and also the type of grain network or porosity [5].

SnO_2 is widely used for diverse devices, such as gas sensors, photocatalysts, photosensors, transparent electrodes, and solar cells [6]. In particular, as a gas sensor is one of its well-known applications [7-8], the synthesis of SnO_2 with particular structure or dopant can offer optimizing gas sensing performances [6]. A lot of pure and doped SnO_2 has been presented with high sensing characteristics [9-11]. Recently, many materials, such as Zn, Pd, La and Pt, have been proved to be effective dopants for the progress of response or reaction speed or other characteristics of SnO_2 [12-13]. The electronic nose is based on Co-doped SnO_2 nanofibers sensor. SnO_2 nanofibers synthesized via an electrospinning method which indicate quick, high response and recovery, and good selectivity [14].

Artificial Neural Networks (ANNs) are used in instrumentation to model complex systems because of multi-variability and strong nonlinearity. The extrapolation errors with ANNs are lower both inside and outside the calibration range [15]. ANNs are very efficient in solving problems in dynamic matter and offer the advantages of simple implementation and less computing time compared with other numerical models [16].

For this purpose, we used ANNs to design an electronic nose based on Co-doped SnO_2 nanofibers sensor. MATLAB interface was used during the design phase and optimization. The model takes into account the nonlinearity response, dependence on temperature in a dynamic environment, as well as dependence on gas nature.

2. Sensor's Characteristics

Pure and Co-doped SnO_2 nanofibers (Fig. 1) are synthesized via an electrospinning method and characterized by X-ray diffraction (XRD), scanning electron microscopy (SEM), and transmission electron microscope (TEM). With comparison between pure SnO_2 nanofibers and Co-doped SnO_2 nanofibers, the second one provides enhanced high sensing properties. Among all the samples (pure, 0.5 wt%, 1 wt% and 3 wt% Co-doped SnO_2 nanofibers), 1 wt% Co-doped SnO_2 nanofibers prove the highest response with very short response/recovery times and good selectivity [14]. The response value Rs was defined as Rs=Ra/Rg, where Ra was the sensor resistance in air and Rg was a mixture of target gas and air.

Experimental response of Gas-sensing are performed at different operating temperatures to find the optimum operating condition. Fig. 2 presents the relationship between the different operating temperature and the response of the sensors to 100 ppm H_2, and Fig.3 shows experimental responses of pure and Co-doped SnO_2 nanofibers to different concentrations of H_2 at 330 ºC. The response increases and reaches its maximum at 330 °C, then the response decreased rapidly with increasing the temperature, and this behavior can be explained from the kinetics and mechanics of gas adsorption and desorption on the surface of SnO_2 or also semiconducting metal oxides [17].

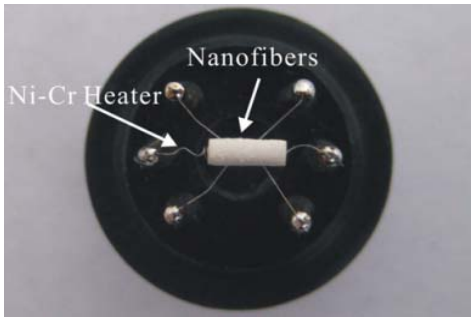

Fig. 1. A photograph of the gas sensor [14].

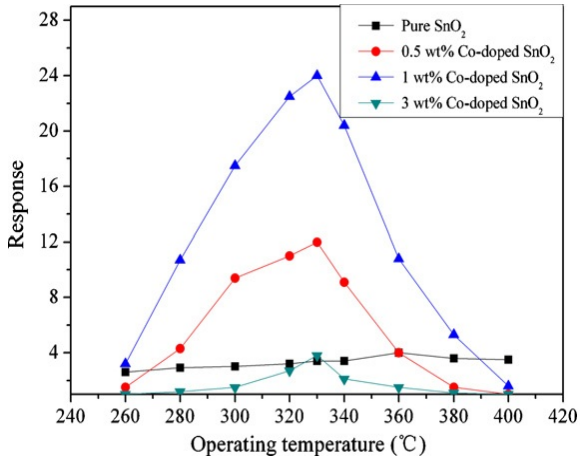

Fig. 2. Experimental responses of pure and Co-doped SnO_2 nanofibers to 100 ppm H_2 at different operating temperatures [14].

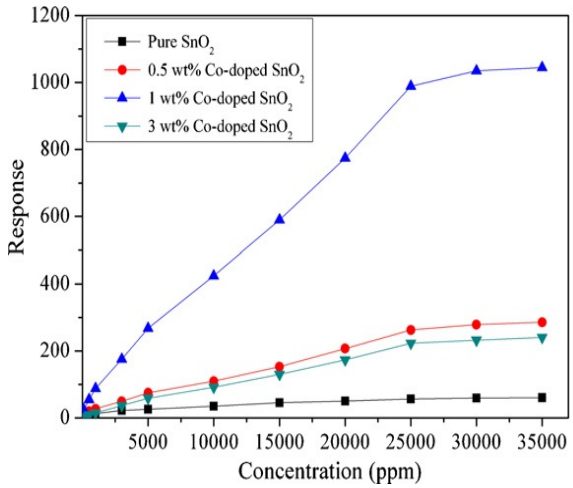

Fig. 3 Experimental responses of pure and Co-doped SnO_2 nanofibers to different concentrations of H_2 at 330 ºC [14].

The 1 wt% Co-doped SnO_2 sensor shows the maximum response of about 24 at the optimum operating temperature of 330 °C, which is 8 times

larger than that of pure SnO_2 (about 3), representing the addition of Co is profit to the H_2 sensing of SnO_2 nanofibers.

3. Neural Networks Model

Using MATLAB interface and based on experimental results from [14], a database was created and arranged as (S, T, C,) input and (RS) as output, where:

S: Selecting the gas;
T: Absolute temperature;
C: Gas concentration;
RS: resistance response.

Most of this database was used mainly in the training phase using algorithm MLP (back propagation of error). The remaining data were used to test and validate the model. The diagram in Fig. 4 illustrates the direct modeling of the sensor, where:

Yd: Desired output;
Y: Network output;
e: Modeling error.

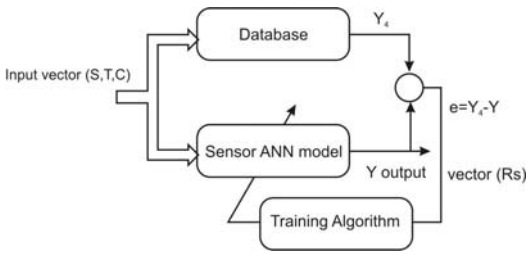

Fig. 4. Modeling of sensor.

To optimize the model architecture an iteration algorithm consisting of the assessment of the total error as a function of number of hidden layers and number of neurons in each layer, and after several tests of different ANN models. The architecture optimized and that present the smallest error is summarized in Table 1.

Table 1. Summarizing of the model optimized parameters.

Property	Characteristic	
Database	Training base	2985
	Test base	627
Architecture	9-15-1 Feed-forward MLP	
Activation functions	Logsig-Logsig- linear	
Training rule	Retropropagation error	
Training MSE	< 0.0001	
Iterations number	3000	

3.1. Model Test

We designed a model based on neural networks by taking into account the dependence on temperature and Gas concentration in the measure point, as well as the gas nature of the sensor. To illustrate this effect, we changed temperature and noted the variation of the resistance of the sensor. Fig. 5 shows the difference between the database and the ANN model for the sensitivity feature of the sensor.

The difference between the database and the ANN model for the dependence on gas concentration is also tested and shown in Fig. 6.

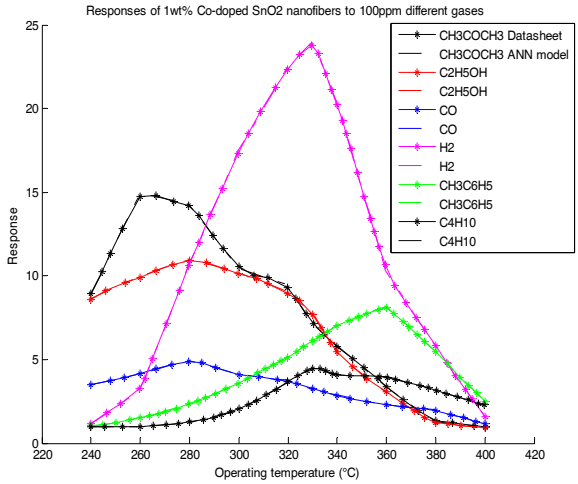

Fig. 5. Model and database response to 100 ppm different gases.

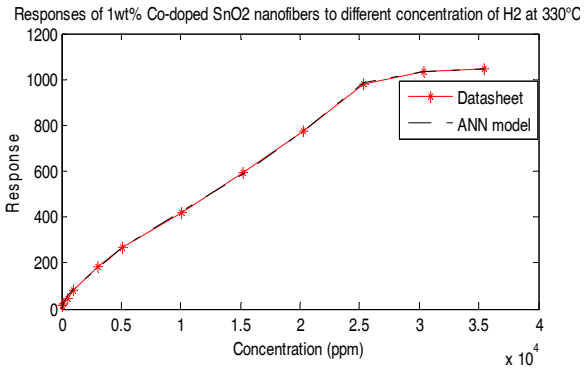

Fig. 6. Model and database response to different concentrations of H_2 at 330 °C.

4. Selector

The goal of electronic nose is select correctly the nature of gas detected by sensor, so we implement the selector

The database is arranged as (T, Rs and VS), where:

T: Absolute temperature;
Rs: Sensor resistance;
Vs: output voltage.

The generation of training base and test base is similar to that of the model's one. However, in the corrector, the temperature T, relative humidity RH and the sensor's output voltage VRL are taken as inputs,

and the corrector's output voltage Vs is taken as output.

The selector was trained in a similar manner as in the case of direct model. After many tests of different ANN models. The architecture optimized and that produces the smallest error is summarized in Table 2.

Table 2. Summarizing of the Selector's optimized parameters.

Property	**Characteristic**	
Database	Training base	2109
	Test base	747
Architecture	12-10-15-1 Feed-forward MLP	
Activation functions	Logsig-Logsig - Logsig-linear	
Training rule	Retropropagation error	
Training MSE	$<10^{-5}$	
Iterations number	1000	

4.1. Selector Test

We designed an ANN-based selector for electronic nose. To illustrate the effect of this selector we change concentration, and then we note the variation of the selector's output. Fig. 7 shows that the selector selects correctly the gases.

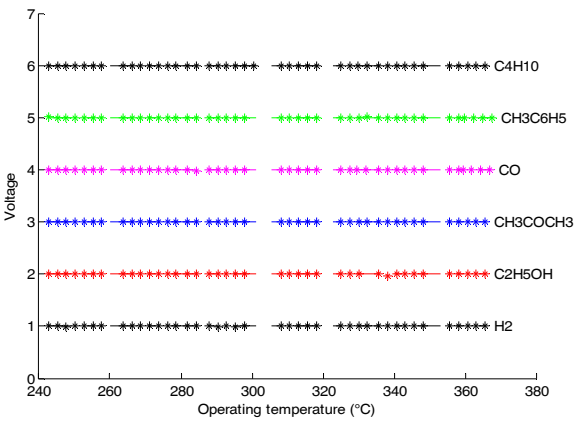

Fig. 7. Selector selectivity feature effect.

5. Corrector

The database of corrector to be designed is arranged as (T, Rs, S, Rc), where:

T: Absolute temperature;

Rs: Sensor's output voltage;

S: Selector output voltage;

Rc: Corrector's output response.

The generation of training base and test base is similar to that of the model's one. However, in the corrector, the temperature T and the sensor's output voltage Rs are taken as inputs, and the corrector's output voltage Vs is taken as output. The diagram of Fig. 8 illustrates the methodology used in the corrector design.

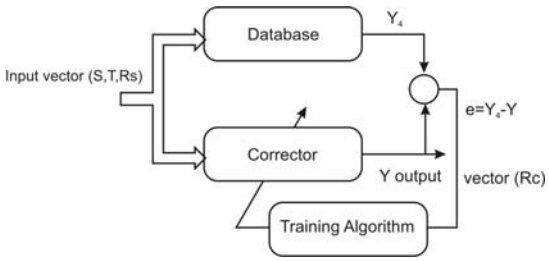

Fig. 8. Modeling of the electronic nose corrector.

The corrector was trained in a similar mode as in the case of direct model. After many tests of different ANN models. The architecture optimized and that presents the minimum error is shown in Table 3.

Table 3. Summarizing of the corrector's optimized parameters.

Property	**Characteristic**	
Database	Training base	2985
	Test base	627
Architecture	9-15-1 Feed-forward MLP	
Activation functions	Logsig-Logsig- linear	
Training rule	Retropropagation error	
Training MSE	<0.00001	
Iterations number	3000	

5.1. Corrector Test

We designed an ANN-based corrector for the electronic nose. To illustrate the effect of this corrector we change temperature, and then we note the variation of the corrector's output. Fig. 9 shows that the correctors compensate correctly the sensor's sensitivity feature (the response increases with the temperature increasing).

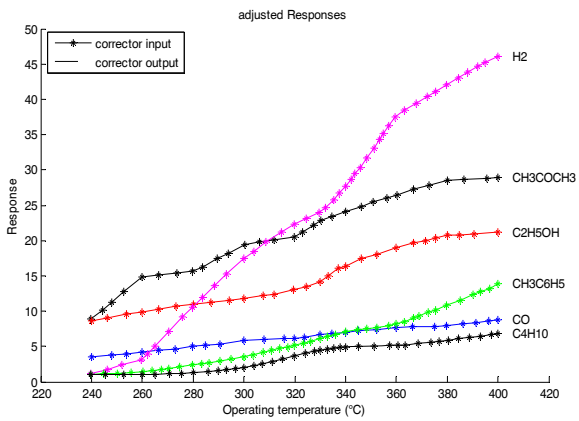

Fig. 9. Corrector sensitivity feature effect.

6. Conclusions

In this paper we modeled electronic noise based on three components: first one is Co-doped SnO_2 nanofibers sensor which has the role of detector, the second is a corrector which compensates the output detector and the last one is selector to select the nature of gas detected.

The Co-doped SnO_2 nanofibers sensor is modeled by using an artificial neural network sensor. It exactly reproduces the behavior of the gas sensor by taking into account the dependence on temperature at the measurement point, in addition to the dependence on the gas nature, to compensate the temperature influences and make the response increase all time with increasing temperature we used a corrector which is designed also by MLP model using the back propagation algorithm. Then we used the ANN capability to design the selector which selects exactly the gas detected by the sensor. The new technique discriminates and qualitatively and quantitatively measured six gases tested between 240 and 380 °C. This technique can be extended to other electronic nose.

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