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Design of a Selective Smart Gas Sensor Based on ANN-FL Hybrid Modeling

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The selectivity is one of the main challenges to develop a gas sensor, the good chemical species detection in a gaseous mixture decreasing the missed detections. The present paper proposes a new solution for gas sensor selectivity based on artificial neural networks (ANNs) and fuzzy logic (FL) algorithm. We first use ANNs to develop a gas sensor model in order to accurately express its behavior. In a second step, the FL and Matlab environment are used to create a database for a selective model, where the response of this one only depends on one chemical species. Analytical models for the gas sensor and its selective model are implemented into a Performance Simulation Program with Integrated Circuit Emphasis (PSPICE) simulator as an electrical circuit in order to prove the similarity of the analytical model output with that of the MQ-9 gas sensor where the output of the selective model only depends on one gas. Our results indicate the capability of the ANN-FL hybrid modeling for an accurate sensing analysis.

Keywords: Fuzzy logic, Artificial neural networks, Gas sensor, Selectivity, Analytical model, Selective model.

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1. INTRODUCTION

Electronic nose is one of the important tasks in civil and military environments. Recently many research activities are interested by the electronic nose development. Most of these researches are interested by decreasing the size and the fabrication cost of microelectronic gas sensors [1-3].

Problem that has been well-known throughout the entire development of gas sensors is the lack of selectivity, where gas sensors present a similar response to a wide variety of gases. Furthermore, they have temperature and humidity dependence. Hence, various researches have proposed an array of gas sensors with pattern recognition algorithms such as ANNs to solve this similarity in response [4-8]. Maziarza in [9] has proposed a FL algorithm to incorporate temperature and humidity dependence.

In this paper, we propose an ANN model for an industrial gas sensor MQ-9 operated under dynamic environment and its selective hybrid model which is developed by combining ANNs and FL algorithm, proposed to perform the gas sensor selectivity. We have designed and implemented in PSPICE software the MQ-9 based-ANN model with its hybrid selective model taking into account temperature, relative humidity, non-linearity response, and gas sensitivity response in a dynamic environment. The classification of the concentration FL_C and the output resistance FL_RS in the selective model, makes possible, if selecting them, to reach only one gas at the output.

2. SEMICONDUCTOR SENSOR MQ-9 CHARACTERISTICS

Semiconductor gas sensor MQ-9 is an industrial, low cost, sensor use the sensitive propriety of SnO_2 to detect different gases that contain CO and other combustible gases. This sensor can be used to detect; Carbon Monoxide CO, Methane CH_4 and Propane LPG.

The basic test circuit of the sensor (see Fig. 1a) need two voltages, heater voltage (*VH*), used to supply certified working temperature, and test voltage (V_C), used to detect voltage (V_{RL}) at the load resistance (R_L) wish is in series with the sensor [10].

$$R_S = \left(\frac{V_C}{V_{RL}} - 1\right) \times R_L\,, \tag{2.1}$$

The sensitivity of MQ-9 gas sensor is given by the experimental results [10] (see Fig. 1b). The ordinate is as described in Fig. 1b represents the resistance ratio of the sensor (R_S/R_0) (R_S sensor resistance and R_0 sensor resistance in 1000 ppm LPG). The abscissa represents the concentration of gases (in ppm).

MQ-9 dependence on temperature and relative humidity is given by [10] (see Fig. 1c). This dependence represents the biggest problem of the sensor after the selectivity.

3. ANALYTICAL MODEL "ANN MODEL"

The experimental results [10] are used to create a database arranged as (*G*, *T*, *RH*, *C*, R_S/R_O), where *G* is the Gas species, *T* is the environment. Temperature in the measurement point, *RH* is the Relative Humidity applied to the gas sensor, *C* is the gas Concentration and R_S/R_O is the gas sensor response. Note here that, in our model, the input *G* takes the value 0 for Air, 1 for CO, 2 for CH_4 and 3 for LPG. Then, the database is arranged into training, validation and test subsets. One-fourth of the data are taken for the validation set, one-fourth for the test set and half for the training set. The sets are picked as equally spaced points throughout the original data. It is important to note that our process not to use any element of training phase. These bases are only reserved for the final performance measurement [11-13].

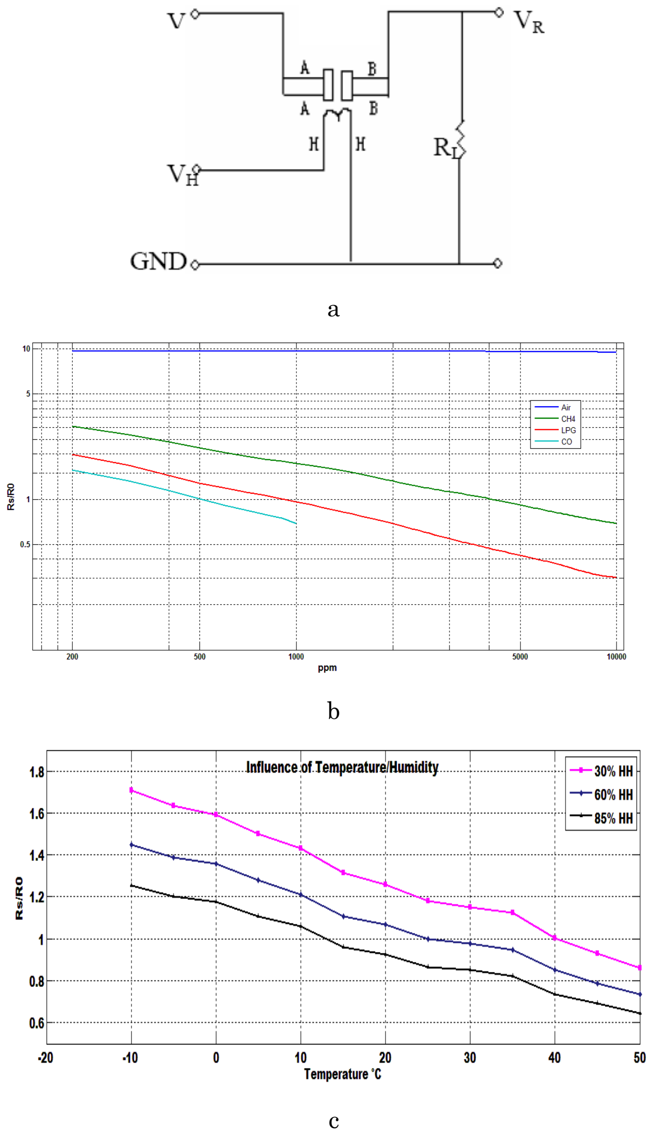


Fig. 1 – Basic test circuit of the MQ-9 sensor (a), sensitivity characteristics of the MQ-9 sensor (b), influence of temperature and humidity on the MQ-9 sensor (c) [10]

3.1 Training

The training phase requires the use of the database, the network architecture selecting and the finding of numbers of layers and neurons in each layer. However, since the neuron numbers in the input and output layers are determined by the input and output numbers of the system to be modeled, the MQ-9 gas sensor analytical model has four inputs and only one output R "Resistance", the input layer has four neurons and only one neuron for the output layer. So, the MQ-9 model can accurately predict the MQ-9 gas sensor response variation by finding the optimal parameters (number of the hidden layers, number of neurons by layer and transfer functions). In order to optimize this model architecture, an iteration algorithm is used to evaluate the total error, as a function of layer number and the number of neurons in each layer.

After many tests of different models; the optimal architecture of the symbolic notation of the ANN optimized model "with the smallest error", is considered with multilayer perceptron (MLP), two hidden layers, with five neurons and Logsig transfer function for the first layer, nine neurons and the transfer function Logsig for the second layer and the transfer function linear for the output layer (see Fig. 2a). The flowchart shows the back-propagation (BP) algorithm used for training the database (see Fig. 2b), where:

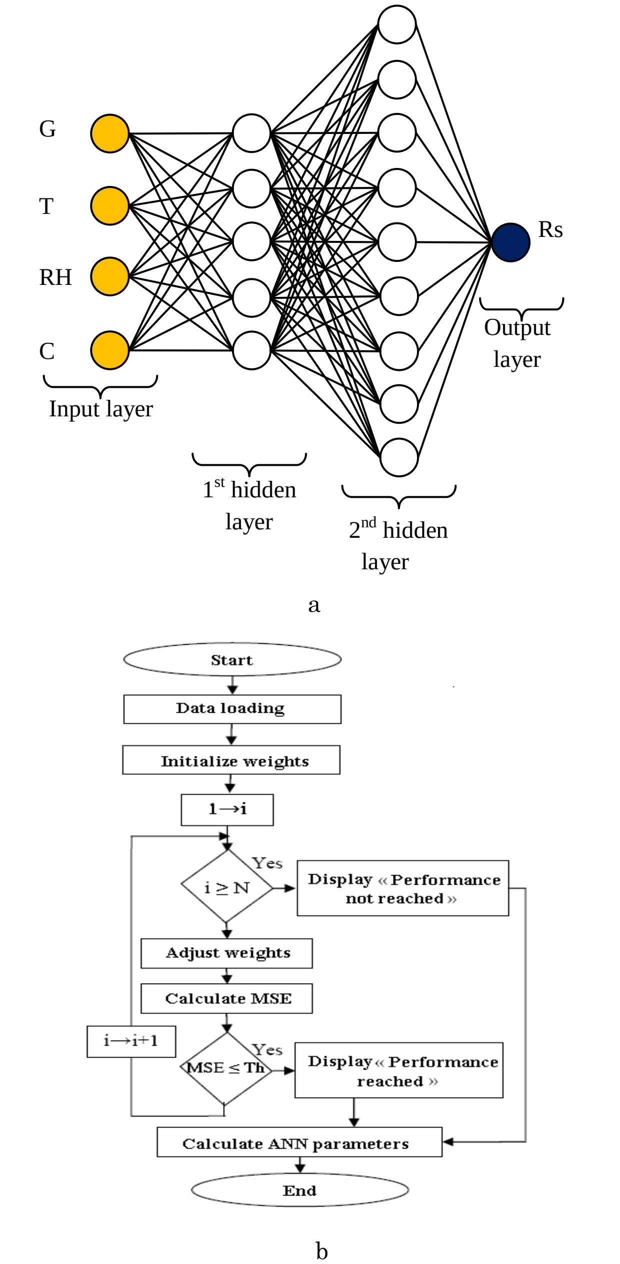


Fig. 2 – symbolic notation of ANN optimized model (a), training program flowchart (b)

Data loading are training base, test base, number of layers and neurons, type of the transfer functions, number of iteration and the estimated threshold. N is the number of iterations. MSE is the mean square error. Th is the estimated threshold "Test MSE". ANN parameters are the neuronal network element (Bni are the bias matrix and Wnji are the weights matrix).

Finally, we measure the model performance obtained with the test base. Table 1 summarizes the obtained parameters.

Table 1 – Optimized parameters of the neural networks model

Database	Training base				27810	
	Test base				13860	
	Validation base				13860	
Number of Neurons and Transfer function	Input layer				4	Logsig
	1st hidden layer				5	Logsig
	2nd hidden layer				9	Logsig
	Output layer				1	Linear
Input	*G*	*RH* (%)	*T* (°C)	*C* (ppm)	Output	Rs/R_0
Max	3	85	50	1000	Max	10
Min	0	30	– 10	200	Min	0.3
MSE «Test» = 10^{-4}			MSE «Training» = $9.778\ 10^{-4}$			

3.2 Model Test

The ANN model simulation at fixed temperature and humidity of 25°C and 60 % respectively, when varying the concentration within the range of 200 to 10000 ppm for the diverse gases, indicates a good performance of our model. The comparison between the initial database and that obtained after the model simulation (see Fig. 3) shows that our model can accurately predict the response variation of the modeled MQ-9 gas sensor.

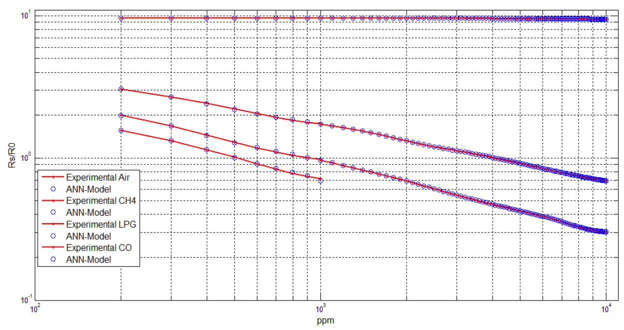


Fig. 3 – Model performance of MQ-9 gas sensor

4. SELECTIVE MODEL

The selective model is a hybrid Model, the classification is done using fuzzy logic based approach. This classification takes into account the values of Rs/R_0 and the concentration (see Fig. 4). It includes a gases separation with a decomposition strategy for an accurate sensing analysis; it only detects one gas. The table 2 resumes the classification parameters of our fuzzy system, where VL, L, ML, M, MH, H and VH are the linguistic terms chosen respectively for the controller as: very low, low, medium low, medium, medium high, high and very high.

The database generation is the second step in the modeling of our selective model. It takes into consideration the above classification. The training procedure is similar to that of the model's one. However, in this model, the temperature *T*, relative humidity *RH* and the sensor's output resistance *RS* are taken as inputs, the resistance and the concentration are taken as classified inputs, the selective model outputs (the three voltages VCH4, VLPG and VCO) are the desired outputs of our sensor, that indicate the gases CH4, LPG and CO respectively. In this work, we realize a program using Matlab environment to obtain the outputs of this new database with three linearized and normalized outputs voltages.

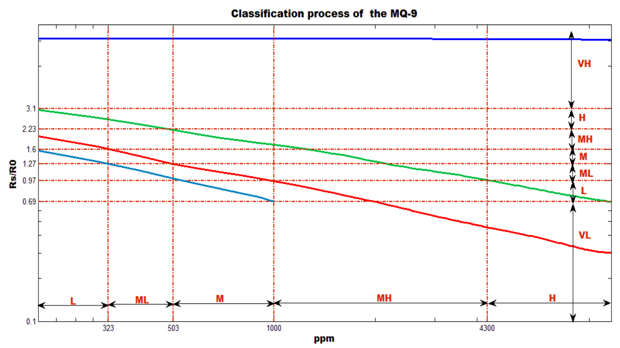


Fig. 4 – The fuzzy logic classification of the gas sensor at fixed temperature 25 °C and fixed humidity 60 %

In the simulation study, a MLP with 5-9-3 structure of the ANN model is chosen for our selective model. The latter is trained in a similar manner as in the case of the model one.

5. MODELS IMPLEMENTATION IN PSPICE AND SIMULATION RESULTS

The MQ-9 Model and the selective Model are modeled using the analog behavioral modeling (ABM) of the PSPICE library. Each neuron of the ANN model is replaced by one ABM which is characterized by the neuron equation (eq), for example, the ABM 1 is characterize the first neuron in the MQ-9 model based ANN is represented by an exponential equation eq (1) as:

$$\mathrm{eq}(1) = 1 / \left(1 + \exp\left(\begin{matrix} -B_{11} + W_{111} \cdot V(G) + W_{112} \cdot V(T) + \\ +W_{113} \cdot V(RH) + W_{114} \cdot V(C) \end{matrix}\right)\right), \quad (5.1)$$

The exponential form of the equation is due to the choice of the transfer function “Logsig” in the first hidden layer, B_{11} is the first bias of the first hidden layer in the bias matrix “Bni”, W_{111} to W_{114} are the first to the fourth weight for the first hidden layer in the weights matrix “Wnij”. The model has 15 equations with 15 bias and 74 weights.

In order to validate our smart sensor, the MQ-9 model and its selector, previously designed, have been implemented in the PSPICE simulator as an electrical circuit (see Fig. 5a). It is to note that the inputs FL_*Rs* and FL_C are the fuzzy logic sets for the parameters, sensor resistance and concentration, respectively. They are classified in the fuzzy system by taking the values 1 to 7 for the classification VL to VH.

Table 2 – Classification parameters of the selective model

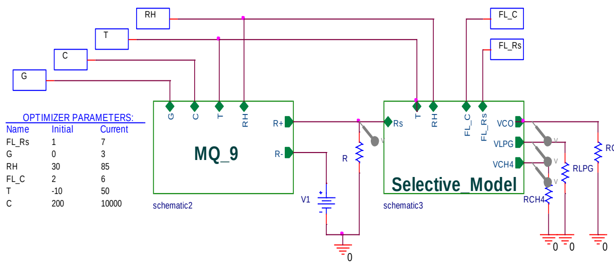
Concentration (ppm)	R_S/R_0						
	VL	L	ML	M	MH	H	VH
L				CO	LPG	CH_4	Air
ML			CO	LPG		CH_4	
M		CO	LPG		CH_4		
MH	LPG	LPG	CH_4	CH_4	CH_4		
H	LPG	CH_4					

The temperature and the relative humidity are fixed at 25 °C and 60 %, respectively, when the concentration is varying within the range of 200-10000 ppm. A parametric SWEEP analysis is used to simulate the MQ-9 model for four gases, in order to confirm the accurate modeling of the MQ-9 gas sensor (see Fig. 5b). This means that the MQ-9 model gives an identical response compared to the experimental one of the MQ-9 sensor.

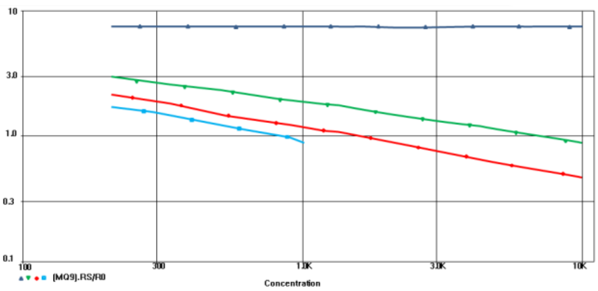
Now, let us consider the model selector outputs for the same parametric simulation. All inputs of the fuzzy logic sets FL_Rs and FL_C are set up using a series of membership functions. The simulation results indicate that our hybrid model, implemented in PSPICE simulator, can accurately estimate the ideal response "linearized and normalized" (see Fig. 5c). Furthermore, each gas response is separated as an output voltage. It is to note that the outputs are normalized by 6.9 V to 12 V as well as the outputs voltages of the selective model are calculated by:

$$V_S = 3 \times log_{10}\left(concentration\right), \qquad (5.2)$$

The model selector inputs FL_Rs and FL_C are fixed at 2 and 5, respectively, for the same parametric simulation (see Fig. 5d). The simulation results indicate the capability of the good selection of our selective model where the output of the sensor only depends on one gas.



a



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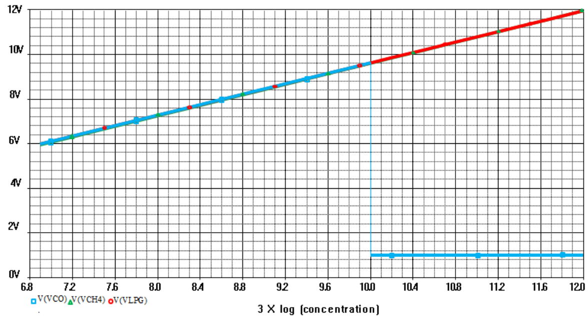

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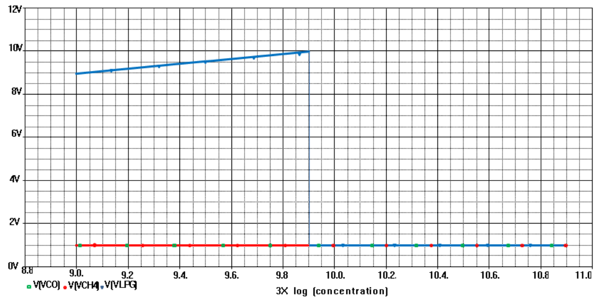

d

Fig. 5 – Smart sensor electrical circuit (a), MQ-9 model output "R_S/R_0 vs concentration" (b), selector model outputs, "V_{CH4}, V_{LPG} and V_{CO} vs (3 × log10 (concentration))" selecting all fuzzy logic inputs of FL_Rs and FL_C (c), selector model outputs, "V_{CH4}, V_{LPG} and V_{CO} vs (3 × log10 (concentration))" when fuzzy logic inputs of FL_Rs = 2 and FL_C = 5 (d)

6. CONCLUSION

In this paper, we have proposed a new method based on artificial neural networks and fuzzy logic algorithm. This method is aimed to solve the most challenge of gas sensors, which is the selectivity. We have established on PSPICE simulator an electrical circuit of a smart gas sensor. The circuit is composed of the MQ-9 model of the industrial gas sensor and the selective model. The MQ-9 model response is modeled by including ANN model, with two hidden layers (MLP). This model can accurately reproduce the behavior of the MQ-9 in a dynamic environment taking into account the nonlinearity of its responses, the dependence on temperature and relative humidity at the measurement point, as well as the dependence on the gas nature. Those undesirable effects are observed in its simulation results.

The selective model is proposed to detect the good chemical species in order to decrease the missed detections. This model incorporates intelligence into the MQ-9 model by using the FL capability for an accurate sensing analysis, wherein, the separation of the gases is done by decomposition strategy or in other words the selective model can detect only one gas after the fuzzification process.

The fuzzy sets extended by this fuzzification, are used to be a separated output voltages. Those voltages are linearized and normalized in order to correct the nonlinearity, the temperature influence and the relative humidity influence on the gas sensor. The new database, obtained by our hybrid ANN-FL model, is used to train the MLP model based-BP algorithm. The obtained models are implemented on PSPICE simulator as an electrical circuit and validated by the simulation results.

This idea can be considered to be fundamental to significantly reduce the processing time and improves the accuracy of the ANN-FL hybrid modeling. It can be applicable to other problems, like systems which need for more accuracy in a specific input or systems in which the responses change abruptly.

In the future, we may report our findings on the effectiveness of the proposed ANN-FL based intelligent model can be implemented into a field programmable gate array FPGA.

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