ANN TECHNIQUE FOR ELECTRONIC NOSE BASED ON SMART SENSORS ARRAY

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Electronic Nose is widely used in environmental monitor because of its ability to recognize and discriminate between a different nature of gases and odors. In this paper, we developed an electronic nose based on a smart MOX sensor array for detect and identify seven different gases. These gas sensors characterized by nanostructure hierarchical/doped, this structure now by the very high sensitivity and low response time, these gas sensors are improved, on the side of linearity response and temperature dependence, using ANN models. We used in Electronic nose a pattern recognition based on artificial neural network, to discriminates qualitatively and quantitatively seven different gases on fast response.

Keywords: Electronic nose, ANN, e-nose, smart sensor, high sensitivity

1. Introduction

Electronic nose (e-nose) is an instrument designed for mimicking the mammalian sensory system, so it's used to detect and identify different gases mixtures. The importance of e-nose is presently the subject of emergent research for many applications [1]. Typically, an e-nose system consists of functional components are: a multi-sensor array, an information-processing unit, software with digital pattern-recognition algorithms, and reference-library databases.

The implementation of the gas sensor in the environment is difficult because of sensor problems (such as sensitivity and reliability) [1]. smart sensor and electronic noses can be used to produce reliable results.

Artificial Neural Networks (ANNs) are widely used to model complex systems because of the multi-variability and strong nonlinearity [4]. ANNs are very efficient in solving problems in the dynamic matter and offer the advantages of simple implementation and less computing time compared with other numerical models [5].

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2. Materials and Methods

In this paper, we have designed an electronic nose based on seven MOX gas sensors (S1, S2, S3, S4, S5, S6 and S7). The diagram of our electronic nose was presented in Figure 1.

We used ANNs to design a smart model for each gas sensor, this smart model contains two sub models (a compensator and a corrector) with the aim of improving the selectivity and eliminating the environmental effects (taking into account the nonlinearity response, depending on temperature in a dynamic environment, as well as dependence on the gas meter.). Then we design a selector module whose specific role is to determine the nature of gas detected and its concentration. The MATLAB interface was used during the design phase and optimization.

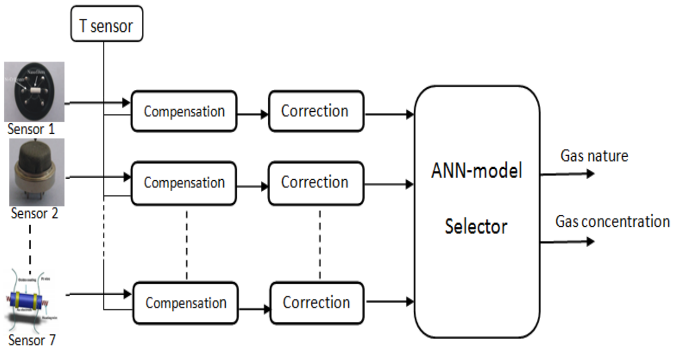


Fig 1. The electronic nose diagram

3. Electronic Nose Data

In the last few years, a large amount of research has focused on oxide nanostructure fabrication and control procedures. In order to improve sensor performance. Oxide nanostructures are promising gas sensor materials compared with commercial gas sensors, due to their highest both gas response and response speed simultaneously and substantially. Because of the fast gas diffusion to the entire detection surfaces via the porous structures. In fact, the method of producing the sensing film can improve the porosity of the material, which will lead to better performance in the gas detection behaviors of sensors [6].

Table 1

Representation of gas sensor array [6-11,2].

Sensors	Targeted gas	Synonyms
Co-doped SnO_2 nanofibers sensor	H_2	S1
Co-doped ZnO electrospun nanofibers	acetone	S2

Ni-doped ZnO electrospun nanofibers	C_2H_2	S3
Vanadium dioxide nanostructured films	CH_4	S4
Quasi-molecular-imprinting SnO_2 nanoparticles	CO	S5
Porous corundum-type In_2O_3nanosheets	NO_2	S6
Semiconducting copper oxide nanospheroids	NH_3	S7

For these reasons, our sensor array used in e-nose system consists of seven nanostructures gas sensors (S1, S2, S3, S4, S5, S6, S7) can successfully distinguish (H_2, acetone, C_2H_2, CH_4, CO, NO_2, NH_3) successively even in a mixed gas, with highest response and quick response/recovery (table 1) [6-11,2].

a. Sensors Characteristics

Figure. 2 show the experimental responses of gas sensors to different concentrations of target gas.

Figure. 3 show the experimental responses of gas sensors at different operating temperatures.

According to experimental results [6-11,2], All of these gas sensors used to detect the gas concentration have a very high response and selectivity, but nonlinear sensitivity (Figure 2); and are strongly dependent on the temperature of the environment (Figure 3).

We have improved the responses of gas sensors used in electronic nose by designed a smart model for each gas sensor, this smart model consists of two sub-models: compensator and corrector. We followed the same steps and the same procedure used for improving the characteristics of the gas sensor S3 (Ni-doped ZnO electrospun nanofibers) to improve the other sensors, this improvement concerned the linearity and dependence in temperature.

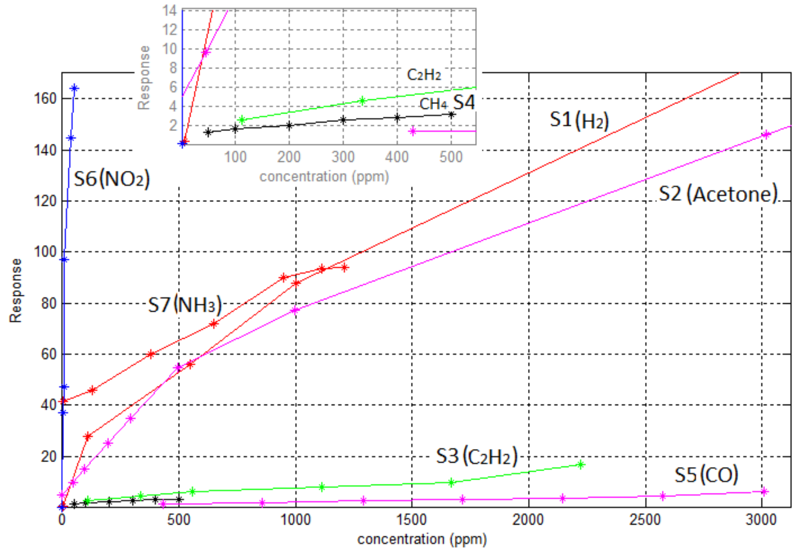


Fig. 2. Experimental responses of gas sensors (S1, S2, S3, S4, S5, S6, S7) to different concentrations of target gas (H_2, Acetone, C_2H_2, CH_4, CO, NO_2, NH_3).

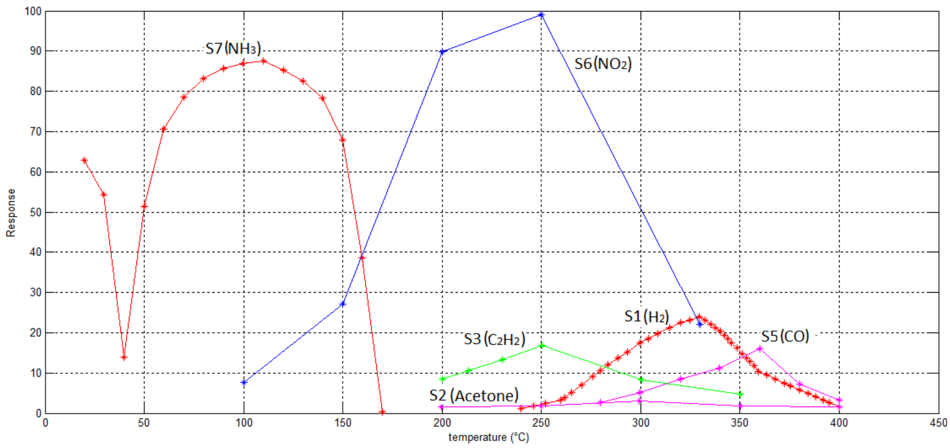


Fig. 3. Experimental responses of gas sensors (S1, S2, S3, S4, S5, S6, S7) at different operating temperatures. of (H_2, C_2H_2 , CO, NO_2, NH_3) respectively.

S3 (Ni-doped ZnO electrospun nanofibers) is one of the seven gas sensors used in our e-nose. According to experimental results [9], this sensor achieves the highest response with very short response/recovery times and good selectivity.

b. Compensator

The principal method of detection by MOX gas sensors are depending to variation of temperature, but this effect is not suitable in output response. For this, the design of a compensator is necessary to eliminate the temperature dependence.

Artificial neural networks (ANNs) have emerged as a highly effective learning technique suitable to perform complex, nonlinear, and dynamic tasks with a high degree of accuracy. ANNs models are much faster than physics/electro-mechanical models and have a higher accuracy than analytical and empirical models. And they are easy to develop for a new device or technology [5].

The design of the ANN compensator for S3 gas sensor requires the determination of database, selecting the network architecture and finding the numbers of layers and neurons in each layer. However, the number of neurons in the input and output layers is the same number of inputs and the number of outputs respectively of the system to be modeled.

Based on experimental results from [9], a database created and arranged as (T, Rs) inputs, and (Rc) as output response, where:

T: Absolute temperature. Rs: Sensor's output response. Rc: Compensator's output response.

To find the optimal parameters of ANNs architecture, we divide the available database into two groups (training data and test data). Then we train parameters using the training data set with MLP algorithm (backpropagation error). The test data used to test and validate the model.

During this research, the ANN compensator of S3 architecture was tested with a different number of hidden layers, neurons by layer and iteration algorithm consists of evaluating the total error. After many tests of different ANN models. The architecture optimized, which presents the minimum error, summarized in Table 2; which show that the ANN model has the 3-5-1 structure. Changing the number of neurons in the hidden layer or the number of layers did not result in correct architecture.

Table 2

The compensator's optimized architecture.

Property	**Characteristic**	
Database	Training base	132
	Test base	126
Architecture	3-5-1 Feed-forward MLP	
Activation functions	Logsig-Logsig- linear	
Training rule	Retropropagation error	
Training MSE	< e-13	

Compensator Test

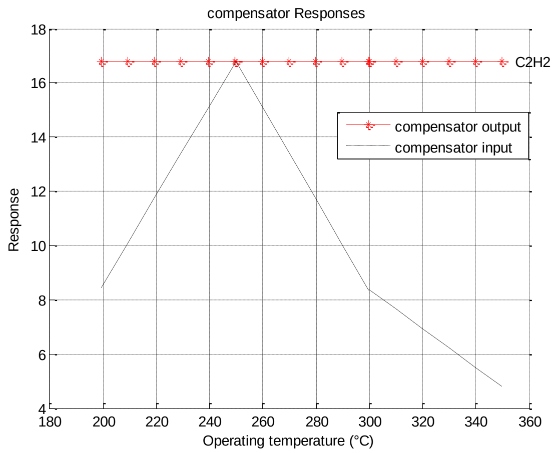


Fig.4. Compensator response.

We designed an ANN-based compensator for the S3 gas sensor. To illustrate the effect of this compensator we change temperature, and then we note the variation of the compensator’s output. Figure 4 shows that the ANNs compensator compensate correctly the sensor’s response (the response is free from the variations of temperature).

c. Corrector

Table 3

The corrector's optimized architecture.

property	Characteristic	
Database	Training base	600
	Test base	540
Architecture	1 Feed-forward MLP	
Activation functions	Linear	
Training rule	Retropropagation error	
Training MSE	10^{-9}	

We design the corrector based on ANNs to linearize the sensor response. The database is arranged as (Rc, C) inputs, and (Rlin) as output, where:

Rc: compensator's output response.

C: gas concentration.

Rlin: Corrector's output response.

The generation of database (training base and test base) is similar to the compensator model. However, in the corrector, the compensator's output response

Rc and gas concentration C are taken as inputs, and the corrector's output response Rlin is taken as the output.

Because the compensator's response is free from variations of temperature, so the architecture of corrector is optimized too simple, accurate and present the minimum error 10-9 given after 4 iterations (Table 3).

Corrector Test

We designed an ANN-based corrector for S3 sensor. To illustrate the effect of this corrector, we change concentration, and then we note the variation of the corrector’s output. Fig.5 shows that the corrector linearizes correctly the sensor’s output (the response is linear with concentration increasing).

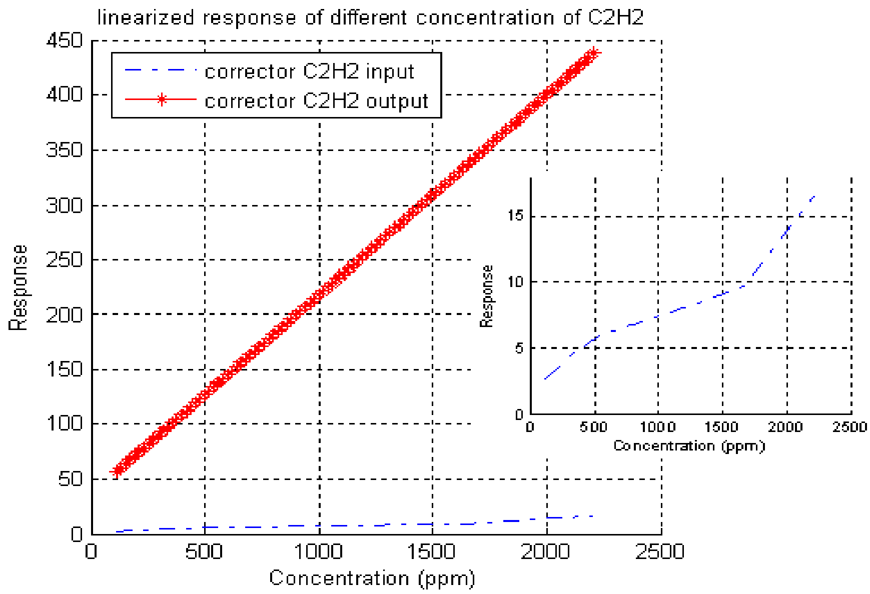


Fig.5. Corrector response of S3 gas sensor to C_2H_2 gas variations.

4. Improvement of other gas sensors

With the same procedure used to improve S3 gas sensor characteristics, the other gas sensors were improved.

In this step, we choose to apply a new technique for classifying the gas sensor data in the gas sensor improvement step. then the response of seven gas sensors will be diverged and separated, so the classification of the gas sensor data will be easy and accurate for the next step.

Figure 6. Shows the linearization of all gas sensor responses used in the electronic nose (the Correctors responses of seven gas sensors). These responses

obtained after compensation of temperature of this gas sensors.

The highest response, as shown in Figure 6, of all gas sensors is less than 610, for gaseous concentrations, decreasing from 2000 ppm, although there are some gas sensors with a higher output response at 810 (S1, S2). This is due to the classification and divergence effect in the response of sensors in the improvement step to avoid intersections between the curves, but the output responses after improvement, for gas sensors, still equal or greater than the realresponse of the gas sensor without improvement. Thus, the response of the electronic nose becomes higher.

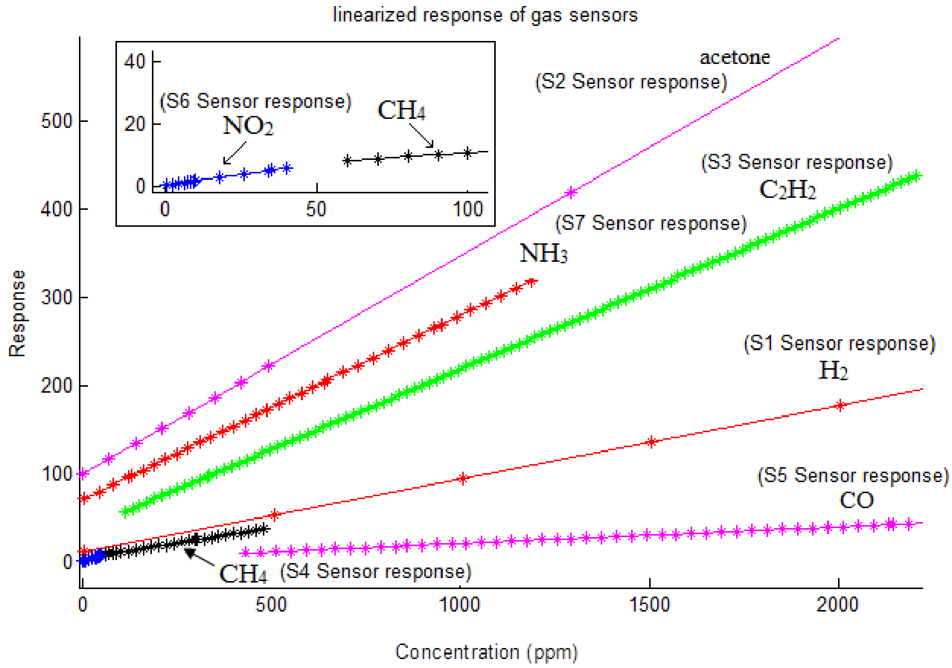


Fig.6. Linearization responses of seven gas sensors used in e-nose (responses of all Correctors of gas sensors)

5. Selector

To correctly select the nature of the gas detected by the sensors, we designed the selector which is the latest model designed for our electronic nose to select seven different gas natures summarized in the table 4.

Table 4

Response and their matched gases

Gas	Response (Ng)
H_2	1
CO	2
C_2H_2	3
NH_3	4
CH_4	5
CH_3COCH_3	6
NO_2	7

The database of ANN selector arranged as (Rlin1, Rlin2, Rlin3, Rlin4, Rlin5, Rlin6, Rlin7, Ng, and Cg) where:

Rlin1: corrector response of S1 gas sensor.
Rlin2: corrector response of S2 gas sensor.
Rlin3: corrector response of S3 gas sensor.
Rlin4: corrector response of S4 gas sensor.
Rlin5: corrector response of S5 gas sensor.
Rlin6: corrector response of S6 gas sensor.
Rlin7: corrector response of S7 gas sensor.
Ng: first output response of selector (gas number).
Cg: second output response of selector (gas concentration).

The generation of training base and test base is similar to that of the other models. However, in the selector, the (Rlin1, Rlin2, Rlin3, Rlin4, Rlin5, Rlin6, Rlin7) are taken as inputs, and the selector outputs response Ng and Cg are taken as outputs.

Table 5

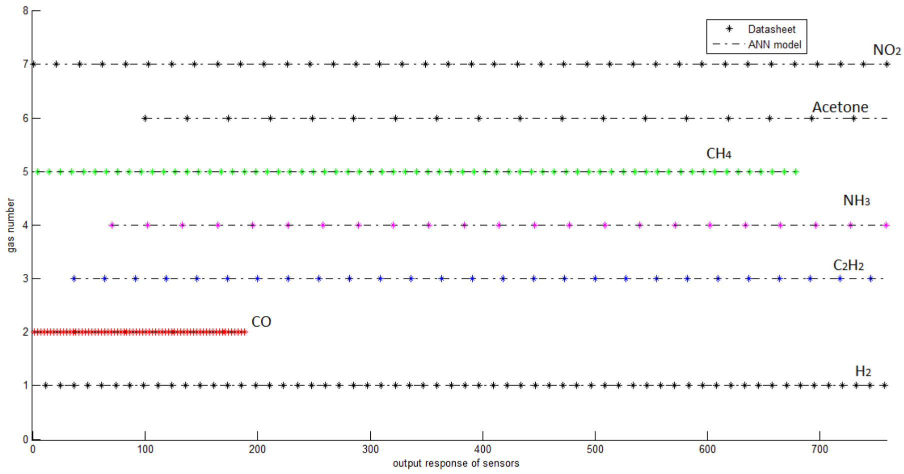
The optimized parameters of Selector.

Property	Characteristic	
Database	Training base	1400
	Test base	1260
Architecture	12-10-15-1 Feed-forward MLP	
Activation functions	Logsig-Logsig- Logsig-linear	
Training rule	Retropropagation error	
Training MSE	$<10^{-5}$	
Iteration number	1000	

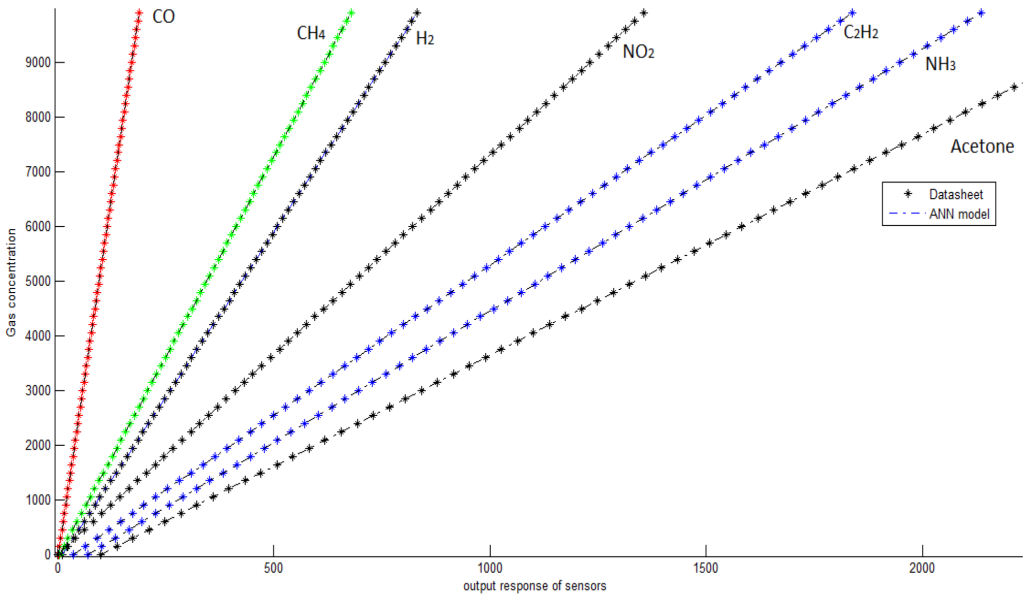
After many tests and training of different ANN models of selector. The architecture optimized and that produce the minimum error summarized in Table 5.

Selector Test

We designed a selector based on artificial neural networks for electronic nose. To demonstrate the effect of this selector we change the corrector's responses, and we note the variation of the selector's response. Fig. 7 shows that the selector selects correctly the gases (each gas Nature presents on special value from (1 to 7)) and the output concentration is accurate.



(a)



(b)

Fig. 7. Selector selectivity feature effect: number of gases detected (a), the concentration of gases detected (b).

The response time of electronic nose equal to the maximum response times of gas sensors (from S1 to S7). The responses time of gas sensors in our sensor array are summarized in table 6. We note that: (S1-S6) sensors have fast response less than 0.5 min, S7 sensor has 2.5 min (it's a fast response compared to other NH_3 gas sensor [2]). Thus, our electronic nose has 2.5 min response time. Note that we can design an electronic nose very fast by six gas sensors (S1-S6) with faster response time equal to 26 s.

Table 6

Time response of gas sensors

Gas sensor	Response time
S1	2 s (very fast response)
S2	6 s (fast response)
S3	5s (fast response)
S4	2.5 min
S5	12.266 s (decreasing with increasing concentration)
S6	5 s (fast response)
S7	26 s (fast response)

6. Conclusions

We design in this paper an electronic nose based on nanostructures MOX sensor array for detect and identify seven different gases (H_2, C_2H_2, CH_4, CH_3OCH_3, CO, NO_2, and NH_3). These gas sensors characterized by hierarchical /doped nanostructure, the combines between hierarchical and doped nanostructure give to gas sensor a very high sensitivity and fast response better than commercial sensors. For improving the characteristics of gas sensors, we design smart sensors using models based on artificial neural networks and in the same time, we classified the database of gas sensors, and we wire all the smart sensors with the selector module for increasing the selectivity. We used in Electronic nose a pattern recognition based on artificial neural network, which discriminates qualitatively and quantitatively seven gases tested between 0 and 2500 ppm, with fast response.

R E F E R E N C E S

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