Rules induction method for the diagnostics of analog systems

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Abstract. The paper presents the rules induction algorithm designed to identify and locate faults in the analog systems. Compared to the most popular numerical methods, such as Artificial Neural Networks, this approach enables presenting knowledge behind the reasoning mechanism. This way it is possible to better understand relations between measured symptoms and particular faults. The method exploits the preliminaries of the AQ algorithm, which was proposed for the discrete data. The modification proposed in this paper covers the analysis of continuous features and adjusting the method to work in the uncertainty conditions. Evaluation of the approach, using DC motor driven servomechanism is performed.

1. Introduction
The growing number and complexity of technical systems requiring supervision justify development and implementation of novel approaches for their monitoring, fault detection, identification and location. The timely determining the actual state of the System Under Test (SUT) allows for repairs in the early stage of the fault manifestation. This way the accurate analysis of the SUT leads to economical savings and better understanding of the fault phenomena. Multiple proposed approaches belong to the Artificial Intelligence (AI) domain. Their advantage is the ability to extract knowledge from the available data. Among many systems the most popular are the ones exploiting variations of Artificial Neural Networks (ANN), such as Multilayered Perceptrons, Radial Basis Function Networks or Support Vector Machines [1]. They are fast and flexible, but their knowledge – illegible, presented in the form of matrices of real numbers. This makes difficult to understand the reasoning process, especially what is the relation between values of measured symptoms and the actual SUT state.

The rule-based approaches are devoid of these deficiencies, as they have clear form, which can be read and modified by the human designer. They are used in diagnostics of industrial processes, installations [2] and mechanical devices [3]. In most applications rules are inserted manually by the human. When knowledge needed for them is not available, automated rules generation methods are used. This paper presents rules induction algorithm used for the on-line diagnostics of electrical machines. Its design and implementation requires determining parameters (diagnostic accuracy, number and complexity of rules, off-line and on-line operation duration) important for the fault detection and location in the selected SUT, i.e. DC motor-driven servomechanism. In Section 2 the diagnostic scheme is presented.

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Section 3 introduces the rules induction algorithm. In Section 4 the analysed SUT is presented. Section 5 contains experimental results. The summary is in Section 6.

2. Diagnostic scheme
The proposed diagnostic scheme (Figure 1) uses the data-driven AI-based classifier. The SUT is tested by measuring output signals at its accessible nodes after providing the excitations to the inputs. Then, characteristic features (symptoms) are collected from measured signals. They are used by the fault identification module to determine if the SUT is in the nominal or faulty state. Diagnostics is realized by the fault classification, i.e. mapping the real-valued symptoms into the discrete SUT states. The classifier is trained on the data set collected during the SUT simulations. The proposed method aims at analysing single parametric faults, where the problem is caused by only one parameter of the system, which has value beyond the (desired) nominal range, but does not affect the SUT topology.

![Figure 1. Diagnostic system architecture.](image)

3. Rules induction algorithm
The autonomous rules inference system is able to work both online (during the normal SUT operation mode) and offline (after disconnecting the SUT for the tests). Its core is the set of rules of the form:

\[ \text{IF premises THEN fault code} \tag{1} \]

The premises part contains conditions that must be met by the symptoms’ values to activate (“fire”) the rule, leading to the particular fault category. During the inference, all rules are checked and the ones with the fulfilled premises point out the fault code. In the presented system, the premise has the form of the complex, i.e. the conjunction of selectors (conditions for the symptoms to meet):

\[ C = s_1 \cap \cdots \cap s_k \tag{2} \]

where \( s_i \) is the inequality or interval selector:

\[ s_{i\leq} : f_i \leq \varphi_i \lor f_i > \varphi_i \quad s_{i\in} : f_i \in (\varphi_l, \varphi_u) \tag{3} \]

The rules induction process requires the data set \( L \). It is usually obtained by the simulations of the model after setting the configuration of parameters, i.e. inserting the single fault by changing the value of the selected parameter beyond the nominal range. The simulation leads to extracting the vector of features \( f \) (diagnostic symptoms) from the output signals. Each vector (example \( e \) in the set \( L \)) is supplemented by the fault code \( c \), containing information about the identifier of the faulty parameter and its degree of deviation from the nominal value [4]. This way tuples \( \{f_i, c_i\} \) are created, making the set \( L \) suitable for learning. The evaluation set \( V \) of the same form is required to check the algorithm’s generalization ability. It contains different examples, processed by the rules during the testing stage. The accuracy of the method is measured as the sample error, i.e. the relative number of mistakes made by the algorithm on \( V \). In the presented research \( L \) and \( V \) sets have identical sizes.
The rules induction algorithm is based on the original AQ scheme [5], adjusted to the processing of continuous data. The following structures are used: temporary set of examples $T$, rules set $R$ and set of complexes $C$. In each iteration the single example (seed) is selected from $T$ (being originally a copy of $L$) and the complex (2) is constructed to cover as many examples belonging to the same category as seed as possible, excluding all other examples. This complex becomes a premise of the new rule and examples covering it are eliminated from $T$. The process is repeated until $T$ is empty. Parameters of the induction include the number of potential complexes considered for the premise $|C|$ during the rule generation and the importance $w(0,1)$ of covering maximal number of examples by the complex. The algorithm requires minimal differences between the symptoms for examples from different categories to consider them during rule generation to eliminate small symptoms changes caused by noise.

4. System Under Test
To verify usefulness of the method, the model of the mechanical SUT was selected, i.e. the DC motor-driven servomechanism. Its structure contains the feedback loop, suppressing deviations of parameters from nominal values. The SUT was excited by the step function. The loop in the operator domain is described by the equation (where $U_{in}$ is the input signal, while $U_{out}$ is the output from the load):

$$U_{out} = \frac{k^2}{(Ls+R)(Js+b)} \cdot (U_{in} - U_{out})$$

![Figure 2. Recorded angular velocity of the load for changing values of armature resistance](image)

Parameters of the SUT with their nominal values are as follows: armature inductance $L=0.5H$ and resistance $R=1\Omega$, gain $k=0.1$, load inertia $J=0.01 \text{kg} \cdot \text{m}^2$ and load damping coefficient $b=0.1$. Multiple output signals are measured: armature current $i(t) \text{[A]}$, angle of the load dislocation $\theta \text{[rad]}$, load velocity $v=d\theta/dt \text{[rad/s]}$ and load angular acceleration $a=d^2\theta/dt^2 \text{[rad/s]}$. From each simulation seven symptoms were extracted: the maximum velocity $v_{max}$, maximum angular acceleration $a_{max}$ and its time instant $t_{max}$, maximum load dislocation $\theta_{max}$ maximum and minimum current value $i_{max}$, $i_{min}$ and its time instant $t_{min}$. Example of changes in load velocity for various values of $R$ is in Figure 2. Simulations considered the tolerances and the additive noise. The number of simulations for every parameter was changed between 5 to 21 to obtain various sizes of the data sets (ranging from 25 examples to 105). The number of faulty states to identify was two (larger or smaller than the nominal value) for every parameter, which gives 11 categories to distinguish (including the nominal state). For instance, the third parameter ($R$) obtains two categories: “-31” and “31”, while the nominal state got the “0” code.

5. Experimental results
The system was trained on the set $L$ and tested on $V$. The following factors were verified:

- Influence of the noise on the ability to extract symptoms and use them to train the classifier
- Dependence between the rules induction parameters and the diagnostic accuracy
- The ability to minimize the set of symptoms used for the fault detection and identification

Examples of results for the classifier trained on the smallest (the most difficult) data set, containing 25 examples, are presented in Table 1. Here the accuracy of the optimal configuration of rules is

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presented regarding each monitored SUT parameter. In most cases the proper single rule is activated, but as \( k \) and \( J \) have smaller sensitivity, their changes are difficult to detect (no rule is used).

**Table 1.** Diagnostic results (percentages of the fault detections) for each parameter of servomechanism.

| All nominal | \( R \) | \( L \) | \( k \) | \( J \) | \( b \) | Overall |
|-------------|-------|-------|-------|-------|-------|---------|
| 100         | 100.0 | 80.0  | 60.0  | 80.0  | 80.0  | 80.0    |

The configuration of the rule-induction influences the accuracy of the fault classifier. The number of generated rules \(|R|\) should be at least equal to the number of possible fault codes (here 11, including the nominal state). Their generalization ability is determined by parameters \(|C|\) and \( w \). Increasing the former makes the process more complex and increases the learning duration, but leads to better results. Decreasing the latter increases the number of rules and maximizes the accuracy. Comparison between various sets of rules for different parameters of the algorithm is in Table 2. Results for larger sets are better as more data is used to separate different faults.

**Table 2.** Experimental results for the diagnostics of servomechanism.

| \(|C|\) | \( w \) | \(|R|\) | acc [%] |
|-------|-------|-------|--------|
| 10    | 0.1   | 11    | 60.0   |
| 20    | 0.6   | 11    | 72.0   |
| 40    | 0.6   | 12    | 76.0   |
| 20\(^a\) | 0.8   | 13    | 80.0   |

The example of the rule is presented below. The analysis of the optimal set of rules showed that the symptom \( \theta_{\text{max}} \) does not have to be acquired, as it was not included in any rule.

\[
\text{IF } v_{\text{max}} \in (0.33; 0.46) \text{ AND } a_{\text{max}} < 0.23 \text{ AND } l_{\text{max}} > 3.73 \text{ AND } i_{\text{max}} > 0.39 \text{ THEN code } = \text{“-31”}
\]

**6. Conclusions**

The presented algorithm is an interesting alternative for the standard, ANN-based diagnostic system. Its accuracy is comparable to other approaches and modifications to the original AQ scheme make it suitable for processing data in the uncertainty conditions. The number of rules depends on the SUT behaviour. If the particular faults are easy to diagnose, a single rule is enough to identify the corresponding fault. Otherwise, multiple rules are required for the single fault and classification error is more probable to occur. Possible modifications include introduction of uncertainty to the reasoning process, for instance by combining the presented approach with fuzzy logic.

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