FAULT DIAGNOSIS IN INDUSTRIAL SYSTEMS VIA CAUSALITY GRAPHS

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Abstract. Some enhanced methods for definition of the diagnosis problems as well as for the creation of logic-based qualitative description of dynamical industrial processes are developed in the presented paper. Specific techniques for application of causality graphs structures for enhanced Fault Diagnosis (FD) in dynamic industrial systems are also proposed. A specific diagnosis algorithm DIACAUSE as well as a particular causality graph structure were developed and respectively implemented for enhanced FD in a real industrial system for treatment of technologic liquids in a hot dip galvanizing plant.

Keywords: fault diagnosis, causality graphs, logic-based description, industrial systems

1. Introduction

The main techniques of the fault diagnosis (FD) procedures performed in industrial processes and systems are focused on the detection of abnormal systems/processes states, as well as on the determination of all principal faults and failures (that actually cause such types of perturbation in the process behavior and the systems states).

In compliance with the FD terminology, such types of diagnostic procedures are respectively called "*fault detection*" and "*fault isolation*" [1, 3, 5, 9].

Most of the diagnosis methods with a practical application are based on specific analytical models of the monitored process [2, 6, 10].

The general form of such models is as follows

$$\mathbf{x} = f(x, u, a), \quad \mathbf{y} = g(x, u, a), \tag{1}$$

where "**x**", and "**y**" are respectively the input and output vectors that define the systems states.

The principal faults in the analytical models are basically defined by the changes occurred in the parametric vector "**a**". Therefore the diagnosis problems may be analyzed and respectively solved via application of estimation methods and/or state observers [6, 8, 11].

However, during the application of analytical models, the generated fault(s) may cause some of the following issues:

a) the systems and/or process fault(s) may generate *structural perturbation* in the diagnosed process which cannot be adequately described by the specific changes occurred in the parametric vector "**a**" (for example a pipeline containing some industrial liquids could be broken, and/or a valve in a hydraulic systems could be blocked, etc.);

b) in some situations, the needed diagnostic information (and especially the information obtained "on-line"), might not be adequately expressed just by using the quantitative measurements performed on the model output "**y**", since a qualitative decision or some particular type of alarm message (for example "the liquid level in tank 3 is low"), should be used for the purpose. This in fact means, that the developed analytical diagnostic models could not (in fact) be applied for processing such of kind of information;

c) generally, it is not possible to develop an adequate analytical diagnostic model like the one, presented in (1).

The presence of all these specific issues means, that in such situations the diagnostic problems might be solved via application of some *specific knowledge* describing the ***discrete cause-effect relations***, (that occur in the process under consideration), and not via analytical models, i.e., some particular *knowledge-based systems* should be developed and applied for the purpose [7, 12].

This fact means also, that some particular diagnostic systems based on artificial intelligence (e.g., neural networks, fuzzy-neural modules, causal graphs structures etc.), should be developed and applied for performing FD in the real industrial systems [5, 7, 8, 9].

However, a general issue for all knowledge-based systems (applied for FD in the real-time dynamic processes), remains the *extensive search spaces* that should be processed. Therefore, some particular knowledge-processing methods that utilize specific features of the diagnosed systems must be developed and applied in order to restrict the search space and respectively to accelerate the performances of the diagnostic algorithms [7, 8, 9].

The results obtained from specific studies [6, 7], showed that the clear logic description of the *cause-effect relations* (that became effective once a fault occurrence is realized), are actually more advanced and able to develop a much more detailed description of the process than the classical event trees (e.g., fault trees) and logic tables developed under the FMECA analysis [3, 5, 7, 8].

The *causal graph structure* developed for a dynamical industrial system may be used to restrict the search space, in order that the developed diagnostic algorithms can become more fit and ready to be implemented under real time constraints [6, 7, 8].

Some enhanced methods for definition of the diagnosis problems as well as for the creation of logic-based qualitative description of dynamical industrial processes are developed in this paper. Specific techniques for the application of causality graphs structures for enhanced Fault Diagnosis (FD) in dynamic industrial systems are also proposed.

2. Definition of diagnosis problems and creation of a logic-based qualitative description of the industrial processes

2.1. Definition of the diagnosis problems

The essence of this study is to create methods and techniques for monitoring of a typical diagnosis situation (during process supervision), where the fault occurrence should be indicated via alarm messages and the fault isolation problems should also be solved (adequately).

The core of the diagnostic problem includes location and isolation of the primary (i.e., the general) faults, which generate deviations in the process signals that can be used for the creation of specific sets of alarms.

The general constraint for this particular case is, that since the faults and the alarm messages are discrete events, then the process should also be described under discrete form (regardless of the fact that the real process might be continuous).

For the same reasons, all control actions and general operating conditions should also be described under the same terms, please see Figure 1.

The set of all *fault symptoms* is described via the set $\{S_i\}$. Therefore, all kinds of alarm messages A_i, control actions U_i, faults F_i, and operational conditions Z_i represent particular subsets of the set $\{S_i\}$, i.e.,

$$\{A_i, U_i, F_i, Z_i\} \in \{S_i\}, \qquad (2)$$

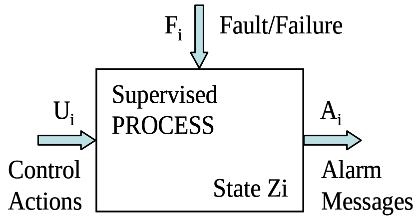

Figure 1. Dynamic process with generated faults/failures

It is also assumed that the current operational conditions Z_i and all control activities U_i, that have been developed in the supervised process *before the fault occurrence* are known.

In a case of a fault occurrence, the process signals (generally) change very dynamically and therefore may be used for generation of alarm messages A_i.

Then, the refined core of the diagnosis problem for the present case is, that for a given set of control actions $\{U_i\}$ and process states $\{Z_i\}$, a particular ***fault set*** $\{F_i\}$, for which the process is capable to generate specific sets of *alarm messages* $\{A_i\}$, must be determined.

2.2. Logic-based qualitative description of the dynamical industrial processes – models and cause-effect relations

A particular model of a logic-based process description must be developed and respectively used in the FD procedures. The model (that has to be developed) should be able to describe some eventual qualitative events which may occur in the behavior of the dynamical industrial process. These qualitative events are generally characterized by their representative signals (or respectively by the process parameters values), which must either exceed the preliminary defined restrictions or remain within the prescribed intervals.

If such type of qualitative events do occur, then some ***specific* (*representative*) *symptoms*** S_i, could be created.

In fact, it is always possible that some kind of a direct (i.e., a straight) statement may be assigned to each specific symptom. The validity of the so-created reasoning can be defined by the specific categories “true” and “false”.

The general *cause-effect relations* (used for the purpose), usually have the following form

$$\mathbf{S} \leftarrow \{S_i \cap S_j \cap \cdots \cap -S_k \cap \cdots \cap -S_m\}, \qquad (3)$$

where the right-hand side of the relation (3) describes the set of specific symptoms, whose simultaneous realization causes the occurrence of the generalized symptom **S**.

If four different sets of symptoms (respectively $\mathbf{S}_A$, $\mathbf{S}_B$, $\mathbf{S}_C$ and $\mathbf{S}_D$) can be created, then the cause-effect relations may be developed as follows

$$\mathbf{S}_A \leftarrow \mathbf{S}_B \cap \mathbf{S}_C\,, \quad (4)$$

$$\mathbf{S}_A \leftarrow \mathbf{S}_D\,. \quad (5)$$

The reasoning obtained by these relations is, that the symptom $\mathbf{S}_A$ is either a particular effect of the appearance of symptom $\mathbf{S}_D$, either an effect of the simultaneous appearance of the symptoms $\mathbf{S}_B$ and $\mathbf{S}_C$.

Therefore, the cause–effect relations may be generalized and respectively be interpreted via the following equivalent relation,

$$\mathbf{S}_A \leftrightarrow (\mathbf{S}_B \cap \mathbf{S}_C) \cup \mathbf{S}_D\,, \quad (6)$$

Then, the logical description M_L of the generalized *cause – effect model* may be developed as follows

$$M_L = M_L^G + M_L^{CE}, \quad (7)$$

where:

M_L^G represents the general relations, describing the current control actions U_i, (that are supposed to be known) and/or the process states Z_i (that are also supposed to be known);

M_L^{CE} – represents the developed cause-effect relations.

Respectively, the alarm sets A_i and the fault sets F_i might also be developed under the representative form (3).

3. Specific properties of the causality graphs developed and applied for Fault Diagnosis (FD) in dynamic systems

The general features of the causality graphs, defined via allegation logic were first introduced in [7].

If the causality graph should be developed and applied for Fault Diagnosis (FD) in dynamic industrial systems, then it should possess the following specific properties:

- for every specific diagnosis symptom $\mathbf{S}_i$, there exists a corresponding peak in the causality graph, i.e., each peak (in the graph) can be expressed by the specific symptom symbol $\mathbf{S}_i$;
- for every existing cause-effect relation (of the type $\mathbf{S}_i \rightarrow \mathbf{S}_j$), there exists a corresponding arrow with direction from "*i*" towards "*j*";
- directed arrows in the graph structure do exist if there is a general relation between the models components (of the modelled structure) M_L^G;
- the peaks of the causal graphs must also be associated with the general relations describing the symptom occurrences;
- each fault event F_i must generate a corresponding alarm message A_i, in cases when there is a corresponding path (in the causality graph), which reflects such relation;
- in cases, when there is a particular path (in the developed graphs structure) from some node (i.e., a peak) $\mathbf{S}_i$ towards another node $\mathbf{S}_j$, and the path is represented by the nodes ($\mathbf{S}_k$, $\mathbf{S}_l$, …, $\mathbf{S}_m$, $\mathbf{S}_n$) then, the symptoms (corresponding to these nodes) occur exactly in the same order, if the cause-effect relations among these (described by the paths) became really effective.

4. Development and application of the causality graphs structure and cause-effect model for enhanced FD in industrial system

4.1. General characteristics of industrial system for treatment of technologic liquids in a hot dip zinc galvanizing plant

The created causality graphs and cause-effect models shall be applied for enhanced Fault Diagnosis (FD) in an industrial Hot Dip Zinc Galvanizing system. The systems modules that are subjected to FD procedures represent special technologic tanks containing the technologic liquids, necessary for the treatment of the so-called "black steel" products, prior to the hot dip zinc galvanizing process. All necessary details, related to the hot dip galvanizing modules, technologic and logistics processes and systems components are presented in [4].

The general structure of the industrial system composed of three hydraulic tanks that contain the necessary technologic liquids (acids, and alkalis), is presented in Figure 2. The system consists of three technologic tanks with big volume (about 50 – 60 m^3), which contain the technologic flux liquids. Two of these tanks (Tank 2 and Tank 3 respectively), are designated for treatment of the "black steel" products in a flux bath.

The purpose of Tank 1 is to be a compensation tank, i.e., designated to compensate the waste liquids that should be processed in a specific waste liquids treatment system (situated in another part of the facility).

The level control loops (which operate the valves and the pumps), ensure that the control of liquids level can be effectuated independently for each tank (depending on the consumed quantities of liquids).

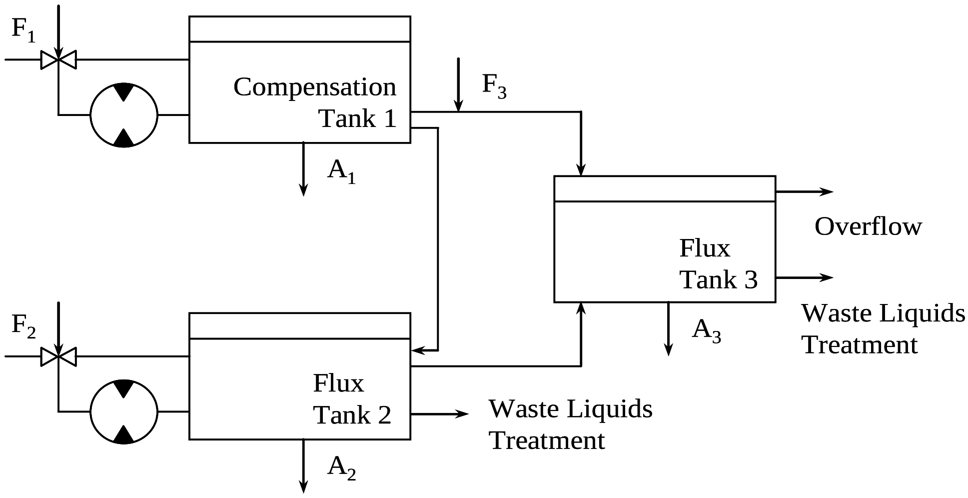

Figure 2. General structure of an industrial system for technologic liquids

4.2. Development of the diagnosis algorithm applied for FD in the industrial system

The structure of the developed diagnosis algorithm "**DIACAUSE**" is presented in Figure 3.

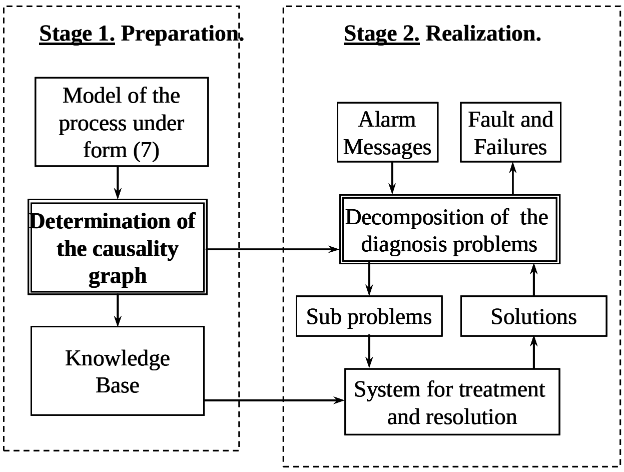

Figure 3. Structure of the diagnosis algorithm "DIACAUSE"

The diagnosis process is described by the modeling relations (7), and a specially developed causality graph. The diagnosis algorithm should be able to define the particular *fault sets* for a given (generated) set *of alarm messages*.

The diagnosis algorithm consists of two parts – developed respectively as **"Stage1. Preparation"** and **"Stage 2. Realization"**, please see Figure 3.

Stage 1 of the DIACAUSE-algorithm is developed as a *model preparation phase*. This part of the algorithm should be accomplished prior to the generation of the first alarm message A_1.

During this first stage of the DIACAUSE-algorithm, the structure of the causality graph must be developed and the corresponding process model under form (7) must be created. Another feature of Stage 1 is, that it also includes the *graph searching* techniques, that must be realized prior to the occurrence of the first alarm event.

Stage **2** of the DIACAUSE-algorithm is developed as *a realization phase* and respectively defines the solution of the actual diagnosis problem, once the alarm sets are generated.

This part of the algorithmic structure consists of two interconnected sub-parts. The upper level part of the algorithmic structure (developed in Stage 2), includes some specific decomposition techniques that are used to divide (i.e., to decompose) the complex diagnostic problems into more simple and easy solvable sub-problems, (which in their turn are related to the respective properties of the already created diagnostic model).

The solution of these groups of sub-problems finally results onto a diagnostic decision, which determines adequately the reason of the fault/failure occurrence events.

4.3. Development of the causality graph structure and its application for enhanced FD under real operation conditions

The structure of a causality graph designated for enhanced FD in a real industrial system for treatment of technologic liquids in hot dip zinc galvanizing facility is developed and respectively presented in Figure 4.

The causality graph structure provides the necessary knowledge regarding the systems faults – $\mathbf{F}_i$, the alarm messages - $\mathbf{A}_i$, the systems states - $\mathbf{Z}_i$, and the diagnosis symptoms - $\mathbf{S}_i$.

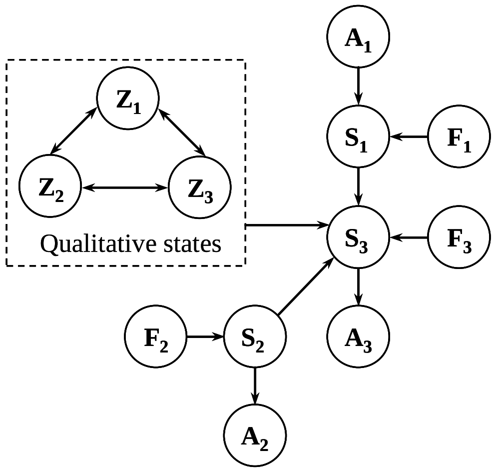

Figure 4. Structure of the causality graph applied for FD under real operation conditions

The characteristics of the causal graph and the applied model may be defined as follows.

1. ***Alarm messages***, generated on the systems output:
   - $\mathbf{A_1}$: Level of Compensation Tank 1 is low.
   - $\mathbf{A_2}$: Level of Flux Tank 2 is low.
   - $\mathbf{A_3}$: Level of Flux Tank 3 is low.
2. ***Faults***, that must be considered:
   - $\mathbf{F_1}$: Valve 1 is closed and blocked.
   - $\mathbf{F_2}$: Valve 2 is opened and blocked.
   - $\mathbf{F_3}$: Connection pipeline from Tank 1 to Tank 2 is blocked.
3. ***Qualitative states*** of the diagnosed process:
   - $\mathbf{Z_1}$: The liquid level of Flux Tank 3 is low.
   - $\mathbf{Z_2}$: The liquid level of Flux Tank 3 is medium.
   - $\mathbf{Z_3}$: The liquid level of Flux tank 3 is high.
4. ***Diagnostic symptoms***, that must be considered:
   - $\mathbf{S_1}$: Level of Compensation Tank 1 is below limit.
   - $\mathbf{S_2}$: Level of Flux Tank 2 is below limit.
   - $\mathbf{S_3}$: Level of Flux Tank 3 is below limit.

The model of the system may now be developed under form (7).

The model of the general relations $M_L^G(S)$ may be developed for all specific system states, under the following form

$$M_L^G(\mathbf{S}) = Z_1 \cup Z_2 \cup Z_3, \tag{8}$$

The cause-effect model $M_L^{CE}(\mathbf{S})$ for the industrial system may be developed as follows:

$$M_L^{CE}(S) = \{[F_1 \rightarrow S_1], [S_1 \rightarrow A_1], [F_2 \rightarrow S_2], [S_2 \rightarrow A_2], [(S_1 \cap S_2) \rightarrow S_3], [(S_2 \cap F_3) \rightarrow S_3], [S_3 \rightarrow A_3], [(S_1 \cup S_2) \cap (Z_1 \cup Z_2)] \rightarrow S_3\} \tag{9}$$

Then, the following sets of logical relations can be obtained from the already developed cause-effect relations

$$F_1 \leftrightarrow \mathbf{S}_1, \tag{10}$$

$$\mathbf{S}_1 \leftrightarrow A_1, \tag{11}$$

$$F_2 \leftrightarrow \mathbf{S}_2, \tag{12}$$

$$\mathbf{S}_2 \leftrightarrow A_2, \tag{13}$$

$$\{[S_1 \cap S_2] \cup [S_2 \cap F_3] \cup [(S_1 \cup S_2) \cap \cap (Z_1 \cup Z_2)]\} \leftrightarrow S_3, \tag{14}$$

$$\mathbf{S}_3 \leftrightarrow A_3. \tag{15}$$

The diagnosis algorithm DIACAUSE may now be realized on the basis of the already developed causality graph, i.e.,

A) The solution of the first sub-problem includes the replacement of the statement A_3, by another statement of the $\mathbf{S}_3$ type. Since A_3 represents a peak in the graph structure, and the only path towards this peak lies from the peak $\mathbf{S}_3$, then, this is in fact the solution to this particular sub-problem (i.e., the replacement of the alarm message A_3 by the symptom $\mathbf{S}_3$).

Thus, the new statement should be: $A_1 \cap \mathbf{S}_3 \cap A_2$.

B) The solution of the next sub-problem includes the replacement of the symptom $\mathbf{S}_3$ by another type of statement based on the symptoms $\mathbf{S}_1$ and $\mathbf{S}_2$, on the states Z_1, Z_2 and Z_3, and on the fault F_3.

Therefore the newly developed statement should be: $\mathbf{S}_1 \cap Z_1 \cap Z_2 \cap Z_3 \cap \mathbf{S}2 \cap A2$.

C) On this stage of the diagnosis algorithm, three particular sub-problems must be solved at the same time, i.e.,
- the statement $Z_1 \cap Z_2 \cap Z_3$ must be solved;
- the term A_2 must be replaced by a term, which includes $\mathbf{S}_2$;
- the term A_1 must be replaced by a term, which includes $\mathbf{S}_1$.

Therefore, the resulting statement is: $\mathbf{S}_2 \cap \mathbf{S}_1$.

D) The symptom $\mathbf{S}_2$ must be replaced by a particular relation, which includes the fault F_2.

E) The symptom $\mathbf{S}_1$ must be replaced by a particular relation, which includes the fault F_1.

F) The generated final statement is: $F_2 \cap F_1$. This in fact means that the ***single fault F_1 has caused the alarm messages.***

5. Conclusions

5.1. Some particular methods and techniques applied for definition of the diagnosis problem as well as for creation of a logic-based qualitative description of the dynamical industrial processes are developed in this paper.

5.2. Some types of enhanced techniques for implementation of the causality graph structure for Fault Diagnosis (FD) in dynamic industrial systems (i.e., under real operating conditions) are also proposed.

5.3. A particular diagnosis algorithm named *DIACAUSE*, a causality graph structure and a system model are developed and respectively applied for enhanced FD in a real industrial system for treatment of technologic liquids in a hot dip zinc galvanizing facility.

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