An Artificial Neural Network for Classification a Quality of a Coal Fuel in Combustion Chambers Using FPAA

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***Abstract*—A hardware artificial neural network for classification a quality of a coal fuel in combustion chambers is presented in the paper. Proposed method is based on an analysis of measured combustion process parameters in the chamber by the feedforward artificial neural network. Measured parameters have been used to train neural network weights with a help of MATLAB program. The preconditioned conjugate gradient algorithm with the Polak-Riberie formula has been used to weights training process. Calculated weights have been used to determine the quality of the coal fuel loaded into the chamber. The ANN has been tested by the MATLAB program and the FPAA implemented network. Obtained results are presented and discussed.**

***Keywords*—neural network; FPAA; feedforward ANN**

I. Introduction

A production of a heat in a huge industrial chamber is usually accompanied by significant heat losses. The losses are a result of incomplete combustion phenomena. The combustion phenomena are based on an incomplete carbon oxidation process. In that process aside from the gas CO_2, undesirable flammable gases CO, H_2 and CH_4 are evaporated as well. The carbon oxidation process depends on several parameters affecting the combustion process 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 gases CO, H_2 and CH_4 or a recognition the quality 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 control 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 to aid the control of the combustion process relies on a fast classification of the coal fuel loaded into the chamber. It is based on a multilayer artificial neural network (ANN) implemented in a field programmable analog array (FPAA) integrated 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 ANN may be easily incorporated into a hardware control system of the combustion process.

II. Proposed Approach

Our method is based on an analysis of measured combustion process parameters in the chamber. Measurements have been made by the use of telemetry system. Measured parameters have been used as data training to calculate the weights of proposed ANN to determine quality of the coal fuel in the chamber. Finally, the network has been implemented in FPAA device and tested to verify hardware solution of the problem.

A. Measurement of the combustion process parameters

Six parameters affecting the combustion process have been measured by the telemetry system in two boiler water grates type WR-25, made in the technology of tight walls using controller S7-300. All of 8479 measurements have been made in similar atmospheric conditions 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 – quality of the coal fuel 1..10.

Measured parameters are shown in Table 1. They are used to determine the quality of the coal fuel as a function of the five remaining parameters. The function is obtained in the ANN weight training process.

TABLE I. TRAINING DATA

	Inputs					Out
	x_1	x_2	x_3	x_4	x_5	y
1	91.9653	43.9306	26.4451	7.4896	11.6474	1
2	95.4335	44.5665	27.0231	7.3925	11.6474	1
3	97.0520	44.5665	27.0231	6.5853	11.6474	1
:	:	:	:	:	:	:
3641	93.5838	41.8208	24.1908	9.5957	11.6474	2
3642	95.2023	43.4971	26.9942	8.1936	11.6474	2
3644	98.0347	45.1445	24.7399	8.5942	11.6474	2
:	:	:	:	:	:	:
8014	134.2197	98.4393	55.8960	6.0815	12.5116	5
8015	133.6416	86.0983	54.7688	4.3760	12.5116	5
8016	135.0867	87.7457	53.6416	4.1818	12.5116	5
:	:	:	:	:	:	:
8477	132.4855	88.9884	49.1040	6.0815	12.5116	8
8478	132.6590	78.9306	42.2832	6.3789	12.5116	8
8479	127.8035	77.8902	41.1561	7.4896	12.5116	8

Own calculation

B. *Neural network solution*

Nowadays, several artificial neural network architectures [16-19] have been applied in variety control systems. Our approach adopts commonly used feedforward multilayer ANN architecture. The ANN is composed of the neurons shown in Fig.1 the artificial neuron is described by the following expression

$$y = f(\boldsymbol{w}^T \boldsymbol{x} + b) \tag{1}$$

where

y. b denote output and bias signal, respectively,

$\boldsymbol{x}$. $\boldsymbol{w}$ denote input, and synaptic weighs vectors, respectively,

f denotes bipolar sigmoidal activation function expressed as

$$f(out) = \frac{2}{1+e^{-\lambda out}} - 1 \tag{2}$$

where $\lambda > 0$ is proportional to the neuron gain.

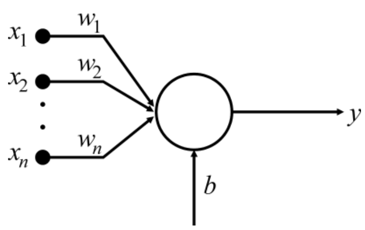

Fig. 1. Model of an artificial neuron.

A multilayer layer ANN is composed of one input, several hidden and one output layers, respectively. Single k^{th} layer of the multilayer ANN shown in Fig. 2 may be described by the following expression

$$\boldsymbol{y}^{(k)} = \boldsymbol{F}[\boldsymbol{W}^{(k)}\boldsymbol{x}^{(k)} + \boldsymbol{b}^{(k)}] \tag{3}$$

where

$\boldsymbol{x}^{(k)}$, $\boldsymbol{y}^{(k)}$ denote input, output and bias vectors of k^{th} layer,

$\boldsymbol{W}$ denotes neuron synaptic weighs matrix of k^{th} layer, respectively.

$\boldsymbol{F}$ denotes bipolar sigmoidal activation function expressed as

$$F[\cdot] = \begin{bmatrix} f(\cdot) & 0 & \dots & 0 \\ 0 & f(\cdot) & \dots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \dots & f(\cdot) \end{bmatrix} \begin{bmatrix} 1 \\ 1 \\ \vdots \\ 1 \end{bmatrix} \tag{4}$$

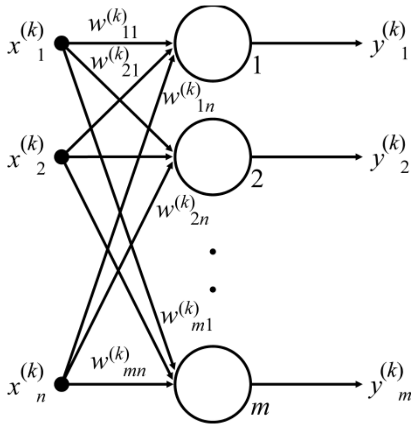

Fig. 2. The k^{th} layer of the multilayer ANN.

For our purpose to map five dimensional input into one dimensional output the multi input single output ANN has been designed. Designed network shown in Fig. 3 is composed of one input layer, two hidden and one output layers of neurons. The first hidden layer consists of five input signals and the output layer has one output signal, only.

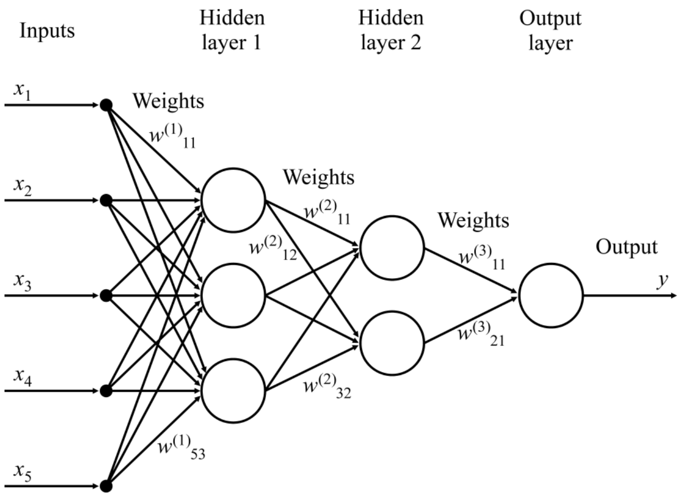

Fig. 3. Architecture of proposed ANN.

Several weights learning rules may be used for the training of the ANN [16-22]. In our approach, a flexible preconditioned conjugate gradient training method has been applied. The preconditioned conjugate gradient algorithm uses the Polak-Riberie formula [20] to weights adaptation

$$\boldsymbol{W}^{(k+1)} = \beta \boldsymbol{W}^{(k)} - \boldsymbol{\nabla} E(\boldsymbol{W}^{(k)}) \tag{5}$$

where $\boldsymbol{\nabla E}(\boldsymbol{W}^{(k)})$ denotes gradient of the error function

$$\beta = \frac{[\boldsymbol{\nabla} E(\boldsymbol{W}^{(k+1)})]^T[\boldsymbol{\nabla} E(\boldsymbol{W}^{(k+1)}) - \boldsymbol{\nabla} E(\boldsymbol{W}^{(k)})]}{[\boldsymbol{\nabla} E(\boldsymbol{W}^{(k)})]^T \boldsymbol{\nabla} E(\boldsymbol{W}^{(k)})} \tag{6}$$

C. *FPAA implementation*

Our idea is to build a cost effective system of classification a quality of a coal fuel in combustion chambers with a help of FPAA. For our work four FPAA AN231E04 device are used [23]. The AN231E04 device is based on switched capacitor technology. Its general structure is shown in Fig 4. The basic four configurable analogue blocks (CABs) are composed of operational amplifiers (OA) surrounded by capacitor banks, local routing resources, local switching, clocking resources, global connection points and input/output (I/O) pads.

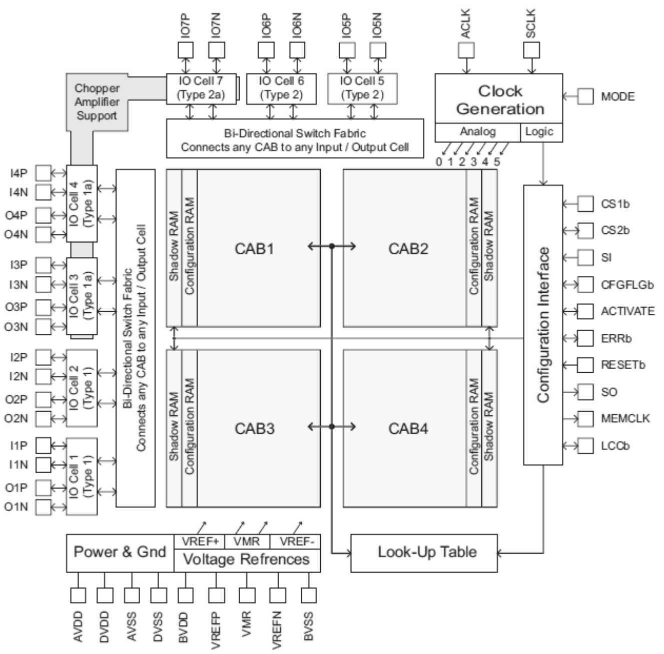

Fig. 4. Architecture of the AN231E04 FPAA.

Proposed FPAA ANN has been implemented in MATLAB program to train the ANN weights. Calculated weights are used in the FPAA ANN to classify the quality of the coal fuel. Structure of the ANN is shown in Fig. 5a. The first hidden layer is composed of FPAA1, FPAA2 and FPAA3 devices. Each FPAA device implements one five input neuron with bias. Any single neuron of the first hidden layer is built of three adders. The first neuron implemented in FPAA1 is shown in Fig. 5b. The second hidden layer and the output layer are implemented in FPAA4 shown in Fig. 5c.

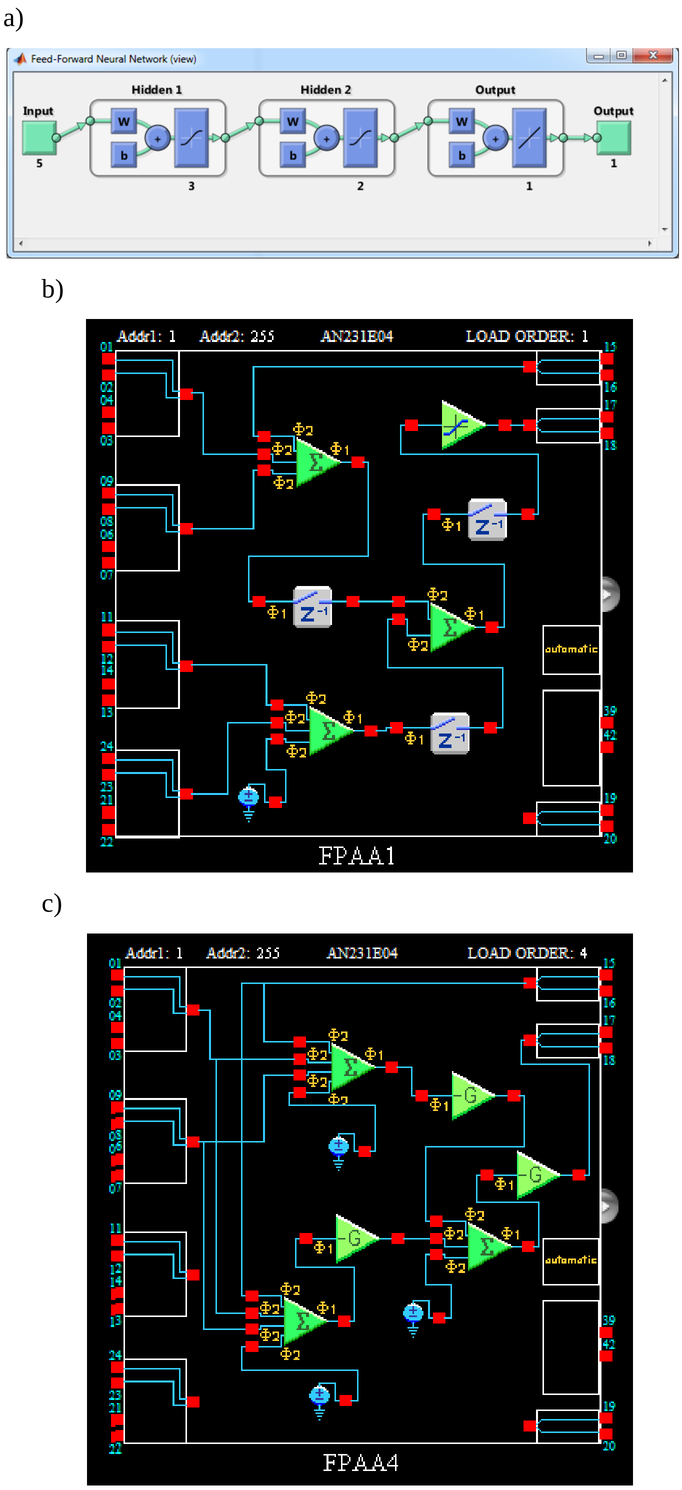

Fig. 5. An implementation of the ANN, a) proposed ANN b) neuron in the first hidden layer in FPAA; c) two neurons in the second hidden layer and output neuron in FPAA device.

III. Experimental Results

Measured parameters of the combustion in the boiler shown in Table 1 have been used to train ANN shown in Fig. 3 by the use of MATLAB program. MATLAB implementation of the ANN weight training process is shown in Fig. 6. The weight training process results in the weigh matrix shown in Table 2. Calculated weights have been used to determine the quality of the coal fuel loaded into the chamber. The ANN has been tested by the MATLAB program and the FPAA implemented network. Obtained data is shown in Table 3. They confirm that the coal fuel quality not needs to be measured and it can be recognized by the ANN very fast. It can be also used in hardware implemented control system of the combustion process.

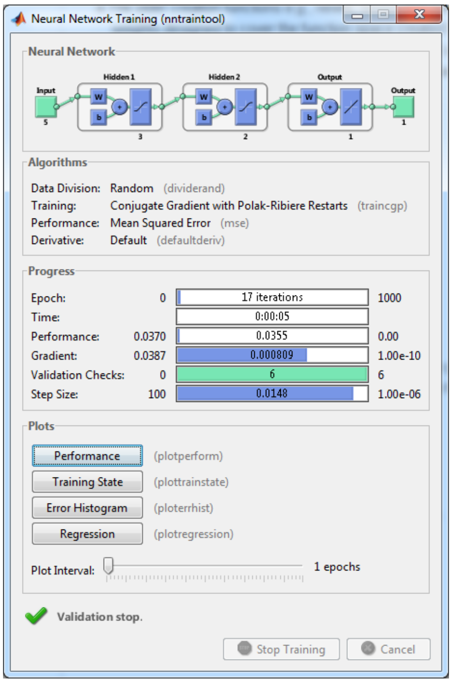

Fig. 6. MATLAB implementation of the weight learning process.

TABLE II. CALCULATED WEIGHTS AND BIASES OF ANN

L.	**ANN**			
	Weights			***Biases***
$w^{(1)}$	w_{11} = -0.5359 w_{12} = -0.3604 w_{13} = 0.9347 w_{14} = 0.1647 w_{15} = 0.7776	w_{21} = -0.1389 w_{22} = 0.6736 w_{23} = -0.2632 w_{24} = -0.7707 w_{25} = 0.6459	w_{31} = -0.6457 w_{32} = 0.7643 w_{33} = -0.1500 w_{34} = -0.0678 w_{35} = -0.6523	b_1 = 0.6797 b_2 = -0.5317 b_3 = -0.0200
$w^{(2)}$	w_{11} = -0.0583 w_{12} = 0.6632 w_{13} = 0.8007	w_{21} = -0.7535 w_{22} = 0.0370 w_{23} = 0.6323		b_1 = -0.7656 b_2 = 0.7854
$w^{(3)}$	w_{11} = 0.3308 w_{12} = 0.7926			b_1 = 0.6981

Own calculation

IV. CONCLUDING REMARKS

Proposed multilayer feedforward ANN has been designed and implemented successfully in the FPAA device to classify the quality of the fuel loaded into the industrial heat chamber. It gives several advantages: low cost, programmability of the neural network structure, fast parallel data processing and hardware implementation. It may be easily incorporated into a hardware control system of the combustion process.

TABLE III. TEST DATA

	Inputs					**ANN**	**FPAA**
	x_1	x_2	x_3	x_4	x_5	y'	y''
1	104.2197	46.5896	24.1908	7.9934	11.6474	1	1
2	99.1908	46.5896	25.8671	9.5957	11.6474	1	1
3	95.1445	44.9133	26.4451	9.3954	11.6474	1	1
:	:	:	:	:	:	:	:
4	124.8555	70.8671	41.1561	5.8812	13.3642	2	2
5	127.2254	72.2832	41.7341	5.7780	13.3642	2	2
6	132.2543	100.0289	56.4451	7.8962	12.9769	2	2
7	133.5260	100.1445	57.0231	7.4896	12.9769	5	5
8	137.6879	100.2890	61.0116	4.6795	12.5116	8	8
9	136.9364	99.5376	61.0116	5.0801	12.5116	8	8

Own calculation

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