ANN modeling of an industrial gas sensor behavior

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***Abstract*—In this paper, we propose the modeling of an industrial gas sensor "MQ-9", where our modeling is based on ANNs "artificial neural networks". The gas sensor model, obtained, operated under a dynamic environment and expresses accurately the MQ-9 gas sensor behavior. Accordingly, it takes into account the nonlinearity and the cross sensitivity in gas selectivity, temperature and humidity. This model is implemented into PSPICE "performance simulation program with integrated circuit emphasis" simulator as an electrical circuit in order to prove the similarity of the analytical model output with that of the MQ-9 gas sensor.**

***Index Terms*— Analytical model, artificial neural networks, cross sensitivity, gas sensor, PSPICE.**

I. Introduction

Gas sensors are the devices which detect the different gases existence, especially those have a harmful influence on humans, on animals or also on plants. The development of gas sensor technology has found wide applications in monitoring, protection, civil and military environments…etc. Recently many researches are interested by the gas sensors development [1, 2].

The lack of selectivity is the well-known problem that has been throughout the gas sensors, where, they present a similarly response to a wide variety of gases, furthermore, they have temperature and humidity dependence. Consequently, the adequate model creation is an essential task toward handling a system. The good modeling is a necessary step for control, setting up planning or prediction methods, as well as for validating and testing them before practical application by simulation environment [3, 4].

Neural models are a powerful tool for modeling, especially for the systems with unknown relationship data. They offer an approach with a high degree of accuracy performed in a real-time to solve nonlinear, complex, and dynamic tasks. [5]. Therefore, ANNs are faster compared with physical and electromechanical models and accurate compared with analytical and empirical models. Furthermore, the development of a new device or a new technology is easy compared with other models [6-7].

In this paper, we propose an ANN model for an industrial gas sensor MQ-9 operated under a dynamic environment. We have established in PSPICE software this model, which carried out takes into account the temperature, the humidity, the non-linearity and the gas sensitivity in a dynamic environment.

II. Characteristics of MQ-9 Gas Sensor

The MQ-9 gas sensor is an industrial, low cost, sensor use the sensitive propriety of SnO_2 to detect different gases, it could be used to detect combustible gases; Carbon Monoxide CO, Methane CH_4 and Propane LPG.

The basic test circuit of the MQ-9 gas sensor need two voltages, heater voltage (V_H), used to supply certified working temperature, and test voltage (V_R), used to detect voltage (V_{RL}) at the load resistance（R_L）wish is series with the sensor [8]. Figure 1 shows the measure circuit of the MQ-9 gas sensor.

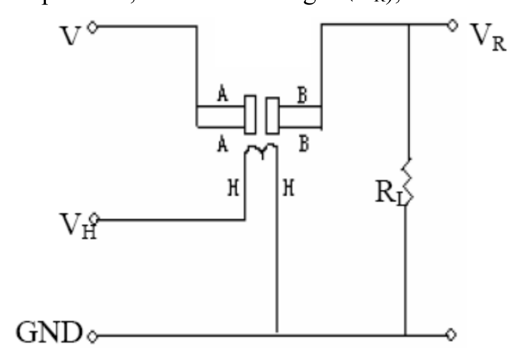

Fig. 1. Basic measure circuit of the MQ-9 sensor [8]

- V_R Can be AC voltage or DC voltage equal 5±0.1 V
- V_H Can be AC voltage or DC voltage among 5±0.1V and 1.4±0.1V
- R_H equal 33.0 Ω ±5% and R_L can adjust
- R_S among 2~20 KΩ in 100 ppm Carbon Monoxide

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The equation characterizes the sensor resistance R_S is :

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

Figure 2 shows the sensitivity of MQ-9 gas sensor, which is giving by the experimental results [8]. The ordinate is 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 is the concentration of gases (in ppm).

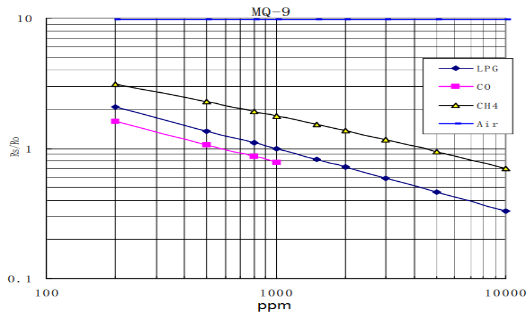

Fig. 2. Sensitivity characteristics of the MQ-9 [8]

The dependence on temperature and on the relative humidity of MQ-9 is given by [8]. Figure 3 shows this dependence at different values of temperature and humidity.

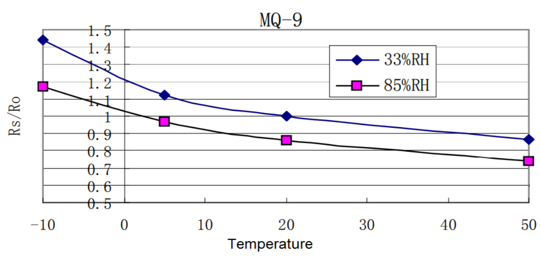

Fig. 3. Typical dependence on temperature and humidity of the MQ-9 [8]

III. Analytical Modeling of MQ-9 Gas Sensor

A. Database creation

The gas sensor MQ-9 experimental results [8] are used to create a database of an analytical model “ANN Model”, the arrangement of this database is (G, T, RH, C, R_S/R_O), where G is the Gas species “takes the value 0 for Air, 1 for CO, 2 for CH_4 and 3 for LPG”, T is the environment temperature in the measurement point “among -10°C to 50°C”, RH is the relative humidity applied to the gas sensor “among 33% to 85%”, C is the gas concentration “among 200 ppm to 10000 ppm” and R_S/R_O is the gas sensor response “among 0.1 to 10.7”. Note here that, the data are divided into three subsets “training, validation and test”. The first half of the data are booked for the training set, the second half of the data are divided by tow subsets, reserved for the validation set and the test set. Throughout the original data, the points of the sets are picked as equally spaced. The elements of the test base and validation base are reserved for the final performance measurement, it is important not to use any element of them in the training phase [9, 10].

B. ANN Training

The phase of training requires the database “mentioned in the above section”, after the database definition we select the architecture of our network; it’s a question of finding the optimal numbers of layers and the optimal numbers of neurons in each layer.

Therefore, the neuron number in the input layer is determined by the inputs of our system to be modeled “MQ-9 gas sensor” which has four inputs “G, T, RH and C”, hence four neurons in the input layer. The neuron number in the output is determined, also, by the system output number, which has only one output “R_0/R_S”, hence only one neuron in the output layer.

Consequently the optimal numbers of the hidden layers, of neurons by layer and the transfer functions are the required parameters that the model of MQ-9 needs to accurately express the response variation of the MQ-9 gas sensor. We use an iteration algorithm, based on total error evaluation, to reach those optimized parameters.

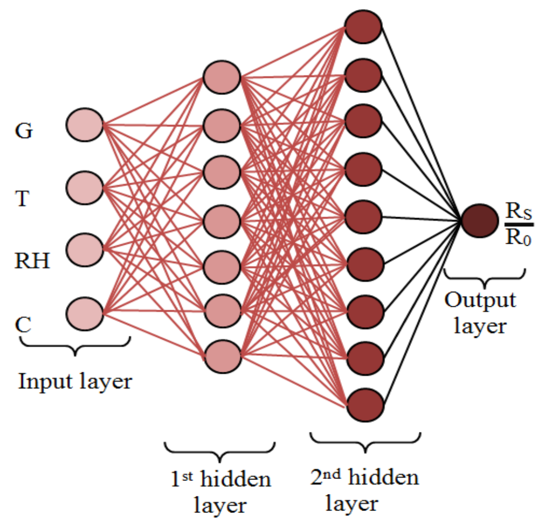

Fig. 4. Symbolic notation architecture of the MQ-9 ANN model

The symbolic notation of the optimal architecture is selected among different models, after several MLP “multilayer perceptron” tests; this optimized ANN model “has the smallest error” is defined with an architecture dispose of two hidden layers; the first one with seven neurons and the transfer function Logsig and the second with nine neurons and the transfer function Logsig. The output layer takes the transfer function linear. This symbolic notation is shown in figure 4.

The database is trained by using a BP “Back propagation” neuronal network algorithm. The program flowchart of this algorithm is shown in Figure 5. Hence, the data loading on the flowchart compound of the training base, test base, validation base, the parameters of optimal architecture are “ number of layers and neurons, type of the transfer functions”. The training also needs the number of iterations and the estimate threshold. So, we note here that the parameters N, MSE, Th, and ANN parameters are respectively the number of iterations, the mean square error, the estimate threshold ” and the neuronal network element (Bni "bias matrix" and Wnji "weights matrix"). The model performance obtained is finally measured by the test base.

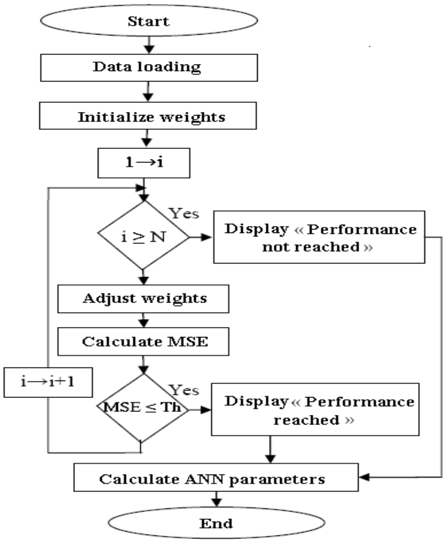

Fig. 5. Flowchart of the training BP algorithm

The table 1 shows the summarized parameters of the optimized architecture which has the smallest error.

TABLE I
OPTIMIZED PARAMETERS OF THE NEURAL NETWORKS MODEL

propriety	characteristic	
	Training base	2296
Database	Test base	1148
	Validation base	1148
Architecture	7-9-1 Feed-forward MLP	
Activation functions	Logsig-Logsig- linear	
Training rule	Retropropagation error	
Training MSE		<0.0001
Iterations number		5000

C. Model test

The choosing model takes into account the nature of the gas, the temperature and the relative humidity dependence in the measuring point, when the sensor is placed in a dynamic environment. Figure 6 shows the initial database and the response obtained by the MQ-9 ANN model, when varying the concentration within the range of 200 to 10000 ppm at fixed temperature 20 °C and fixed relative humidity 65 %.

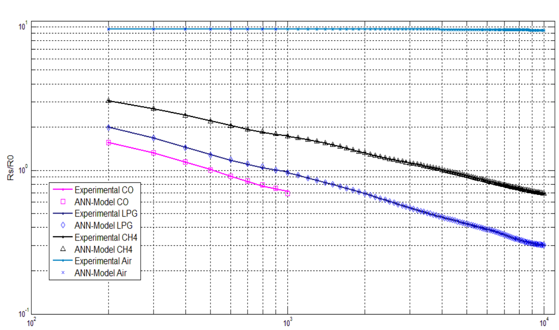

Fig. 6. MQ-9 model performance at the temperature 20°C and the humidity 65%.

IV. IMPLEMENTATION OF MQ-9 MODEL IN PSPICE SIMULATOR

The MQ-9 Model is implemented in PSPICE library, we use ABM "analog behavioral modeling" component, situated in the same library of PSPICE, we replace each neuron of the ANN by ABM component, the equation characterizes the ABM is the neuron equation, for example, the ABM 1 equation 'eq (1)' in the MQ-9 model is:

$$eq(1) = 1/(1 + \exp(-B_{11} + W_{111}\,V(G) + W_{112}\,V(T) + W_{113}\,V(RH) + W_{114}\,V(C)) \quad (2)$$

The exponential of the equation is due to the transfer function choosing in our model, which is Logsig. Where, 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 17 equations with 17 bias and 100 weights. The model of MQ-9 implemented in the library of PSPICE simulator, is validated by an electrical circuit, this circuit is shown in figure 7.

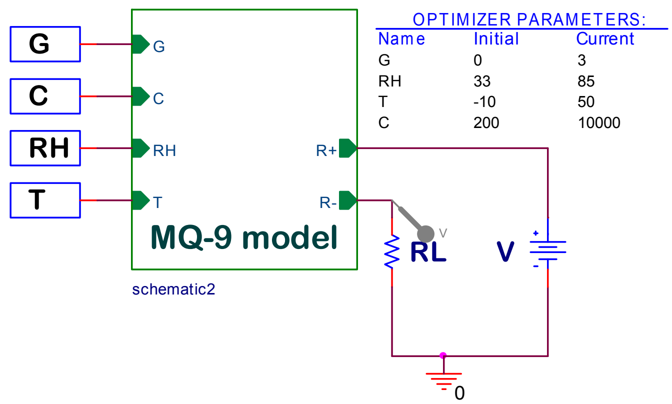

Fig. 7. The gas sensor MQ-9 electrical circuit.

V. SIMULATION RESULTS

The measure circuit, previously mentioned, is used to simulate the MQ-9 gas sensor. The temperature and the relative humidity are fixed at 25°C and 60%, respectively, when concentration is varying within the range 200-10000 ppm. A parametric SWEEP analysis, demonstrate the precise modeling of the MQ-9 gas sensor effect, figure 7 shows the result reached at the MQ-9 model output. This means that the MQ-9 model gives an identical response compared to the experimental one of the MQ-9 sensor.

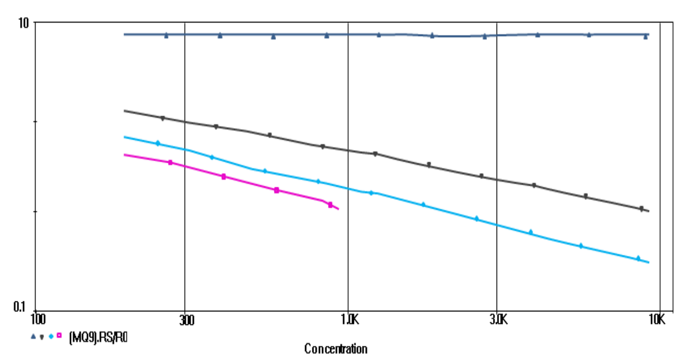

Fig. 7. MQ-9 model response "Rs/R0 vs concentration" at the temperature 20°C and the humidity 65%.

Figure 8 shows the response delivered at the MQ-9 model output, with a parametric SWEEP analysis for three relative humidity values 33%, 65% and 85%, when the temperature is varied within the range -10 °C to 50 °C.

This simulation proves that the MQ-9 model expresses the gas sensor dependence on temperature and humidity. Furthermore, it proves a good prediction of this model at the humidity value 65% which do not belong to the database.

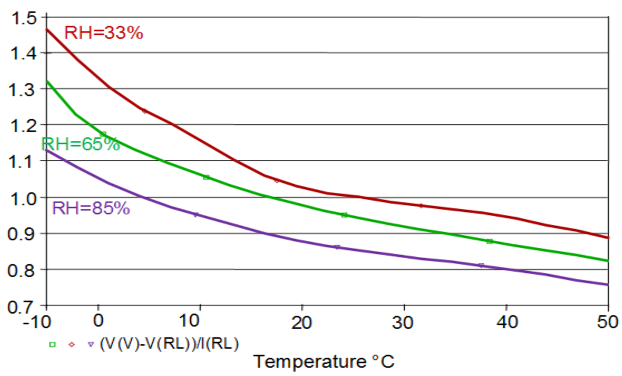

Fig. 8. MQ-9 model response “Rs/R0 vs concentration” at the temperature 20°C and the humidity 65%.

The above simulations prove that the component “MQ-9 model” introduced in the simulator PSPICE expresses exactly the behavior of the experimental results [8] of the MQ-9 gas sensor.

VI. Conclusion

In this paper, we have proposed a modeling of an industrial gas sensor MQ-9, could be used to detect three combustible gases; Carbon Monoxide CO, Methane CH_4 and Propane LPG. When the ambient temperature and the relative humidity change, the nonlinear response of the MQ-9 changes in a complex manner. The data points are obtained from the sensor characteristics at different gases response. Then we use a back propagation algorithm to train the MLP model via these data. This trained MLP model, produces accurately the MQ-9 gas sensor behavior in a dynamic environment. It takes into account the dependence on temperature and relative humidity at the measurement point, the response nonlinearity, as well as the dependence on the gases nature. We use the bias matrix and the weights matrix obtained from the ANN training, to establish the “MQ-9 model” on PSPICE simulator, which is introduced in an electrical circuit, the last is simulated to verify the response of the modeled sensor.

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