Anna TIMOFIEJCZUK

IDENTYFIKACJA REGUŁ DIAGNOSTYCZNYCH Z ZASTOSOWANIEM ALGORYTMU EWOLUCYJNEGO

IDENTIFICATION OF DIAGNOSTIC RULES WITH THE APPLICATION OF AN EVOLUTIONARY ALGORITHM

Referat dotyczy sposobu identyfikacji reguł asocjacyjnych i diagnostycznych, które opisują relacje między cechami obserwowanych procesów. Reguły są identyfikowane za pomocą metody opartej na zastosowaniu algorytmu ewolucyjnego. Opracowano specjalne sposoby kodowania, operacje genetyczne i ocenę osobników. Podejście opisane w referacie jest częścią metody wnioskowania diagnostycznego z uwzględnieniem kontekstu. Identyfikowane reguły asocjacyjne są przekształcane do postaci reguł diagnostycznych z uwzględnieniem kontekstu.

***Słowa kluczowe**: wnioskowanie diagnostyczne, identyfikacja reguł, kontekst*

The paper deals with a way of identification of associative and diagnostic rules, which determine relationships between features of observed processes. Rules are identified by means of a method based on the application of an evolutionary algorithm. Special ways of coding, genetic operations and individual assessments were elaborated. The approach described in the paper is a part of a method of diagnostic inference with the use of contexts. Identified associative rules are transformed into diagnostic rules within given contexts.

***Keywords**: diagnostic inference, rule identification, context*

1. Introduction

A goal of diagnostic research of technical objects is to identify cause-effect relationships between features of parameters recorded during operation of objects and characteristics of their technical states. Examples of recorded parameters are useful (working) and residual processes, as well as parameters determining object control and supply. An inference process begins with interpretation of results of analysis of these parameters. It requires that both results of the analysis as well as diagnostic knowledge are to be expressed properly. The most common ways is to represent them in the form of rules.

One distinguishes two types of rules. Their definitions were assumed according to an approach presented in the paper. Providing a resulting part of a rule is possible to be determined the rule is called a diagnostic one. One should emphasize that identification of credible diagnostic rules is often impossible. However, in most cases the goal of diagnostic research is to identify relationships between changes of properties or parameters of the object and observed processes, not to determine a particular technical state. Such relationships are called associative rules. They are considered to be a background of determination of new diagnostic rules. The identification of such rules is especially important in cases of large sets of results of the analysis of processes recorded during observation of technical objects.

In such cases the inference process is usually difficult. Even the set of diagnostic (or associative) rules is provided the most crucial stage of this process is to select proper rules. There are numerous approaches to diagnostic inference that takes into account specific rule selection. One of such methods is to choose diagnostic rules in some contexts that represent different conditions of operation.They are also able to focus inference process on some malfunctions or parts of the object. Such method were presented in details in [5, 6, 8]. The inference is realized in two stages, presented in Fig.1.

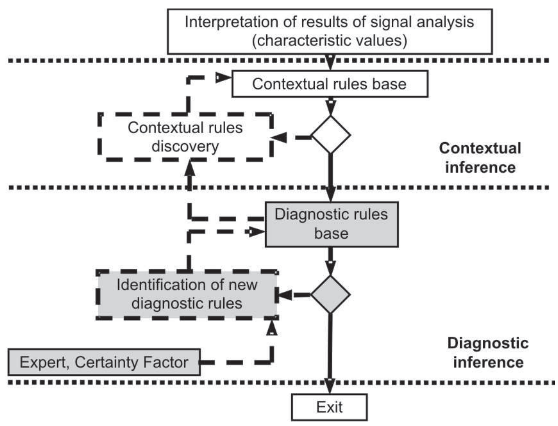

Fig. 1. A scheme of elaborated approach of context based inference

The goal of the first stage is to select an present context. It is performed on the basis of analysis of observations. Within the second stage proper diagnostic rules are being selected. Some characteristic, representing similarity between selected rules and the observation are being calculated. On the basis of these characteristics, results including diagnoses in forms of technical states that are likely to be determined are being provided. In order to make such actions possible a set of diagnostic rules have to be provided.

2. Research problem

A research problem, described in the paper was to elaborate a method that enables us to identify diagnostic rules. The paper deals with a way of identification of associative and diagnostic rules, which determine relationships between features of observed processes. The approach described in the paper is simplified due to some assumptions related to the interpretation of features of observed processes and limitation of sets of data. Presented approach concerns the second stage of the inference process (Fig.1 fields marked with grey).

According to assumptions of the method, to identify a diagnostic rule, a given set of initial diagnostic rules has to be defined. It is necessary in order to establish a conclusion of the rule. In case these rules are unknown only associative rules are possible to be determined.

It is obvious that one of the most important factors of the inference presented in Fig. 1 is to define contexts. Determination and identification of contexts is performed by means of similar methods to these presented in the paper. Details of these operations were presented in [8].

3. Elaborated approach

The identification of rules was performed by means of the application of an evolutionary algorithm. Individuals represent observations and rules to be identified. Having a population whose estimators fulfil our demands, individuals are additionally estimated. Results of these estimations are conclusions that derive from diagnostic rules that were previously defined or approved.

Consecutive populations are being generated on the basis of recorded observations of the object and are evaluated according to the fitness function, determined as a set of conditions. The approach presented in the paper required suitable manners of coding of results of the analysis of observed processes. The most essential aspect of the approach is an appropriate manner of the application of genetic operations, and first of all a suitable definition of a fitness function. Special algorithms, based on commonly applied genetic methods were elaborated [2, 3, 4]. It allows us not only to identify diagnostic and associative rules but also to cluster them automatically according to common criteria. Clustering criteria are related to determined properties of the object or conditions of its operation. The criteria exemplify inference contexts. It lets us to guide the selection of proper diagnostic rules, thus to focus the inference process on selected groups of symptoms of object properties.

It was assumed that results of signal analysis are coded in the form of series of symbols belonging to given sets. Two types of symbols were used, binary and real numbers. In each case results of signal analysis are taken into account within some intervals whose length is constant. Binary coding is simple and makes it only possible to characterize a general trend within the interval [7]. It is not explained in details in the paper. In Fig 2 there are results of signal analysis. These signals were captured simultaneously. They are vibrations measured in two perpendicular directions. This analysis consisted in estimation of mean values, application of time frequency methods and trajectory estimation.

Depending on signal features that are estimated within consecutive intervals determined numbers of symbols are used to code them in the form of one vector, which is called an observation. It is visible in the bottom part of Fig. 2.

To begin identification of associative rules a base of examples must be determined. It gathers observations. Examples do not represent single observations but observations that fulfil some requirements. At this stage of the research it was assumed that one observation belongs only to one example.

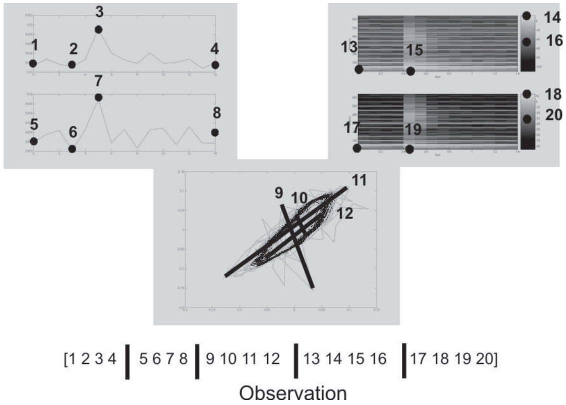

Fig. 2. A way of coding of results of signal analysis

In case of binary coding examples and observations have the same codes [7]. Exemplary if an example gathers ten observations they are all characterized by the same individuals.

In case of coding by means of real numbers examples are defined as some ranges (determined individually for each signal feature). An observation belongs to an example if all values in its code fit to each range. Such an approach has disadvantages which were revealed during the research was performed. However, this approach is correct enough to obtain satisfactory results.

An observation that does not fit to any example becomes an example with single observation.

Each example is additionally characterized by a counter that determines numbers of observations that belong to this example.

Identification of associative rules is performed by means of an evolutionary algorithm. In case of binary coding it was a simple genetic algorithm [7]. Starting population is being selected randomly. It is very important that in case of coding by means of real numbers starting codes (according to signal features) met some requirements. Mean value changes differently comparing to the spectrum or trajectory.

Consecutive populations have different numbers of individuals. They are generated by means of genetic operations (crossover and mutation). These operations have to be determined for each piece of the code (each signal feature) separately. Correctness of this part of the application of evolutionary algorithm strongly influences its convergence and results.

Populations are estimated on the basis of a fitness function that is represented in form of a few conditions. Estimation is performed on the basis of examples and their counters as well as on the basis of contexts that at this stage of the inference process are known. Identification of associative (or diagnostic) rules is performed at the beginning of the inference process and whenever a new observation which does not have its representation in form of associative (or diagnostic rules) is considered.

Such approach has very important property. Each application of evolutionary algorithm during the inference process makes it possible to order a set of rules. Properly defined fitness function enables us to remove rules that are useless and add rules that are of great importance. Such operation is possible because rules are also estimated in contexts.

A population that meets determined criteria (fitness function) is considered to be a set of associative rules. If a set of diagnostic rules is known (it must be determined by an expert of acquired from any other sources) it is also possible to find approximate conclusions for identified rules.

It was assumed that one rule (diagnostic or associative) can be considered within a few contexts. According to these assumptions transformation of an associative rule into diagnostic one (conclusion is determined) must be performed within contexts. The same sets of premises may end with different conclusion in various contexts.

In Fig. 3 and 4 transformation of the associative rules into diagnostic one is shown. To make this stage of rule identification clear, figures present rules coded by means of binary symbols. The rule is estimated within a context. Similarity measures characterize similarity of associative rules to premises of diagnostic rules that belong to the context (Fig. 4). Then consecutive signal features (coded in this case by means of one number) are multiplied by weights, which may be different (for the same features) in different contexts (Fig. 4).

A conclusion (or conclusions) is determined on the basis of measure called certainty factor. It determines the conclusion which fits the best to the set of premises (associative rule).

Context [1 # 1 1 # 0])

Associative rule

1	0	1	1	1	0

Diagnostic rules						
Premises						Conclusions
1	1	1	1	0	0	C1
1	1	1	1	1	0	C2
1	0	1	1	1	0	C3
1	0	1	1	0	0	C4

Similarity measures SM

1	0	1	1	0	1	**4**
1	0	1	1	1	1	**5**
1	1	1	1	1	1	**6**
1	1	1	1	0	1	**5**

Fig. 3. Estimation of similarity measure

Premises						Conclusions
1	1	1	1	0	0	C1
1	1	1	1	1	0	C2
1	0	1	1	1	0	C3
1	0	1	1	0	0	C4

Weights (in context [1 # 1 1 # 1])

0,2	0,1	0,5	0,2	0,8	0,2

Certainty factor

x0,2	x0,1	x0,5	x0,2	x0,8	x0,2	CF
1	0	1	1	0	1	**1,1**
1	0	1	1	1	1	**1,9**
1	1	1	1	1	1	**2,0**
1	1	1	1	0	1	**1,2**

Fig. 4. Identification of an approximate conclusion (in a selected context)

4. Experiment

The method of diagnostic inference with the use of context, and identification of diagnostic rules were applied to data recorded during operation of a laboratory stand RotorKit. The stand was observed during operation in 21 states. They are combinations of different elementary states. The object operated either in steady or unsteady conditions.

During observation of the laboratory stand three signals were recorded. They are rotating speed and vibrations measured in two perpendicular directions. Exemplary results of observation of the object were shown in Fig. 5 and 6. The first three plots represent observation of the stand during operation under constant rotating speed. In plot (b) there are signals recorded while periodical clattering was observed. In plot (c) there are signals that include results of observation of another object in the neighbourhood of the observed one.

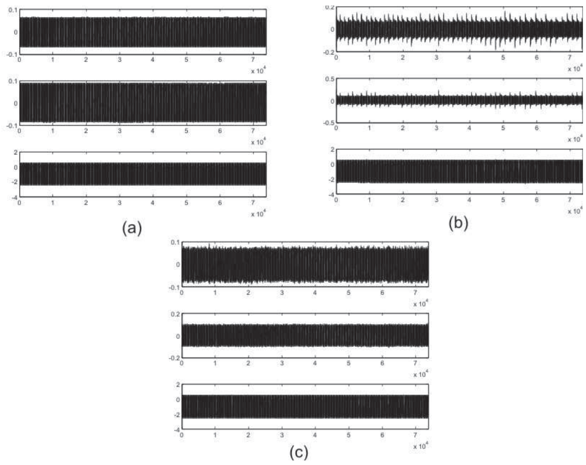

Fig. 5. Examples of recorded signals (constant rotating speed)

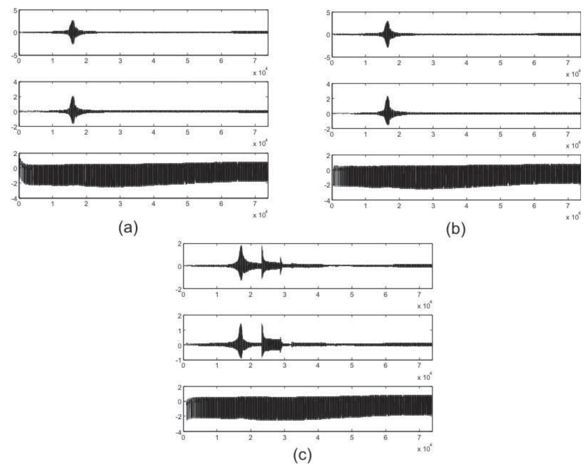

Fig. 6. Examples of recorded signals (varying rotating speed)

Plots shown in Fig. 6 represent observation of the stand during operation under run up conditions. In plot (b) there are signals recorded when another object operated in the neighbourhood of the observed one. In plot (c) there are signals recorded while random clattering was observed.

Fig. 7 and 8 present mean values estimated for above presented signals. In Fig. 9 and 10 there are shown trajectories estimated on the basis of vibration signals. Results of time-frequency analysis (Short Time Fourier Transform) are shown in Fig. 11 and 12.

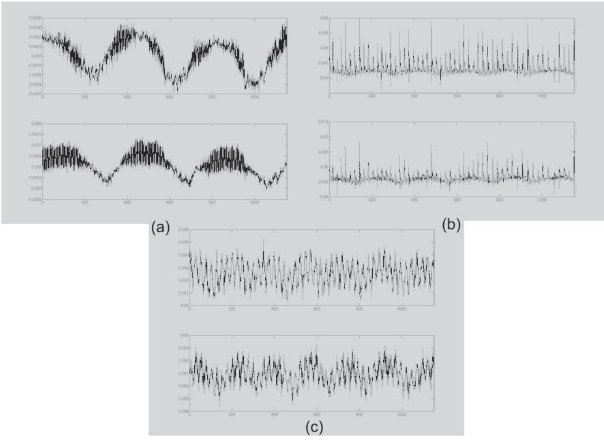

Fig. 7. Mean values of signals from Fig. 5

Results of signal analysis (Fig. 7 – 12) were coded (within constant length intervals) by means of real numbers. 9 diagnostic rules were defined a priori (Tab 1). They were based on well known diagnostic rules defined for rotating machinery [1]. All of them can be considered within more then one context. Contexts were defined according to different conditions of operation. Characteristic of building of a base of examples is presented in the previous paragraph.

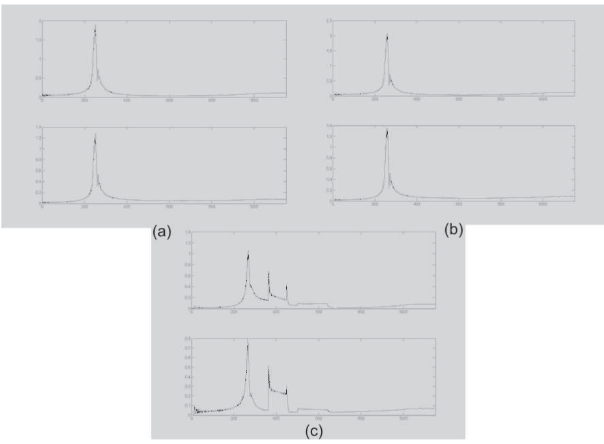

Fig. 8. Mean values of signals from Fig. 6

Tab.1. Diagnostic rules defined a priori

R1	*Constant rotating speed*
R2	*Run up*
R3	*Run down*
R4	*Random values of rotating speed*
R5	*Periodical clatter*
R6	*Other object operates in the neighbourhood*
R7	*Friction*
R8	*Overload*
R9	*Random clatter*

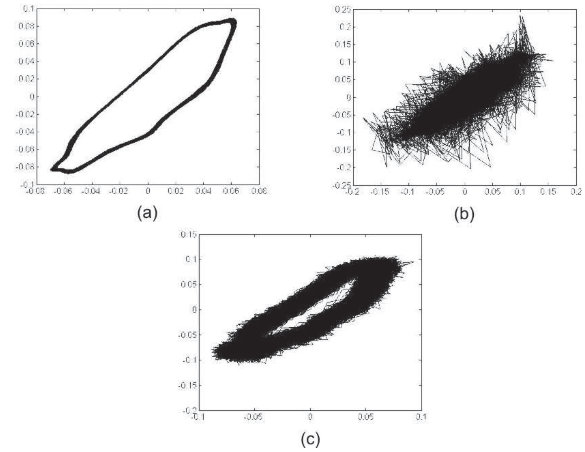

Fig. 9. Trajectories of signals from Fig. 5

Individuals representing observations, examples, rules and contexts have 29 genes. Mean values are coded by means of 4 genes that represent first, last, maximum and minimum values estimated within a given interval. Trajectories are coded by means of four numbers. They express the longest and shortest axes of the trajectory in two perpendicular directions. Trajectories were not averaged. Spectrograms are represented by means of 8 genes. Three most significant components were considered (frequency and magnitude, 6 genes were used). Spectrograms were processed in order to obtain simplified plots. Components are approximate with horizontal lines. One impulse component is taken also into consideration. It was assumed that it is visible as a single vertical line. This component is coded by means of 2 genes (time moment and magnitude). The last gene represents rotatin speed.

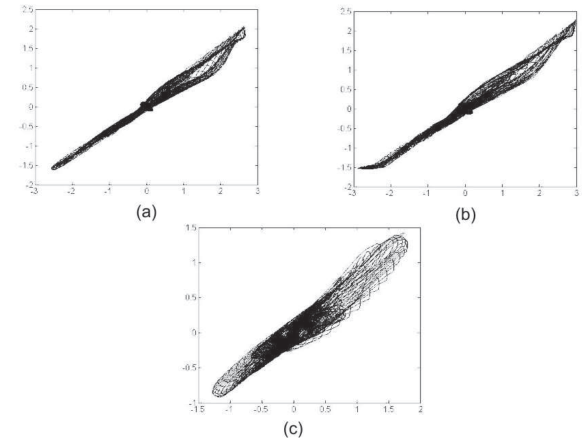

Fig. 10. Trajectories of signals from Fig. 6

Proper way of division of signals into intervals makes the identification of components easier. If any value does not appear in a code it is replaced with a unique value.

Experiment consisted in the application of elaborated procedures for all recorded signals (contexts) separately. Correctness of selection and identification of rules was tested. In such cases, efficiency of rule identification for most contexts was high. However, obtained results let us to state that correct rule identification in most complex conditions (contexts) requires that some features (especially spectral components) have to be more unambiguously coded.

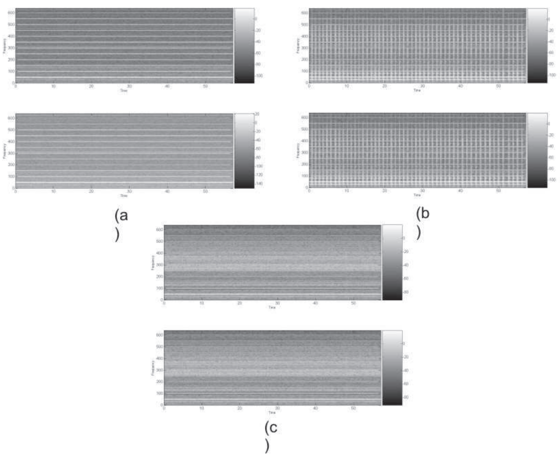

Fig. 11. Spectrograms of signals from Fig. 5

The second part of the experiment consisted in realisation of the following tasks:

- from each signal, representing one of 21 context, a characteristic interval (or intervals) was chosen,
- intervals were joined according to some common conditions (e.g. signals recorded under constant rotating speed),
- new signal were input data for inference process and diagnostic rule identification.

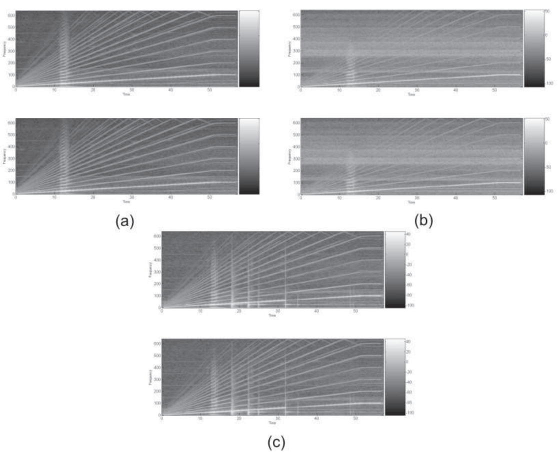

Fig. 12. Spectrograms of signals from Fig. 6

Results of experiments with 9 diagnostic rules defined a priori and 21 contexts let us to draw the following conclusions:

- when only signals recorded in one context were recorded and analysed, context and diagnostic rules were correctly selected and identified,
- efficiency of rule identification was lower when the stand was observed in two contexts (e.g. run up and friction); initial and final intervals of run up and run down were mixed up with steady conditions,
- the rule related to the situation when another machinery operated in the neighbourhood (additional component in spectrogram and characteristic shape of the trajectory) was mixed up with rules related to friction and overload,
- periodical and random clattering were mutually mixed up,
- division of signal into intervals has significant influence on results; if length of these intervals is to long results were always burden with relatively high errors.

General correctness of the proposed approach was proven. Exemplary (for 50 iterations, acceptable error 0.2), for signals shown in Fig. 5 all contexts and assumed diagnostic rules were correctly identified. It is important that analysis of conditions plots (b) and (c) was correct. In these cases two rules were identified in some periods. Results shown in Fig. 6 were also correct. In this case signals presented in plots (a) and (b) were recognized as, signals recorded under the same conditions. Signals shown in plot (c) do not include clattering. Here, one rule was identified for initial and final intervals. This result is not true, and the fault was probably effect of coding.

The second part of experiment in which signals consisted of different signals recorded in different conditions was analyses gave very interesting results. In this case rules related to constant rotating speed and run up or run down are identified unambiguously. When more then one diagnostic rules were analysed within one context, the best results were obtained for random clattering. In other contexts results were not so good.

It must be stressed that in the case of the research presented in the paper contexts are defined a priori. It seems that they strongly influence high correctness of obtained results. Test with contexts identified also by means of evolutionary algorithms gave worse results.

An additional aspect of the research is the fact that owing coding procedures and value diversity data used in the experiments are very difficult. AS the result of that genetic operations had crucial influence on identified rules. Moreover, individuals representing features are relatively long, what makes the application of evolutionary algorithm difficult. In spite of all these shortcomings obtained results shown that the approach may give correct results.

More general conclusion and direction of further research whose goal is to increase effectiveness of the elaborated approach are presented in the next paragraph.

5. Conclusion

Described experiments were performed with different parameters of evolutionary algorithms. Results of these experiments let us to draw conclusions that deal with broad range of signals (not only signal recorded during operation of rotating machinery). Two main tested factors were a number of iterations of the algorithm and different values of acceptable errors. Results obtained at this stage of the research show that correctness of obtained results depends on:

- division of signals into intervals in which signal features are estimated,
- a value of an error of fitting of observation to examples, rules to contexts and associative rules to diagnostic rules; at this stage of the research it was done within defined ranges; In most cases only one common value of error was assumed (values for different signal features were not distinguished); this value must be defined individually for each feature; initial tests shown that better results can be obtained with

the use of a fuzzy measure that characterizes a degree of fitting,
- genetic operations, and especially mutation; it was stated that random way of mutation must be strictly matched with character of a feature; in the opposite case, even when very large number of iterations is performed, the algorithm provides us with faulty results,
- crossover must be also carried out with taking into account a character of changes of a given feature; if this operation is wrongly defined it may happen that a feature whose values are from the range (0,1) will be higher as the result of crossover; such individuals are removed because they do not fulfil fitness function but in case of large populations such operations make the algorithm slower.

6. References

[1] Cempel C.: (1982) *Podstawy wiborakustycznej diagnostyki maszyn*. WNT Warszawa.
[2] Goldberg D. E.: (1998) *Algorytmy genetyczne i ich zastosowania*. WNT. Warszawa.
[3] Richards R. A.: (1995) *Classifier Systems & Genetic Algorithms*. Chapter 3 of Zeroth-order Shape Optimization Utilizing and Learning Classifier System. PhD Dissertation, Mechanical Engineering Department, Stanford University.
[4] Rutkowski L.: (2005) *Metody i techniki sztucznej inteligencji*. PWN Warszawa.
[5] Timofiejczuk A.: *Zastosowanie podejścia kontekstowego w diagnostyce maszyn*, Diagnostyka vol. 30, tom 2, 2004, s.129-132.
[6] Timofiejczuk A.: *Context-based approach In technical diagnostics*. CAMES Computer Assisted Mechanics and Engineering Sciences, Nr 2/2005.
[7] Timofiejczuk A.: *Identyfikacja reguł asocjacyjnych z zastosowaniem algorytmu genetycznego*. XXXIV Ogólnopolskie Sympozjum „Diagnostyka maszyn”, Węgierska Górka 05-10.03.2007.
[8] Timofiejczuk A.: *Zastosowanie algorytmów ewolucyjnych w procesie wnioskowania diagnostycznego*. VIII krajowa konferencja Diagnostyka procesów procesów systemów DPS, 2007, Słubice 10-12.09.2007.

Dr inż. Anna TIMOFIEJCZUK
Silesian University of Technology
Department of Fundamentals of Machinery Design
Gliwice, Konarskiego 18a, Poland
tel. 48 32 237 13 60,
e-mail: anna.timofiejczuk@polsl.pl