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ROBUST DIAGNOSTICS OF COMPLEX CHEMICAL PROCESSES: MAIN PROBLEMS AND POSSIBLE SOLUTIONS

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The paper is aimed at presenting a study of the main limitations and problems influencing the robustness of diagnostic algorithms used in diagnostics of complex chemical processes and to present the selected exemplary solutions of how to increase it. The five major problems were identified in the study. They are associated with: uncertainties of fault detection and reasoning, changes of the diagnosed process structure, delays of fault symptoms formation and multiple faults. A brief description and exemplary solutions allowing increase of the robustness of diagnostic algorithms were given. Proposed methods were selected keeping in mind applicability for the on-line monitoring and diagnostics of complex chemical processes.

Keywords: complex systems, diagnostic system, alarm systems, diagnosis robustness, diagnostic inference

1. INTRODUCTION

Despite the application of highly reliable devices, the faults of the components, measuring devices and actuators are inevitable in the technological installations in chemical, petrochemical and many other industries. They cause significant and long term disturbances of the production process reducing more or less its performance. Sometimes they lead to the process shut down by the Safety Instrumented System (SIS), and sometimes even to a disaster, e.g. the case of fire set at Buncefield, England, by sensor fault.

The alarm systems (AS) are commonly used to detect arising faults. Together with process operator interventions they constitute a separate security-protective layer according to the standards IEC/EN 61508 and IEC/EN 61511. A SIS system is a separate layer. The task of AS together with the process operator interventions is to early recognize the risks and to take the appropriate actions that recover the nominal state of the process. If it cannot be achieved, the SIS will work. Its task is to bring the process to a safe state which is usually associated with the shutdown of the whole or a part of the process. This might cause significant economic losses. Therefore, it is appropriate to use solutions that can guarantee the rejection of hazards at their early phase and prevent the activation of SIS and discontinuation of the process.

The limit controlling methods applied in the ASs are used for fault detection. These methods do not guarantee detection of all faults due to the masking effect of symptoms caused by control loops. The leakage of toxic liquid from the tank in which the level is controlled can be an example of such a fault. The leakage is compensated by the increase of liquid inflow caused by the controller in order to keep the desired level in the tank. Long detection times and a large number of possible causes of

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a particular alarm are also the disadvantages of AS. However, the biggest problem for the operators is the occurrence of flood of alarms, i.e. a very large number of generated alarms in case of serious failures. The data of the Engineering Equipment and Materials Users' Association (EEMUA) show that the average daily number of alarms in the petrochemical industry is approximately 1500 while, according to the recommendations, it should not exceed 144. Interpretation of the large number of alarms generated in a short time interval is very difficult, especially, given that ASs usually do not make use of fault isolation. The phenomena of operator's information overload and stress might occur in this case (Willsky, 1976). This may lead to additional operator mistakes which cumulate with pre-existing faults causing serious breakdowns. The mechanism of such unfavorable feedback was the cause of many severe accidents. Disadvantages of ASs make it difficult for operators to isolate existing faults that are the real cause of observed alarms. Thus, the actions of operators do not always finish with the recovery of nominal process state conditions. However, ASs can be treated as the simple versions of diagnostic system (DS).

The disadvantages of AS make researchers focus on fault detection and isolation methods. There are many monographs (Basseville and Nikiforov, 1993; Blanke et al., 2004; Chen and Patton, 1999; Gertler, 1998; Himmelblau, 1978; Isermann, 2006; Korbicz and Kościelny, 2010; Korbicz et al., 2004; Patton et al., 2000; Witczak, 2007), survey papers, e.g. (Calado et al., 2001; Frank and Marcu, 2000; Frank, 1987, 1990; Isermann and Balle, 1997; Isermann, 2005; Korbicz, 2006; Leonhardt and Ayoubi, 1997; Patton et al., 1999; Schubert et al.,2006; Venkatasubramanian et al., 2003a, 2003b, 2003c) and works dealing with many detailed issues. Different DSs were developed for industrial processes (Betz et al., 1992; Kościelny et al., 2006; Lore et al., 1994; Milne and Travé-Massuyès, 1997; Natarajan and Srinivasan, 2014; Schlee and Simon, 1994; Syfert et al., 2011; Theilliol et al., 1997). Known applications are pilot implementations and industrial research (Cassar et al., 1994; Häjhä and Lautala, 1997; Jouma and Parkkinen, 1991; Kościelny et al. 2010; Liu and Chen, 2014; Monroy et al.,2012; Syfert et al., 2005; Van den Kerkhof et al., 2012). DSs have potentially many advantages. The automated execution of diagnostic tasks in on-line mode significantly reduces the fault detection and isolation time in comparison with the diagnostics performed by the AS and the operator. One can observe an increase of some indices characterizing process safety and reliability such as: availability factor (AF), diagnostic-coverage factor (DC) or safety failure fraction (SFF). On the basis of the generated diagnoses the system can further advise maintenance staff by supporting instructions to be followed in the abnormal and emergency states of the process. In this way they can serve as quick and effective protective activities avoiding activation of the SIS.

However, so far, the DS had not been widely adopted in the chemical, petrochemical and other industries despite its better capabilities compared to ASs. DSs are still not offered by the leading manufacturers of DCS and SCADA systems. The reasons for this, according to the authors' knowledge, are:

- insufficient robustness of emerging DSs against: structure changes, delays and uncertainties of symptoms, models and experts' knowledge uncertainty or multiple faults,
- problems connected with start-up and operation of DSs based on process models and the necessity to decentralize diagnostic tasks in case of complex industrial processes,
- lack of sufficient number of experts.

The methods based on process models are mainly used for fault detection in DSs. They are sensitive to process nonstationarity as well as maintenance works which change the process parameters. Therefore, it is necessary to continuously or periodically tune the models. This imposes certain requirements on the operation of DS.

However, the main reason for the lack of applications of DSs in the chemical and other industries is insufficient robustness of fault detection and isolation methods. There are many works devoted to the robust fault detection, among others (Chen and Patton, 1999; Milanese, 2004; Mrugalski, 2013; Patan et al., 2008; Puig et al., 2006; Witczak, 2007), while few are devoted to robust fault isolation. Analysed DS solutions do not provide adequate flexibility and adaptability of the DS for structural changes in the diagnosed installation.

This paper concerns broadly understood robustness of fault detection and isolation to existing limitations and problems of the diagnostics of complex chemical processes. The aim of this paper is to review those limitations and problems and to indicate the ways of how they can be effectively solved. The requirements for different types of robustness will be given in the descriptive form due to the absence of widely accepted measures of robustness.

Discussed issues are formulated based on many years of theoretical research and practical experience related to the development of the systems of advanced process diagnostics DIAG (Korbicz et al., 2004), AMandD (Kościelny et al., 2006) and DiaSter (Korbicz and Kościelny, 2010; Syfert et al., 2011) as well as their pilot implementations in the chemical and food industries (Kościelny et al., 2010; Syfert et al., 2005).

The paper is organized as follows: Major problems and limitations of the diagnostics of technical processes are formulated in Section 2. Section 3 examines symptom uncertainty and methods introducing the robustness of fault detection. Section 4 deals with the methods of robust diagnostic reasoning. The inference methods introducing robustness against changes of diagnosed system structure are the subject of Section 5. The problem of symptom formation delays and the ways to ensure the robustness of inference against these delays is discussed in Section 6. The necessity for recognition of multiple faults and efficient algorithms of solving this problem are indicated in Section 7. Section 8 summarizes the paper.

2. ISSUES AND LIMITATIONS IN THE DIAGNOSTICS OF CHEMICAL PROCESSES

The main purpose of DSs in industrial processes is fault detection, isolation reasoning and support of operators in abnormal and emergency states. Realization of these tasks is very complex due to the complexity of diagnosed installations consisting of hundreds or even thousands of devices working usually in harsh and variable conditions. This might result in the large number of differential faults. The additional difficulty is uniqueness of chemical installations. In contrast, the conventional industrial power plants are similar, which simplifies the design of DS.

There are many problems and limitations in the diagnostics of industrial processes that must be addressed and solved in order to make the DS robust and able to effectively identify emerging faults. The most important are:

- *Uncertainties of fault detection*. In practice, one deals almost exclusively with uncertain signals. The measurements of process variables are affected by the uncertainty and measurement noise. The process models are also uncertain. Processes are not stationary. There is a difficulty in determining decision thresholds. As a result, determined diagnostic signals are also uncertain.
- *Uncertainty of reasoning based on uncertain values of diagnostic signals*. The diagnostic reasoning can lead to false diagnoses if the uncertainty of diagnostic signals is not taken into account. There is also a need to identify unknown states of a diagnosed process. Unknown states of the process are the result of the occurrence of false values of diagnostic signals and faults not covered in the design phase.
- *Changes of the diagnosed process structure*. These changes are related to switching off and on technological devices, disconnecting instruments for maintenance purposes, etc. The variability of structure is a very important limitation in the design of DS.

- *Delays of fault symptom formation*. The diagnosed process is a dynamic system and therefore, a certain time elapses, depending on the dynamic properties of the tested part of the process, from the time of fault occurrence to the time of observation of measurable symptoms of this fault. The same fault is detected after different time by various diagnostic signals. The isolation algorithm may generate false diagnosis if it does not take symptom delays into account.
- *Multiple faults*. In the case of complex industrial installations multiple faults are a serious problem due to the large number of devices and their reliability figures. Multiple faults may occur in a sequence of consecutive faults or simultaneously. The most difficult to recognize are faults occurring at the same time. Special algorithms must be used to deal with this issue.

The algorithms for fault detection and isolation used in DS should take into consideration the above-mentioned problems and effectively solve them. It is a necessary demand for obtaining an appropriate robustness diagnosis. Robust DS is characterized by the ability to formulate proper diagnoses, despite the presence of the problems mentioned above. Therefore, the choice of appropriate methods of fault detection and isolation is a key issue in the diagnostics of complex technological systems. The possibility of application of each method is determined by the uniqueness of the diagnosed process, and on the other hand, by the form and knowledge about the process, imposed by this method.

In the scientific literature one can find many diagnostic methods requiring knowledge of the mathematical description of the processes taking into account influence of faults (Chen and Patton, 1999; Frank, 1987; 1990; Gertler, 1998; Patton et al., 2000). Their applicability is very limited, since the modeling of processes including fault influence is very difficult and costly, even for simple systems. It seems even impossible for chemical processes. Attempting to build such models can be justified only in the critical installations. However, they allow obtaining the highest quality of diagnosis, e.g. the highest fault distinguishibility.

It is difficult to develop analytical models of the process referring to physical phenomena. The nature of some phenomena taking place in industrial processes is not fully recognized. In this case it is not possible to develop analytical models. Only models based on the measurement data for the nominal state of the process may be used in this case. The range of applications of such models is limited to the span of variation of the input and output signals on the basis of which the model was taught and tuned.

Practically, there is no available process data for an industrial process with faults. In the databases of control systems (DCS and SCADA) there are large sets of measurements, but relatively few are registered in abnormal and emergency states. In contrast, it is required that faults that occur for the first time and are not recorded in archival data sets, should be also recognized. This limits the applicability of many known diagnostic methods, which are based on measurements originating from emergency conditions (Frank and Marcu, 2000; Isermann, 2006; Korbicz et al., 2004; Patton et al., 1999; Venkatasubramanian et al., 2003a; 2003b; 2003c). The methods of classification requiring the training data for each state of the process become useless. Collecting of measurement data for all the faulty process states is impossible in the case of chemical processes. The number of hypothetic faults is very large but various abnormal and emergency conditions take place rarely.

Therefore, fault isolation should be carried out on the basis of the automatic inference, while the knowledge about the fault-symptom relationship should be determined on the basis of experts' knowledge. Good process knowledge of the installation allows to define this relationship in a relatively simple way. The diagnostic system designer can additionally use the knowledge of process engineers, process operators and maintenance staff. However, it should be mentioned that not all approaches to automated reasoning are useful. Diagnostics based on signatures or diagnostic trees developed at the process design stage does not provide sufficient robustness against the variability of the process structure, changes in the set of available measurements, etc.

3. UNCERTAINTY OF SYMPTOMS

3.1. Characteristics of the problem

Two main groups of fault detection methods can be distinguished: model based – using different types of partial models of diagnosed process (Fig. 1) and signal based – making use of the analysis of signals (Fig. 2). It is preferred to use model-based methods in the DS, because of their advantage of early detection of the small size faults. In both cases, the decision about fault detection is taken as a result of presence of symptoms. A symptom of a fault occurs when a value of residual or specified parameter of the signal exceeds predefined thresholds, i.e. a symptom is such a value of diagnostic signal that appears when the fault is present (Fig. 3). If the acceptable range of variation of these signals, characterizing the normal process state, is narrow then short fault detection time will be obtained, but the likelihood of false symptom formation will be high. If this range is wide, the detection time will be extended, but it will reduce the number of false symptoms. Therefore, there is a conflict between the demand on detection time reduction and the need to obtain certain detection.

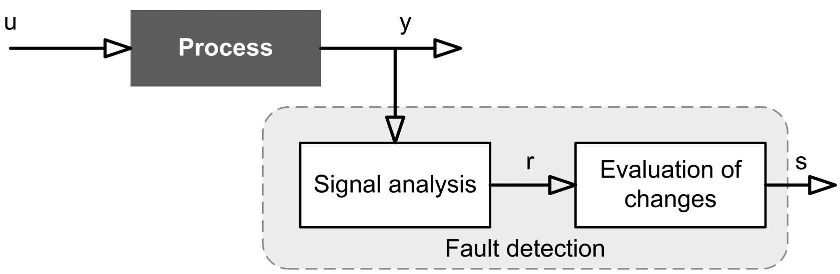

Fig. 1. Fault detection based on signal analysis

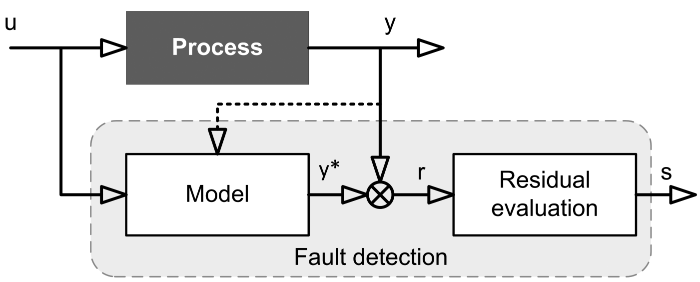

Fig. 2. Fault detection with process model

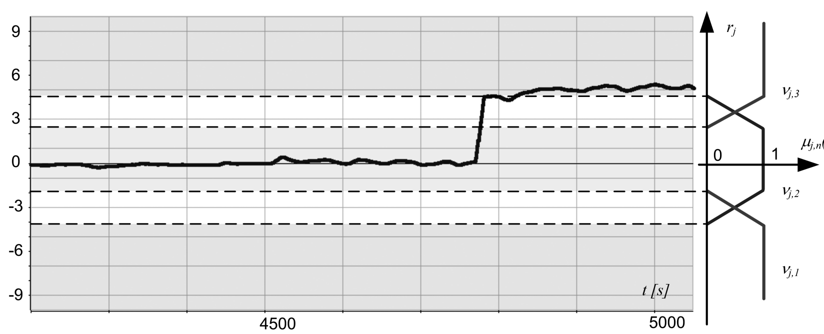

Fig. 3. Fuzzy, tri-valued residual r_j evaluation. Three fuzzy sets are used: $\nu_{j,1}, \dots, \nu_{j,3}$ with appropriately defined membership functions $\mu_{j,n}(r_j)$

The variation of residuals or signals makes it difficult to set proper thresholds. This is associated with uncertain measurements, disturbances and measurement noise, inaccuracies of used models and non-stationarity of process parameters. The robustness of the detection is influenced by the algorithms making decisions about symptoms and on the methods of determining the thresholds in order to minimize false symptom generation.

3.2. The methods providing robust fault detection

The reduction of false detection is obtained by:

- *The use of adaptive thresholds*. It is necessary to estimate uncertainty of the model used for the fault detection in order to determine these thresholds. The appropriate robustness is achieved by identification with limited value of an error or by statistical determination of the envelope of uncertainty, i.e. adaptive thresholds (Korbicz and Kościelny, 2010; Milanese, 2004; Mrugalski, 2013; Patan et al., 2008). The second approach is more practical. However, it requires large computational capabilities in order to determine an adaptive threshold. It is difficult to predict the applications of these methods in the real-time DS.
- *Detection of exceeded acceptable limits based on the mean value of residual (or another signal) in a sliding window containing the N recent values*. This extends detection time, but dramatically improves the robustness against the dominant group of not vanishing faults.
- *Application of fuzzy evaluation of signal values* (Frank and Marcu, 2000; Frank, 1994; Korbicz et al., 2004; Kościelny et al., 1999). An effective way of taking into account the uncertainty associated with decision-making process of the fault detection is the use of fuzzy logic. An example of fuzzy evaluation of residuals is illustrated in Fig. 3.
- *Dependence of the threshold values on the statistical data characterizing the course of the residual in the normal process state*. Thresholds cannot be easily calculated in an analytical way. Determination of the statistical parameters (mean and standard deviation) based on the residual time series recorded at the process start-up stage is the most effective method of their calculation. The values of decision thresholds might be dependent on the value of the standard deviation, taking into account the conflicting demands on the robustness and time of detection. DS should be equipped with an algorithm for automatic determination of the value of these thresholds, both crisp as well as fuzzy ones. Alternatively, the system engineer should set them based on his/her experience.

According to the authors, the use of a combination of the above methods, i.e. fuzzy evaluation of residuals in a sliding window and determining the limit values based on statistical parameters characterizing residual time series in the normal process state is the simplest and most effective method of providing robust fault detection. In the application of fuzzy evaluation of residuals, natural or even necessary is the use of fuzzy reasoning at the stage of fault isolation.

4. INFERENCE UNCERTAINTY

4.1. Characteristics of the problem

The cause of false diagnosis might be, among others:

a) *false and uncertain symptoms*; The problem of uncertain symptoms was presented in Section 3. The other possibilities are the cases when false symptom is generated or the symptom is omitted (not observed when the fault is present).

b) *lack of knowledge of all possible faults during the design of DS*; In the practice, one can never be sure whether during the design phase of the DS all possible faults were taken into account. The occurrence of faults, for which the knowledge about the fault-symptoms relationship was not introduced, is then possible.
c) *incomplete or inaccurate knowledge about the fault-symptoms relation*; Besides the cases of erroneously entered knowledge about the diagnostic relationship, in industrial practice, one must deal with uncertain symptoms and uncertain (incomplete) knowledge about the fault-symptoms relation. It is particularly important during the first period of diagnostic system operation.

In general, the false symptoms (a), the occurrence of unknown fault (b) or the use of incomplete or inaccurate knowledge about the fault-symptoms relation (c) leads either to indication of other faults (indistinguishable with omitted in the case of unknown fault or just false ones in other cases), or to the occurrence of a combination of test results different from the pattern ones defined in the knowledge base, i.e. the observation of unknown process state.

Many of the above mentioned problems cannot be solved. However, the diagnostic system should provide algorithms that enable to take into account discussed uncertainties, i.e. make it possible to conduct proper (although less precise) inference despite the presence of uncertainties. The applied method of reasoning about faults on the basis of uncertain diagnostic signals and in the case of uncertain diagnostic relation has a significant impact on the robustness of the DS.

4.2. The methods providing robustness of inference to the diagnostic signals and diagnostic relation uncertainties

A combination of fuzzy residual evaluation and the application of fuzzy inference on the basis of rules determining the relationship between the faults and diagnostic signals is an efficient and simple approach (Korbicz et al., 2004; Kościelny and Syfert, 2006; Kościelny et al., 1999). The schematic of such an approach is shown in Fig. 4.

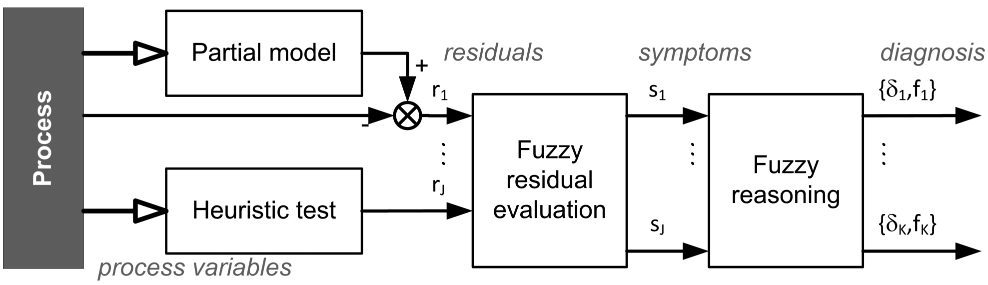

Fig. 4. The schematics of diagnosing with the use of fuzzy logic

In this case, the diagnosis points out faults f_k along with the degree of belief of their occurrence δ_k (Korbicz et al., 2004; Kościelny and Syfert, 2003, 2006):

$$\mathrm{DGN} = \{\langle \delta_k, f_k \rangle : \ \delta_k > G\} \tag{1}$$

while: δ_k denotes the degree of activation of the rule of the fault f_k occurrence, G is a threshold value of the degree of rule activation, at which the fault is indicated in the diagnosis, e.g. $G = 0.1$.

In the inference algorithm it is appropriate to calculate not only the certainty of existence of particular faults, but also the confidence of formulated diagnosis. This is possible if the PROD operator is used in the inference and the indistinguishable faults are combined into separate functional blocks and treated as one complex fault (Kościelny and Syfert, 2006). In this case, contradictory rules, i.e. rules with the same premises but different conclusions, are vanishing from rule base. The value of the sum of degrees of activation of all rules in the database is the measure of certainty of obtained diagnosis. Its value belongs to the interval [0, 1]. The more the value of the sum is closer to 1, the diagnosis is more reliable. A low value of the sum may indicate missing faults in the database or the observation of false values of diagnostic signals.

The measure of uncertainty of the diagnosis, and thus a measure of belief in the occurrence of another unknown system state, is the value of index μ_{US}:

$$\mu_{\mathrm{US}} = 1 - \sum_{m=0}^{M} \delta_{E_m} \tag{2}$$

where δ_{E_m} denotes the degree of activation of the rule corresponding to the subset of indistinguishable faults E_m in respect to given set of diagnostic signals.

Diagnostic inference algorithms corresponding to this approach were presented in (Korbicz and Kościelny, 2010; Korbicz et al., 2004; Kościelny and Syfert, 2006).

The calculation of the confidence of formulated diagnosis enables to solve the problem of lack of knowledge of all possible faults during the design of DS in the case when the occurrence of unknown fault causes the occurrence of a combination of test results different from the pattern ones defined in the knowledge base.

The application of fuzzy reasoning allows to take into account, aside from symptom uncertainty, the uncertainty of diagnostic relation. Kościelny and Syfert (2006) proposed the use of fuzzy diagnostic relation. This relation allows to introduce the uncertainty of experts' knowledge at the levels of: (a) single diagnostic rule, (b) each pair of diagnostic signal and fault $\langle f_k, s_j \rangle$, or (c) particular symptoms defined for each pair of diagnostic signal and fault $\langle f_k, s_j \rangle$. The general form of the rules of the knowledge base of such a system, in the case of binary diagnostic matrix (BDM), takes the following form:

$$\left[\begin{array}{c} \text{if } ([s_1 = v_{1,k}] \text{ with } \delta_{n,1}) \ldots \cap \big([s_j = v_{j,k}] \text{ with } \delta_{n,j}\big) \ldots \\ \cap ([s_J = v_{J,k}] \text{ with } \delta_{n,J}) \text{ then } (f_k) \end{array} \right] \text{ with } \delta_n; \; v_{j,k} \in \{0,1\} \tag{3}$$

where $v_{j,k}$ is a value of a diagnostic signal s_j in the state with fault f_k, δ_n is a believe factor of the n^{th} rule and $\delta_{n,j}$ is a believe factor of the pair $\langle f_k, s_j \rangle$ in the n^{th} rule.

The influence of the given above method of taking into account the uncertainty of diagnostic relation on conducted reasoning and formulated diagnosis was discussed in (Syfert, 2006).

This form of diagnostic relation notation allows to conduct the reasoning even in the case when experts' knowledge is incomplete and uncertain. Thus, it is possible to increase the robustness of inference mechanism in this way. In such a case, the conceived diagnosis is usually less precise but not false. It is extremely important in the case of diagnostics of complex processes.

5. CHANGES OF THE DIAGNOSED SYSTEM STRUCTURE

5.1. Characteristics of the problem

In the design phase of a DS, the following sets are determined: X – process variables (measured outputs Y and control signals U) used in the detection algorithms, S – diagnostic signals generated at the outputs of these algorithms, F – faults. The relationship between diagnostic signals and process variables used for their calculation is determined by the relation R_{XS}, while the relation R_{SF} expresses the sensitivity of the diagnostic signals to particular faults. In practice, the DS should not work with the sets: X, S, F, R_{XS}, R_{SF} but with their subsets that are dynamically modified during DS operation due to the variations of the diagnosed process structure. This is illustrated in Fig. 5.

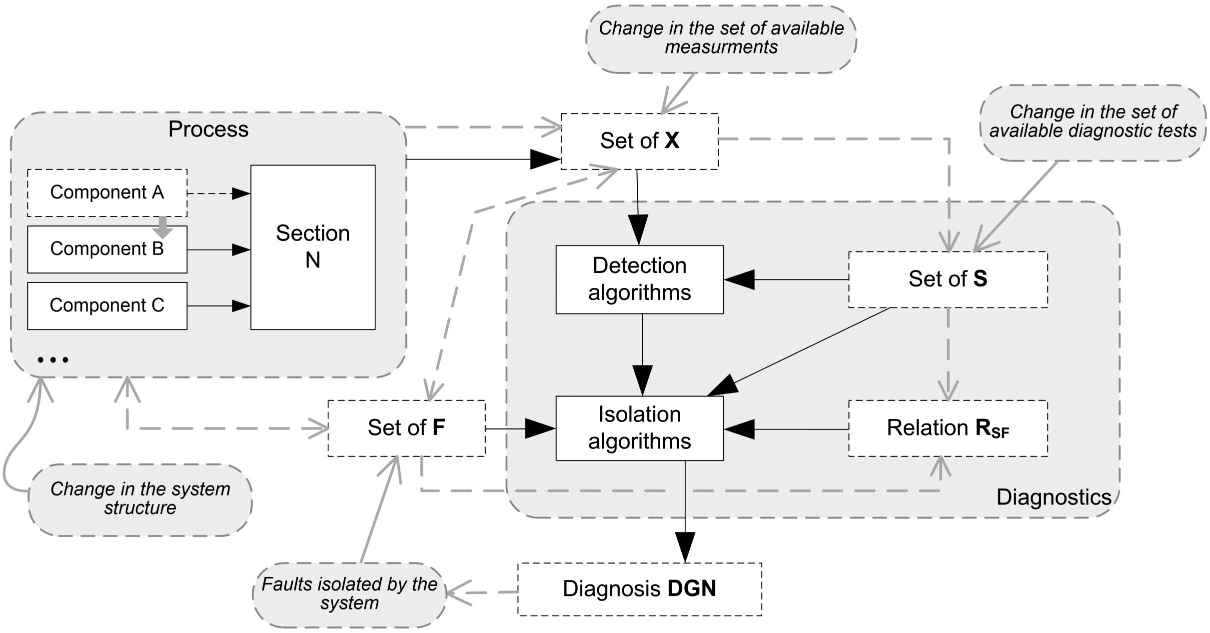

Fig. 5. Scheme of diagnosing with marked sets which are subject of changes during system operation

The variability of structure is caused by:

- temporary switching off and on of the technological apparatus,
- maintenance of devices,
- temporary disconnecting of instruments and actuators needed for their tuning,
- faults in technological components, instruments and actuators.

The variability of a set of implemented diagnostic algorithms and a set of calculated diagnostic signals S also results from the reconfiguration of the diagnostic algorithm. The results of detection algorithms that control pre-recognized faults become temporarily useless, i.e. cannot be used to formulate diagnosis. They cannot be used until restoration of the normal state of a particular part of the process.

As a consequence of the above-mentioned operations there is a need to adapt the diagnostic system by an adequate reduction of the sets: X, S, F and the modification of the relations: R_{XS}, R_{SF} to the relevant subsets directly used in the process of ongoing inference about the state of the process (Syfert and Kościelny, 2009a). DS for industrial processes must take this problem into account and effectively solve it. The ability to formulate correct diagnoses, despite the system structural changes, is the basic requirement for the robust DS.

5.2. The methods providing robustness of inference to the structural changes

The notation choice of fault-diagnostic signal relation, denoted usually as fault-symptom relation, is important in order to ensure DS robustness against the changes of the process structure. Various forms of notation of this relation are given in the works of (Isermann, 2006; Korbicz and Kościelny, 2010; Korbicz et al., 2004).

In case of binary evaluation of residuals this relation can take the form of: a logic function, diagnostic trees, binary diagnostic matrix, and rules of the forms:

$$\text{if } (s_1 = v_{1,k}) \ldots \cap (s_j = v_{j,k}) \ldots \cap (s_J = v_{J,k}) \text{ then } (f_k); \quad v_{j,k} \in \{0,1\} \tag{4}$$

or

$$\text{if } (s_j = 1) \text{ then } (f_a \ldots \vee f_n) \tag{5}$$

where $v_{j,k}$ is a value of a diagnostic signal s_j in the state with fault f_k.

Rules in the form given by Eq. (4) correspond to the columns, and the rules in Eq. (5) to the rows of a binary diagnostic matrix (Bartyś, 2014; Korbicz and Kościelny, 2010; Korbicz et al., 2004). Similar forms of notation are used in case of multi-valued residual evaluation. Here, the Fault Isolation System (FIS) (Korbicz et al., 2004; Kościelny and Syfert, 2003; Kościelny et al., 1999) is used. It is an extension of binary diagnostic matrix consisting in:

a) there can exist an individual set of values V_j for each diagnostic signal s_j,
b) the set V_j can be multivalued,
c) any element of FIS can contain a single diagnostic signal value as well as their subset.

In the case of FIS, the rules take the shape:

$$\text{if } (s_1 \in V_{1,k}) \ldots \cap (s_j \in V_{j,k}) \ldots \cap (s_J \in V_{J,k}) \text{ then } (f_k) \tag{6}$$

or:

$$\text{if } (s_j = v_{j,i}) \text{ then } (f_a \ldots \vee f_n) \tag{7}$$

where: $V_{j,k}$ is a subset of possible values of diagnostic signal s_j in the state with fault f_k, $v_{j,i}$ is the i^{th} value of diagnostic signal s_j.

The rule (7) corresponds to the subset of all faults $F(s_j = v_{j,i})$ that generate symptom $s_j = v_{j,i}$.

The robustness of DS against changes in the structure of the diagnosed process, including the changes in the set of properly operating measurement paths, plays a crucial role during choosing the form of notation of the fault-symptoms relation. The logical functions, diagnostic trees, binary diagnostic matrix and information system determined at the DS design stage are inflexible and not robust against changes of the process structure. Also the set of premises will change in the rules of type (4) and (6) if the set of available measurement signals changes. Furthermore, in the case of large-scale systems, where the number of tests is very large, the rules referring to the columns of the binary diagnostic matrix or information system are inconvenient because of the very large number of premises.

The robust method of notation of the diagnostic relation, in terms of possible changes in the process structure, is illustrated by the rules in the form (5) and (7) in which the subset of faults are assigned to the particular symptoms. This relation is invariant in respect to the changes of process structure or previously generated diagnoses. One only needs to eliminated temporary rules from the set of active ones. Moreover, such a rule has a compact form, since the number of possible faults indicated in the conclusion is not large, particularly in partial models used for fault detection. Such a form of a rule is also convenient when expanding the rule base after the introduction of new detection algorithms.

An effective method that allows easy adaptation of the inference system to the changes is the method of process dynamic decomposition (DDS – Dynamic Decomposition of Diagnosed System) (Kościelny et al., 2012). It is based on extracting a subsystem in which a fault is searched starting from the first observed symptom. A set of possible faults $F^1 = F(s_x = v_{x,i})$ is determined on the basis of the rule (5) or (7) describing that symptom. It contains the faults indicated in the conclusion part of this rule. Then, they are selected from the database rules, whose successors include faults from the set F^1. Such a subset of rules is used to recognize the process state. It unambiguously determines the set of diagnostic signals $S^1 = \{s_j \in S : F^1 \bigcap F(s_j = v_{j,i}) \neq \emptyset\}$ which will be used to formulate a diagnosis. Non-available diagnostic signals are eliminated from the set S^1. It usually reduces the fault distinguishability but protects against erroneous inference.

An example of the extraction of the subsystem of diagnostic relation initiated by the presence of the symptom $s_5 = 1$ is shown in Fig. 6. The corresponding rule has the form: if $(s_5 = 1)$ then $(f_5 \vee f_6 \vee f_7)$. The faults indicated in the rule's conclusion part are also present in the conclusions of the rules corresponding to the rows No. 3, 4, 6 and 8. Thus, only these rules will be used to formulate a diagnosis.

	f_1	f_2	f_3	f_4	f_5	f_6	f_7	f_8	f_9	f_{10}
s_1	1	1	1							
s_2		1	1							
s_3			1	1	1	1				
s_4		1				1				
s_5					1	1	1			
s_6						1	1	1		
s_7								1		
s_8						1			1	
s_9									1	1
s_{10}			1	1						

	f_5	f_6	f_7
s_3	1	1	
s_4		1	
s_5	1	1	1
s_6		1	1
s_8		1	

Fig. 6. The way of determining the subsystem of the diagnostic relation initiated by the occurrence of symptom $s_5 = 1$

The inference regarding faults in an extracted subsystem is an independent fault isolation thread that is usually run under the assumption of single faults. A set of available diagnostic signals, as well as a set of utilized diagnostic rules, should be reduced after working out a diagnosis by these diagnostic signals, which are sensitive to isolated faults. In fact, their values are determined by the present fault. They can be re-included into the set of available diagnostic signals after recognition of the recovery of the normal state of faulty component.

Multiple inference threads can be run in parallel mode. This relates to the recognition of multiple faults occurring in very small time intervals, i.e. simultaneous faults. The condition for correct inference conducted under the assumption of single faults, using DDS, is the disjointness of the diagnostic signal subsets used in different threads (Kościelny et al., 2012). If this condition is not satisfied, then the inference algorithm adapted to isolate multiple faults must be applied. Such algorithms are given in the works by (Kościelny, 1995; Kościelny et al., 2012).

6. SYMPTOMS DELAYS

6.1. Characteristics of the problem

The problem is that the same fault is not indicated simultaneously by various diagnostic signals. This can lead to false diagnosis. Additionally, when considering symptom forming delays it is possible to increase fault distinguishability and, in many cases, reduce the time of diagnosing. Robust DS should have the ability to formulate correct diagnoses despite existence of symptom delays.

6.2. The methods providing robustness of inference to the symptom delays

The problem of symptom delay was investigated in the works (Combastel, 2003; Daigle et al., 2005; Kościelny and Syfert, 2007; Kościelny, 1995; Meseguer et al., 2008; Pulido et al., 2005; Syfert and Kościelny, 2009). Assuming that the order of symptoms cannot be determined analytically due to the lack of the process models with influence of faults, the following solutions apply:

a) *The inference on the basis of symptoms* (Kościelny and Syfert, 2007). In this algorithm only the symptoms, i.e. non-zero values of diagnostic signals, are taken into account while the zero values of these signals are omitted. It means that the lack of a symptom does not exclude the faults that cause that symptom. However, this leads to a reduction of fault distinguishability. The greater number of possible faults is pointed out in the diagnosis than in the case when both zero and different from zero values of diagnostic signals are taken into account.

b) *The inference on the basis of symptoms taking into account known relations between the delays of different symptoms of the same fault*. The different values of diagnostic signals are not the only basis for distinguishing of faults. The order of symptoms appearance (symptoms sequence) can be also used. The inclusion of additional knowledge about symptom order can lead to an increase of fault distinguishability. The relation about symptom sequence can be defined, in some cases, intuitively based on knowledge of the process and applied detection algorithms. Much more reasonable solution is the use of a qualitative model of the process in the form of a TCG graph (Daigle et al., 2005) or GP graph with fault influence (Kościelny and Ostasz, 2003). An example of reasoning algorithm based on symptoms taking into account known relation between the delays of different symptoms of the same fault is given in (Syfert and Kościelny, 2009b). This work presents an extension and improvement of the inference algorithm based on symptoms. It is worth underlining that available and utilized knowledge about symptoms sequence does not need to be complete.

c) *The inference using the tests of the steady-state of the process*. The diagnosis is formulated just after the values of residuals are steady. The recognition of steady states for certain subsets of residuals is not a simple task.

d) *The inference using the maximum symptom delays* (Kościelny, 1995). The inference is based not only on symptoms, but also on the information about zero values of diagnostic signals, i.e. the lack of symptoms. Zero values of diagnostic signals are taken into account after a specified maximum time delay that is independently determined for each signal. The values of the maximal symptom delays must be determined on the basis of experts' knowledge. They are usually given in a safe manner, what extends the inference time.

e) *The inference taking into account the range of symptoms delays for each pair of fault-symptom* (Kościelny et al., 2008, Meseguer et al., 2008). This method is an extension of the method d). It allows to achieve greater fault distinguishability and shorten the time of diagnosing. However, it requires the introduction of knowledge about the range of symptom delays, which is difficult to determine.

The greatest practical importance among the above have the methods a) and b). The use of additional knowledge about the relationship between the delays of the pairs of different symptoms of the same fault (method b) allows to increase accuracy of diagnosing. The increase of the distinguishability is as great as complete the knowledge about the relationship between symptom delay.

7. MULTIPLE FAULTS

7.1. Characteristics of the problem

In the case of complex industrial installations multiple faults can be a serious problem due to the large number of devices and their limited reliability. Multiple faults can occur sequentially or simultaneously. The most difficult to recognize are the faults occurring at the same time. It might seem that, in practice, such a situation may occur very rarely in case of independent faults. However, as an example, it turns out, that this problem occurs practically in each start-up of the system diagnosing complex technological installation. In this case all existing faults are seen by the system as simultaneous.

The lack of multiple fault isolation mechanism can lead to erroneous functioning of the DS. Thus, the necessary condition to ensure robustness of the DS is to equip it with adequate algorithms of multiple fault isolation.

7.2. The methods providing robustness of inference to the multiple faults

The problem of multiple faults was the subject of many publications, but those works are usually not related to large-scale processes. AI method based on Reiter's theory (1987) (Cordier et al., 2000; de Kleer and Williams, 1987; Hwee, 1991; Nyberg and Krysander, 2003), also known as the method of model-based diagnosis (de Kleer and Kurien, 2003), allows to specify not only single faults but also multiple ones. The diagnoses are generated as minimal sets of intersections (hitting sets) of all minimal conflict sets. The advantage of this approach is a possibility to consider effects of residual compensation. However, the method was, so far, applied only for simple objects. It is not suitable, according to the authors, to diagnostics of large-scale industrial processes due to the complexity and high design costs. A new approach to multiple fault diagnosis, based on a combination of diagnostic matrices, graphs, algebraic and rule-based models, is given in (Ligęza and Kościelny, 2008).

If faults occur subsequently at intervals longer than the time needed to formulate subsequent diagnoses, the generated diagnoses assuming occurrence of the single faults are correct. However, it should be underlined, that after each diagnosis formulation a set of available diagnostic signals must be reduced by these signals, which are sensitive to detected fault (discussed in Section 5).

Kościelny et al. (2012) showed that both single as well as the majority of multiple faults can be effectively isolated assuming single faults if the reasoning algorithm uses the DDS method (see Section 5.2). It is important, because the assumption about single faults significantly simplifies the isolation algorithm.

Multiple inference threads used in DDS method can be run in parallel mode. It was shown that faults occurring simultaneously or within a short period of time will be isolated properly assuming single faults if the subsets of tests useful for their isolation are disjoint: $S_A^1 \bigcap S_B^1 = \emptyset$. Consequently, the subsets of faults in the separated subsystems are also disjoint. This means that separate reasoning threads connected with each of the dynamically separated subsystems may be carried out in parallel mode. A large reduction in the size of considered subsets of diagnostic relation in respect to the full binary diagnostic matrix can be observed. It reduces the computational effort to formulate diagnosis.

Diagnostic inference using the DDS method in case of multiple faults is illustrated in Fig. 7. On the basis of simultaneously observed symptoms $(s_{11} = 1)$ and $(s_{20} = 1)$ the subsets of possible faults are

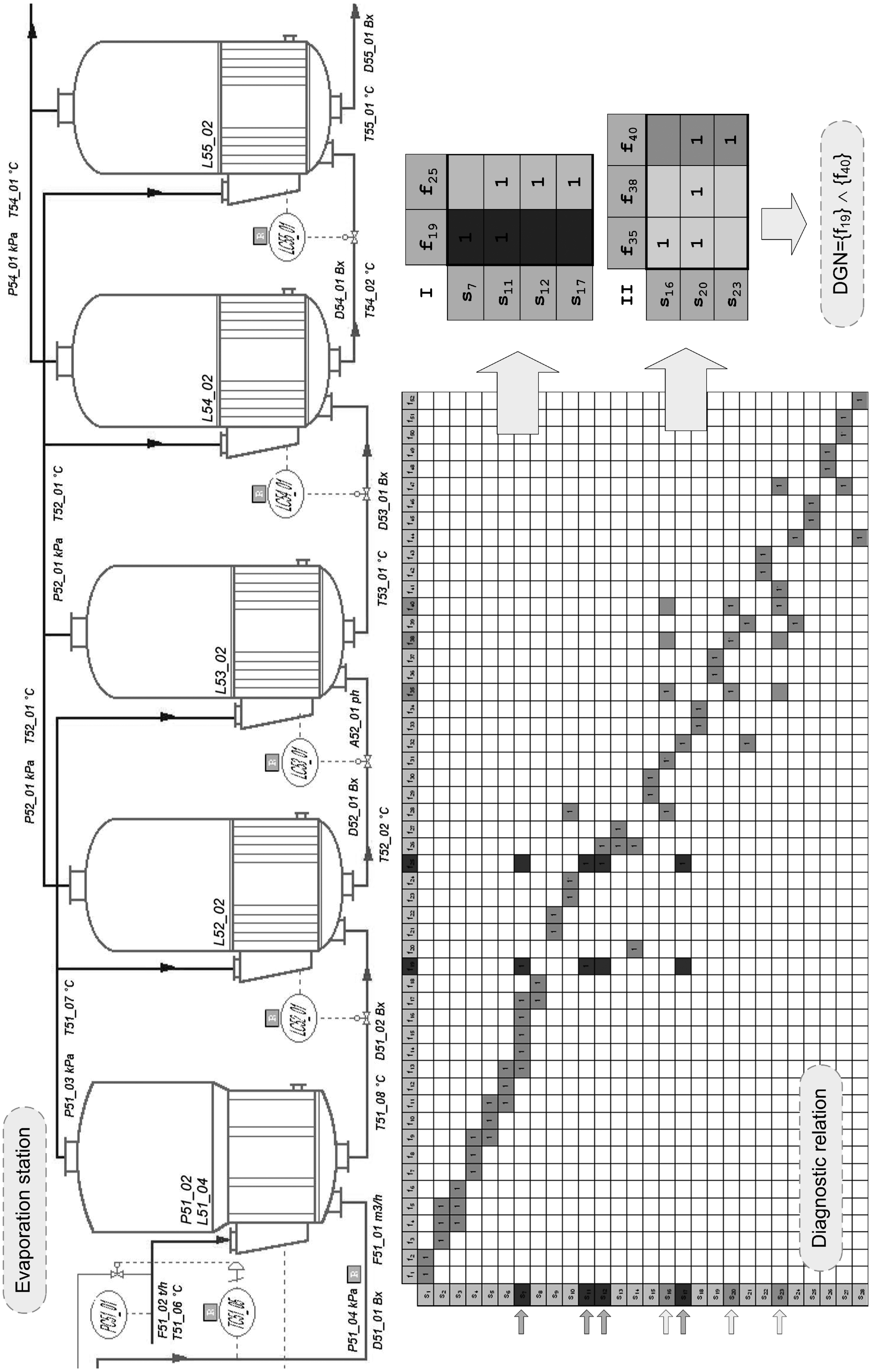

Fig. 7. The illustration of diagnostic reasoning for evaporation station with the use of DDS method

determined: $(s_{11} = 1) \Rightarrow F_A^1 = \{f_{19}, f_{25}\}$, $(s_{20} = 1) \Rightarrow F_B^1 = \{f_{35}, f_{38}, f_{40}\}$. Corresponding subsets of diagnostic signals: $S_A^1 = \{s_7, s_{11}, s_{12}, s_{17}\}$ and $S_B^1 = \{s_{16}, s_{20}, s_{23}\}$ are disjoint. Suppose that the symptoms $(s_7 = 1)$ and $(s_{23} = 1)$ occurred. Diagnosis formulated on the basis of separated subsets of diagnostic relations indicate faults f_{19} and f_{40}. Both simultaneously occurring faults were isolated in the separate inference threads conducted under the assumption of single faults. It should be noted that in the case of reasoning based on signatures of the single faults any of the faults can be recognized.

If the subsets of tests in separated subsystems are not disjoint, the process of reasoning should be carried out assuming double or in general, multiple faults. A subset of the diagnostic signals $S_A^1 \bigcap S_B^1$ is used to formulate a diagnosis. Diagnosis is formulated according to the following relation:

$$\mathrm{DGN} = \bigcup_{j:s_j \neq 0} F(s_j) / \bigcup_{j:s_j = 0} F(s_j) \tag{8}$$

where $F(s_j)$ denotes a subset of faults detected by the diagnostic signal s_j.

The approach pointing out the possible combinations of multiple faults was presented in the work (Kościelny et al., 2012). This approach is very efficient, i.e. significantly (by the order of tens of times) reduces the number of considered states with multiple faults and in consequence the computational effort.

8. CONCLUSIONS

In the diagnostics of industrial chemical processes there is a need to take into account the problems, that do not exist or are not important in case of simple systems. The paper deals with the five problems related to the implementation of on-line diagnostic systems intended for complex processes, including chemical and petrochemical ones. The ways how indicated problems influence the robustness of the inference consequently leading to the generation of false diagnoses were presented. It was shown, that the specificity of diagnostics of complex processes must be taken into account at the design stage as a necessary condition. It is the only way to obtain a diagnostic system, which is likely to be applied in real industrial conditions.

The general scheme of proceeding allowing to make a diagnostic system more robust were presented for each of the identified problems. The highlights of the proposed solutions are as follows:

- fuzzy reasoning allows to handle the uncertainties of symptoms as well as diagnostic relation (uncertainty of the expert knowledge),
- the proper form of notation of the diagnostic relations and the application of dynamic reconfiguration of the diagnostic system allow to respond flexibly to the changes of the process structure,
- there were shown the methods of making the diagnostic inference more robust despite symptom time delay,
- algorithms of dynamic decomposition allow, in many cases, to conduct correct inference in the case of multiple faults despite the assumption of single fault; Otherwise, it is necessary to apply the algorithm for multiple fault isolation.

The integration of all listed above solutions in one system is not an easy task. However, it is necessary for industrial applications. Most of the discussed methods were implemented in the diagnostic systems AMandD (Kościelny et al., 2006) and DiaSter (Korbicz and Kościelny, 2010; Syfert et al., 2011).

The pilot implementations demonstrated the effectiveness of these systems in the diagnostics of complex installations in the PKN Orlen refinery (Kościelny et al., 2011) and in the Lublin sugar factory (Syfert et al., 2005).

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