A Competitive WTA ANN for Classification a Calorific Value of a Coal Fuel in Combustion Chambers Using FPAA

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***Abstract* — A hardware approach based on a winner takes all artificial neural network to classify a calorific value of a coal fuel in combustion chambers is proposed in the paper. The approach is based on an analysis of measured combustion process parameters in the chamber. Measured parameters have been used to train neural network weights with a help of MATLAB program. The winner takes all formula has been used to train synaptic weights. Calculated weights have been used in the recall mode to find out the calorific value of the coal fuel loaded into the chamber. The winner takes all artificial neural network approach has been verified by the MATLAB program and in the FPAA implemented network. Obtained results are presented and discussed.**

***Keywords*— artificial neural network; winner takes all circuit; FPAA; calorific value of a coal fuel**

I. INTRODUCTION

Significant heat losses accompany a production of a heat in a huge industrial chamber. The losses are a result of incomplete carbon combustion phenomena and depend on many factors i.e. a diversity and a quality of a fuel loaded into the chamber, an amount and a pressure of an inflating air and a temperature in the chamber. A detection of the amount of evaporated undesirable flammable gases CO, H_2 and CH_4 or a recognition the calorific value of the coal fuel loaded into the chamber require specialized measurement equipment[1-2]. Determining the fuel parameters during the combustion process in the chamber delivers real time feedback data to the hardware control of the combustion process. Recently, several artificial intelligence (AI) approaches to aid the control of the combustion process and to reduce the heat losses in the industrial chambers have been developed [3-10]. Our approach relies on a fast classification of the calorific value of the coal fuel loaded into the chamber. The classification results in feedback data to optimize combustion parameters. The method is based on winner takes all (WTA) artificial neural network (ANN) implemented in a field programmable analog array (FPAA) device. The ANN methods are successfully used to solve multidimensional classification problems. The FPAA device provides with several advantages to build hardware systems [11-15] i.e. programmability, parallel processing and prototyping. Proposed FPAA WTA ANN may be easily incorporated into a hardware control system of the combustion process.

II. PROPOSED APPROACH

Our method relies on an analysis of measured combustion process parameters in the chamber. A telemetry system is used to measure the parameters. The parameters have been used to calculate the weights of the proposed ANN. In the recall mode the ANN is used to determine the calorific value of the coal fuel in the chamber. Finally, the network has been implemented in the FPAA device and tested to verify hardware solution of the ANN.

A. Measurement of the combustion process parameters

The telemetry system in two boiler water grates type WR-25, made in the technology of tight walls using controller S7-300 have been applied to measure six parameters affecting the combustion process. All of 8479 measurements have been made at the ambient air temperature 3-5^{o}C. Both heat sources have been supplied by the fuel of 22230 kJ/kg. The following parameters have been measured:

- x_1 – output boiler temperature of the circulating water in ^{o}C,
- x_2 – thickness of the fuel layer in cm,
- x_3 – pressure of inflating air to the boiler kPa,
- x_4 – velocity of grill movement in %,
- x_5 – amount of an oxygen in the boiler in %,
- y – calorific value of the coal fuel 1..4,

where 1 – 22000 kJ/kg - 22750 kJ/kg
2 – 22751 kJ/kg - 23500 kJ/kg
3 – 23501 kJ/kg - 24250 kJ/kg
4 – 24251 kJ/kg - 25000 kJ/kg

Results of the measurements, shown in Table 1, are used to determine the calorific value of the coal fuel as a function of the five remaining parameters. The function is achieved in the WTA ANN weight training process.

TABLE I. TRAINING DATA

No.	Inputs					Out
	x_1	x_2	x_3	x_4	x_5	y
16	107,5145	54,8844	36,0694	5,4806	11,6474	1
17	113,1214	54,5954	34,9422	5,7780	11,6474	1
18	116,0116	63,7861	40,0289	6,3789	11,6474	1
:	:	:	:	:	:	:
5656	123,5838	63,3526	40,0289	6,7795	12,0145	2
5657	123,9884	63,3526	40,0289	6,6824	12,0145	2
5658	116,3006	63,4682	40,0289	7,1861	12,0145	2
:	:	:	:	:	:	:
7993	113,6994	75,1156	34,9133	8,4910	12,5116	3
7994	115,1445	74,3064	34,9133	7,8902	12,5116	3
7995	113,1214	74,7399	35,4913	7,5867	12,5116	3
:	:	:	:	:	:	:
8191	118,4971	66,7630	41,7052	6,4821	12,5000	4
8192	121,6185	64,3353	39,4509	6,3789	12,5000	4
8193	120,5202	67,0231	41,7052	6,7795	12,5000	4

B. *WTA neural network formulation*

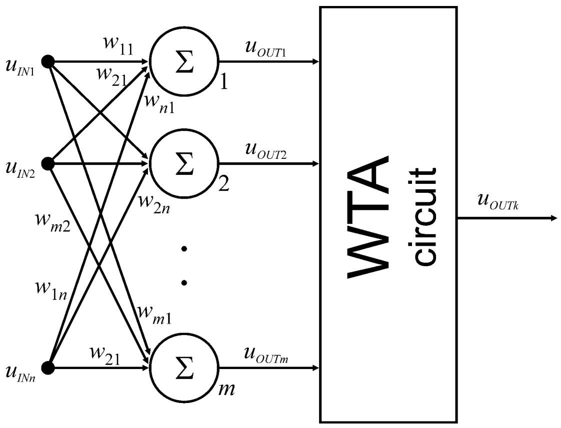


Fig. 1. WTA neural network.

Recently, plenty of artificial neural network architectures [16-19] have been applied in many control systems. Our approach adopts a competitive WTA architecture [18-23]. The WTA network consists of *m* neurons with programmable synapse weights and WTA circuit as shown in Fig. 1. In the WTA network the weight vectors are represented by

$$\boldsymbol{W_i} = \{w_{i1,}w_{i2,},\ldots,w_{in}\} \tag{1}$$

the input voltage vector is represented by

$$\boldsymbol{U_{IN}} = \{u_{IN1,}u_{IN2,},\ldots,u_{INn}\} \tag{2}$$

and the output voltage vector

$$\boldsymbol{U_{OUT}} = \{u_{OUT1,}u_{OUT2,},\ldots,u_{OUTm}\} \tag{3}$$

where *n* denotes number of input signals, *m* denotes number of neurons and

$$u_{OUTi} = \boldsymbol{W_i^T U_{IN}} = \sum_{j=1}^{n} w_{ij}u_{INj} \quad i = 1,2,\ldots,m \tag{4}$$

is defined. The WTA function consists of identifying the largest among components of $\boldsymbol{U_{OUT}}$. The m^{th} output current winner selection is based on the following criterion of maximum activation among all *m* neurons participating in a competition

$$u_{OUTk} = \boldsymbol{W_k^T U_{IN}} = \max_{i=1,2,\ldots,m}(\boldsymbol{W_i^T U_{IN}}) = \max_{i=1,2,\ldots,m}\sum_{j=1}^{n} w_{ij}u_{INj} \tag{5}$$

Weights of the winning neuron with the largest u_{OUTk} are adjusted, while the weights of the others remain unaffected. As such, WTA basic learning law to update synaptic weight of the k^{th} neuron that won the competition can be expressed as [16]

$$\boldsymbol{W_k^{new}} = \boldsymbol{W_k^{old}} + \alpha(\boldsymbol{U_{IN}} - \boldsymbol{W_k^{old}}) \tag{6}$$

where $\alpha > 0$ is a small learning constant. The losing neurons are not allowed to change its weights. Equation (6) can be rearranged to update each vector element (synaptic weights of the k^{th} winning neuron) as follows

$$W_{kj}^{new} = (1-\alpha)w_{kj}^{old} + \alpha u_{INj} \tag{7}$$

C. *FPAA implementation*

Our idea is to build a cost effective classification system of the calorific value of a coal fuel in combustion chambers with a help of FPAA. For our work four FPAA AN231E04 device is used [24]. Five input programmable competitive 4-WTA ANN circuit has been implemented in the FPAA to classify caloricity of the coal fuel. It consists of three 2-WTA circuits shown in Fig. 2. The 2-WTA circuit identifies the smaller of its two voltages and produces an output voltage which is a copy of its local winner. The 4-WTA circuit shown in Fig. 3.

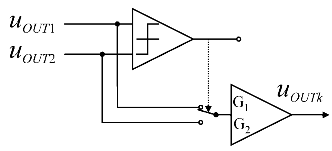


Fig. 2. 2-WTA circuit.

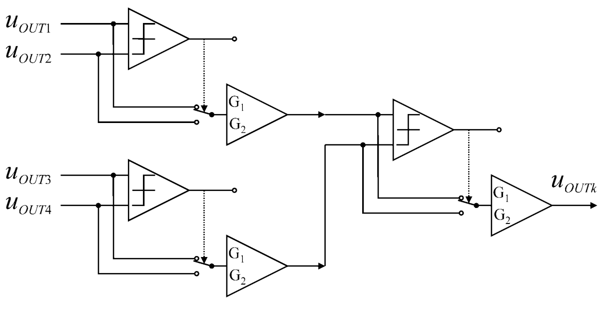


Fig. 3. 4-WTA circuit structure.

Programmability of synaptic weight w_{kj} with respect to learning signal u_{skj} is usually the following linear function

$$w_{kj}^{new} = f(u_{Skj}) = \boldsymbol{c} u_{Skj} \tag{8}$$

where c is constant. Taking equation (8) into account in equation (7) the following update for learning signal can be obtained

$$u_{Skj}^{new} = (1-\alpha)u_{Skj}^{old} + \frac{\alpha}{c} u_{INj} \tag{9}$$

The learning signal is obtained in a structure composed of summer, delay circuit and amplifiers where appropriate gains are equal $1-\alpha$ and α/c. The programmable synaptic weight circuit is shown in Fig. 4.

Proposed FPAA competitive ANN has been implemented in MATLAB program to train the ANN synaptic weights. Obtained weights are implemented in the FPAA ANN to classify the calorific value of the coal fuel. The structure of the 4-WTA ANN is implemented in FPAA1 and in shown in Fig. 5a. The programmable weight structure is implemented in FPAA4 shown in Fig. 5b.

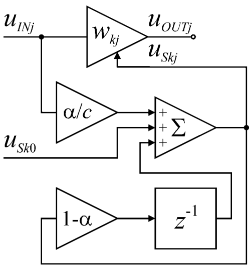
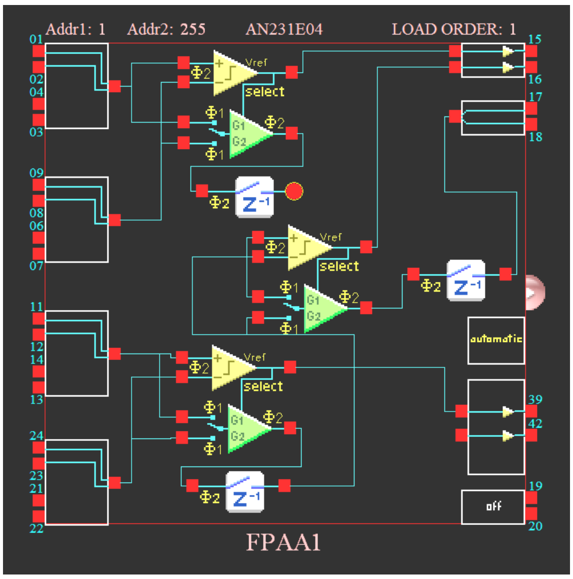


Fig. 4. Programmability of a synaptic weight circuit structure w_{kj}.

a)



b)

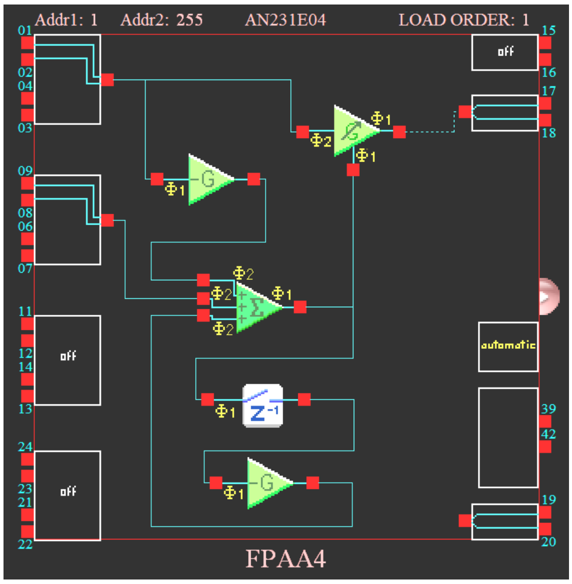


Fig. 5. An implementation of the WTA ANN, a) proposed 4-WTA ANN b) proposed programmable synaptic weight.

III. Experimental Results

The combustion process parameters in the boiler have been measured and gathered in Table 1. They have been used to train ANN shown in Fig. 1 by the use of MATLAB program. MATLAB implementation of the WTA ANN weight training process is shown in Fig. 6. The weight matrix after training process is shown in Table 2. Obtained weights have been used to determine the calorific value of the coal fuel loaded into the boiler. The WTA ANN has been verified in the recall mode by the MATLAB program and the FPAA implemented network. Obtained data shown in Table 3 confirm that the calorific value of the coal fuel not need to be measured and it can be recognized by the WTA ANN very fast. The results can be easily used in any hardware system to control a combustion process.

TABLE II. Calculated Weights and Biases of ANN

	ANN			
w	$w_{11} = 0.7144$ $w_{12} = 0.6713$ $w_{13} = 0.4230$ $w_{14} = 0.3088$ $w_{15} = 0.8932$	$w_{21} = 0.8684$ $w_{22} = 0.9129$ $w_{23} = 0.6819$ $w_{24} = 0.2915$ $w_{25} = 0.9253$	$w_{31} = 0.5528$ $w_{32} = 0.4975$ $w_{33} = 0.2576$ $w_{34} = 0.3421$ $w_{35} = 0.8422$	$w_{41} = 0.7965$ $w_{42} = 0.7816$ $w_{43} = 0.5125$ $w_{44} = 0.3081$ $w_{45} = 0.9180$
b	$b_1 = 10.8922$	$b_2 = 10.8860$	$b_3 = 10.8642$	$b_4 = 10.8502$

IV. Concluding Remarks

Proposed competitive WTA ANN has been designed and implemented successfully in the FPAA device to classify the calorific value of the fuel loaded into the industrial heat boiler. The hardware implementation of the WTA ANN results in several advantages such as: programmability of the neural network structure, fast parallel data processing and low cost. Proposed WTA ANN may be easily incorporated into a complex hardware system to control the combustion process.

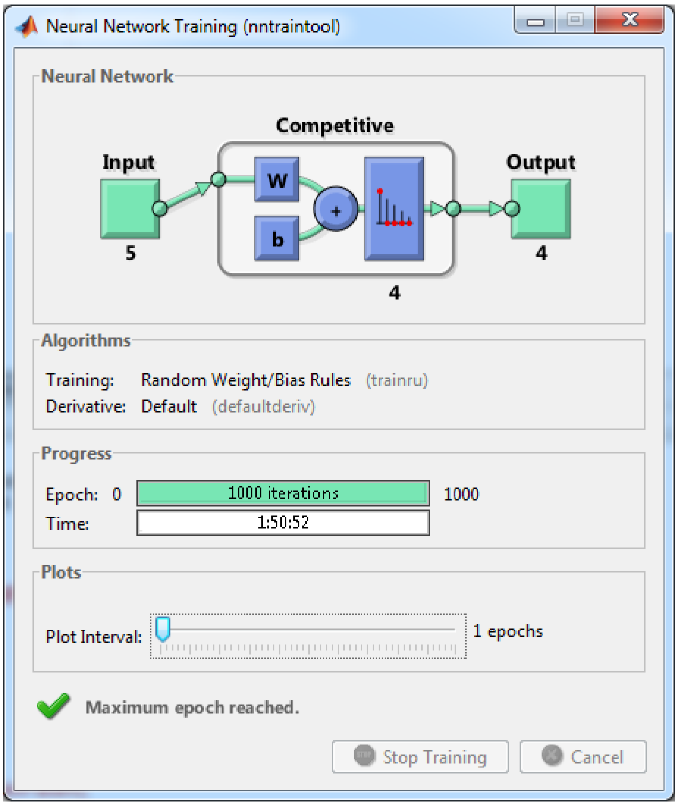


Fig. 6. MATLAB implementation of the weight learning process.

TABLE III. TEST DATA

No.	**Inputs**					**ANN**	**FPAA**
	x_1	x_2	x_3	x_4	x_5	y'	y''
1	117,3410	59,5665	34,9422	7,3925	11,6474	1	1
2	114,6243	58,8150	34,3642	7,2893	11,6474	1	1
3	113,4682	59,8844	35,4913	7,5867	11,6474	1	1
31	98,0925	60,6069	40,0289	8,4910	12,0145	2	2
32	97,2254	59,3931	40,0289	8,5882	12,0145	2	2
78	120,1156	75,1156	35,4913	6,6824	12,5116	3	3
79	117,8035	74,4509	34,9133	6,5853	12,5116	3	3
93	129,7688	72,7457	45,1156	5,1772	12,5000	4	4
94	130,4624	71,2428	42,8613	5,4806	12,5000	4	4

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