A New Method for Diagnosis of Analog Parts in Electronic Embedded Systems with Two-Center Radial Basis Function Neural Networks

Zbigniew Czaja[1], Michał Kowalewski[2]

Gdansk University of Technology, Faculty of Electronics, Telecommunications and Informatics,
Department of Optoelectronics and Electronic Systems,
G. Narutowicza str. 11/12, 80-952 Gdansk, Poland,
[1] *phone: ++48 58 347-14-87, fax: ++48 58 347-22-55, e-mail: zbczaja@pg.gda.pl*
[2] *phone: ++48 58 347-16-57, fax: ++48 58 347-22-55, e-mail: Michal.Kowalewski@eti.pg.gda.pl*

Abstract **-** An approach of self-testing of analog parts in mixed-signal embedded systems controlled by microcontrollers is presented. It bases on a dictionary method of detection and localization of single soft faults of passive components in analog electronic circuits. At the *Measurement Stage* the tested analog part is stimulated by a square impulse generated by the microcontroller, and its response is sampled by microcontroller's ADC in moments exactly established by an internal timer. Fault detection is made by the two-layer feed-forward perceptron. If the analog part is classified as faulty, the fault localization is performed by the specialized neural network based on Two-Center Radial Basis Functions (TCRBF). Both networks are created and trained on the *Before Test Stage* on the basis of family of localization belts, which are created by dispersion of identification curves under assumption of components tolerances. The proposed method with TCRBF classifier is dedicated for testing and localization of single soft faults in analog electronic circuits. It can also be simply adopted for rough identification of analog circuits' components.

I. Introduction

At present, input-output methods of fault detection and localization are still required in diagnosis of analog and mixed-signal circuits. It is the after-effect of an increase in packing closeness of circuits assembled on printed boards, limited access to internal nodes and introduction of diagnostic buses (e.g. IEEE 1149.4) for on-board analog parts testing. These methods can also be needed in parametric identification of non-electronic objects in biomedicine, chemistry, modeled by electrical circuits in the form of multi-element two-terminals or two-ports.

Currently, mixed-signal electronic systems, which are characterized by an "intelligent unit" often based on a microcontroller, a digital signal processor (DSP) or a programmable device (e.g. FPGA, CPLD), predominate on the market, because information about operation environment and controlled objects are often gained over via analog sensors. Analog signals are transmitted and initially processed in analog parts, however analog-to-digital conversion and data processing are realized by digital parts. Therefore, the analog part has to work correctly, because incorrect measurement signal can cause wrong decision of the control unit, what can even result in damage of a controlled device. Hence, the embedded system should be able to run self-testing of analog parts.

Testing and self-testing of analog circuits is still insufficient. It follows from the fact that components of analog circuits have continuous values, stimulation and response signals are also continuous and they can assume a shape of any function. Additional problems of fault diagnosis are the presence of components' tolerances and circuits' nonlinearities. Sometimes, especially for no electrical objects modelled by electrical circuits, we have only poorly defined system models. Thus, neural networks can be very efficient solution of these problems. Many types of neural networks are used as fault classifiers: back-propagation [1], probabilistic [2], self-organizing [3] and radial basis function [4,5]. However, it seems that neural networks based on Two-Center Radial Basis Function (TCRBF) [6] are ideally suited for fault localization problems in embedded electronic systems. It follows from the fact, that they in natural way "fit in" or "describe" fault clusters represented by dispersed identification curves (localization belts) [7].

In this paper a new diagnostic method with TCRBF neural classifier will be presented. With some simplifications in TCRBF construction this method can be used in reconfigurable Built-In Self-Testers of analog parts in electronic embedded systems.

II. Principles of the method

The proposed diagnostic method belongs to *Simulation Before Test* (SBT) methods. It enables on-board detection and localization of single soft faults of passive components in analog parts of mixed-signal electronic systems with control units [8].

In the paper the control unit is represented by the Atmega16 microcontroller of Atmel as an example (Fig. 1a). The first internal timer of the microcontroller generates a square test impulse with the duration time $T = 1$ ms and the amplitude $V_{cc} = 5$ V, while the microcontroller ADC samples K-times the response signal of the tested analog part at moments assigned by the second timer.

Components' values deviations of the tested circuit are presented as a family of identification curves placed in the measurement space [8] (Fig. 1b). Assignment of the measurement point to the nearest identification curve enables to locate a faulty component.
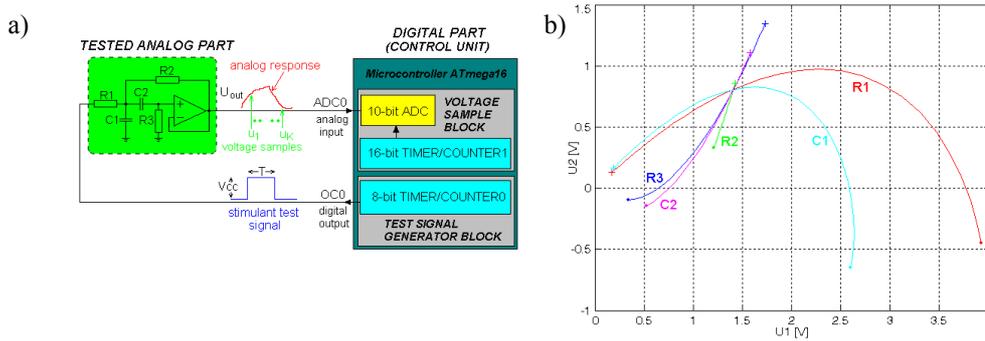

Figure 1. a) Example of a mixed-signal electronic system with analog part, where R1 = R2 = 5.1 kΩ, R3 = 10 kΩ, C1 = C2 = 180 nF, b) Family of identification curves for the tested analog part.

In practice analog circuits' components have tolerances, which cause dispersion of identification curves. As shown in Fig. 2, they take the form of localization belts. Occurrence of equivalent faults causes overlapping of some localization belts and makes it difficult to locate faults correctly. Additionally, belts need complex descriptions and fault localization algorithms. Thus, the good and effective solution of this problem can be usage of TCRBF neural networks as fault classifiers.
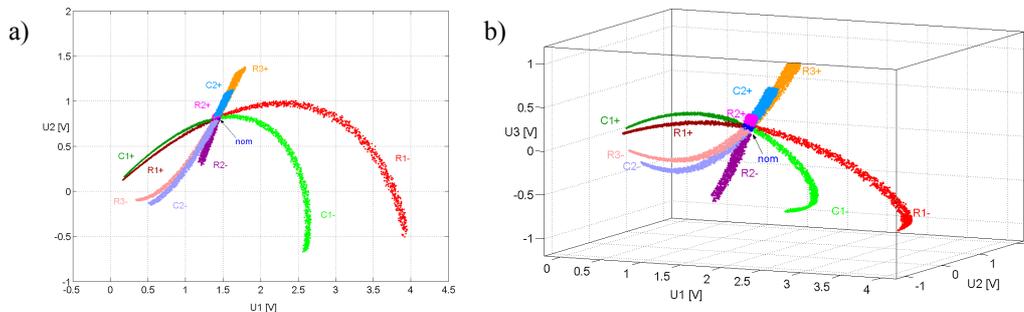

Figure 2. Families of localization belts for the tested analog part shown in Fig. 1a, for:
a) $K = 2$, b) $K = 3$, with assumption of components tolerances (1% for resistors and 5% for capacitors).

III. Construction of the Two-Center Radial Basis Function

Authors' research proved that the most appropriate types of neural networks for localization of soft faults in analog electronic circuits are *Radial Basis Function* and *Two-Center Radial Basis Function* networks. The usefulness of RBF networks for detection and localization of faults was evaluated by Catelani [4]. A hidden layer neuron in RBF network radially maps space around the center $c = [c_1, c_2, ..., c_n]$ with the Gauss basis function, described in n-dimensional space with equation

$$y(\mathbf{x}) = \exp\left(-\frac{1}{2\sigma^2}\sum_{i=1}^{n}(x_i - c_i)^2\right),$$
(1)

where σ is the scaling factor that characterizes the area of activation region.

RBF networks are specially suited for classification of radially dispersed data clusters. This is the main drawback in soft faults classification problems, where fault clusters are represented with localization belts. In that case, fulfilling generalization capabilities requires application of many neurons in a hidden layer. To avoid this inconvenience it is possible to apply TCRB functions, which are better fitted to localization belts and allow significant decrease in the hidden layer neurons.
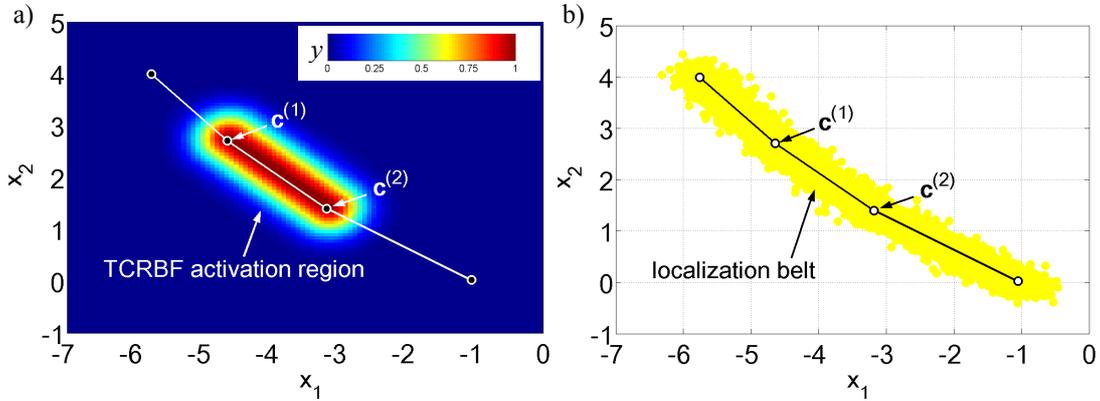

Figure 3. a) Radial mapping of space around line segment by TCRB function.
b) Exemplary localization belt.

The basic task of TCRB function is radial mapping of space around line segment with known endpoints: $c^{(1)}$ and $c^{(2)}$ (Fig. 3a). TCRB function can be expressed with equation

$$y(\mathbf{x}) = \exp\left(-\frac{1}{s^2(\mathbf{x})}\sum_{i=1}^{n}(x_i - w_i(\mathbf{x}))^2\right), \tag{2}$$

where: $s(\mathbf{x})$ is *scaling function* describing identification curve dispersion and $w_i(\mathbf{x})$ ($i = 1, 2, …, n$) are *center functions* depending on coordinates of centers $c^{(1)}$ and $c^{(2)}$ [6]. Only a few connected segments will be enough to get a broken curve, which will cover the identification curve with sufficient accuracy (Fig. 3b). For every identification curve some TCRB functions need to be assigned. For curve similar to a straight line only one TCRBF is needed. The more bent curve is, the more TCRB functions are required. For exemplary localization belt shown in Fig. 3b only three TCRB functions are required.

Two variants of TCRB functions were proposed [6]: with constant (σ = const) and variable ($\sigma \neq$ const) *scaling factor*, suitably to different shapes of localization belts. Constant scaling factor σ determines constant scaling function $s(\mathbf{x})$ and step-wise shape of center functions $w_i(\mathbf{x})$. However variable scaling factor determines conical shapes of both functions and more complex computational procedure. Exemplary TCRB functions for constant and variable scaling factors in 2- and 3-dimensional input spaces are shown in Fig. 4 and 5.
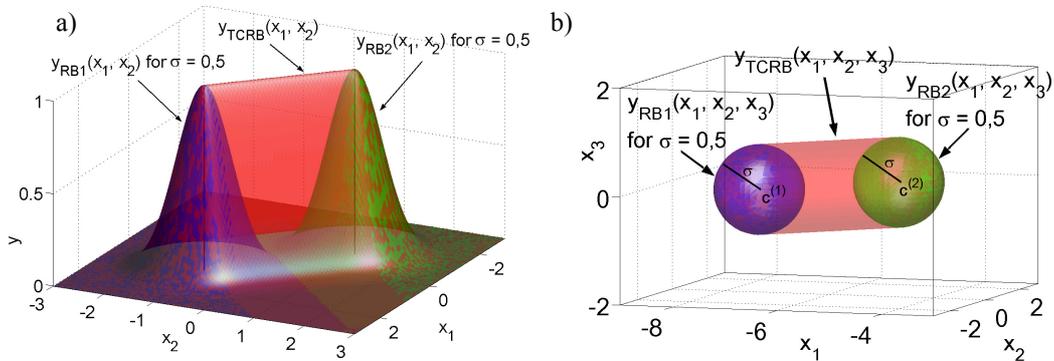

Figure 4. Exemplary TCRB functions in comparison with RB functions for $\sigma = 0.5$:
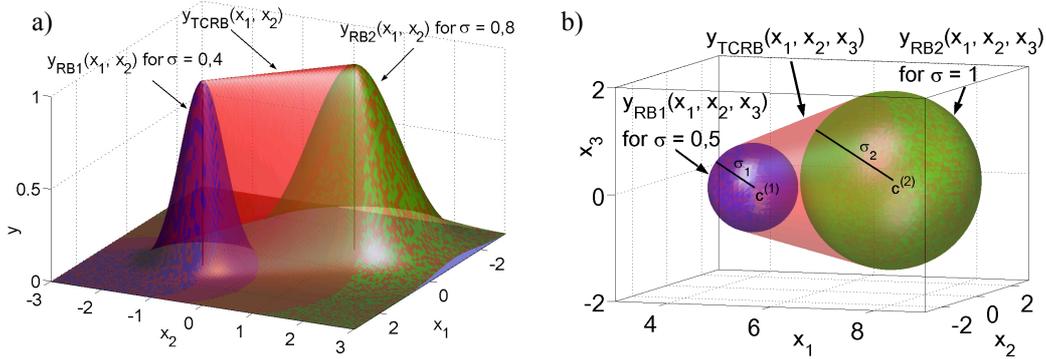a) in 2-dimensional space, b) in 3-dimensional space

Figure 5. Exemplary TCRB functions in comparison with RB functions for $\sigma \neq$ const.:
a) in 2-dimensional space, b) in 3-dimensional space

IV. Fault diagnosis procedure

The presented self-testing approach bases on the fault diagnosis method, which belongs to a SBT class of methods.

On the *Before Test Stage* two classifiers are constructed and trained:
1. Two-layer perceptron for testing of analog part,
2. TCRBF neural network for localization of fault.

During testing the analog part is stimulated with the square test impulse and K samples of the output response are acquired to create a fault signature. The measured signature is first applied on the input of the perceptron to detect state of the analog part (faulty or fault-free). Than, if the analog part is classified as faulty, the signature is applied to the TCRBF network to locate a faulty component.

A. Fault detection

Fault detection is performed by the two-layer feed-forward perceptron with the architecture $K - n_h - 1$, where n_h is the number of hidden layer neurons. Sigmoidal transfer functions are used (hyperbolic tangent in the hidden layer and logarithmic in the output neuron). Network targets contained in a training set are defined as 'ones' for faulty and 'zeros' for fault-free circuits. Circuit testing depends on applying K measured samples to the network input, calculating network output value y and rounding it to integer value y_R. If $y < 0.5$ than $y_R = 0$ and the testing circuit is fault free. Otherwise $y_R = 1$ and the testing circuit is classified as faulty. In such case specialized network with TCRB functions is used to localize fault.

B. Fault localization with TCRBF neural network

The neural network classifier with TCRB functions is two-layer feed-forward network (Fig. 6). TCRB functions, assigned to localization belts, are placed in the hidden layer. Neurons in the output layer group TCRB functions in classes and produce maximum values (M) of TCRBF outputs. Fault classification depends on indication of the largest value in the output layer. Neuron with the greatest output value determines the fault class number. The TCRBF neural network presented in Fig. 6 is dedicated to classify soft faults in circuits, which are classified as faulty by the fault detection classifier. Hence there are no neurons associated to the fault free state of the circuit.
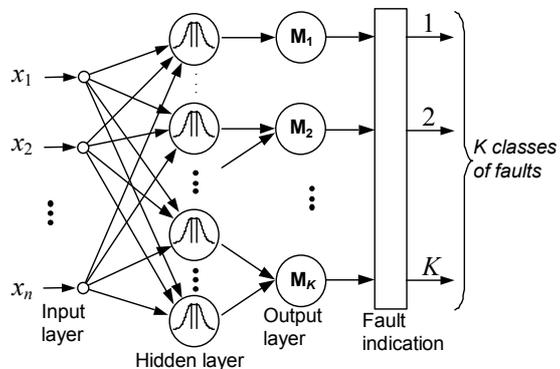

Figure 6. Typical architecture of the neural network with TCRB functions.

However transformation of input space by TCRB functions gives possibility to extend diagnosis information about testing circuit, as opposed other types of neural classifiers (back-propagation, probabilistic, self-organizing). Additional possibilities concern detection of fault-free state of the circuit without special neurons dedicated to that functionality and distinguish between single soft faults and multiple soft faults. To this aim al least one center of TCRB functions assigned to every identification curve needs to be placed in the point corresponding to the nominal state of the circuit. Than simple classifier output vector analysis needs to be performed.

Let us assume a constant threshold parameter $\lambda = 0.5$. If all y_k values of the output vector are greater than λ, than circuit is classified as fault-free (Fig. 7a). Otherwise, if the largest value in the output vector is greater than λ and the rest of values is lower than λ, than we deal with single soft fault (Fig. 7b). However, if more than one output values (but not all) are greater than λ, than we deal with ambiguity group of soft faults (Fig. 7c). Finally if all output values are lower than λ than multiple soft fault occurs (Fig. 7d).

Parameter λ does not need to be constant for every step of above processing procedure. In effect, there is a possibility to dynamically describe activation regions of TCRB functions and decision limits in the input space. If grater tolerances of circuit components are considered, than lower threshold value needs to be assumed. On the other hand, if TCRBF classifier is expected to indicate state of the circuit with lower uncertainty level, than higher threshold value is required.
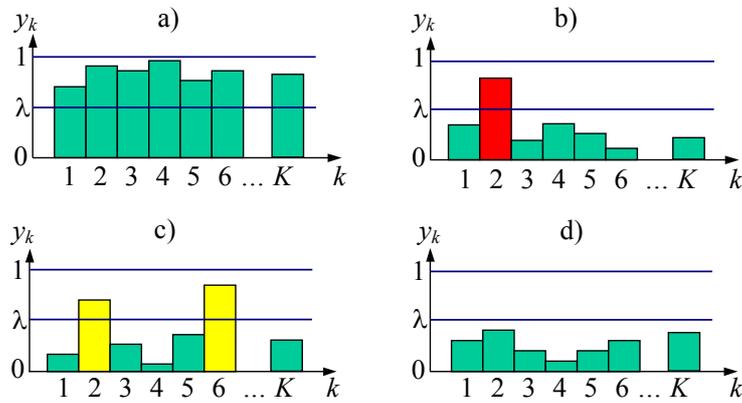

Figure 7. TCRBF classifier output vector interpretation:
a) fault-free circuit, b) single fault, c) ambiguity group, d) multiple fault.

V. Simulation results

The proposed diagnosis procedure was used for detection and localization of single soft faults of resistors and capacitors in the bandpass 2th order filter, shown in Fig. 1a.

Fault detection was performed by the two-layer feed-forward perceptron with the architecture $K - 8 - 1$. Three sets of input-target vectors, including 1000 signatures each, were created: learning, validation and test. The following components' tolerances were assumed: $tol_R = 1\%$, $tol_C = 5\%$. The network was trained for 50 epochs with the Levenberg-Marquardt optimization method. For the testing set, less than 1% classification error for $K = 2$ and less than 0.5% for $K = 3$, was obtained, which gives very good generalization capabilities.

In the second step different architectures of TCRBF networks for localization purposes were studied. Two aspects determining TCRBF classifier architectures were considered: the number of samples K and the number of fault classes n_C. Graphical illustrations of TCRBF activation regions in 2- and 3- dimensional input spaces are shown in Fig. 8. As one can see some localization belts cover each other and produce ambiguity groups. Hence, three variants of ambiguity groups were considered: a) 10 classes including 5 components soft faults and two directions of deviations with respect to nominal values, b) 8 classes with 7 singletons and one ambiguity group {R2+, R3+, C2+}, c) 5 classes with 2 singletons and three ambiguity groups: {R1+, C1+}, {R2+, R3+, C2+}, {R2–, R3–, C2–}. Thus six TCRBF classifiers with the general architecture $K - n_h - n_C$ were created, where: $K = 2, 3$, $n_C = 5, 8,$ 10, and n_h is the number of TCRB functions ($n_h = 29$ for $K = 2$ and $n_h = 36$ for $K = 3$).

Testing circuit was simulated 100 times for each component and two directions of deviations, which gave 2000 samples in the fault dictionary. Faults localization results are shown in Table 1.
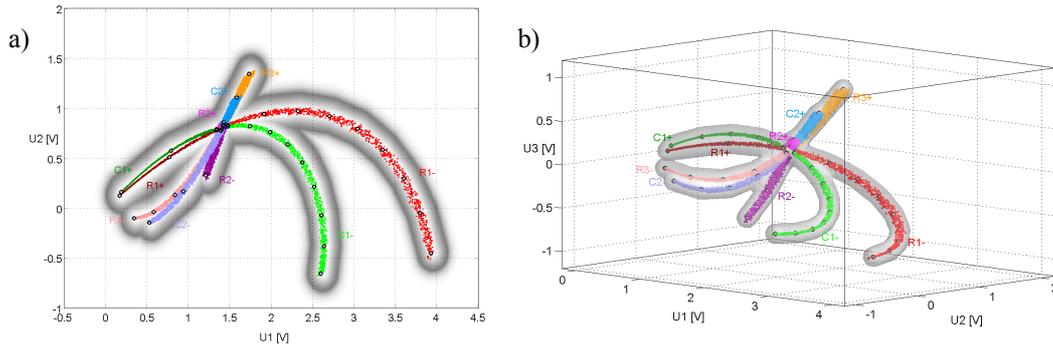
Figure 8. Activation regions of TCRB functions for: a) $K = 2$, b) $K = 3$.

The best results were obtained for 5 classes. Relatively greater classification errors obtained for 8 and 10 fault classes were caused by overlapping of localization belts for equivalent faults. Increase in measured samples from 2 to 3 and in number of TCRB functions from 29 to 36 improved generalization capabilities by decreasing the classification error even five-times for low tolerances (1%, 5%) and 5 classes. Assumption of greater components' tolerances (2%, 10%) caused on increase in misclassified signatures concentrated near the nominal point, but the classification error did not exceed 2% for $K = 3$.

Table 1. Faults classification results for the tested analog part shown in Fig. 1a.

Number of samples (K)		2			3		
Number of centers / **TCRB functions**		39 / **29**			46 / **36**		
Number of classes		10	8	5	10	8	5
Classification error [%]	$tol_R = 2\%$, $tol_C = 10\%$	27.22	17.55	6.28	17.02	6.74	1.85
	$tol_R = 1\%$, $tol_C = 5\%$	20.68	9.72	**1.81**	12.01	3.48	**0.32**

VI. Conclusions

Presented diagnosis method with specialized TCRBF neural network is an efficient way to locate single soft faults of analog parts' components in mixed-signal electronic systems. TCRBF classifier require fewer hidden layer neurons than RBF neural network if fault dictionary is constructed as a family of identification curves. Simultaneously there is an improvement in generalization capabilities. Additional functionalities characteristic to TCRBF classifier are detection of fault-free state of the circuit and distinguish between single soft faults and multiple soft faults. With some simplifications TCRBF classifiers can be used in mixed-signal systems with control units, allowing on board Self-Testing of these systems.

References

[1] Czaja Z., Zielonko R.: "Fault diagnosis in electronic circuits based on bilinear transformation in 3-D and 4-D spaces", *Trans. on Instr. and Measurement*, vol. 52, No. 1, pp. 97-102, 2003.
[2] Yang Z. R., Zwolinski M.: "Applying a robust heteroscedastic probabilistic neural network to analog fault detection and classification", *IEEE Trans. CAD IC&S*, vol. 19, pp. 142-151, 2000.
[3] Collins P., Yu S., Eckersall K. R., Jervis B. W., Bell I. M., Taylor G. E.: "Application of Kohonen and supervised forced organization maps to fault diagnosis of electronic analog circuits", *Electronic Letters*, vol. 30, No. 22, pp. 1846-1847, 1994.
[4] Catelani M., Fort A.: "Fault diagnosis of electronic analog circuits using a radial basis function network classifier", *Measurement*, vol. 28, Issue 3, pp. 147-158, 2000.
[5] Toczek W., Kowalewski M.: "A neural network based system for soft faults diagnosis in electronic circuits", *Metrology and Measurements Systems*, vol. 12, No. 4, pp. 463-474, 2005.
[6] Kowalewski M.: "Two-center radial basis function network for classification of soft faults in electronic analog circuits", *In proc. of the IMTC'2007 Conference*, Warsaw, Poland, 2007.
[7] Czaja Z., Załęski D.: "Employing a fuzzy logic based method to the fault diagnosis of analog parts of electronic embedded systems", *In proc. of the IMTC'2007 Conference*, Warsaw, Poland, 2007.
[8] Czaja Z.: "A diagnosis method of analog parts of mixed-signal systems controlled by microcontrollers", *Measurement*, vol. 40, Issue 2, pp. 158-170, 2007.