International Journal of Electrical and Computer Engineering (IJECE)
Vol.2, No.6, December 2012, pp. 739~747
ISSN: 2088-8708

Neural Network for Electronic Nose using Field Programmable Analog Arrays

Helmy Widyantara, Muhammad Rivai, Djoko Purwanto
Department of Electrical Engineering, Institute Teknologi Sepuluh Nopember (ITS)

Article Info

Article history:

Received in Jun 12, 2012
Revised in Nov 18, 2012
Accepted in Nov 26, 2012

Keyword:

Analog Neural Network
Electronic Nose
Field Programmable Analog Arrays
Gas Sensor

ABSTRACT

Electronic nose is a device detecting odors which is designed to resemble the ability of the human nose, usually applied to the robot. The process of identification of the electronic nose will run into a problem when the gas which is detected has the same chemical element. Misidentification due to the similarity of chemical properties of gases is possible; it can be solved using neural network algorithms. The attendance of Field Programmable Analog Array (FPAA) enables the design and implementation of an analog neural network, while the advantage of analog neural network which is an input signal from the sensor can be processed directly by the FPAA without having to be converted into a digital signal. Direct analog signal process can reduce errors due to conversion and speed up the computing process. The small size and low power usage of FPAA are very suitable when it is used for the implementation of the electronic nose that will be applied to the robot. From this study, it was shown that the implementation of analog neural network in FPAA can support the performance of electronic nose in terms of flexibility (resource component required), speed, and power consumption. To build an analog neural network with three input nodes and two output nodes only need two pieces of Configurable Analog Block (CAB), of the four provided by the FPAA. Analog neural network construction has a speed of the process 0.375 µs, and requires only 59 ± 18mW resources.

Corresponding Author:

Helmy Widyantara,
Department of Computer Engineering,
STIKOM Surabaya,
Raya Kedung Baruk 98, Surabaya 60298, Indonesia.
Email: helmywid@stikom.edu

1. INTRODUCTION

Nowadays, gas sensor has developed vastly, it begins for detection gas in our surrounding environment such us carbon dioxide, carbon monoxide, ethanol, methane and oxygen. This invention of gas sensor has lead to many researchers to explore and do experiment in several fields such us in medical, industry and military.

The gas sensor usually is put in robot and designed like human nose and it is called electronic nose. Lilienthal et al in the research was success in mapping gas concentration in building using mobile robot [1]. Zang et al designed mechanical electronic nose with the sensor arrays inside [2]. This research has problem that gas sensor can not detect similar gas which has similarity chemical characteristics. This problem can be addressed using algorithm neural network.

However, processing algorithm neural network has constrained of flexibility when it was used in robot. Because of this, new tools must replace computer for handling the computation. One of the tools which can help to solve this problem is Field Programmable Analogue Array (FPAA). FPAA provides two advantages in this research. First, FPAA has ability in parallel processing and made faster computation. Second, FPAA has small size, low consumption power [3] and easy programmable. Moreover, FPAA will provide good performance from the previous system in electronic nose because it does not need conversion from digital to analogue.

1.1 Neural Network

Neural Network (NN) can design non linear complex functionS. When it is used to design Multi-Input Single-Output (MISO) systems, NN map n-dimension input to single dimension output [4]. In field control, input usually comes from error which is difference from real outputs and set point. In this paper, NN has function as processing nose electronic to identify certain gas.

Neuron in artificial intelligent acts as a biology nerve. Several input (x) will multiply with each appropriate weight (w). Then add all the result of multiplication with output from inside activation function to take singal degree output F(x,w) [5], this process can be seen in Figure 1.

$$in_i = \sum_j W_{ji} * a_j \quad (1)$$

To activate each neuron in NN network need activation function such as hiperbolic function, step, impulse and sigmoid. In many reseachs, they usually use sigmoid function. This is because the function is close to the real function of brain. Figure 2 shows three kinds of activation function.

Set of neuron can become a network which has function as computation equipment to solve problem. The amount of neuron and network architecture for each problem has different solution. NN architecture for generall can be seen in Figure 3. From the Figure 3, two inputs (v1 and v2) are connected to hidden layer with weight w11 until w16. Output from hidden layer is connected to output layer with weight w21 until w23 [6][7].

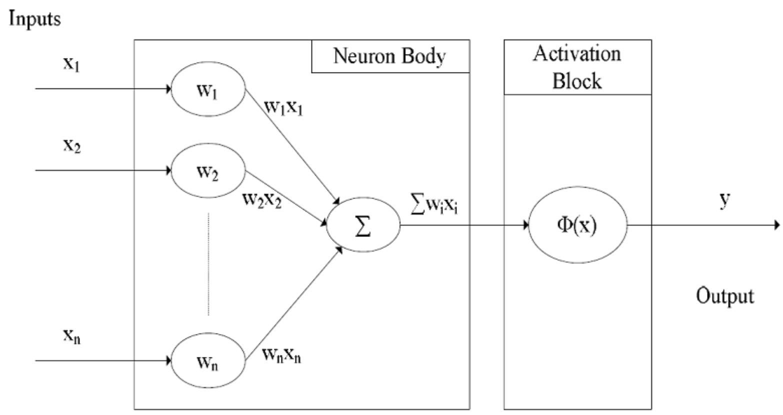


Figure 1. Neuron Model

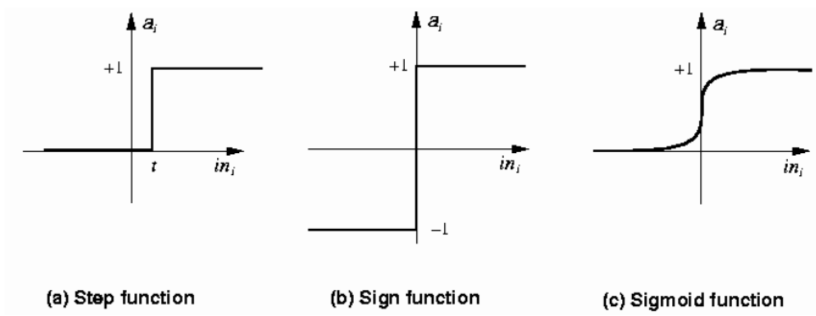


Figure 2. Activation Function

1.2 Gas Sensor

Three gas sensor which were built by Figaro Engineering Inc were used in this research. They are TGS 2610, TGS 2611 and TGS 2612. Main part of TGS is a semiconductor metal oxide. TGS sensor has a resistance sensor that is dependent to oxygen concentration contacting directly with semiconductor metal oxide. The changes of potential barrier integrain from tin oxide gas sensor can be seen in Figure 4. Figure 4 (a) shows the changes without any chemical gas, while Figure 4 (b) shows movement when there is any chemical gas. Oxygen is increasing barrier potential level. This causes increase resistance of resistor. If there is any chemical substance that is detected by sensor, then oxygen concentration will reduce tin oxide surface. This situation leads the reduction of the barrier potential intergain as it is seen in Figure 4(b) and reduce the resistance of resistor.

Relation between sensor resistant and gas concentration can be seen in equation 2 [8].

$$R = A\,[C]^{-\alpha} \tag{2}$$

Which R is resistant sensor metal-oxide, C is gas concentratrion, A is respon coefficient for some gases, and α is sensitifity. A and α depend on material type of sensor and temperature sensor.

Sensor TGS has two main parts; first part is tin oxide (SnO2) as sensor material. This material is connected to pin 2 and 3. Second part is the heater for heating sensor material. This heater is connected to pin 1 and 4. Figure 5 (a) show the structur of gas sensor TGS 26XX. Schematic for Sensor TGS can be seen in Figure 5 (b). Sensor TGS needs supply circuit (Vc) and also heater which has input power (VH) respectively in pin 1 and pin 4. A load is connected to pin 2. This load will be used as concentration measurement of gas which is in.

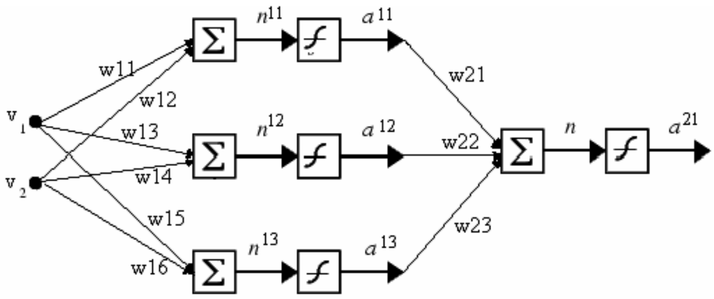


Figure 3. Architecture Neural Network

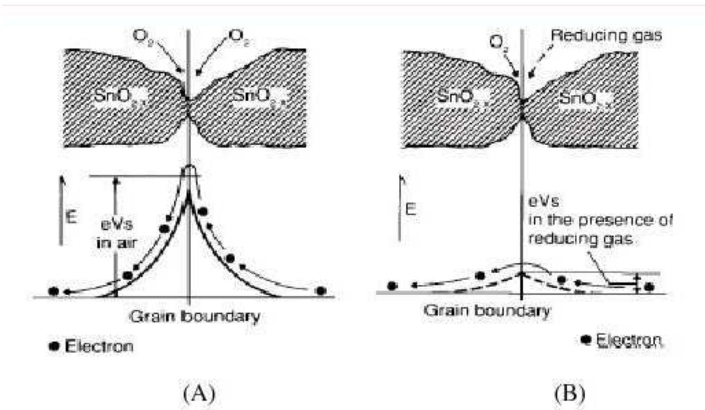


Figure 4. Intergrain Potential Barrier

1.3 Field Programable Analog Array (FPAA)

FPAA is an integration circuit that can configure several analog functions using Configurable Analog Blocks (CAB) and network interconection to connect between one CAB to other CAB. It has been equipped with Input-Output (I/O) block and storage memory (Random Acces Memory).

CAB can be implemented to several signal function process such us amplifier, integrator, differentiator, adder, subtraction, multiplication, and comparator.

FPAAs directed toward analog design typically feature a cab containing an operational amplifier, programmable capacitor arrays (PCAs), and either programmable resistor arrays for continuous time circuits or configurable switches to switch capacitor circuits [9],[10]. Anadigm FPAA family is based on switched capacitor architecture, the switched capacitor technology is the technique in which equivalence can be implemented by alternatively switching the input of a capacitor. Figure 6 (a) gives illustration how switched capacitors are configured as resistors.

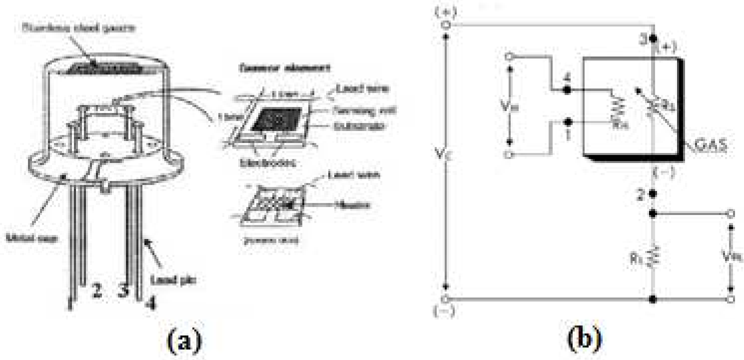


Figure 5. TGS Sensor, (a) Structure (b) Schematic

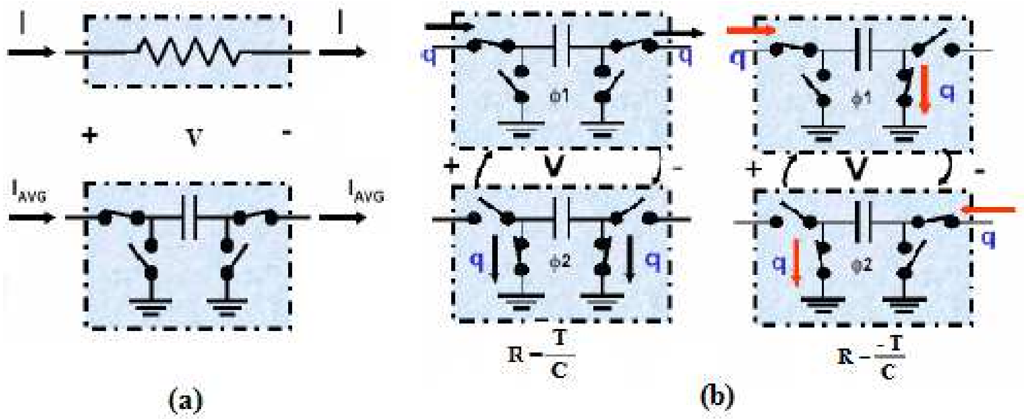


Figure 6. Switched capacitor , (a) Switched Capacitors are Configured as Resistors
(b) Negative R with a Switched Capacitor

$$R = \frac{V}{I} \tag{3}$$

$$IAVG = \frac{CV}{T} \tag{4}$$

Based on equation (3) and (4), Req the switched capacitor is as follows:

$$Req = \frac{VT}{CV} = \frac{T}{C} \tag{5}$$

How switched capacitor acts as a negative resistor is shown in Figure 6 (b).

In this research, we use FPAA type AN231E04 which has two CAB. Programmable Interconnections Networks is used to make connection between CAB1 and CAB2 then it can be used to make cascade circuit [11]. Type AN231E04 has four configurable Inputs/outputs and two dedicated Outputs [12],[13]. Figure 7 shows FPAA AN231E04 architecture.

2. RESEARCH METHOD

Previous research about methanol and ethanol has been done by Marques [14]. Marques used gas sensor as robot navigation tool to locate gas location. In our research, gas sensor that consist of array sensor will be used as electronic nose input which has different feature and sensitivity in detecting the difference of gasses such as methane, butane and propane. In this research, three kinds of gas sensors were used to process the input. They are TGS 2610, TGS 2611, and TGS 2612. Three procedures use in this project. Firstly, taking sampling array sensor data form different gases, for instance gasoline, methane, ethane, propane, and butane. Secondly, after getting data, the process was done in computer using MATLAB. Data training from MATLAB was done to get weight and bias for each neuron. Finally, this weight can be implemented in FPAA using the same architecture when it was trained. Figure 8 shows block diagram system. The result of electronic nose detection was displayed by LED indicator.

Figure 9 shows the analog neural network architecture that was used in this research. Figure 9 (a) revealed that input analog (x) comes from array sensor and bias then multiply with weight (w). The result is output neuron that has function $\sum$ from multiplication (x) and (w) and then for each activation uses step function.

$$\text{Step}(y) = 1 \text{ if } y \geq t \text{ else } 0 \quad (6)$$

Step function is actualized using comparator in FPAA.

AnadigmDesigner2 is used to implement neuron in FPAA. It consists of many components that can be integrated to become one with other components. The component is called Configurable Analog Modules (CAMs). CAMs can be configured as “SumDiff” component and this component can build neuron [15]. Figure 9 (b) illustrates neuron with CAM.

3. RESULTS AND ANALYSIS

Results and discussion of the research include retrieval data from gas sensor, training process at computer, until the implementation in FPAA. The discussion can be made in several sub-chapters.

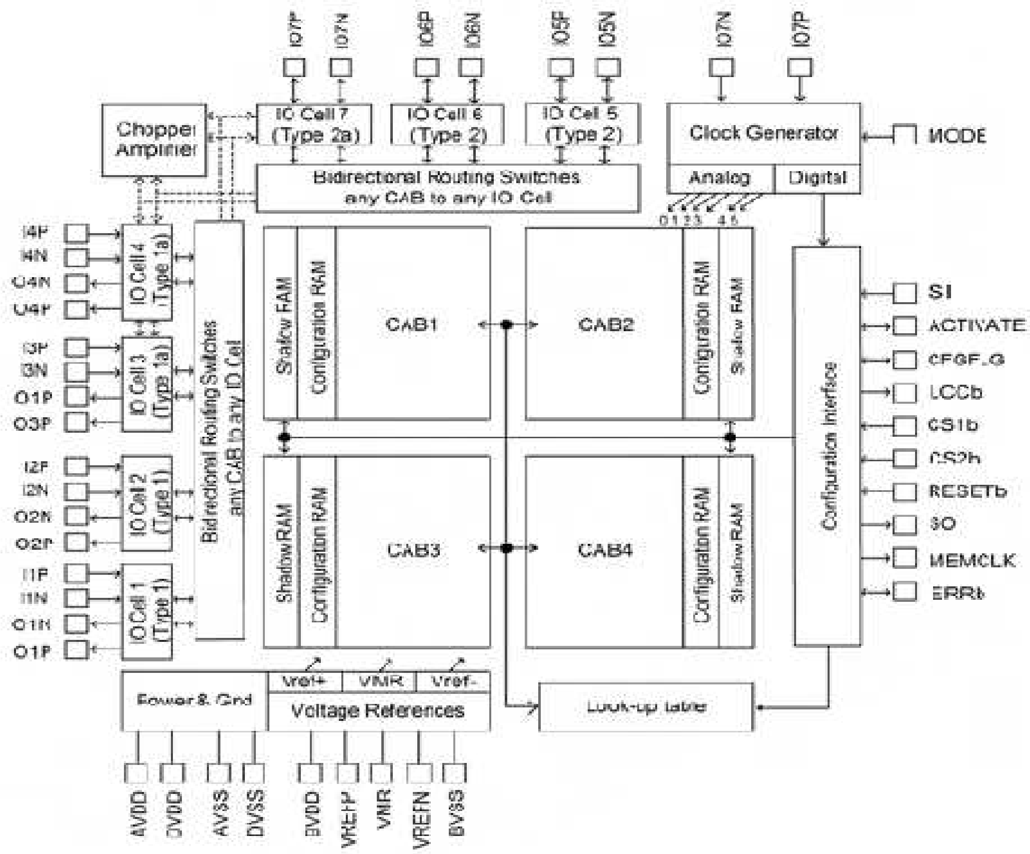


Figure 7. Architecture FPAA AN231E04

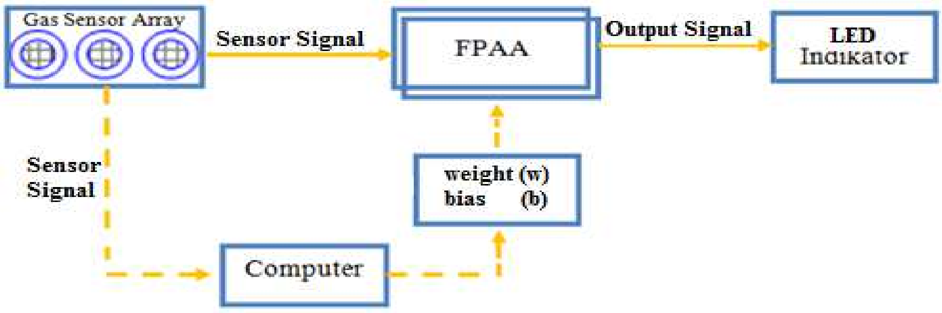


Figure 8. Block Diagram of System

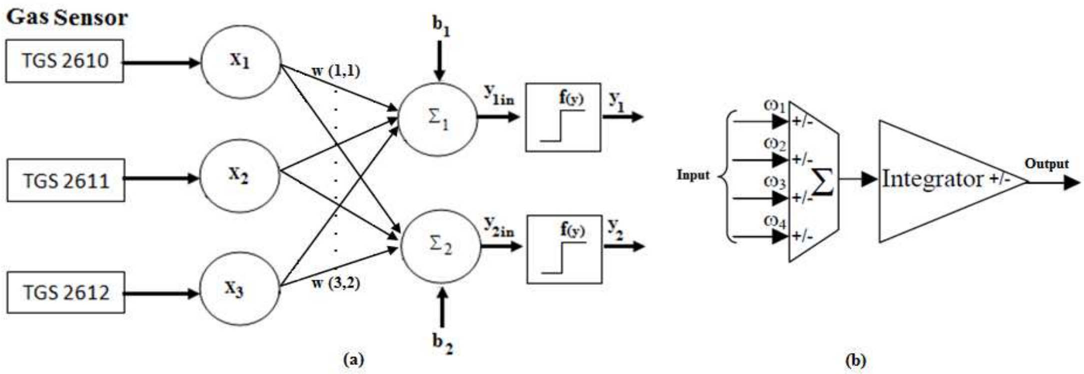


Figure 9. Design Analog Neural Network, (a) Perceptron Architecture for Electronic Nose (b) Implementation Neuron with CAMs

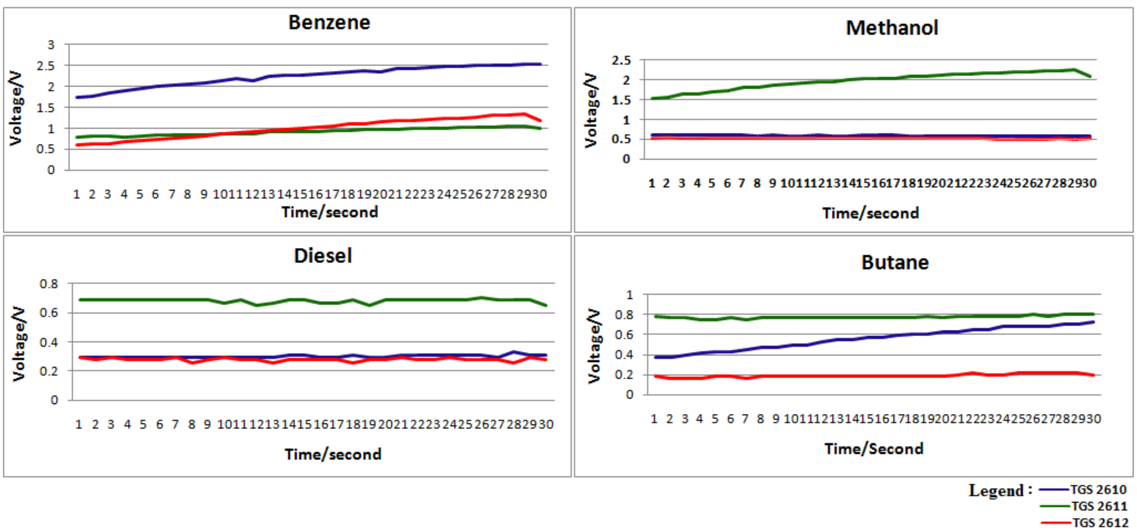


Figure 10. Output of Gas Sensors

Table 1. Neural network target

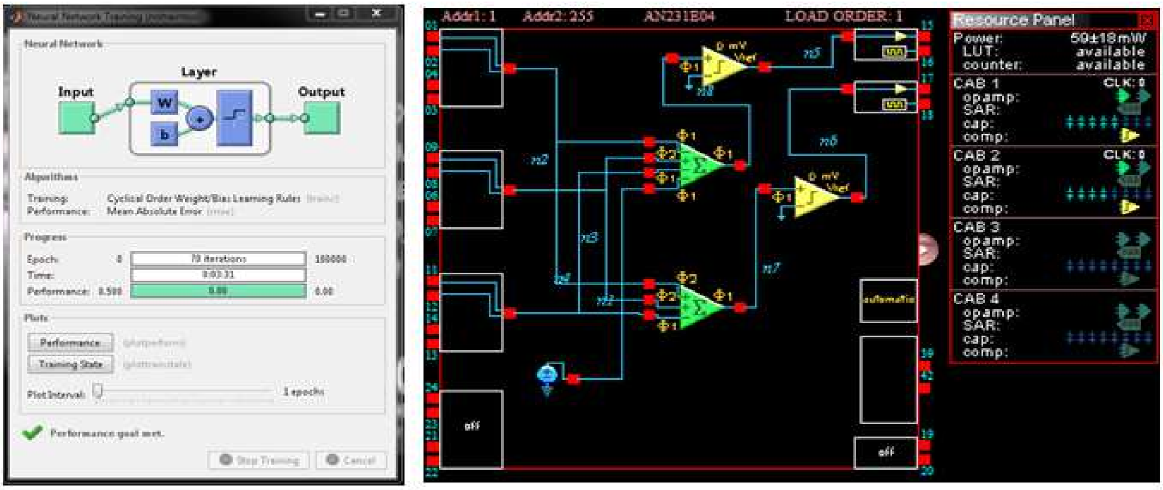
Jenis Gas	Target n_1	Target n_2
Diesel	0	0
Benzene	0	1
Methanol	1	0
Butane	1	1

3.1. Response gas sensor

Data which are received from gas sensor are used as data training to determine the weight and bias. Gas sensors (TGS 2610, TGS2611, and TGS 2612) were tested with benzene, methanol, diesel, and butane. Output signal from gas sensors can be presented in figure 10.

3.2. Neural network training

The target output of neural network was able to recognize the gas coming from the vapor of diesel, benzene, methanol, and butane. The target of the neural network can be seen in table 1. Data from gas sensor and neural network target were used to search weight (w) and bias (b). Weight and bias were obtained by entering data training and target in matlab program, the process to get the weights and bias was shown in Figure 11 (a).



(a) (b)

Figure 11. Analog Neural Network Implementation, (a) Searching Process Weight and Bias (b) Schematic and Resource Panel Analog Neural Network

3.3. Analog neural network

The implementation process of the weights and biases in the FPAA used AnadigmDesigner2 program. The result of this research which was ANN for electronic nose was successfull to be implemented using FPAA AN231E04. Table 3 shows the neuron output for the fourth sample gas after the training process,compared to the table 2, it is indicates that ANN wass 100% sucessfuly implemented. Figure 11 (b) shows neuron configuration electronic nose in FPAA AN231E04. The circuit was successfully built in FPAA using only 2 pieces of 4 available CAB. The figure shows 2 comparators, 2 Opamp, and 9 Capacitors which are used to implement the circuit and it takes less power consumption (only 59±18mW).

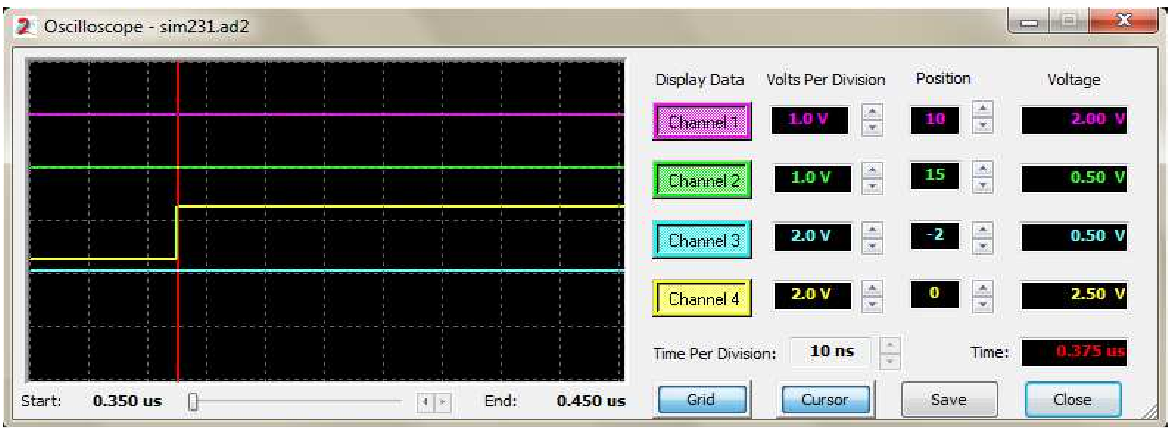


Figure 13. Signal Response

Table 2. Weight and bias

Weight						Bias	
W_{11}	**W_{12}**	**W_{21}**	**W_{22}**	**W_{31}**	**W_{32}**	**B_1**	**B_2**
-0.035294	0.165294	0.34902	0.015686	-0,12941	-0,91765	-0.2	0

Table 3. Neuron Output

NO	Liquid	Output Sensor (Voltage)			Output	
		TGS2610	TGS2611	TGS2612	N1	N2
1	Diesel	0.294118	0.68628	0.294118	0	0
2	Diesel	0.294118	0.68628	0.27451	0	0
3	Diesel	0.294118	0.68628	0.27451	0	0
4	Diesel	0.313725	0.68628	0.27451	0	0
5	Diesel	0.294118	0.68628	0.27451	0	0
6	Diesel	0.313725	0.68628	0.27451	0	0
7	Diesel	0.313725	0.70588	0.27451	0	0
8	Diesel	0.294118	0.68628	0.27451	0	0
9	Benzene	1.54902	0.70588	0.490196	0	1
10	Benzene	1.686275	0.70588	0.54902	0	1
11	Benzene	1.411765	0.70588	0.470588	0	1
12	Benzene	1.490196	0.70588	0.470588	0	1
13	Benzene	1.607843	0.72549	0.509804	0	1
14	Benzene	1.72549	0.72549	0.54902	0	1
15	Benzene	1.960784	0.72549	0.666667	0	1
16	Benzene	2.019608	0.7451	0.686275	0	1
17	Methanol	0.607843	2.03922	0.529412	1	0
18	Methanol	0.588235	2.07843	0.529412	1	0
19	Methanol	0.607843	1.62745	0.529412	1	0
20	Methanol	0.607843	1.86275	0.529412	1	0
21	Methanol	0.607843	2.01961	0.509804	1	0
22	Methanol	0.607843	1.80392	0.529412	1	0
23	Methanol	0.588235	1.80392	0.529412	1	0
24	Butana	0.56863	0.7647	0.17647	1	1
25	Butana	0.54902	0.7647	0.17647	1	1
26	Butana	0.59824	0.7647	0.17647	1	1
27	Butana	0.41176	0.7451	0.15686	1	1
28	Butana	0.43137	0.7451	0.17647	1	1
29	Butana	0.58824	0.7647	0.17647	1	1
30	Butana	0.60784	0.7647	0.17647	1	1

4. CONCLUSION

Analog neural network for the electronic nose was successfully implemented in FPAA with a small resource (only 2 CAB for 2 neurons), low power consumption (only59±18mW), and has a fast response (0.375µs) to process data to be output. Figure 12 shows signal response output (blue and yellow signal) when it detects benzene. The test input signal from TGS 2610 (pink) gives 2V, input from TGS 2611 and TGS 2612 (green colour) gives the same voltage 0.5V

REFFERENCES

[1] A. Lilienthal and T. Duckett, “Building gas concentration gridmaps with a mobile robot”, *Journal Elsevier Science,* Vol.48, Issue 1, August 2004, pp. 3-16.

[2] P. Rocke, J. Maher and F. Morgan, “Platform for Intrinsic Evolution of Analogue Neural Networks”, *Proc.2005 International Conference on Reconfigurable Computing and FPGAs,*Washington DC, USA, 2005.

[3] D. Berenson, N. Este’vez and H. Lipson, “Hardware Evolution of Analog Circuits for In-situ Robotic Fault-Recovery”, *Proc 2005 NASA/ DoD Conference on Evolvable Hardware,* June 2005.

[4] J.F.M. Amaral, J.L.M. Amaral, C. Santini, R. Tanscheit, M. Vellasco and M. Pacheo, “Towards Evolvable Analog Artificial Neural Networks Controllers”, *Proc.2004 NASA/DoD Conference on Evolution Hardware,* June 2004.

[5] C.P. Raj. P and S.L. Pinjare “ Design and Analog VLSI Implementation of Neural Network Architecture for Signal Processing”, *European Journal of Scientific Research,* Vol.27, No.2, 2009, pp.199-216.

[6] N.Chasta, S. Chouhan and Y. Kumar, “Analog VLSI Implementation of Neural Network Architecture for Signal Processing”, *International Journal of VLSI Design & Comunication System,* Vol.3, No.2, April 2012.

[7] X. Zang, M.Zang, J. Sun and C. He, “Design of a Bionic Electronic Nose for Robot”, *ISECS International Colloquium on,* Vol.2, 2008, pp. 18-23.

[8] P. Pasini, N. Powar, R.G. Osuna, S. Daunert and A. Roda, “ Use of a Gas Sensor Array for Detecting Volatile Organic Compounds (VOC) In Chemically Induced Cells” *Anal Bional Chem,* 2004, pp.76-83.

[9] S. Koneru, E. Lee, and C. Chu, “A flexible 2-D switched-capacitor FPAA architecture and its mapping algorithm,” *Midwest Symposium on*, Vol.1, 1999, pp. 296–299.

[10] H. Kutuk and S.-M. Kang, “A field-programmable analog array (FPAA) using switched-capacitor techniques,” *ISCAS International Symposium on,* Vol. 4, 1996, pp. 41–44.

[11] E.K.F. Lee and P.G. Gulak, “A Cmos Field Programmable Analog Array”, *IEEE Journal of Solid-State Circuits*, Vol.26, No.12, December 1991.

[12] G. Gyrok, M. Mako and J. Lakner, “ Combinatoric at Electronic Circuit Realization in FPAA”, *Acta Polytechnica Hungarica*, Vol.6, No.1. 2009.

[13] F. Jabeen A and M.Y. Sanavullah, “ Autonomus Reconfiguration using FPAA for Bandwitdh Recovery in Satellite Subsystem”, *International Journal of Computer Science and Network Security,* Vol.8, No.7. July 2008.

[14] L. Marques, U. Nunes and A.T. de Almeida, “Olfaction-based mobile robot navigation” , *Journal Elsevier Science,* Vol.418, Issue 1, October 2002, pp.51-58.

[15] P. Roche, B. McGinley, J. Maher, F. Morgan and J. Harkin, “ Investigating The Suitability of FPAAs for Evolved Hardware Spiking Neural Network”, *Proc.2008 International Conference on Evolvable System*, Prague, Czech Republic, September 2008.

BIOGRAPHIES OF AUTHORS

Helmy Widyantara received BE degree from STIKOM Surabaya in 2002, ME degree from Gadjah Mada University in 2010. He is currently a lecturer at Computer Engineering Department, STIKOM Surabaya, Indonesia. His research interest in embedded system.

Muhammad Rivai received BE degree from Institute of Technology Sepuluh Nopember in 1993, ME degree from University of Indonesia in 1997, PhD degree from University of Airlangga in 2006. He is currently a lecturer at Electrical Engineering Department, Institute of Technology Sepuluh Nopember, Surabaya, Indonesia. His research interest includes odor sensors, electronic circuits, and neural network applications.

Djoko Purwanto received Master and Phd from Keio University Japan. His research interest in Industrial Robot and Robot Vision.