Spiking Neural Network Trained by Metaheuristics for Gas Sensing

J. Enriquez-Gaytan[1], F. Gómez-Castañeda[1], J.A. Moreno-Cadenas[1], L.M. Flores-Nava[1]
[1] Department of Electrical Engineering, CINVESTAV-IPN, Mexico City, Mexico
Phone (52) 55 5747 3800 ext. 6262
E-mail: { jenriquezg, fgomez, jmoreno, lmflores }@cinvestav.mx

***Abstract* – In this manuscript, we propose a bio-inspired method of signal processing in a task for the detection of gases (Methane and Iso-Butane) using an array of four gas sensors by Figaro and Spiking Neural Network (SNN-Izhikevich's model), supported by the synaptic current model. Our SNN is trained by the metaheuristic algorithm of Artificial Bee Colony algorithm (ABC algorithm) in a supervised manner. This is demonstrated using Matlab.**

Keywords – Spiking neural networks (SNN-Izhikevich's model); bio-inspired signal processing; Metaheuristic algorithm; Artificial Bee Colony algorithm (ABC algorithm)

I. INTRODUCTION

In different industrial fields, there are always processes in which the presence of gases can be harmful; for this, we propose a system which allows to perform a discrimination between two gases (Methane and Iso-butane – which are toxic, corrosive, highly flammable and explosive) in concentrations in the range of tens per million (PPM) inside a specific range, with an array of 2 x 2 gas sensors.

The use of these sensors has become more common because it is efficient, reduced in cost and with large sensitivity to different gases (Figaro Engineering Inc, Japan), wherein each gas sensor is a transducer based on a chemical reaction of a gas by means of the change of resistance in a thin-layer semiconductor oxide [1]. Having as applications the pharmaceutical industry, food industry and safety industry, mainly.

The variations of the multiple responses from the sensor would require using very specific algorithms, which had the quality of self-adaptive learning and fault tolerance; this fits perfectly with Artificial Neural Networks (ANN). They are inspired by the parallel processing of the human brain, trying to mimic the behavior of the neuron by electronic elements [2].

The spiking neural networks or SNN are considered the 3rd generation of artificial neural networks, which have been applied in various fields such as robotics, modeling of some brain regions, computational neurosciences, image processing and, pattern recognition, for mention a few.

There are different models of SNN, ranging from behavior and modeling nearly identical to a real neuron, but with high computational cost or prohibited (for example: Hodgkin-Huxley model), and other models are simpler (for example: Integrate and Fire model) but they sacrifice its relationship with biological neurons with a lower computational cost. It has been demonstrated that SNN is easier to implement and requires simpler neuron configuration and, evenly a single spiking neuron can solve problems of pattern recognition [2], [3], [4].

The Izhikevich's model [5] is a simple model of a spiking neuron, which is characterized by low computational requirements and can produce spiking and bursting patterns resembling biological neurons. Fig. 1 shows a comparison of different models of spiking neurons, with respect to their implementation costs and their biological plausibility.

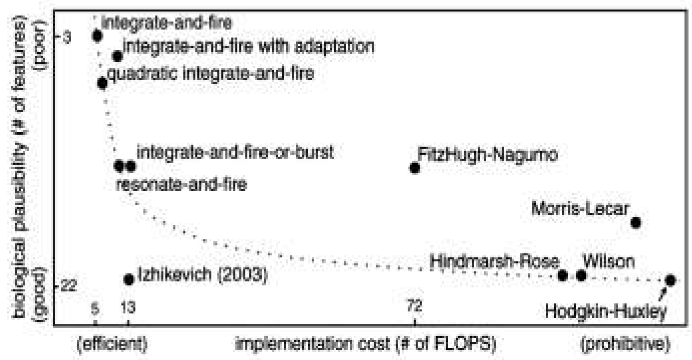


Fig. 1 Comparison of neuro-computational properties of different models of SNN [5].

Usually, the training process of ANN is performed by deterministic algorithms (numerical), an example is the algorithm of back-propagation, which is a supervised learning method of descending gradient. It could be divided into two phases namely, first an input random pattern, which propagates through the different layers towards the output, where is compared to the desired output and the error for each output neuron is calculated. Second, it is transmitted backwards from the output neurons to all intermediate layers of neurons. However, it might be difficulty finding the set of weights that allows to using the network as a function approximation in complex patterns; another disadvantage appears if the rate of change of the gradient is small, then the convergence to optimal solutions becomes slow and so demanding a high processing time. Otherwise, if the rate of change of the gradient is high, it leads to a counterproductive effect in which the algorithm might start to show oscillations. Other detractive effect is also associated to the initial parameters [6]. Looking for a non-numeric alternative, we propose using of the artificial bee colony algorithm – ABC algorithm, which is considered as a metaheuristic method. This is referred to as a general-purpose algorithm with an iterative operation designed to solve difficult combinatorial optimization problems, which is guided by a strategic search namely, *Exploration* and *Exploitation* in an intelligent way [7]. At the same time, it is classified as a Swarm Intelligence algorithm, this is because each member of the system has information of other members and with this information they generate a synergistic and self-learning system with a common goal: finding a more abundant source of food (Global Optimum Function), mimicking the behavior of bees in nature in the task of foraging (exploration of a workspace and searching for the optimal or more abundant source of food) [2], [3], [4].

II. ANALYSIS OF GAS SENSORS

The gas sensors used for this work are taken from Figaro Engineering Inc., these sensors are electrochemical, meaning that they are designed using a film of semiconductor oxide (sensory film), having contact with the gas-air mixture react producing a change in resistance of the sensory film. They should be previously activated with heat of a heater. The electrical circuit (Fig. 2) is used to converting the conductivity of the output signal per the corresponding gas concentration. The higher density of gas in the gas-air mixture leads to larger conductivity.

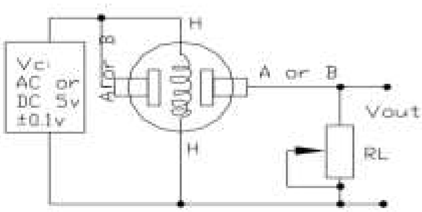


Fig. 2 Diagram measuring sensors Figaro.

Taking the nominal characteristic curves according to the datasheet of sensors: TGS-842 (Fig. 3) and TGS-2620 (Fig. 5), it has been elaborated an approximation of the methane and isobutane gases, using Microsoft Excel. This numerical task considers the sensor output, which is nonlinear and it is necessary to have their characteristic equations (Fig. 4 and Fig. 6).

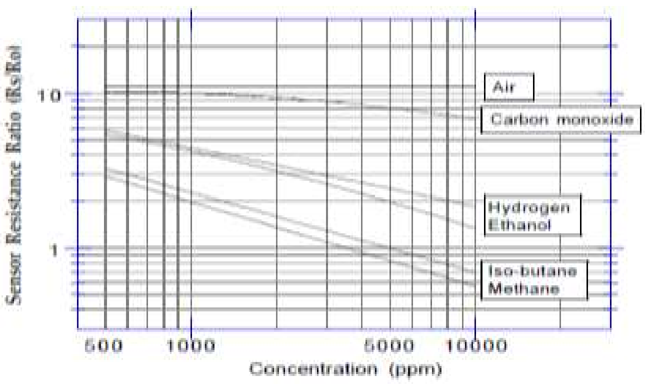


Fig. 3 Sensitivity to various gases (Rs/Ro) TGS-842.

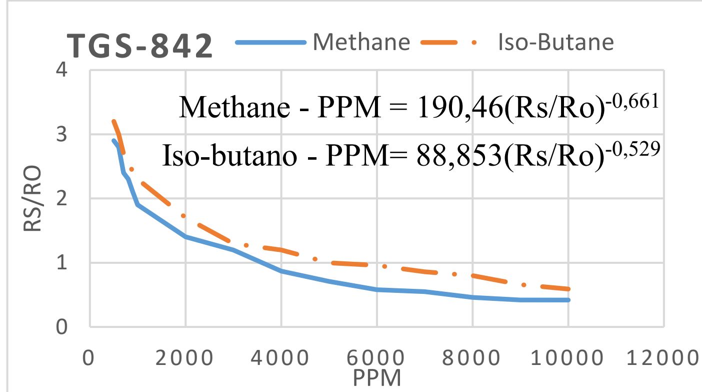


Fig. 4 Sensitivity to Methane and Iso-butano gases (Rs/Ro) TGS-842.

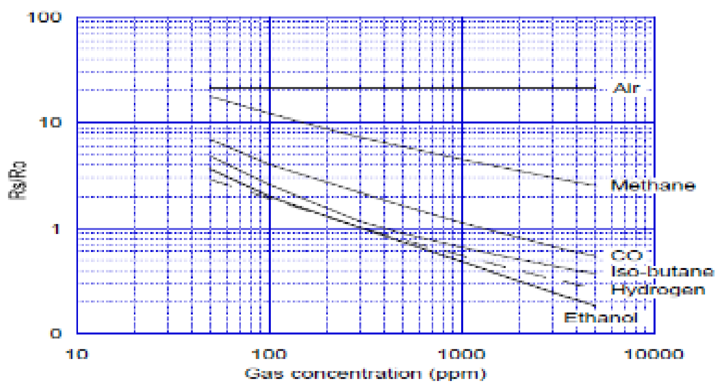


Fig. 5 Sensitivity to various gases (Rs/Ro) TGS-2620

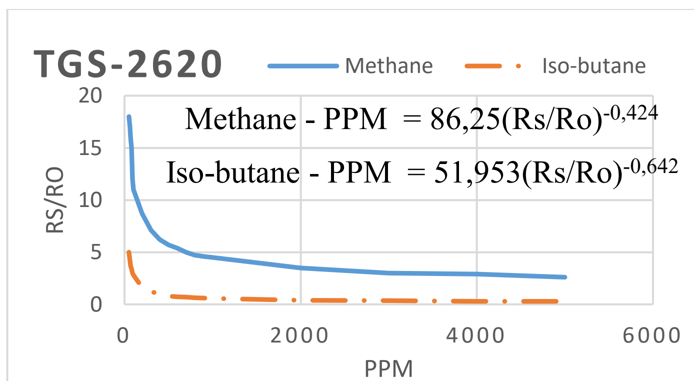


Fig. 6 Sensitivity to Methane and Iso-butano gases (Rs/Ro) TGS-2620.

After obtaining the characteristic equation of methane and isobutene sensors, Fig. 4 and Fig. 6, their behavior is defined by the resistance Rs (sensory film), which varies per the gas concentration, following Eq. (1).

$$Rs = \frac{Vc - V_{out}}{V_{out}} \; x \; R_L \qquad (1)$$

Observing the measurement circuit in Fig. 2, it can be established that is a voltage divider represents. Also, once Eq. (1) is evaluated then the concentration of the gas can be estimated from the numerical approximation made with Microsoft Excel. To increase the probability of a good measurement, an array of sensors is required and their collective response analyzed by an intelligent system that takes into consideration the possible technological variability. Therefore, the SNN working with TGS-842 and TGS-2620 sensors reads excitatory and inhibitory currents, fixing the mean response value into a practical range. The learning process that finds the conductance values between pulsed neurons is performed by the optimization process of the metaheuristics property of the artificial bee colony algorithm. In Fig. 7 is observed the architecture of the SNN.

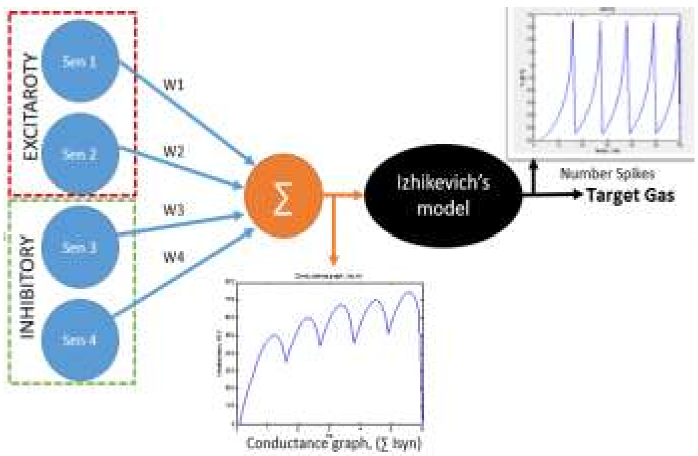


Fig. 7 SNN, architecture.

III. Izhikevich neuron model and proposed method

The model presented by Eugene M. Izhikevich [5], took relevance because it has a pretty good balance between computational efficiency and the real biological behavior of the neuron. This model can perform a reproduction of the dynamics of different types of neocortical neurons and nearly compared to the Hodgkin-Huxley model [4].

We chose it because it is a versatile and simple model, consisting of nine parameters; it is modeled with two differential Eqs. (2).

$$C\frac{dV}{dt} = k(V - V_{rest})(V - V_{th}) - U + I_{syn}(t) \qquad \frac{dU}{dt} = a[b(V - V_{rest}) - U] \tag{2}$$

When the voltage V exceeds a threshold value, then the resetting action is accomplished according to Eq. (3).

$$if\ V \geq V_{peak}\ : V = c\,, U = U + d \tag{3}$$

V denotes the membrane potential and U is the membrane recovery; a, b, k, c, d and V_{peak}, are parameters that shape the pulse. The current I_{syn} is obtained using the sensor voltage V_{sen}, it is normalized to get the inputs q_{sen}^{ex} and q_{sen}^{ih} by dividing it by α, whose value is 5V, which represents the peak conductance of the excitatory and inhibitory currents[9], [10], [11], [12]. This is given by Eqs. (4).

$$q_{sen}^{ex} = \alpha V_{sen};\ (4a) \qquad q_{sen}^{ih} = \alpha V_{sen}\ ;\ (4b)$$

The conductance is obtained by excitation/inhibition synaptic connections supported by Eqs. (5).

$$\frac{g_{sen}^{ex}(t)}{dt} = -\frac{1}{\tau_{ex}} g_{sen}^{ex}(t) + q_{sen}^{ex} \tag{5a}$$

$$\frac{g_{sen}^{ih}(t)}{dt} = -\frac{1}{\tau_{ih}} g_{sen}^{ih}(t) + q_{sen}^{ih} \tag{5b}$$

Where τ_{ex} and τ_{ih} are the time constants for excitatory and inhibitory synapses taken from the biological neurons to improve the shape of the current illustrated in the Fig. 7. The current, Eq. (6), is injected directly into the neuron, through the synaptic weight factors: $W_1, W_2, W_3\ and\ W_4$, which in turn adapt their values.

$$\begin{aligned} I_{syn}(t) = W_1 * g_{Sen1}^{ex}(t)\big(E_{ex} - V(t)\big) \\ +W_2 * g_{Sen2}^{ex}(t)\big(E_{ex} - V(t)\big) \\ +W_3 * g_{Sen3}^{ih}(t)\big(E_{ih} - V(t)\big) \\ +W_4 * g_{Sen4}^{ih}(t)(E_{ih} - V(t)) \end{aligned} \tag{6}$$

This is a dynamic event, where the membrane potential V and the recovery U change. A singular point is when V reaches the peak value V_{peak}. This is considered a pulse of the neuron.

The adjustment of the weights is performed by the ABC algorithm. There is another and similar but analytical methodology such as the description of biological receptive fields [13]; in our case, the weights are adjusted automatically to both excitatory weights and the inhibitory weights so performing a balance between the input conductance and the number of pulses of the output neuron.

IV. Artificial bee colony and supervised learning

The artificial bee colony algorithm (ABC algorithm) is a metaheuristic procedure, which mimics the behavior of bees in nature, approaching the task of exploring their environment to find the food source [14]. It can be defined as a smart metaheuristic strategy to improve general heuristic procedures with high performance (Fred W. Glover in 1986); whereas, heuristics are numerical methods which have a high degree of reliability finding the optimal solution with low computational cost. There is a variety of studies on the behavior of bee colonies focused on allocation task, dance and communication, nest site selection, mating, marriage, etc. [15]. The ABC algorithm is simple and able to find acceptable results at a low computational cost.

The algorithm refers to a set of food sources (possible solutions), each food source is represented by a position in the space $X_{i,j}: X_{i,j} \in \mathbb{R}^D, i = 1, \dots, SN$, $\mathrm{j} = 1, 2, \dots, \mathrm{D}$; where, D is the parameter of total number of variables and SN the number of food sources.

The global optimization problem is solved when the vector $X_{i,j}$ finds the parameters that minimize the optimization function $f(x)$, given by Eq. (7), also known as search space S.

$$f(x) = \frac{1}{\sqrt{\frac{1}{T}\left(Target_1^{pattern} - Output_1\right)^2 + \left(Target_2^{pattern} - Output_2\right)^2}} \quad (7)$$

The search is realized in a supervised manner, with a single neuron for the two gas targets, which correspond to $Output_1$ (methane) y $Output_2$ (Iso-butane). In order to the number of pulses generated by the SNN be equal to each corresponding gas target. These targets are defined in a convenient way to conduct the search and in a heuristically manner, fulfilling that each $Target_1^{pattern}$ must be different from each $Target_2^{pattern}$. It is noteworthy that the pulse shape generated is not important for this application, what is important is the number of pulses generated during the outcome-time interval, because this simplifies the analysis of SNN.

The fundamental characteristic of the ABC algorithm is the exchange of information among bees creating a collective knowledge to obtain the food source, which is more profitably or deciding to abandon the sources that can no longer be exploited or with low profitability, this is carried out in an iterative manner.

Description of the ABC algorithm:

1. Population Initialization.
   The algorithm starts initializing SN, using a random process, with Eq. (8).

$$X_{i,j} = X_j^{low} + rand(0,1) \cdot \left(X_j^{high} - X_j^{low}\right); \quad (8)$$

   Where, X_j^{high} is the upper limit and X_j^{low} is the lower limit, previously established.

2. Sending the employed bees.
   In this section the employed bees are responsible for generating a new source of food, looking around the area where they are located. This is done using the source candidate vector $v_{i,j}$ in Eq. (9).

$$v_{i,j} = X_{i,j} + \emptyset_{i,j}\left(X_{i,j} - X_{k,j}\right); \quad k \in \{1,2,\ldots,SN\}; \quad j \in \{1,2,\ldots,D\}; \quad (9)$$

   The parameters X are controlled by j y k which are obtained randomly; they are integer and should fulfill with: $i \neq k$. If $v_{i,j}$ exceeds the limits, it should be adjusted into the set range. The parameter $\emptyset_{i,j}$ is a random number in the range [-1,1], which once obtained the new source candidate vector $v_{i,j}$ is evaluated by Eq. (9); then, the probability distribution function Eq. (7) evaluates the quality of the source of food. It is known as food quality or greedy evaluation.

$$fit_i = \begin{cases} \dfrac{1}{1 + f(v)_i} & if\ f(v)_i \geq 0 \\ 1 + |f(v)_i|, & if\ f(v)_i < 0 \end{cases} \quad (10)$$

   If fit_i of $f(v)$ is better than fit_i of $f(x)$, then the parameters $X_{i,j}$ are replaced by $v_{i,j}$

3. Selection of food sources. Onlookers bees.
   The selection of the food source depends on estimating a probability; it is obtained with Eq. (11).

$$Prob_i = \frac{fit_i}{\sum_{i=1}^{N_p} fit_i} \quad (11)$$

   The onlooker bee selects a food source, according to the probability of the quality of the food source. After selecting the food source, the onlooker bee goes to the selected position and determines a new source of food in the neighborhood, this is done by Eq. (9). If it improves the quality of the food source, it is replaced by the new food source, otherwise it remains.

4. Determination of scout bees.
   After a predetermined number of attempts L (counter assigned to each food source), if it is not possible to improve the food source i, the food source is abandoned and this bee will become in scout bee, suggesting a new food source, according to Eq. (8).
   The ABC algorithm is shown in Pseudo-code 1, which was taken from [2].

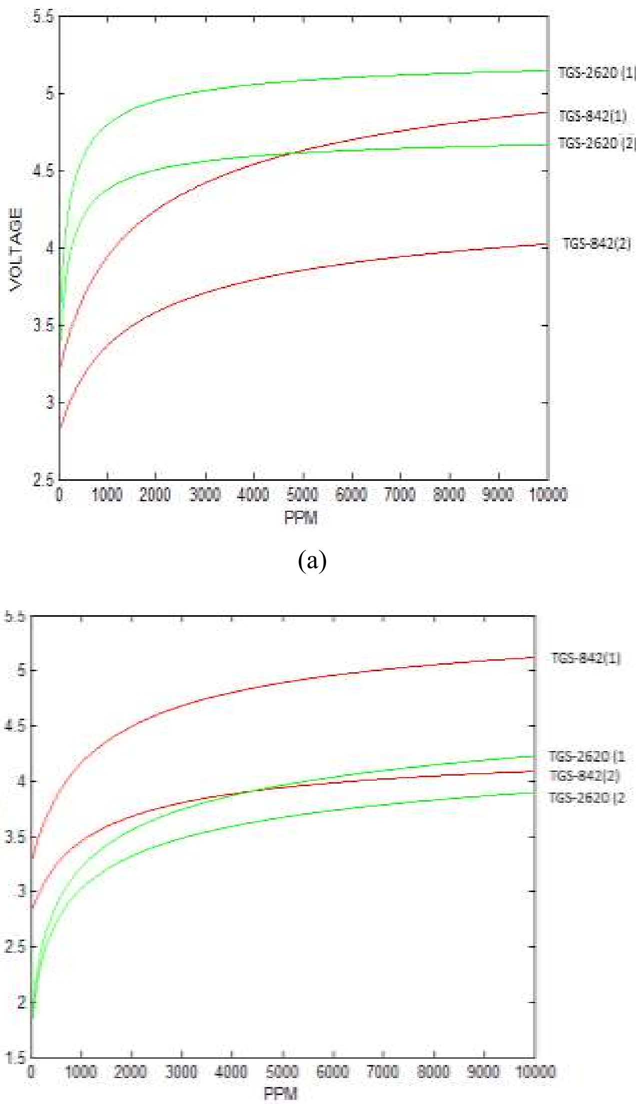
```
    1)  Initialize the population of solutions, X_i.
    2)  Evaluate the population X_i.
For iter = 1 to max_iter do
    3)  Produce new solutions v_i, employed bees by
        using Eq. (9), verify boundaries and evaluate
        them.
    4)  Apply the greedy selection process, Eq. (10).
    5)  Calculate the probability, Eqs. (11) and (10).
    6)  Produce the new solutions v_i for the onlookers
        from the solutions X_i selected depending on
        Prob_i verify boundaries and evaluate them.
    7)  Apply the greedy selection process.
    8)  Determine the abandoned solution for the
        scout, if exist, and replace it with Eq. (8).
    9)  Memorize the best solution.
    10) Iter=iter+1
End for.
```

Pseudo-code 1

V. Testing and Results

The aim of test is probing the feasibility of using a spiking neural network, trained by the ABC algorithm as a gas sensor system based on the electrical response in voltage of Figaro gas sensors TGS-842 and TGS-2620 (Fig. 8). This is done by using the maximum and minimum voltage values that they can reach, according to the nominal characteristics in the manufacturer datasheets.

Selecting a point of interest (PPM) by using the manufacturer database becomes our starting point or target for the SNN to be able to recognize the gas despite environmental conditions. Using as selection criteria that the amount of PPM that are dangerous to live in industrial processes.



(b)

Fig. 8 Graphic voltage response of TGS2620 and TGS842 sensors, (a) Target Gas: Iso-butane and (b) Target Gas: Methane.

The parameters in Table 1 are used for generating spikes of the Izhikevich's model.

For the ABC algorithm, we have found a balance of parameters for both the algorithm and for the objective function; this reduces and optimizes workout time of processes.

Table 1 Control parameters of SNN

Parameter	Value	Parameter	Value
V_{rest}	-60 mv	**a**	0.03
V_{th}	-40mv	**b**	-2
C	35mv	**c**	-50
K	0.7	**d**	100
T	60ms	E_{ex}	0
E_{ih}	-75mv	τ_{ex}	4 ms
τ_{ih}	10 ms	**Sen1**	TGS-2620
Sen2	TGS-842	**Sen3**	TGS-842
Sen4	TGS-2620		

There is no an optimal condition for the parameters in the ABC algorithm this because the algorithm fits to the problem. In our case, we use a moderate population of bees, but a wide search limit which led us to reduce the number of iterations. In Table 2, the parameters used in the ABC algorithm and objective function are provided. It was also looked for having a quick response, sacrificing the similarity with biological neurons, but it increases processing speed.

Table 2 Control Parameters of ABC algorithm.

Parameter	Value
N_p	30
L	200
UPPER BOUNDS	100
LOWER BOUNDS	-100
TARGET ISO-BUTANO	50
TARGET METANO	15

The results get better as the number of pulse increases. We remark that the shape of the spikes is not our interest but the number of them.

VI. Conclusions

We conclude that the recognition of gases by SNN is possible and it can be potentiated for future works. The ABC algorithm also presents an excellent performance on the task of training the used SNN. The purpose of this work is designing a security system with gas sensors using a bio-inspired process that optimize the system and facilitate its computational synthesis. It also allows us to look at an implementation with more sensors to generate an electronic nose, with a broader range and sensitivity for recognition of gases.

The next step in this research will be the implementation in hardware (FPGA), taking into consideration fast response time. The aim is having a real-time analysis of the environment, oriented to identify any harmfulness to humans at work, food product or manufacturing process. The implementation is feasible because the system is simple and flexible.

VII. Referencias

[1] L. G. Corona Ramírez, G. S. Abarca Jiménez and J. Mares Carreño, Sensores y actuadores aplicaciones con Arduino, Ciudad de México, México: Grupo editorial PATRIA, S.A. DE C.V., 2015.

[2] R. A. Vazquez and B. A. Garro, "Training Spiking Neural Models Using Artificial Bee Colony.", Computational Intelligence & Neuroscience, vol. 2015, nº ID 947098, pp. 1-14, 2015.

[3] E. Deniz Yigitbasi and N. Akhan Baykan , "Edge Detection using Artificial Bee Colony Algorithm", International Journal of Information and Electronics Engineering, vol. 3, nº 6, pp. 634 - 638, 2013.

[4] E. Izhikevich, "Which Model to Use for Cortical Spiking Neurons?", IEEE Transactions on Neural Networks, vol. 15, nº (5), pp. 063-1069, 2004.

[5] E. M. Izhikevich, "Simple Model of Spiking Neurons", IEEE Transaction on neural networks, vol. 14, nº 6, pp. 1569-1572, 2003.

[6] M. T. Hagan, "Neural network design", Martin T. Hagan, 1996.

[7] K. Sörensen, "International Transactions in Operational Research", vol. 22, pp. 3-18, 2015.

[8] D. Karaboga, "An Idea Based on Honey Bee Swarm for Numerical Optimization. Technical Report-TR06", Erciyes University, Engineering Faculty, Computer, Kayseri - Türkiye, 2005.

[9] Q. Wu, M. McGinnity, L. Maguire, A. Belatreche and B. Glackin, "Edge Detection Based on Spiking Neural Network Model", Advanced Intelligent Computing Theories and Applications. With Aspects of Artificial Intelligence, vol. 4682, pp. 26-34, 2007.

[10] P. Dayan and L. F. Abbott, "Theoretical Neuroscience Computational and Mathematical Modeling of Neural Systems", 2001.

[11] Eugene M. Izhikevich, "Hybrid spiking models", Philosophical Transactions of The Royal Society a Mathematical Physical and Engineering Sciences, vol. 368, pp. 5061–5070, 2010.

[12] I. C. Matadamas Ortiz and J. H. Sossa Azuela and O. Espinosa Sosa, Aplicación de las redes neuronales pulsantes en el reconocimiento de patrones y análisis de imágenes, Ciudad de México, México: Centro de Investigación en Computación - IPN, January 2014.

[13] E. Kandel, J. H. Schwartz and T. Jessell, Principles of Neural Science, McGraw-Hill Companies, 2012.

[14] D. Karaboga and B. Basturk, "Artificial Bee Colony (ABC) Optimization Algorithm for Solving Constrained Optimization Problems", Foundations of Fuzzy Logic and Soft Computing, vol. 4529, nº LNAI 4529, pp. 789-798, 2007.

[15] D. Karaboga, B. Gorkemli and C. Ozturk, "A comprehensive survey: artificial bee colony (ABC) algorithm and applications", Artificial Intelligence Review, vol. 42, pp. 21-57, 2014.

[16] Z. Fountas, "Spiking Neural Networks for Human-like Avatar Control in a Simulated Environment", Computing Science of Imperial College London, 2011.

[17] A. N. Perez-Garcia, G. Tornez-Xavier, L. Flores-Nava, F. Gomez-Castaneda and J. Moreno-Cadenas, "Multilayer perceptron network with integrated training algorithm in FPGA", International Conference on Electrical Engineering, Computing Science and Automatic Control (CCE), Ciudad de Mexico, 2014.