ANN Modeling of a Gas Sensor

H. Baha† and Z. Dibi*

Abstract - At present, Metal Oxide gas Sensors (MOXs) are widely used in gas detection because of its advantages, including high sensitivity and low cost. However, MOX presents well-known problems, including lack of selectivity and environment effect, which has motivated studies on different measurement strategies and signal-processing algorithms. In this paper, we present an artificial neural network (ANN) that models an MOX sensor (TGS822) used in a dynamic environment. This model takes into account dependence in relative humidity and in gas nature. Using MATLAB interface in the design phase and optimization, the proposed model is implemented as a component in an electronic simulator library and accurately expressed the nonlinear character of the response and that its dependence on temperature and relative humidity were higher than gas nature.

Keywords: ABM, ANN, Gas sensor, Implementation, Modeling

1. Introduction

Artificial Neural Networks (ANNs) are used in instrumentation to model complex systems because of multivariability and strong nonlinearity. The extrapolation errors with ANNs are lower both inside and outside the calibration range [1]. 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 [2].

The high sensitivity of metal oxide sensors (MOX) has made it one of the most popular technological choices for sensor arrays [3]. The main disadvantage , however, is its lack of selectivity. The working principle of these sensors is based on the variation of their conductivity in the presence of oxidizing and reducing gases. The magnitude of the response depends on the nature and concentration of the gas, as well as on the type of metal oxide involved [4].

Studies approached the effect of nonlinearity of the MOX response over certain gases [5]-[7], such as its dependence in temperature [8]-[9]. However, dependence on relative humidity and gas nature has not been investigated and no model of the MOX sensor has been implemented on a simulator.

For this purpose, we used ANNs to design and establish a model on SPICE software for an industrial MOX TGS822 (Figaro firm). MATLAB interface was used during the design phase and optimization. The results (optimal architecture, bias, and weights of the network) were used in the implementation of the model as a component in the PSPICE simulator library. The model takes into account the nonlinearity response, dependence on temperature and relative humidity in a dynamic environment, as well as dependence on gas nature.

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2. Characteristics of the Sensor

According to experimental results [10], the sensor used (TGS 822) to detect the gas concentration had a nonlinear sensitivity feature (Fig. 1) (representation is in logarithmic scale) and was dependent on the temperature and humidity of the environment (Fig. 2) where it was placed. R0 denotes

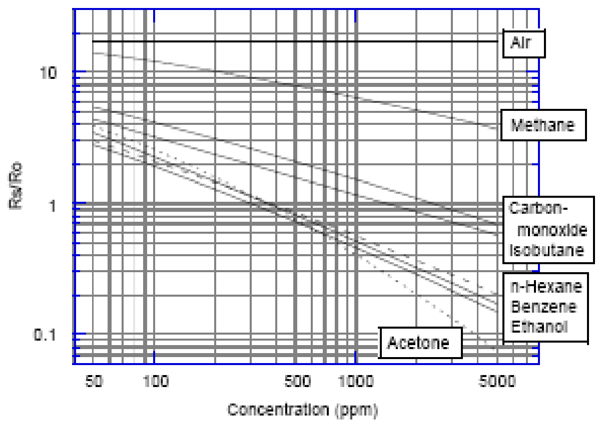

Fig. 1. TGS822 sensor's sensitivity feature [10].

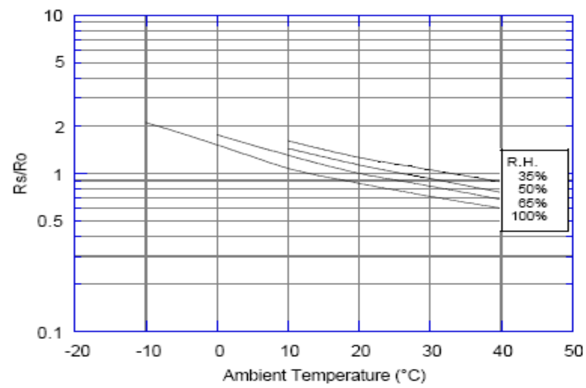

Fig. 2. TGS822 dependence on temperature and relative humidity [10].

the sensor´s resistance in 300 ppm of ethanol, and RS denotes the sensor´s resistance to different concentrations of various gases.

2.1 Use of the Sensor

In Fig. 3, a basic gas concentration measure circuit is presented with sensor TGS822.

The variation of the resistance of the TGS sensor is measured indirectly similar to the voltage drop, which appears on the reading resistance RL. If gas, such as methane, butane and propane, comes into contact with the surface of the sensor, its resistance is reduced in correlation with the present gas concentration. To work with the features of the provided sensor, in this case, the Figaro firm, the output voltage (VRL) has to be processed and the resistance of the sensor RS has to be achieved using the following equation:

$$R_s = \left(\frac{v_c}{v_{RL}} - 1\right) R_L \tag{1}$$

The configuration of the connected circuits of the sensor has to ensure the following conditions:

- VC can be 5, 6, 12 or 24 V;
- VH heating voltage has to be 5 V±0.2 V; and
- The power supply on the sensor should be a maximum of 15 mW.

If we determine the sensitivity feature of the sensor using standard testing conditions, this one has to coincide with the sensitivity feature given to us by the producing Figaro firm. The sensitivity feature is determined with a relative representation of the resistance of the sensor. Standard testing conditions, as indicated by the producer, include the following:

- Atmospheric conditions: temperature 20 ºC±2 ºC and relative humidity 65%±5%;
- VC: 10±0.1 V, VH: 5±0.05 V, RL: 10 K±1%;
- Time for the sensor´s supply maintenance seven days or more;
- Testing gas: Ethanol;
- Heating resistance: 38.0 Ω±3 Ω;
- Sensor resistance: 1-10 KΩ at Ethanol 300 ppm; and
- Resistance ratio:

$$\frac{R_s \ \ in \ \ Ethanol \ \ 300\,ppm}{R_s \ \ in \ \ Ethanol \ \ 50\,ppm} = 0.4 \pm 0.10\,. \tag{2}$$

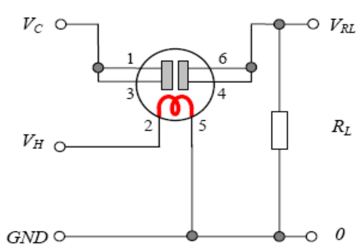

Fig. 3. Measure circuit with TGS sensor.

Once the value R_0 is measured, the resistance of the sensor at different concentrations of various gases, different temperatures, and relative humidity are determined as follows. Relative to (1), we calculate R_S; then from Fig. 2 we read the value R_S/R_0 in the given conditions and obtain a value *x* for temperature and relative humidity. We multiply value *x* with R_0 and obtain a value *y*. We divide R_S with *y* and obtain R_S/R_0, which is uninfluenced by temperature and relative humidity; this will help determine the appropriate concentration from Fig.1.

3. Neural Networks Model

Using MATLAB interface and based on experimental results from [4], a database was created and arranged as (S, T, RH, C) input and (RS) as output, where:

S: Selecting the gas;
T: Absolute temperature;
RH: Relative humidity;
C: Gas concentration; and
RS: Sensor resistance.
We suppose that Ro=10kΩ.

Most of this database was used mainly in the training phase using algorithm LP (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; and
e: Modeling error.

To optimize the model architecture, an iteration algorithm consisting of the evaluation of the total error as a function of layer number, the number of neurons per layer and the results of several tests of different ANN models, was used. The most optimized architecture optimized, which produced the smallest error is summarized in Table 1.

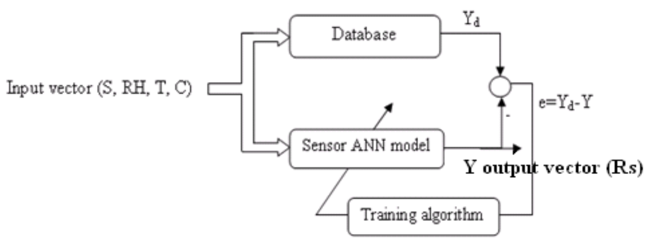

Fig. 4. Modeling of the TGS822.

Table 1. Summary of model optimized parameters

Property	Characteristic	
Database	Training base	3800
	Test base	504
Architecture	9-5-1 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 relative humidity in the measure point, as well as the gas nature of the sensor placed in a dynamic environment. To illustrate this effect, we changed concentrations and noted the variation of the resistance of the sensors. 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 temperature and relative humidity is shown in Fig. 6.

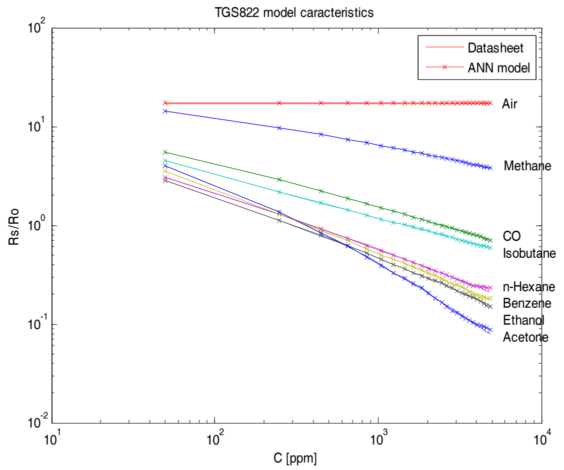

Fig. 5. Model and database TGS822 of the sensitivity feature of the sensor.

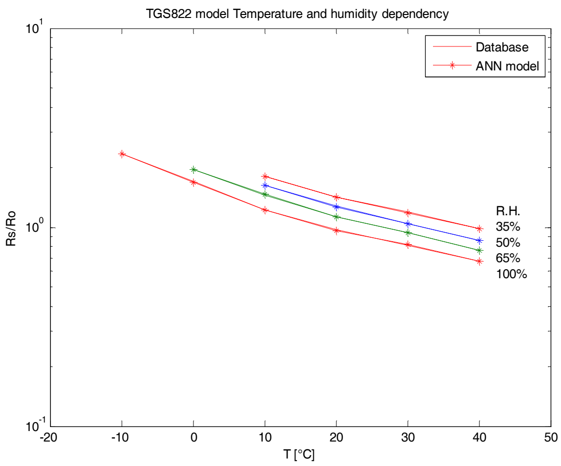

Fig. 6. Model and database TGS822 dependence on temperature and relative humidity.

3.2 Implementation of the TGS822 Model

Using the Analog Behavioral Modeling (ABM) components of the SPICE Library, the results (i.e., optimal architecture, bias, and weights of the network) of the previously designed sensor model was implemented as a component in the SPICE simulator library.

3.2.1 Simulation Results

The model introduced on the SPICE simulator (Fig. 7) was implemented in the electrical circuit in order to test and validate it.

The temperature was fixed at 20 °C, relative humidity at 65%, and concentration varied from 300 to 5000 ppm. A PARAMETRIC DC SWEEP analysis provided the variation of the resistance against concentration C with different gases. Results are represented in Fig. 8, where:

- $R_s = \left(\dfrac{v_c}{v_{RL}} - 1\right) R_L$
- R1=Ro=10kΩ

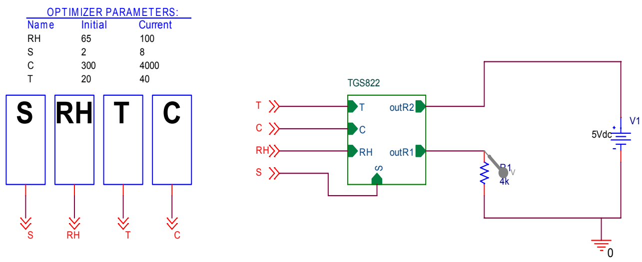

Fig. 7. Simulation circuit.

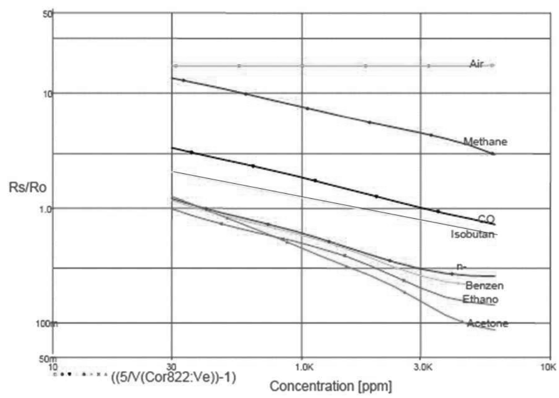

Fig. 8. Variation of the résistance ratio (Rs/Ro) vs gas concentration C at 20°C and 65%RH.

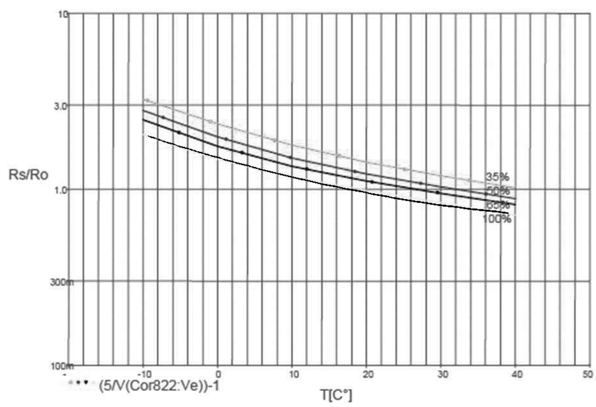

Fig. 9. Variation of the résistance ratio (Rs/Ro) vs temperature T at 300ppm of Ethanol.

4. Conclusion

Even In this paper we modeled TGS822 sensor by using an artificial neural network sensor. This one accurately reproduces the behavior of the gas sensor in a dynamic environment by taking into account nonlinearity of its response, the dependence in temperature and relative humidity in the measure point in addition to the dependence in gas nature. The proposed ANN model was implemented as a component on SPICE simulator library, and this model was tested and validated. This technique can be used with other sensors.

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