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A GRAPH THEORY–BASED APPROACH TO THE DESCRIPTION OF THE PROCESS AND THE DIAGNOSTIC SYSTEM

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The paper proposes an original, comprehensive, and methodically consistent graph theory-based approach to the description of the diagnosed process and the diagnosing system. The main baseline of the presented approach is in the dichotomous approach to diagnosing. It involves a separate description of both the process and the diagnostic system. This approach reflects the practice of designing implementable diagnostic systems. Thus, it can be seen as a proposal of a new, alternative, and, at the same time, flexible design procedure with great potential for applications. The primary motivation behind it was an attempt to circumvent the numerous limitations of well-known and well-established diagnosis approaches proposed by the communities working on fault detection and isolation (FDI) and artificial intelligence theories for diagnosis (DX). Accordingly, the paper identifies and provides an extensive discussion and a critical analysis of the existing limitations. Numerous examples and references to practical applications of the approach are indicated.

Keywords: graph of the process, graph of the diagnostic system, fault detection and isolation, qualitative models, limitations of diagnostic approaches.

1. Introduction

The role of diagnostics of dynamic systems is constantly increasing. It is expected that model-based diagnostic systems may soon replace commonly used but imperfect alarm systems. Diagnostics is extensively used in fault-tolerant control systems (Blanke *et al*., 2015; Mejdi *et al*., 2020; Hamdi *et al*., 2021). Moreover, the advanced diagnostics is an essential tool for the development of efficient and rational maintenance strategies.

Over the past forty years, many approaches, methods and frameworks have been developed to detect, isolate, and identify faults of dynamic systems. They are derived from automatic control, modeling and identification theories, and computational intelligence techniques. Descriptions of these can be found primarily in the monographs by Gertler (1998), Chen and Patton (2012), Blanke *et al*. (2015), Ding (2008), Isermann (2006), Witczak (2007), Korbicz and Kościelny (2010) or Bartyś (2014).

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The practical utility of diagnostic methods is often limited to a specific class of objects or systems. Each diagnosing method makes use of a model which, in fact, is a specific description of the diagnosed system. Such a model defines, collects, and expresses the knowledge necessary to make a diagnosis. Clearly, the design perspectives, limitations, and performance indices are strictly associated with the class of model chosen for diagnosing purposes. The potential applications are determined by the form and degree of knowledge about the diagnosed system, and in fact, are specific for the chosen diagnostic method.

Most diagnostic methods proposed within the FDI and DX communities have rather limited applicability, particularly when considered for the use for diagnosing complex dynamic processes. The limitations of the known methods will be discussed in more detail in Section 2. One might even to say that there is no diagnostic method that is free from at least one limitations listed below:

- the requirement of using only a specific type of models (usually analytical),

- the use of only binary evaluated residuals,
- neglecting the knowledge about sequences of symptoms,
- the requirement of models reflecting impacts of faults,
- the requirement of data representing states with faults,
- a limited set of faults considered,
- a limited multiplicity of faults considered.

In order to eliminate the aforementioned limitations, a holistic graph-based approach has been proposed to the description of the diagnosed process and the diagnosing system referred to as FDPS (fault diagnostics of processes and systems). A model FDPS represents the portion of knowledge used for diagnosing, rather than specification of the diagnostic algorithms. The FDPS consists, first of all, of a graph model of the diagnosed process, GP, and a graph model of the diagnostic system, GDS. Clearly, various diagnostic algorithms can be derived from the FDPS.

This paper is aimed to present the essential elements of the FDPS approach and to demonstrate its application properties with respect to the diagnosis of complex dynamic systems.

The FDPS can be seen as an extension of the family of FDI methods. Its elements and subsequent extensions have been the subject of many publications. However, holistically it has never been presented before. Also, the comparison with other methods has not been the subject of any publication yet.

The goal of the ongoing research works, the results of which are summarized in this paper, was to seek an approach that:

- enables the use of various models for fault detection (depending on the knowledge possessed about the diagnosed system and the availability of inputs),
- makes use of models representing the fault-free state of a system being diagnosed,
- does not require measurement data representing the states of the diagnosed system affected by faults,
- enables the use of trinary diagnostic signals,
- enables diagnostic inference which also makes use of the knowledge of sequences of symptoms,
- enables inference about single and multiple faults,
- makes it possible to obtain high distinguishability of faults,
- makes it possible to ensure immunity to the diagnoses which are inconsistent with the physical state of a diagnosed system.

Summing up, the paper contributes to the field of fault detection and isolation by presentation of an original and comprehensive graph-based approach to the formalized description of the diagnosed process and diagnostic system, together with a review of their applications.

The rest of the paper is structured as follows. Section 2 presents the analysis of the most significant limitations of the known approaches. The conducted analysis is the starting point for the proposal of the FDPS graph approach which is presented in Section 3. This Section presents a graph description of the diagnosed process and the diagnostic system. Applications based on the introduced description are presented in Section 4. The following are presented: selection of model structures for fault detection, determination of fault–symptom relationships, analysis of fault detectability and distinguishability, selection of sensors, methods of system decomposition, principles of derivation of inference rules, real-time decomposition, and principles of managing structural changes in the diagnosed system. Section 5 presents the basic properties of the proposed approach. Section 6 is devoted to a comparative analysis of the proposed solution with other known methods. The summary in Section 7 highlights the most important key-points of the paper.

2. Limitations of known diagnostic methods

2.1. Limitations in the usage of some models. The formal model of the system in the FDI (fault detection and isolation) approach (Cordier *et al.*, 2004; Travé-Massuyés, 2014b) has been defined as a pair $\langle Z, X\rangle$, in which Z is the set of input and output process variables, and X is the set of its internal states. The equation associating the residuals with the values of the measured or control variables is referred to as the residuum generator (Travé-Massuyés, 2014a) or analytical redundancy relations (ARRs) (Cordier *et al.*, 2004). The following techniques are used for fault detection:

- state estimation methods (Frank, 1987; Xu *et al.*, 2017; Rotondo *et al.*, 2021),
- parity space methods (Chow and Willsky, 1984; Gertler, 1998; Patton and Chen, 1991; Odendaal and Jones, 2014; Cho and Jiang, 2019; Song *et al.*, 2020),
- parameter estimation methods (Isermann, 1984; Zhai *et al.*, 2015).

In practice, linear models are mainly used. The reason is in the serious difficulties of obtaining nonlinear analytical models.

The formal description of the system in the artificial intelligence theories for diagnosis, abbreviated as DX (Reiter, 1987; de Kleer and Williams, 1987; de Kleer and Kurien, 2003; de Kleer, 2011; Rodler, 2020), includes a set of system components, a description of their operation (the system description), and a collection of observations OBS. The system description takes the form of a set of sentences of the first-order predicate logic. The DX approach assumes the use of analytical models, and excludes the use of data-driven ones.

There are also known diagnostic methods based on data-driven models. They use statistical models (PCA, PLS) (Qin, 2012; Ding, 2014; Jung, 2020; Jakobsson *et al.*, 2020), additive models (Łabęda-Grudziak and Lipiński, 2021) or artificial intelligence models: neural, fuzzy, their combinations, etc. (Patan, 2008; Mrugalski, 2014; Witczak, 2014; Simani *et al.*, 2018; Pulido *et al.*, 2019; Mur *et al.*, 2022; Romero *et al.*, 2022). Such models require training data from the fault-free state of the diagnosed system. They reflect the operation of the system in a range of input variability which was used for training.

The need to use various process modelling techniques for the purpose of fault detection was a requirement imposed on the FDPS approach.

2.2. Use of binary diagnostic signals. Most model-based diagnostic methods use binary evaluation of residuals. As a result, the so-called binary diagnostic signals are then used for inference of faults both in the FDI and DX diagnosing approaches. The relationship between the faults and binary diagnostic signals is defined as the fault signature matrix (Cordier *et al.*, 2004; Travé-Massuyés, 2014b; Jung *et al.*, 2018).

In the structural analysis (SA) (Blanke *et al.*, 2015; Krysander, 2006; Frisk and Krysander, 2007; Travé-Massuyés *et al.*, 2006; Chanthery *et al.*, 2020; Jung, 2020) the system is modelled as a set of components.

The SA is used, among others, for solving the sensor placement problem, as well as for seeking the structures of models for fault detection and isolation tasks. Each component is described by a set of equations representing its state in normal operation conditions. Faults are understood as disturbances of specific equations, but indeed they are not directly represented in the model. The derived residual equations are interpreted as residual generators. The residuals are usually evaluated in a bi-valued manner. A structure corresponding to the signature matrix is used for fault isolation. Such a structure is referred to as the effect of the faults on the residuals (Blanke *et al.*, 2015).

The binary representation is also present in the DX approaches. The concept of a conflict set was introduced by Reiter (1987), de Kleer and Williams (1987), de Kleer and Kurien (2003), Travé-Massuyés (2014b) and Rodler (2020). It is interpreted as a subset of system components; at least one of which must be faulty, in order to keep a consistency with observations.

An alternative solution is the tri- or multivalued residual evaluation (Vanden-Daele *et al.*, 1997; Kościelny, 1999; Bregón *et al.*, 2014; Daigle *et al.*, 2009; Kościelny *et al.*, 2021c; Kościelny and Bartyś, 2021). In this case, the relationship between faults and diagnostic signals takes the form of a fault isolation system (FIS). The FIS was intensively exploited by Kościelny *et al.* (2016) as well as Kościelny and Bartyś (2021).

The use of three-valued estimation of residuals, in contrast to the bi-valued one allows us to achieve better fault distinguishability (Bregón *et al.*, 2013; Kościelny and Bartyś, 2021; Kościelny *et al.*, 2021b). Moreover, application of binary evaluation of residuals may lead to generation of diagnoses that are if fact unrealistic. In other words, it can also generate incorrect diagnoses of physically impossible states. This was demonstrated by Kościelny and Bartyś (2021). Thus, in order to obtain high distinguishability of faults and robustness of inference of faults, it was assumed that the FDPS should enable the use of multivalued diagnostic signals.

2.3. Neglecting information of symptoms sequences. The vast majority of diagnostic inference methods, including those developed in the FDI and DX, make only use of the current values of process variables and the knowledge of the relationship between faults and diagnostic signal values. However, as shown by Kościelny *et al.* (2021c), it is advisable to take also into account the knowledge about the timed order (sequence) of symptoms. This knowledge can be used for increasing fault distinguishability. The FDPS approach assumes the possibility of using such knowledge as far as it is possible to be acquired.

2.4. Requirement of models reflecting the impacts of faults. Many mathematical descriptions of processes affected by faults are provided in the literature (Frank, 1990; Chen and Patton, 2012; Witczak, 2007; Pazera *et al.*, 2020; Witczak *et al.*, 2020). Usually, simplified linear residual equations are used for diagnosing. The computational form of these equations is used for fault detection purposes. It determines the relationship between the residuals and the known inputs and outputs of the model. In turn, the internal form reflects the relationship between residuals and faults. Various forms of notation of this relation are used, such as structural and directional residuals (Gertler, 1998; Chen and Patton, 2012) or sequential residuals (Kościelny *et al.*, 2016). Approaches based on unknown input observers are also widespread (Chen and Patton, 2012). All of these methods allow for the design of secondary residuals based on primary ones, in such a way as to shape the sensitivities of the residuals to different subsets of faults.

However, the applicability of these approaches is limited, as the modelling of the process affected by faults is very difficult and expensive even for simple systems. For complex industrial systems it is almost impossible. The nature of some phenomena occurring in industrial processes is not fully known. For example, there are not known models of such phenomena as emissions of toxins in conventional power plants or biomass combustion. Attempts to build such complex models can only be economically justified in the case of critical installations.

Therefore, in the FDTS it was assumed that only those model based fault detection methods will be used which represent fault-free states of the diagnosed processes.

2.5. Assumption of the availability of data representing faults. In industrial processes, measurement data representing states with faults are practically unavailable. The number of possible faults is excessively large and, moreover, the abnormal and emergency states are rare. Big sets of process data are available in the databases of contemporary control and process monitoring automation systems. But most archive data are related to the states of normal process operation and few are registered for abnormal and emergency states. On the other hand, diagnostic systems require recognizing faults that occur for the first time. This limits the use of many known diagnostic methods that assume the availability of data from the abnormal (faulty) system states. For example, the classification methods that require training data for particular states of the process become useless.

The fault isolation in the FDPS approach is carried out based on automatic inference approaches. Therefore, the knowledge about the relationship between a fault and its symptoms is designed based on expert knowledge, rather than on process data.

2.6. Limitation of the set of faults. In all FDI methods, three main types of faults are considered: the process component faults F_C, the actuator faults F_U, and the instrument faults F_Y. However, many known diagnostic methods assume only one type of faults, presuming that the others do not occur. Known examples of diagnostic schemes are: instrument fault detection (IFD), actuator fault detection (AFD), and component fault detection (CFD). Also, a limited set of faults is considered in many publications. For example, in the work of Taheri *et al.* (2020) sensor and actuators faults, as well as cyber attacks, are analyzed, but the occurrence of component faults is ignored.

In each of such cases, the question arises on how the diagnostic system will react when the faults omitted at the design stage appear in reality. Such approaches seem to be significant simplifications and therefore their practical usefulness is very limited.

In the FDPS, the possibility of any kind of faults is assumed and not excluded.

2.7. Limitation of the multiplicity of faults. The FDI approaches initially considered only single faults. In contrast, the formal description of the system in the DX approach is faultless. Faults are principally identified with elements in the COMP set. Although, there are known modifications of this approach, which consist in modelling faults through various modes of operation of a given component (Jung *et al.*, 2015). The assumption about single faults is not applied. The diagnoses are generated as minimal hitting sets (HSs) of all observed minimal conflict sets and indicate not only single but also multiple faults. The HS tree algorithm is used for fault isolation (Reiter, 1987; Greiner *et al.*, 1989; de Kleer, 2011).

Limiting the inference to consideration of only single faults is unacceptable in the case of complex systems. Therefore, in the FDTS, both single and multiple faults are being analyzed.

3. FDPS approach

3.1. GP graph as a qualitative model of the process. The directed process graph GP is a qualitative model describing the cause–effect relationships between process variables including effects of faults. An application of the GP to design model structures was given by Sztyber *et al.* (2015). The directed GP graph is an extension of the well-known signed directed graph (SDG), which is used to represent causal relationships between process variables or alarms (Iri *et al.*, 1979; Yang *et al.*, 2010). The GP extension is in including faults into graph.

The vertices of the GP graph represent the variables. The arcs reflect the impact of the variables on one another. The set of all variables characterizing the system will be denoted by X. In this set the following subsets can be distinguished:

$$X = X_U \cup X_D \cup X_X \cup X_Y, \tag{1}$$

where X_U is the set of control variables, X_D stands for the set of the inputs of unknown values (disturbances), X_X means the set of internal variables (not measured), X_Y signifies the set of output variables (measured).

The control system generates signals $u \in U$; in the case of the fault-free communication channel (Fig. 1(a)) they are equal to the actual control signals $x \in X_U$.

All variables in X_Y are measured. The set of measured signals Y is therefore as large as the set X_Y, and the values of the corresponding elements in these sets are consistent (taking into account the uncertainty of measurements) in the case of fault-free measurement paths (Fig. 1(b)).

The set of faults F includes control path faults F_U, component faults F_C and instrument faults F_Y,

$$F = F_U \cup F_C \cup F_Y. \tag{2}$$

In addition, we will assume, that the process is affected by disturbances D whose values are unknown. The set of values V describing the diagnosed system can therefore be represented by the union of the disjoint subsets,

$$V = U \cup Y \cup X \cup F \cup D. \tag{3}$$

From a formal point of view, a GP graph is a weighted version of Berge's directed unigraph without loops. It can be written as follows:

$$GP = \langle V, A, \phi \rangle\,, \tag{4}$$

$$A \subset \langle V \times V \rangle\,, \quad |V| = n, \quad |A| = m, \tag{5}$$

where V is the set of vertices, A is a bipartite relation defined on the set of vertices being a set of ordered pairs $\langle v_i, v_j \rangle \in V \times V$ representing graph arcs, $\phi : A \to \{+, -, \pm\}$ is a function specifying the sign of the interaction along a given arc.

In a GP, several subgraphs can be separated based on the type of vertices. Figure 2 shows such a separation and defines mutual relations between subgraphs.

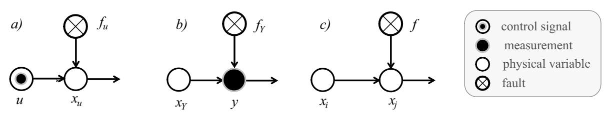

Fig. 1. Representation of the impact of faults in a GP graph.

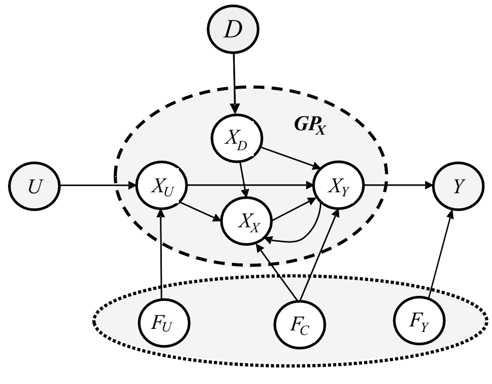

Fig. 2. GP graph structure.

A subset X of the GP graph vertices forms a subgraph GP_X representing the relationships between the variables:

$$\mathrm{GP}_X = \langle X, A_X \rangle\,, \quad A_X \subset \langle X \times X \rangle\,. \tag{6}$$

Here, the partial process models represent the nominal state of the part of the diagnosed system. Therefore, they do not reflect the impacts of faults F and disturbances D. The partial models are used for the generation of residuals which are indicative to faults when their values deviate from zero.

Examples of GPs were presented for a set of serially interconnected tanks (Sztyber *et al.*, 2015; Kościelny and Sztyber, 2018), a distillation column (Sztyber *et al.*, 2015), and a setup of four serially connected pressure vessels (Kościelny *et al.*, 2019).

3.2. Model structures. The model structure is defined (Sztyber *et al.*, 2015) as the pair

$$M = \langle o, I \rangle\,, \quad o \in X_Y, \quad I \in X \tag{7}$$

containing one output o and a set of inputs I that satisfies the following conditions:

- for each $i \in I$, there exists a path from input i to output o, which does not contain any other vertex from the set I,

- for each vertex $v \in \mathrm{GP}_X$ there exists a path from some $i \in I$ to v if there exists a path from v to o, which does not contain vertices from the set I.

The first condition ensures that each input of the model has an effect on the modelled variable and this effect cannot be described by other variables in the set I. In contrast, the second condition ensures that the modelled variable is completely described by the set of inputs.

Each model structure corresponds to a subgraph in GP_X. A model structure is identifiable if the values of all input and output signals are known. Thus, the inputs $i \in I$ must be known as well as control or measured signals belonging to the set X_Y. Also, the variable being modelled must be measured, so that $o \in X_Y$. Obviously, the control signals $u \in U$ and measured signals $y \in Y$ are taken for identification of model structures. The identified model structures are thus subgraphs in the GP.

Further, the set of model structures which will be chosen for implementation in diagnosing system is determined based on the GP graph. The method of determining all model structures is given by Sztyber *et al.* (2015). For each model structure, a test algorithm is specified. It contains two parts: the first related to the model-based residual generation and the second related to decisive part.

Various types of models can be used to generate the residuals. Also, the test algorithms can use models based on data acquired from the normal state of the system. However, in our opinion, these should be nonlinear models because only such models are useful in diagnostics of industrial process. The set of all Z variables used for fault detection includes control signals U and measurement signals Y,

$$Z = U \cup Y = \{z_i : i = 1, \ldots, I\}. \tag{8}$$

The residual is understood as the difference between the modelled and measured variables or as the difference between the left and right-hand sides of the equation describing the part of the system being tested. The latter case applies to analytical models that include the output signal.

The decisive part of the test algorithm includes an algorithm for evaluating (classifying) the residual value. Various approaches can be used for this: binary or multivalued, crisp or fuzzy, based on the instantaneous value of the residual or averaged over a sliding window. All these approaches can be used to describe and implement in the diagnostic system (DS). However, the fuzzy trinary residual evaluation is preferred due to the ability of reduction in the number of false diagnoses and enhanced fault distinguishability figures. The result of the selection of a set of model structures, in terms of the required fault detectability, distinguishability, and model identifiability is a set of residuals

$$R = \{r_j : j = 1, \ldots, J\}. \tag{9}$$

Tests are performed periodically in the DS in order to detect emerging faults.

3.3. Graph model of the diagnostic system.

The graph model of the diagnostic system GDS presented in this section is a result of many works. However, in the present form it has not been presented in any publication yet.

The residual values are calculated in the course of the operation of the DS. The j-th diagnostic test generates a diagnostic signal s_j. As a result of all tests, we obtain a set of diagnostic signals S (crisp or fuzzy):

$$S = \{s_j : j = 1, \ldots, J\}. \tag{10}$$

A relation R^{SZ} can be defined on the Cartesian product of the sets S and Z:

$$R^{SZ} \subset S \times Z. \tag{11}$$

The expression $\langle s_j, z_i \rangle \in R^{SZ}$ means that the value of the process variable z_i is used by the j-th test to generate the diagnostic signal s_j. Define a bipartite graph

$$G^{SZ} \subset \left\langle S, Z, R^{SZ} \right\rangle \tag{12}$$

whose set of vertices consists of diagnostic signals S and process variables Z. The set of edges of the graph is described by the relation R^{SZ}.

The diagnostic system should detect and isolate the set of faults

$$F = \{f_k : k = 1, \ldots, K\}. \tag{13}$$

The sensitivity of diagnostic signals to faults can be determined by a relation defined on the Cartesian product of the sets S and F,

$$R^{SF} \subset S \times F. \tag{14}$$

The expression $\langle s_j, f_k \rangle \in R^{SF}$ means that the signal s_j is sensitive to the fault f_k, i.e., the fault f_k affects the value of the signal s_j. The ordered vector of diagnostic signal values corresponding to a given fault forms the binary signature of that fault. Signatures of all faults constitute the fault signature matrix (FSM). In the case of the binary evaluation of residuals the diagnostic signal is equal to 1 if $\langle s_j, f_k \rangle \in R^{SF}$, otherwise it is set as 0.

For the trinary residual evaluation, we assign the following function to the graph arcs represented by the relation R^{SF}:

$$\Theta : R^{SF} \to \{1, -1, +1, c\}, \tag{15}$$

where $\Theta(s_j, f_k) = 1$ corresponds to binary and the other values to trivalued diagnostic signals; $\Theta(s_j, f_k) = -1$ means that a fault f_k results in a negative value of the diagnostic signal s_j while $\Theta(s_j, f_k) = +1$ results in a positive value; $\Theta(s_j, f_k) = c$ indicates the possibility of both negative and positive values.

Thus, the function Θ assigns weights to the arcs of the graph G^{SF} representing the fault symptoms. Therefore, the relationship (15) can be represented as a directed weighted graph G^{SF}. The set of vertices of this graph contains sets S and F. The set of directed arcs running from faults to diagnostic signals is determined by the relationship between these sets. In turn, the signs of the impacts of faults on diagnostic signals are determined by the function Θ. We have

$$G^{SF} = \left\langle F, S, R^{SF}, \Theta \right\rangle, \tag{16}$$

Trivalued evaluation of residuals may be considered a special case of multivalued evaluation. This corresponds to the fault isolation system (FIS) by Kościelny *et al.* (2016; 2021c). The FIS is an array structure that assigns specific reference values of diagnostic signals to all faults considered. Each diagnostic signal can have its own individual set of values V_j. The k-th fault signature corresponds to a FIS column. It is defined by the relation

$$V(f_k) = [V_{1k}, V_{2k}, \ldots, V_{Jk}]^T. \tag{17}$$

Thus, in the graph model, we allow each residual to be evaluated either as binary or trinary. In the case of binary evaluation, the set of values of the diagnostic signal is $V_j = \{0, 1\}$, and in the case of the trinary evaluation $V_j = \{0, -1, +1\}$. The zero value always corresponds to the lack of the sensitivity of the diagnostic signal to the fault i.e., the case where a residual value is close to zero. In the graph model, there is no arc linking the fault vertex to the diagnostic signal vertex in this case. The other values different from zero are considered as symptoms of faults. The union of the graphs G^{SZ} and G^{SF} results in a graph whose set of vertices contains the sets Z, S, F, and its set of arcs is defined by the relations R^{SZ}, R^{SF} and the function Θ. Such a graph will be called the graph of the diagnostic system (GDS):

$$\mathrm{GDS} = \left\langle Z, S, F, R^{SZ}, R^{SF}, \Theta \right\rangle. \tag{18}$$

A GDS for a steam superheater and an attemperator was presented by Kościelny and Sztyber (2018) along with the version for the three-tank system. This paper proposes extension of the graph description by signs of impacts of variables and faults.

The GDS does not refer immediately to the components of the diagnosed system. However, they can be introduced for design purposes. The level of detail in distinguishing between components can vary depending on the design needs. For example, instruments can be treated as separate components or can be parts of more complex units. In the latter case, each element c_n in the component set $C = \{c_n : n = 1, 2, \dots, N\}$ is associated with a subset of measurement devices Y_n and a subset of faults F_n. Each component is represented in the GP as its subgraph.

3.4. Sequences of symptoms. The relationship between faults and diagnostic signals given in the form of an FSM or an FIS does not contain any information on the order of symptoms related with particular faults. The knowledge of this order is informative and can be used to distinguish between faults. The symbol $\mathrm{es}_{j,p}(f_k) = \langle s_j, s_p \rangle$ denotes the so-called elementary sequence, i.e., the sequence of two symptoms j and p specific for fault f_k (Kościelny *et al.*, 2021c). The notation $\langle s_j, s_p \rangle$ means that symptom s_j will occur before symptom s_p.

Different symptom sequences may be characteristic for faults that are indistinguishable on the grounds of diagnostic signals. Thus, it is sufficient for distinguishing a pair of faults if at least any pair of symptoms for these faults is different: $\mathrm{es}_{j,p}(f_k) = \langle s_j, s_p \rangle$, $\mathrm{es}_{j,p}(f_n) = \langle s_p, s_j \rangle$.

However, it is usually not possible to unambiguously determine the order of symptoms for all faults. Thus, the knowledge obtained in this way is usually incomplete. The greater the increase in fault distinguishability, the more complete the knowledge of the relationships between symptom delays (Kościelny *et al.*, 2021c). The set of known elementary sequences used for fault isolation is

$$\mathrm{ES} = \{\mathrm{es}_{j,p}(f_k) = \langle s_j, s_p \rangle\}, \quad f_k \in F, \quad s_j, s_p \in S. \tag{19}$$

The FDPS does not require knowledge of a mathematical model of the diagnosed system. It is based on a qualitative model, which can be determined based on expert knowledge. The impact of faults, as well as causal relationships between variables are represented in the GP, while the GDS defines the relationships between process variables, diagnostic signals and faults.

4. FDPS applications

A schematic use of the FDPS approach is shown in Fig. 3. It demonstrates the use of the FDPS both in the design phase and by the real time implementation.

It should be mentioned that a detailed discussion of all applications of the FDPS approach is beyond the scope of this paper. A selection of chosen applications will be briefly characterized along with an indication of the publications in which they were presented.

4.1. Selection of model structures. Sztyber *et al.* (2015) provide a method for determining the structures of all models that can be used for fault detection and isolation. It includes the following steps: searching for and connecting strongly consistent components of the graph, topological sorting of vertices, searching for model structures, and choosing models which contain more than one vertex belonging to one strongly consistent component. For each model structure, an appropriate model, i.e., analytic, fuzzy, neural, additive or other, can be developed and used for fault detection.

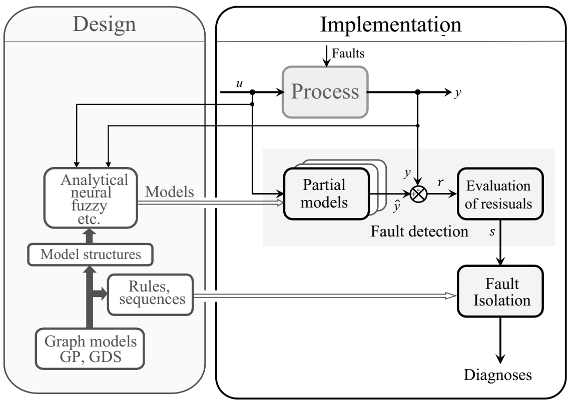

Fig. 3. Scheme of diagnosing with the FDPS approach.

4.2. Determination of the fault–symptom relationship. Based on the GP, also the sensitivity of model structures to faults can be determined (Sztyber *et al.*, 2015). A model structure is sensitive to fault affecting the modelled variable if there is a directed path leading from the fault to the variable. FSMs can be specified for the structures intended to be implemented in a diagnostic system. Trivalued signatures results from the G^{SF} (16). They have been used, among others, by Kościelny *et al.* (2021a) or Kościelny and Bartyś (2021).

4.3. Deriving elementary sequences. The GP is useful for supporting expert knowledge when analyzing the sequences of fault symptoms. The sequence of symptoms sometimes follows directly from the GP, as shown by Kościelny *et al.* (2016).

4.4. Detectability analysis. Fault detectability analysis can be performed based on both the GP and the GDS. A fault is detectable in terms of a GP if there is at least one diagnostic signal (one model structure) sensitive to that fault (Sztyber *et al.*, 2015). Detectability can also be derived from the GDS. Sensitivity of a diagnostic signal to a given fault means that there exists an arc connecting the fault and diagnostic signal vertices. This corresponds to the existence of at least one non-zero value in the fault signature.

4.5. Distinguishability analysis. The fault distinguishability analysis for binary diagnostic signals is possible with the GP. Two faults f_1 and f_2 are distinguishable in terms of the GP if both are detectable and there is a model structure sensitive to f_1 and insensitive to f_2 or sensitive to f_2 and insensitive to f_1 (Sztyber *et al.*, 2015). However, it is more convenient to conduct the distinguishability analysis based on the GDS. It makes it possible to consider multivalued residuals, and thus to identify not only subsets of distinguishable and indistinguishable faults, but also pairs of conditionally distinguishable faults (Kościelny *et al.*, 2016). Taking into account sequences of symptoms, we are able to assess the obtainable fault distinguishability (Kościelny *et al.*, 2021c).

4.6. Selection of sensors. Frequently the set of instruments installed for technological reasons is insufficient to provide the assumed distinguishability of faults. If it is the case, the question arises as to which instruments should be added to improve the distinguishability and/or whether it is possible to distinguish all faults. These questions should be answered during the design phase. Sztyber (2017) presents a method for selecting a set of sensors based on a GP that satisfy certain requirements regarding fault detectability and distinguishability. Fault detectability and distinguishability requirements are meant as a diagnostic specification containing a set of faults to be detected and a set of pairs of faults which are distinguishable from each other. Here, only single faults are considered.

4.7. Decomposition of the process and diagnostic system. Kościelny and Sztyber (2018) use a GP to divide the process installation into a finite number of subsystems (defined by the number of process variables and faults). On the other hand, a GDS, i.e., a tripartite graph of diagnostic system was used to assign subsets of tests, and thus subsets of diagnostic signals, to the separated diagnostic subsystems in such a way as to minimize the links between them. The decomposition ensures minimization of interdependencies between subsystems, thereby reducing, among other things, the need for mutual exchange of information between them.

4.8. Determination of inference rules. The FSM or FIS used for fault isolation can be determined based on G^{SF} (16). Inference can be carried out using both rules corresponding to the fault signatures and rules representing FSM or FIS rows. In the case of multivalued residual evaluation, the complex signature (17) corresponds to a rule of the form:

$$\text{if } (s_1 \in V_{1,k}) \wedge \cdots \wedge (s_J \in V_{J,k}) \text{ then } f_k. \tag{20}$$

Such a rule can be decomposed into a set of simple rules. The number of such rules is determined by the number of possible combinations of the values of the diagnostic signals in each test. This allows for specifying the rules corresponding to the rows for the FSM or the FIS. In the case of the FSM, there is a single rule. For the FIS and trinary diagnostic signals, we obtain

$$\begin{aligned} &\text{if } (s_j = -1) \text{ then } f \in F\,(s_j = -1)\,, \\ &\text{if } (s_j = +1) \text{ then } f \in F\,(s_j = +1)\,, \end{aligned} \tag{21}$$

where $F(s_j = -1)$ and $F(s_j = +1)$ are subsets of faults for which the diagnostic signal takes the value $s_j = -1$ or $s_j = +1$. Inference becomes more complex when elementary symptom sequences (19) are added. An inference algorithm based on trinary evaluated residuals and the knowledge of elementary sequences is given by Kościelny *et al.* (2021c).

4.9. Decentralized diagnosis. Diagnosis algorithms in single-level and two-level decentralized structures based on the FDPS approach and fuzzy logic are presented by Syfert *et al.* (2018).

4.10. Supporting HAZOP analysis. HAZOP is a part of risk assessment analysis focussing on how the system deviates from the intended operation. In this respect, in the paper by Kościelny *et al*. (2017), a qualitative process description in the form of a GP was applied. The GP was used to find out the causes of parameters deviations. In a classic HAZOP analysis, the connections between nodes may not be considered, especially in the case when there are internal process feedbacks. The use of a GP increases the probability of considering all hazards, due to the explicitly defined links between nodes.

4.11. Alarm-based diagnostic design. The GP is also useful for designing alarm based fault inference rules. It also makes it possible to reduce the number of alarms that are signaled to process operator. However, these issues have not yet been the subject of publications.

5. Properties of the FDPS

The FDPS approach exhibits the following properties:

- It allows the use of different types of partial models representing the fault-free nominal state of a diagnosed system. Among others, the analytical, neural, fuzzy, and additive models can be used for fault detection. In addition, it does not require any analytical models unlike several other approaches. These can be used of course, but this is not necessary. The graph description proposed in the FDPS may be based exclusively on expert knowledge, while for fault detection data-driven models derived from data sets acquired by the fault-free operation of the diagnosed system can be used.

- It does not impose the need to use any particular way of residual evaluation. It allows the use of both binary and trinary evaluation. In addition, the way each residual is evaluated can be different. The evaluation can be crisp or fuzzy depending on the adopted fault inference algorithm.

- The use of trinary residuals combined with the knowledge gained from the analysis of symptom sequences makes it possible to obtain better fault distinguishability (Kościelny *et al*., 2021c).

- Complex and difficult to obtain models that reflect the impacts of faults are not needed.

- Knowledge of data from faulty states of the diagnosed system is not required.

- The FDPS approach takes into consideration faults that can affect components, actuators, and instruments. Furthermore, other dysfunctional events, such as parasitic reactions in a chemical processes, shortages of reactants entering a reactor or a cyber attacks can also be classified as faults. The impacts of faults are modelled in a qualitative way. Faults are directly embedded in the graph models of both process and diagnostic system. In contrast, the quantitative models used for fault detection do not refer to faults. Moreover, the proposed approach seems to be natural and much more convenient for inferring faults compared with methods that identify faults with components.

- It allows us to obtain inference rules corresponding to both FSM or FIS rows and columns. This makes it possible to apply various algorithms for diagnostic inference.

- The FDPS allows us for identifying single and multiple faults (Kościelny and Bartyś, 2021). In the case of three-valued residuals, the rules of calculation of diagnostic signals are different than these in the case of binary evaluation. They take into account the possibility of an effect of compensation of the impacts of faults on the residual value. The applied rules are presented in Table 1.

- It allows for searching for an optimal set of sensors, as well as a set of model structures for fault detection with respect to fault detectability and distinguishability, as shown by Sztyber *et al*. (2015).

- Based on the proposed formal description of the FDPS, it is possible to generate diagnostic inference rules in an automatic way. The graph description also allows us to manage structural changes of the diagnosed and diagnostic systems. This feature yields high robustness of fault isolation.

- It enables the use of various approaches to handle the uncertainty of fault symptoms. To cope with the uncertainty of fault symptoms, a hybrid diagnostic inference method based on the fusion of the Bayesian approach and fuzzy inference was proposed Kościelny *et al*. (2021a). On the other hand, in the work of Sztyber and Kościelny (2016) the uncertainties of the symptoms were accounted by combining fuzzy logic and the Dempster–Shafer theory.

Table 1. Principles of determining three-valued signatures of double faults.

v_j/v_k	0	-1	$+1$	$-1,+1$
0	0	-1	$+1$	$-1,+1$
-1	-1	-1	$-1,0,+1$	$-1,0,+1$
$+1$	$+1$	$-1,0,+1$	$+1$	$-1,0,+1$
$-1,+1$	$+1,-1$	$-1,0,+1$	$-1,0,+1$	$-1,0,+1$

The above properties make the FDPS capable of diagnosing complex dynamic systems including large-scale processes.

6. Discussion

In this section we will discuss and compare the FDPS with other known methods, mainly in terms of its usefulness for diagnosing complex processes. Further, we will refer to those methods that use exclusively quantitative models for fault detection. Our discussion will be also focussed on key solutions, primarily those for which a formal model of the diagnostic system has been formulated and published. These are therefore the models developed within the FDI and DX communities. The similarities and differences between them have been discussed by Cordier *et al.* (2004) and Travé-Massuyés (2014b). We will also refer to the structural analysis (Düstegör *et al.*, 2006; Krysander *et al.*, 2007; Blanke *et al.*, 2015). SA is frequently used for design, among others, of model structures as well as for solving the sensor placement problem of fault diagnosis. It can be used in both FDI and DX approaches.

Principally, the diagnostic methods differ on how the knowledge of the fault–symptom relationships is acquired. This knowledge is obtained from:

(a) models that reflect the impacts of faults (internal form of residuals),

(b) data-driven models acquired from data sets reflecting fault-free and faulty states of the diagnosed system,

(c) experts.

In Case (a), the relationship between faults and diagnostic signals, which is necessary for fault isolation, is derived directly from equations accounting for the effect of faults (Frank, 1990; Gertler, 1998; Chen and Patton, 2012; Ding, 2008; Witczak, 2007). It can be stated that the portion of knowledge about the impact of faults on the model outputs and residuals, is the highest in this case. Such rich knowledge promises achieving fast and precise diagnoses. However, usually, this is not the case. The reason is that the use of structural or directional residuals for fault isolation substantially reduce the knowledge of the dynamics of the impacts of faults on the residual values. On other hand, only quantitative models that account for the impacts of faults make it possible to identify faults, i.e., determine their magnitude and variability over time. It is worth mentioning that the applicability of such approaches is limited since modelling systems that take account of faults is very difficult and expensive even for non-complex systems. In addition, the essence of some phenomena occurring in industrial processes is not fully recognized. Attempting to build such complex models may be economically justified only for critical installations.

In Case (b), classification methods are applied for fault isolation (Chen and Patton, 2012; Witczak, 2007; Patan, 2008). For classification purposes some reference data are needed for the fault-free and faulty states of the system. The different states of the system correspond to different locations in the residual space. In the case of industrial processes, and also in the case of other complex systems, acquiring learning data from states with single faults is practically impossible, and even more so for states with multiple faults. Technological installations in chemical industry, power industry, food industry, etc. are usually unique or implemented in short series. Therefore, it is not easy or possible to transfer expertise from one to other even similar facilities. All this makes it almost impossible to obtain learning data records representing particular system states with faults.

The number of possible faults is typically very large, but the abnormal behaviour and states with faults are rare. On the other hand, the diagnostic system should be capable of recognizing faults that occur for the first time. This limits the applicability of the discussed approaches for the diagnosis of complex systems.

In Case (c), knowledge about the fault–symptom relationship is obtained from experts, and fault isolation is carried out by automatic inference methods. This solution is used in the classic version of FDI and DX (Cordier *et al.*, 2004; Travé-Massuyés, 2014b), as well as in the FDPS. This knowledge is qualitative and takes the form of the FSM or the FIS.

In the DX approach, according to Reiter's theory, faults are identified with components, similarly as in SA. Therefore, dysfunctional states in equipment resulting from, e.g., an incorrect process flow or the occurrence of parasitic reactions in a chemical reactor are difficult to capture. Introducing different modes of component operation does not sufficiently solve the problem. In reality, components may operate in different modes, and several faults may be associated with each component. The formal model of the diagnosis system adopted in the DX approach is useful for describing electronic systems, but inconvenient for describing complex dynamic objects. The FDI and FDPS approaches use modelling processes, rather than faults. In our opinion, such a solution, is definitely better suited for applications in the case of complex industrial processes.

The conflicts in the DX are binary. This is a significant drawback of this approach (similarly to other approaches using binary evaluated residuals). This drawback consists, on the one hand, in the possibility of generating physically impossible diagnoses, and, on the other hand, in the low fault distinguishability in comparison with approaches which use trinary evaluated residuals. In the paper by Kościelny and Bartyś (2021), it was shown that binary evaluation does not guarantee physically true diagnoses due to the loss of information about the residual sign.

The possibility of generation of physically impossible diagnoses is an inherent feature of diagnosis using models for fault detection and inference based on binary diagnostic signals. This is true for all model-based approaches. In the work of Kościelny and Bartyś (2021) it was shown that the common belief that methods based on Reiter's theory allow correct isolation of multiple faults by the occurrence of fault compensation effects is unjustified. In fact, compensation can occur only in those cases where the impacts of the faults on the particular residual are opposite. Otherwise, physically impossible potential diagnoses are generated. Thus, the property commonly attributed to this method of correct inference, in situations where fault compensation effect occurs, often fails in practice.

The low fault distinguishability obtained by the DX approach results not only due to the binary evaluation of the residuals, but also due to neglecting knowledge about the time order in which the symptoms emerge, and due to adoption of the symptom exoneration assumption. This assumption makes the inference take into account only these conflicts that really occurred, and omits the knowledge of conflicts that did not occur. This eliminates the effect of generating transient false diagnoses resulting from different instants of symptom formation time, albeit at the cost of reduced fault distinguishability. As shown by examples (Kościelny *et al.*, 2019), the achievable fault distinguishability of the classic DX approach is lower compared with signature-based inference approaches.

Structural analysis focuses on structural properties of systems, that is, properties that do not depend on values of model parameters. This approach is used at the design stage. A system is modelled as a collection of components (Blanke *et al.*, 2015; Krysander *et al.*, 2007; Frisk and Krysander, 2007; Travé-Massuyés *et al.*, 2006; Düstegör *et al.*, 2006). Each component is described by an equation or a set of equations that are satisfied under normal system operation conditions. The structural model describes only the relationships between variables, parameters and equations. The graph in AS illustrates the relationships between equations and variables (known and unknown). Equations describe physical relationships, but also mathematical relationships (derivatives).

The mathematical description contains a set of equations that describe the elements. To account for the dynamic properties of the system, equations are added that bind the variable and its derivative. This leads to a very large number of equations for complex systems. A fault is modeled as a perturbation in the consistency of a given equation. It is also common to include faults as additional variables in the equations. The causality is not specified in the models used in AS in contrast to GP.

FDI and SA approaches differ in their generation of residuals. In structural analysis, they can be obtained as an equation referring exclusively to known variables, but also as a chain of calculations, leading to the elimination of unknown variables or the determination of the same variable from two different equations, with possible prior elimination of unknown variables.

In our opinion, the AS is not suitable for applications to complex systems, i.e., those in which the number of faults is of the order of hundreds or thousands. The AS method assumes the use of analytical models and excludes the use of models derived from experimental data, e.g., neural or fuzzy.

In Table 2, the properties of FDI and DX approaches in their classical versions together with the FDPS approach are presented. In terms of the design of diagnostic systems, the applications of the GP being part of the FDPS approach are compared with other graph approaches by Sztyber *et al.* (2015).

7. Summary

This paper presents a graph-based approach to process and diagnostic system description, referred to as the FDPS. It was designed with the aim to apply mainly for diagnosing of large-scale processes. The FDPS consists of a graph model of the process being diagnosed (GP) and a graph model of the diagnostic system (GDS). Both are supplemented with a knowledge derived from the sequences of symptoms ES. Generally, the FDPS could be recognized as a form of a knowledge container useful for real-time diagnostics. Various diagnostic algorithms can be implemented based on this knowledge.

The FDPS was targeted to bypass the limitations imposed by other known models of diagnostic system description. The idea was to propose a general framework intended for the formulation of fault detection algorithms based on various models of the process, as well as on various variants of fault isolation algorithms. Various applications of the FDPS were pointed out.

The main properties of the FDPS are characterized and compared with other solutions for which a formal model of the diagnostic system has been formulated. These are FDI and DX approaches, as well as structural analysis. It is worth mentioning that structural analysis is not a diagnostic method but an approach to design diagnostic systems.

It was shown that the proposed approach bypasses the specified limitations characteristic for other methods. Moreover, it provides the ease of designing diagnostic systems. It also makes it possible to obtain high values of performance indices because of the possibility of making use of trinary residuals, immunity to fault compensation effects and robustness to diagnoses of non-physical states of the diagnosed system. The proposed description is also very useful for the real-time management of structural changes in the diagnosed system, which, however, was not

Table 2. Summary of properties of diagnostic methods.

Property/method	FDI	DX	FDPS
Models of	processes	components	processes
Types of models	analytical	analytical	analytical, neural, fuzzy, etc.
Models of faults in formal system description	yes	no	yes
Ability of accounting for dysfunctional events other than faults	yes	no	yes
Diagnostic signals applied	binary	binary	trinary fuzzy binary
Diagnostic inference based on	columns	rows	columns & rows
Multiple faults	no	yes	yes
Consideration of the fault compensation	no	partially	yes
Uncertainty of inference	yes	no	yes
Fault distinguishability level	average	low	high
Making use of sequences of symptoms	no	no	yes

exposed in the paper.

The performed comparison and discussion of the features of the FDPS with other approaches shows the advantages of the proposed one. It is much more comprehensive than others and more useful in applications for diagnosing of complex dynamic systems.

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