12th IMEKO TC10 Workshop on Technical Diagnostics
New Perspectives in Measurements, Tools and Techniques for Industrial Applications
June 6-7, 2013, Florence, Italy

Fault detection in complex analog circuits using Support Vector Machines

Adrian Bilski[1], Jacek Wojciechowski[2]

[1] *Institute of Radioelectronics, Warsaw University of Technology, Nowowiejska 15/19, 00-665 Warsaw, Poland and Faculty of Applied Informatics and Mathematics, Warsaw University of Life Sciences, Nowoursynowska 159, 02-776 Warsaw, blindman26@o2.pl*
[2] *Institute of Radioelectronics, Warsaw University of Technology, Nowowiejska 15/19, 00-665 Warsaw, Poland, jwojc@ire.pw.du.pl*

Abstract- The aim of this paper is to bring the reader closer to the diagnostics of complex analog systems with parametric faults, using Support Vector Machine (SVM) as a tool for fault location. The results of diagnostics of a video enhancer and two low-pass filters with the help of SVM network are presented, and various SVM kernel functions tested. A strategy for finding the optimal kernels and their parameters for the particular system under test is proposed. This paper is focused on linear systems diagnostics.

Keywords- Complex analog systems, Support Vector Machine, parametric fault detection.

I. Introduction

The complex analog systems process continuous signals and consist of large number of elements. The decision regarding the system as the complex one is not strict and depends on the designer's intuition and experience. Even the ill-conditioned system having a small number of parameters can pose a challenge, because of nonlinearities or ambiguities in the fault identification [1]. Nevertheless it is commonly agreed in publications concerning analog systems diagnostics, that the system is identified as complex if the number of parameters is larger than twenty. The information about the nature of the system is collected from the systems' signals, therefore the lesser number of elements that shape these outputs, it is more likely the faulty element will be found. To facilitate the diagnostic process and acquire better results, simple systems are mainly investigated (i.e. induction machines [2], dc motors [3], wind turbines [4] or pumps [5]).

Although general methods to effectively diagnose complex analog systems do not exist, some approaches in that field have been made [6,7]. There are various methods of complex analog systems analysis, with the decomposition approach being one of the more interesting one [7,8]. In this method, developed in early 80s, test equations are derived for a partitioned network from Kirchhoff current law equations at the partition points. Voltages at these points are used to identify network parameters and reduce the effect of a faulty element to a local area, facilitating the procedure. The high computation time of such a method limits the size of testable circuits. Thus, the method became obsolete with the advent of modern heuristic approaches. To this day, methods to effectively diagnose complex analog systems are not satisfactory and the probability of a proper fault identification decreases with the increase of the system size. This justifies the application of new, more efficient methods.

The SVM classifier application in analog systems diagnostics has already been a subject of some studies [2],[9]. Although proven useful, the problem of optimal kernel selection and its parameters remains [10]. This paper demonstrates how diagnostics of complex systems can be successfully conducted using SVM networks. The additional rationale for this method selection is its efficiency in noise conditions. The exploratory problems that are solved here concern the examination of different kernel functions and their usefulness in diagnostic process, the selection of a kernel parameter proper for the task and the classifier learning process based on parametric simulation [10]. It is a novel approach to diagnosis of a complex analog system.

II. Diagnostic principles

The Support Vector Machine is a binary classifier, whose behavior is similar to the one of a single perceptron [11]. Its main purpose is to differentiate linearly nonseparable data into distinguishable categories assuming a parametric kernel function. It can be described as a quadratic programming problem concerning the inequality constraints. There are different variations of the SVMs, with Least Squares one recently proposed [12,13]. In this case the solution of the example separation problem is obtained by solving a system of linear equations. It has been shown in [12], [14] that LS-SVMs and SVMs provide similar results in terms of assigning nonclassified examples the right categories. The aim of this paper is to introduce SVM classifiers to diagnostics of large Systems Under Test (SUT), independently from their physical nature (electrical and electromechanical systems, industrial processes, and so on).

A particular focus is given to input-output analysis (time and frequency). The reason for that is the tendency to integrate modern analog circuits in a single chip, which limits the set of accessible nodes. The output node is always accessible, so it can be used all the time. The fault detection method proposed here is based on a series of parametric simulations, that the diagnosed system has to be subjected to in order to acquire the knowledge about its behavior. Each simulation produces a measurable output signal, from which a set of characteristic points can be registered. These points provide the data on the SUT deviation from the nominal state. As such characteristic points, the following were used: in the case of time domain analysis - the value of the first maximum and first minimum in the output signal and the time instant required to reach these values. In the case of frequency domain, the 3db-frequency was taken into consideration. Here the sine input signal was used as a system excitation in time domain. The selection of the excitation signals' parameters and characteristic points from the output signal requires the experience of the human expert. The proposed stamp selection was chosen for this task, because it allows to acquire the most information from the output signal. Even though the systems analyzed here are linear, the time and shape of the signal which is stabilizing needs to be taken into consideration.

The diagnostic process is limited to single faults detection. This means that during each parametric simulation, only one elements' value changes, while the rest of the elements remain unchanged. Based on this information, the training and testing databases are created. The training base holds the information about the characteristic points acquired from the parametric simulation of each element of the system, the time instant in which these points occurred, the code of the element associated with the change and a class that has been assigned to the elements, that indicates whether the system is a go or nogo. In the case of binary classification, 0 describes the fault-free state, while 1 the faulty one. In the case of the multiclass categorization, additional fault category numbers are added. The testing base is created in a similar way, but it contains the examples that haven't been classified yet. Such databases can be used to teach the SVM classifier to built relations between the values of the characteristic points and the category assigned to them. In the presented research each element was described by eight examples (sets of characteristic points, acquired from the parametric simulation where only one element value changes). Because the change of certain elements' values is not visible in the output signal, they are excluded from the data set. Some system elements require greater deviation from the nominal value in order for the change in the output signal to be visible. During the selection of element' faults, sensitivity should be taken into consideration. The uniqueness of the fault signatures will be have an impact on the SVMs classification efficiency and the size of the training and testing databases.

The learning-testing procedure was repeated multiple times, in order to check the optimal configuration of the classification method. At each iteration the kernel parameter value was changed, so to see the impact of this on the behavior of the SVM. The diagnostic quality was measured as the percentage of the correctly classified examples. The element tolerances are included in the problem. The values of the parameters are allowed to randomly change in the interval +/- 5% around the nominal value. It is assumed that the system works according to the specification if the parameter value does not exceed the tolerances. Two types of fault detection are considered – the binary one, i.e. go/nogo (system operates properly/improperly) and the more precise one, i.e. parameter identification (the value of a parameter is smaller, larger, much smaller, much larger than the nominal value, and so on).

The number and types of kernel functions vary, depending on the SVM toolbox used in the experiment. The largest number of kernel functions is supported by the Steve Gunn's toolbox. The optimized parameter depends on the kernel type. The accuracy of these kernels were experimentally tested on each system and the best ones were selected. The range of optimization parameters in case of particular kernel functions for which the classification process gives positive results (the examples are classified to the correct categories) were also included. It is a vital step, because the range is unlimited, while a single simulation for a particular value of a parameter (i.e. Fourier kernel) can last even couple of hours for a learning base consisting of 80 examples.

For multiclass classification, a set of binary SVM classifiers is used. Each of the systems' elements has a particular class assigned to it, which distinguished it from other elements. Each of the SVM classifiers is trained to recognize only one of these classes (one-vs-all strategy). The SUT consisting of 22 elements would require 22 SVMs. This means that the number of SVMs used in the classification process equals the number of elements of the system. The purpose of that would be to localize the fault, after the decision on the faulty behavior of the system has been made. To decrease the number of modules, a coding scheme can be applied, where the combination of particular SVMs creates the code indicating the particular fault source. For example, a set of outcomes from multiple SVMs is [1, 0, 0, 0, 0] can be coded into the category 0, a set of outcomes [1, 1, 0, 0, 0] is regarded as the category 1 and so on. The exemplary SUT of 22 elements would require only five binary classifiers.

Three different types of SVM toolboxes are used in these studies. Two of them are distributed on GNU license: Steve Gunn's SVM toolbox and LSSVMlab toolbox. The third one is the Matlab 2011a SVM toolbox. The test complex linear analog systems chosen for this paper are 26-element video enhancer (already diagnosed in [16]) and two low-pass filters, consisting respectively of 35 and 48 elements. Majority of these systems have already been the subject of diagnostic studies in various publications [6], [8], [16] but methods used in these analysis are considered to be unsatisfactory. They were selected according to the increasing number of elements to check the efficiency of the SVM classifier on the various sizes of systems. The 48-element low-pass filter is in Figure 1, while the 35-element low-pass microvawe filter is in Figure 3.

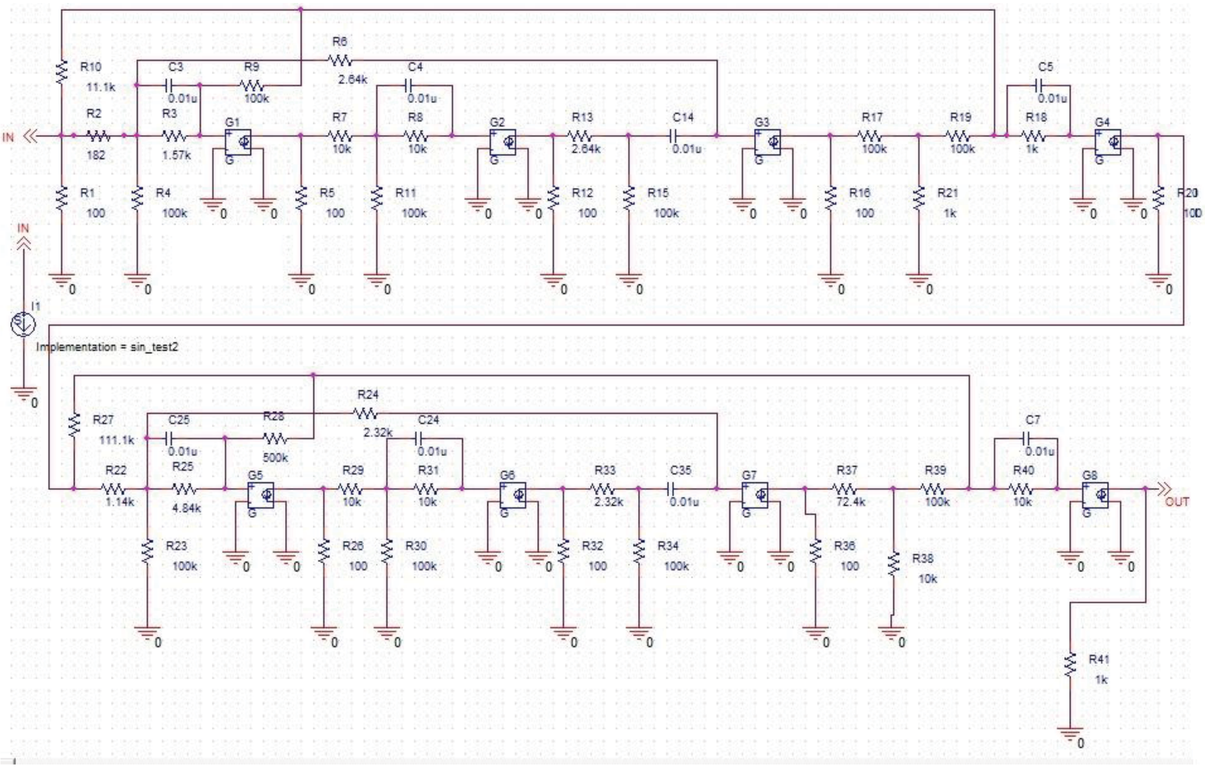

Figure 1. The 48-element low-pass filter system, modeled in Orcad Pspice

The system in Figure 1 is a fourth-order elliptic active low-pass filter. It consists of 8 operational amplifiers, 40 resistors and 8 capacitors. The system has been excited by a 10mA current source of a 10kHz frequency (Fig. 2). Each of these amplifiers is modeled by a controlled source (VCCS) and an output resistance [6]. There are two positive feed-backs in this system. This system has already been tested for catastrophic faults in [6], [8], however none of them has neither considered soft parametric faults nor used SVMs in the diagnostic process.

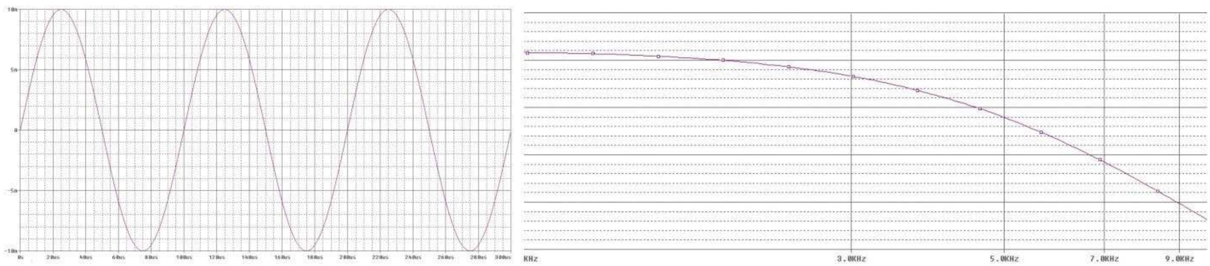

Figure 2. Sine current source of the 48-element low-pass filter system (a) and its frequency response (b)

The system of Figure 3 is a 35-element low-pass microwave filter. There are 11 capacitors, 10 coils, 14 resistors and 2 gates (which are of 100 Ohm resistances). It is a 7-th order filter. 3 dB frequency of this filter is 36Mhz (Fig. 4).

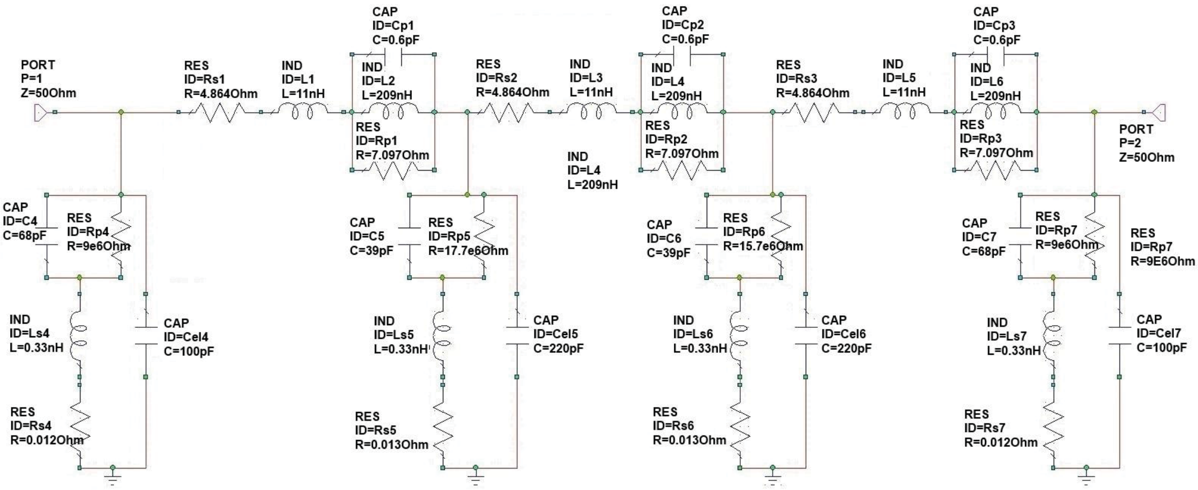

Figure 3. The 35-element low-pass filter system, modeled in Microwave Office

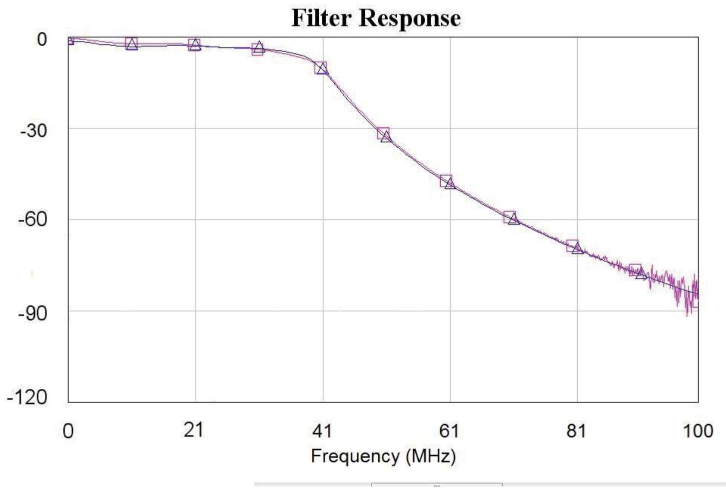

Figure 4. Frequency response of the microwave system. The red line represents the measured value, while the blue one is the result of the simulation

III. Experimental results

The classification for each kernel is repeated 10000 times. In each iteration the value of the kernel parameter is increased by 1e-5. This is the smallest increment for which the changes in the classification process are visible. In most cases (except the polynomial and anovabspline kernels) the classification started with the parameter value of 0.00002. The simulation of a single kernel learning 140 examples lasted about five hours. The classification results for each kernel function have been compared. The learning base for the 48-element system consists of 336 verses (8 verses per element). Six elements of the system were undetectable in the output signal. The training base for this system consists of 192 verses.

The best efficiency for binary classification was obtained for rbf and erbf kernels. The result is the same for all tested toolboxes. Gaussian kernel functions give similar results for the multiple classification. Although Steve Gunn's Toolbox contains multiple kernels, most of them are not good enough for the presented problems. Besides the Gaussian kernels, the best results were acquired with polynomial function of higher degree (between 33 and 103). Polynomials lower than 33 gave random classification results, while for polynomials bigger than 103 the training process of the SVM classifier would not complete. Such a high degree required for the correct

classification proves the complexity of the training data. The classification based on spline functions turned out to be unsatisfactory. The classifiers using these kernels assign all testing examples to the predominant category in the learning set. Therefore if the category "1" is the most frequent in the learning set, all testing examples will have this value assigned.
In Table 1 some results of binary and 15-class classification efficiency for various kernel functions using a Steve Gunn's Toolbox are presented. For over 15 classes the detection process produced random results. Each of the SVM toolboxes classifies up to 8 different elements with the 100% efficiency in binary classification. The values of optimization parameters used for various kernels are different for each toolbox.
Based on the collected data, it can be stated that the results of binary classification with tolerance inclusion (+/-5% for each element) for rbf and erbf kernel functions are indifferent to those acquired in the case of tolerance exclusion. As for the remaining kernel function, their classification efficiency decreases, which forces me to draw a conclusion, that they are inadequate to this assignment. As for the multiclass classification, the inclusion of tolerance makes the efficiency of classification to drop.

Table 1. Binary and 15-class classification efficiency for various kernels (Steve Gunn's Toolbox) presented for 48-element low-pass filter

Binary classification (with tolerances)			
Kernel type	**Efficiency**	**Kernel parameter**	**Parameter value**
Rbf	70%	Width of rbfs	0.000039-0.000096
Erbf	70%	Width of rbfs	0.00108-0.00207
Polynomial	60%	Degree of polynomial	33 – 103 degree
Sigmoid	50%	Scale and offset	0.02068 and 0.08646
Bspline	50%	Degree of bspline	Any
Anovabspline	50%	Max order of terms	Any
Anovabspline 1/2/3	50%	Max order of terms	Any
15-class classification (with tolerances)			
Rbf	69%	Width of rbfs	0.000039 - 0.000096
Erbf	69%	Width of rbfs	0.00108 - 0.00207
Polynomial	50%	Degree of polynomial	33 - 103 degree
Sigmoid	50%	Scale and offset	0.02068 and 0.08646
Bspline	50%	Degree of bspline	Any
Anovabspline	50%	Max order of terms	Any

The research was performed on a computer equipped with a double core processor Intel Core i5 2.67 GHz. The execution time of the presented algorithm is also shown (Table 2). In the aforementioned classification process, the best results are for the Gaussian (rbf and erbf) and the polynomial kernel functions. For Gaussian functions 70% of examples from the testing base were successfully classified, while for polynomial function it was only 60%. Subsequently, it can be stated, that the classification method based on SVMs can be used in real time (classification time of unclassified elements from the testing base takes seconds).

Table 2. Execution time of classification for various toolboxes

Classifier type	Number of elements	Kernel type	Classification time
Steve Gunn' SVM Toolbox	22	Rbf	1.6
	22	Erbf	1.6
	22	Sigmoid	1.3
	22	Bspline	1.5
	22	Polynomial	1.3
	22	Anovabspline	1.6
	22	Anovabspline 1/2/3	1.9
	12	Spline	0.6
	12	Fourier	0.6
LSSVMlab Toolbox	22	Rbf	1.8
	22	Polynomial	1.6
Matlab SVM Toolbox	22	Rbf	30
	22	Polynomial	40

IV. Conclusions

The important problem is the optimization of the kernel parameter. Although searching for the best value is time-consuming, it is the off-line part of SVM work regime. Therefore, its duration is perhaps costly but not time-critical. The most efficient SVM toolboxes to diagnose the presented systems were Steve Gunn's SVM and LSSVMlab Toolbox due to the shortest time of diagnostic process and the higher than the Matlab SVM Toolbox classification precision. Subsequently Steve Gunn's SVM toolbox provides the largest variety of kernel functions. Practical implementation of SVM to the on-line diagnostics (for instance, in the microprocessor system), requires the separate design of the method. In order to increase the classification efficiency, the acquisition of characteristic points from signals provided by the accessible nodes should be considered to provide the information on the minimal number and the type of nodes needed to provide sufficient accuracy.

This work is supported by the Polish National Centre of Science, grant No. 2011/03/D/ST8/04309.

References

[1] Stenbakken, G. N., Souders T.M., Stewart G.W., "Ambiguity groups and testability", *IEEE Transactions on Instrumentation and Measurement*, vol. 38, issue 5, pp. 941-947, 1989.
[2] Osowski S., Kurek J., "Support vector machine for fault diagnosis of the broken rotor bars of squirrel-cage induction motor", *Neural Computing & Application*, vol. 19, issue 4, pp. 557-564, 2010.
[3] Bilski P., "Automated diagnostic system using graph clustering algorithm and fuzzy logic method", *Circuit Theory and Design 2007*, ECCTD 2007, 18th European Conference on, pp. 779-782, 2007.
[4] Schlechtingen M., Santos I., F., "Comparative analysis of neural network and regression based condition monitoring approaches for wind turbine fault detection", *Mechanical Systems and Signal Processing*, vol. 25, no. 5, pp. 1849-1875, 2011.
[5] Tax D.M.J., Ypma A., Duin R.P.W., "Pump failure detection using support vector data description", *Lecture Notes in Computer Science*, vol. 1642, pp 415-425, 1999.
[6] Tadeusiewicz M., Korzybski M., "A method for fault diagnosis in linear electronic circuits", *International Journal of Circuit Theory and Applications*, vol. 28, issue 3, pp 245-262, 2000.
[7] Starzyk J.A., Dai H., "A Decomposition Approach for Testing Large Analog Networks", *Journal of Electronic Testing: Theory and Applications*, vol. 3, pp. 181-195, 1992.
[8] Salama A. E., Starzyk J. A., Bandler J. W., "A Unified Decomposition Approach for Fault Location in Large Analog Circuits", *IEEE Transactions on Circuits and Systems*, vol. 31, issue 7, pp 609-622, 1984.
[9] Aravindh K. B., Saranya G., Selvakumar R., Swetha S. R., Saranya M., Sumesh E.P., "Fault detection in induction motor using WPT and multiple SVM", *International Journal of Control and Automation*, vol. 2, no. 2, pp. 9-20, 2010.
[10] Bilski P., "Automated selection of kernel parameters in diagnostics of analog systems", *Przegląd Elektrotechniczny (Electrical review)*, no. 5, pp. 9-13, 2011.
[11] Widodo A., Tang Bo-Suk, "Support vector machine in machine condition monitoring and fault diagnosis", *Mechanical Systems and Signal Processing*, vol. 21, issue 6, pp. 2560-2574, 2007.
[12] Gestel T. V., Suykens J. A. K., Baesens B., Viaene S., Vanthienen J., Dedene G., De moor B., Vandewalle J., "Benchmarking least squares support vactor machine classifiers", *Machine Learning*, vol. 54, no. 1, pp 5-32, 2004.
[13] Suykens J.A.K., Gestel T. V., Brabanter J. D., Moor B. D., Vanthienen J., *Least Squares Support Vector Machines*, World Scientific Pub. Co., Singapore, 2002.
[14] Zhang P., Peng J., "SVM vs regularized least square classification", ICPR 2004, Proceedings of the 17th International Conference on Patter Recognition, vol. 1, pp. 176-179, 2004.
[15] Bilski A., "Diagnostic of complex analog systems with parametric faults using Support Vector Machines", *Computing in Science and technology 2012*, University of Rzeszów, 2012.
[16] Rutkowski J., *Słownikowe metody diagnostyczne analogowych układów elektronicznych,* WKŁ, Warszawa, 2003 (in polish).