Sensors of Single Faults - Remarks on Measurements in Diagnosis of Industrial Processes

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Abstract. Measurements play a crucial role in diagnosis of industrial processes. The main aim of this paper is to discuss selected problems connected with the role of measurements in model-based diagnosis. The issue of the separation of the diagnostics of measuring instruments and process diagnosis is discussed. The idea of self-diagnosable sensors of single faults is shown as a solution. A short review of existing techniques meeting the requirements for sensors of single faults is presented. We also discuss practical heuristic rules, that can be used in the selection of measuring instruments and diagnostic tests for diagnostic system.

Keywords: Fault diagnosis · Measurements · Sensors of single faults

1 Introduction

The main task of the automatic, on-line diagnostic system of industrial processes is to detect and accurately distinguish (isolate) faults occurring in installation components, measuring instruments and actuators. All faults can lead to serious accidents with subsequent economic losses, or can even be hazardous to people and the environment.

Diagnostics is the process of formulating hypotheses about the occurrence of faults as a result of acquisition, processing and analysis of sensor signals. Therefore, without measurements there is no diagnostics. There is also a need for diagnostics of measuring instruments because sensor faults can lead to serious failures, such as the catastrophe in Buncefield, United Kingdom [2]. There was a series of explosions and a tank farm fire on 11th September 2005. This was one of the largest fires in post-war Europe. The level sensor fault caused an overflow in a tank and ignition. As a result, there were 40 injured and serious financial losses (£5 billion).

In this paper we discuss the following problems:

1. Is it possible to separate process diagnostics from the diagnostics of measuring instruments? Which conditions allow for such separation?

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It is quite common to design the diagnostics system with the default assumption that measuring instruments cannot be faulty or that their faults will be detected separately. This approach is unrealistic because in many real cases such a separation is impossible.

2. Which criteria should be taken into account by a process engineer during the selection of the set of process variables used in the diagnostic system? Often there is a variety of possible choices of sensors measuring different process variables. So there is the engineering problem of which physical quantities should be measured. Which criteria should be taken into account?

There is also a wide variety of formal optimal sensor placement methods [3,5,11,14], but optimisation of the set of measuring instruments with respect to the needs of the diagnostic system is very rare, so it is important to have some practical hints on how to choose an appropriate instrumentation.

2 Formal Description of Relations: Process Variables - Diagnostic Signals - Faults

The process is traceable when measurements Y and control signals U from the control system are known. These values form the set of process variables X used in process diagnosis.

$$X = \{x_n : n = 1, \ldots, N\} \tag{1}$$

Fault detection and isolation is based on a set of diagnostic tests. Each j-th diagnostic test outputs a diagnostic signal s_j indicating the result of the check. As a result of all the tests we obtain the set of all diagnostic signals S:

$$S = \{s_j : j = 1, \ldots, J\}. \tag{2}$$

Therefore, fault detection is a mapping of the space of process variables X into the space of diagnostic signals S:

$$X \in \mathbb{R}^N \Rightarrow S \in \mathbb{R}^J, \tag{3}$$

where $\mathbb{R}$ denotes the set of real numbers.

Relation R_{XS} is defined over the Cartesian product of X and S:

$$R_{XS} \subset X \times S. \tag{4}$$

The expression $x_i R_{XS} s_j$ means, that the value of process variable x_i is used in the j-th diagnostic signal generation.

We define the bipartite graph G_{XS} as the following tuple:

$$G_{XS} =< X, S, R_{XS} >, \tag{5}$$

containing the set of process variables X and diagnostic signals S as vertices. Relation R_{XS} describes the graph edges.

The presented definitions and ideas will be illustrated by an industrial example of the steam draught of a boiler from a power plant (for details on diagnostic system implementation see [8]). The steam draught contains an installation section between the boiler drum and the system outlet to the turbine. The section is built for the most part inside the steam boiler. It is possible to select three recurring elements in the installation: the steam superheater, the cooling water injector and the injecting water control valve. The last two elements form the steam attemperator. The installation section containing these three elements is shown in Fig. 1, where: T_P, F_P, P_P - steam temperature, flow and pressure, respectively, F_W, P_W - cooling water flow and pressure, respectively, U - signal denoting position of the injecting water control-valve, X - feedback signal denoting position of the valve.

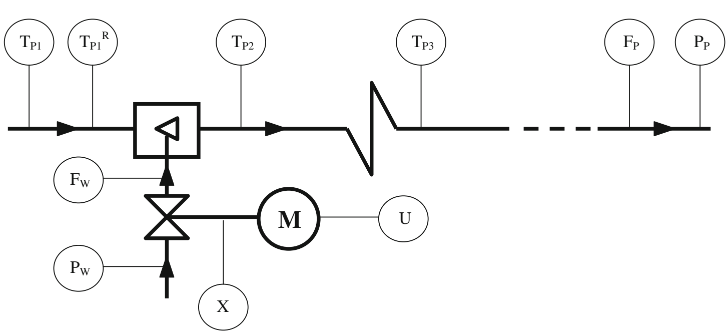

Fig. 1. System of the steam superheater and attemperator.

The faults that should be isolated within the system are presented in Table 1 and the residuals used in the diagnostic system are shown in Table 2. Each residual r_i corresponds to diagnostic signal s_i.

Relation R_{XS} for the steam draught is shown in Table 3. The graph connected with this table is shown in Fig. 2.

To isolate the faults, it is necessary to know the relationship between the faults forming the set:

$$F = \{f_k : k = 1, \dots, K\} \tag{6}$$

and the values of the diagnostic signals. Expert knowledge about the fault-symptom relation can be described and archived in many different forms [9]. A binary relation can be represented by: logic functions, diagnostic trees, a binary diagnostic matrix or a set of rules. The rules often take the form: if symptoms $s_1 \wedge s_2 \wedge \dots \wedge s_n$ then fault f_k or: if symptom s_i then fault $f_k \vee f_m \vee f_s$. In the case of multivalued residual evaluation, more complex rules are used. The set of such rules can be represented as a Fault Isolation System (FIS) [7].

The most popular method of fault-symptom relation representation is a binary diagnostic matrix (Table 4). It is defined over the Cartesian product of S and F, so it specifies the relation:

$$R_{FS} \subset F \times S. \tag{7}$$

Table 1. The set of faults for the steam draught

F	Faults
f_1	Measuring path T_{P1} fault
f_2	Measuring path T_{P1R} fault
f_3	Measuring path T_{P2} fault
f_4	Measuring path T_{P3} fault
f_5	Measuring path F_P fault
f_6	Measuring path P_P fault
f_7	Measuring path F_W fault
f_8	Measuring path X fault
f_9	Measuring path P_W fault
f_{10}	Servomotor fault
f_{11}	Injection water control-valve fault
f_{12}	Injector fault

Table 2. The set of the residuals for the steam draught

R	S	The algorithms of generation of the residuals
r_1	s_1	$r_1 = T_{P2} - \hat{T}_{P2}$; $\hat{T}_{P2} = f(T_{P1}, F_P, F_W)$
r_2	s_2	$r_2 = T_{P3} - \hat{T}_{P3}$; $\hat{T}_{P3} = f(T_{P2}, F_P)$
r_3	s_3	$r_3 = F_W - \hat{F}_W$; $\hat{F}_W = f(X, P_W - P_P)$
r_4	s_4	$r_4 = X - \hat{X}$; $\hat{X} = f(U)$
r_5	s_5	$r_5 = T_{P1} - T_{P1R}$

Table 3. Binary matrix of R_{XS} relation

$S \backslash X$	T_{P1}	T_{P1R}	T_{P2}	T_{P3}	F_P	P_P	F_W	X	P_W	U
s_1	1		1		1		1			
s_2			1	1	1					
s_3						1	1	1	1	
s_4								1		1
s_5	1	1								

The expression $f_k R_{FS} s_j$ means that diagnostic signal s_j is sensitive to fault f_k. The occurrence of f_k sets the value of s_j to one, i.e. indicating a fault symptom. The matrix of this relation is called a binary diagnostic matrix. Each matrix entry is defined as follows:

$$v_{jk} = \begin{cases} 0 & \Leftrightarrow < f_k, s_j > \notin R_{FS} \\ 1 & \Leftrightarrow < f_k, s_j > \in R_{FS} \end{cases} . \quad (8)$$

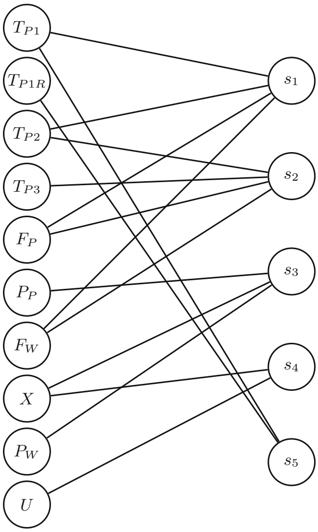

Fig. 2. Graph G_{XS} of the relation process variables - diagnostic signals.

Table 4. Binary matrix of R_{XS} relation

$S\backslash F$	f_1	f_2	f_3	f_4	f_5	f_6	f_7	f_8	f_9	f_{10}	f_{11}	f_{12}
s_1	1		1		1		1					1
s_2			1	1	1							
s_3						1	1	1	1		1	
s_4								1		1		
s_5	1	1										

Matrix element v_{jk} has the value 1, if signal s_j detects fault f_k, and 0 otherwise. A fault signature is a column vector, containing the values of the diagnostic signals for this fault:

$$\begin{bmatrix} v_{1k} \\ v_{2k} \\ \dots \\ v_{Jk} \end{bmatrix}, \tag{9}$$

where $v_{jk} \in \{0, 1\}, \forall j = 1, \dots, J \qquad k = 1, \dots, K$.

Therefore, the columns of the binary diagnostic matrix (Table 4) correspond to fault signatures. Each signature represents the following rule: if $(s_1 = v_{1k}) \wedge \dots \wedge (s_j = v_{jk}) \wedge \dots \wedge (s_J = v_{Jk})$ then f_k. The interpretation of this rule is as follows: if the values of the diagnostic signals are consistent with the signature of f_k then f_k is a possible root cause.

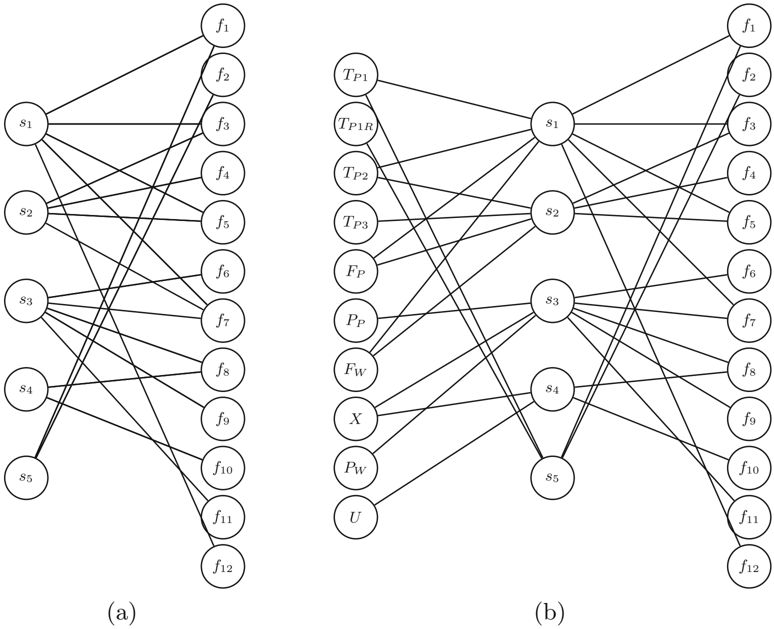

Fig. 3. Diagnostic graph G_{FS} (a) and composition of R_{XS} and R_{FS} (b).

Each row of the binary diagnostic matrix represents the following rule: if $s_j = 1$ then $f_k \vee \cdots \vee f_p$. The interpretation is as follows: in the case of the occurrence of symptom s_j possible root causes are faults detected by this signal (the faults with 1 in the jth row of the diagnostic matrix).

The binary diagnostic matrix can be represented by a bipartite graph (Fig. 3a), with vertices from sets F and S, and edges representing relation R_{FS}:

$$G_{FS} =< F, S, R_{FS} > . \tag{10}$$

The composition of both relations is depicted in Fig. 3b. It illustrates dependencies between sets X, S, and F, so it is a qualitative model of the diagnostic system. The set of all faults F contains the set of faults of measuring instruments F_M. The remaining part of F contains faults of process components and actuators F_C; $F = F_M \cup F_C$. Each measuring instrument x_i has exactly one corresponding fault in F_M. It is worth noting that for the sensor faults relation $R_{F_M S}$ is identical to relation R_{XS} (assuming equal ordering of measurements and their corresponding faults in sets X and F_M). In the binary diagnostic matrix in Fig. 4 $F_M = \{f_1, f_2, f_3, f_4, f_5, f_6, f_7, f_8, f_9\}$ and $F_C = \{f_{10}, f_{11}, f_{12}\}$. The shaded part of the matrix corresponds to the relation $R_{F_M S}$.

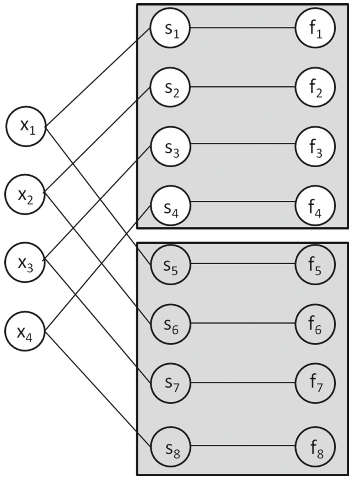

Fig. 4. Exemplary diagram of the diagnostics with SSF.

3 Diagnostics of Measuring Instruments and Process Diagnostics

Process engineers often need to separate the diagnostics of measuring instruments from the diagnostics of the process components. This is motivated by a need to monitor the quality of the measurements used in balance calculations or process optimisation. In such cases, the diagnostics system does not take into account the faults of process components and actuators. On the other hand, it is quite common to build a diagnostic system with a default assumption that the measuring instruments cannot be faulty. So the question arises: is it possible to separate on-line process diagnostics and the diagnostics of measuring instruments? In what conditions is it possible?

Unfortunately, in the case of traditional measuring instruments such a separation is impossible. Each diagnostic test uses the model of a part of a process, and measurements of the input and the output signals are needed. Therefore, the tests are sensitive to the faults of measuring instruments and to the faults of components of the modeled part of the process.

In the general case, it is possible to design a diagnostic system for measuring instruments, process components and actuators, with all faults fully diagnosable. In such a case, diagnoses generated by the system are sufficient for all automation system tasks. However, it is often impossible to obtain such a high fault distinguishability because of the costs of measuring instruments (see Table 4, where all faults are detectable but not all of them can be isolated). Therefore, situations when faults of measuring instruments are indistinguishable from the other faults are possible (elementary block $\{f_6, f_9, f_{11}\}$ in Table 4, where $f_6, f_9 \in F_M$, $f_{11} \in F_C$). Important method for detection of faults of measuring instruments is modelling of signals, using other measurements, resulting in so called virtual sensors, providing analytical redundancy to hardware measuring instruments [12].

The separation of the diagnostics of the faults of measuring instruments from the other faults is possible only if measuring instruments have self-diagnostic capabilities; moreover, the self-diagnostics must be complete, i.e. deal with all possible faults. This requires redundant sensors and a microprocessor unit embedded in the measuring instrument. The simplest solution is to compare values indicated by the redundant sensors and to indicate a fault in the case of inconsistency - as a residual r_5 in the example of the steam draught. An exemplary structure of a measuring instrument with two redundant sensors, two parallel signal processing paths (in the ASIC unit and microprocessor unit), and with self-diagnostics, is presented on a web page [1].

Often, many different kinds of sensors can be used for different process variables. So there is an engineering problem: which physical quantities should be measured? How to choose them? In practice, optimisation of the selection of measuring instruments, with respect to fault diagnosis, is very rare. Therefore, it is important to have some practical clues about the measurement selection.

Some clues can be derived from the analysis of a binary diagnostic matrix. The particular form of the diagnostic matrix is a diagonal matrix (Table 5).

Table 5. Diagonal diagnostic matrix.

$S\backslash F$	f_1	f_2	f_3	f_4	f_5
s_1	1				
s_2		1			
s_3			1		
s_4				1	
s_5					1

With the diagonal diagnostic matrix, each test detects exclusively one fault. This solution has many advantages:

- full detectability and distinguishability is achieved [6];
- the symptoms unambiguously points to the faults, so diagnostic reasoning is very simple;
- multiple faults can be easily handled;
- there are no problems with the variation of the structure of the diagnosed process and symptoms dynamics, which complicates diagnostic reasoning in other cases [13].

These advantages of the diagonal diagnostic matrix encourage researchers to search for methods for designing a set of residuals leading to a such diagnostic matrix. For this purpose, a model of a process with faults influence is needed.

After linearization, the computable and inner form (with fault influence) of residuals can be obtained [4,6,7,10]. It is then possible to design additional residuals to obtain the desired properties of a residual vector (in particular diagonal diagnostic matrix). Each residual must be sensitive to only one fault and each residual should detect different sets of faults. There is a serious limitation to this approach: the number of faults cannot be greater than the number of measurements. In practice, this restriction is never met because we should consider the faults of measurements and the faults in the process components.

Therefore, the diagonal diagnostic matrix may be interpreted as a two-dimensional structure reflecting the outputs of **sensors of single faults**. However, not every fault can be directly measured.

The optimal diagnostic system uses sensors of single faults. Measuring instruments can also be faulty, so each symptom is related with its designated fault and with the possible fault of a sensor. To obtain a diagonal binary diagnostic matrix it is necessary to:

- have a dedicated sensor for each fault of the process components and actuators,
- use measuring instruments with redundant sensors and an embedded diagnostic system.

These requirements can be summarized as a need for self-diagnosable sensors of faults (SSF).

With SSF, the diagnostics of measuring instruments can be separated from process diagnostics. The diagnostic system is reduced to two diagonal diagnostic matrices, one for the measurements and the second for the other faults. An exemplary diagram of the diagnostics with SSF is presented in Fig. 4, where $\{x_1, x_2, x_3, x_4\}$ is a set of process variables measured by SSF. The set: $\{f_1, f_2, f_3, f_4\}$ denotes sensor faults, where fault f_1 corresponds to the measurement of x_1. The faults in the set $\{f_5, f_6, f_7, f_8\}$ denotes components faults measured respectively by $\{x_1, x_2, x_3, x_4\}$. The number of diagnostic signals is equal to the number of faults in both matrices. Such a solution does not yet exist, but it is a good direction for the further development of diagnostic systems.

In the case of model-based diagnostics, a diagonal diagnostic matrix is very hard to obtain. Using models in diagnostics means that each test uses measurements of the inputs and the output of the model. The test using this model is sensitive to the faults of those measuring instruments and to the faults of components and actuators included in the modelled part of the process. In the example (Fig. 1) residual r_4 is the difference between the measured and calculated valve position. The related diagnostic signal s_4 is sensitive to the servomotor fault (f_{10}) and to the fault of the measuring path of X. Even in the case of a residual calculated using redundant sensors (r_5), the related diagnostic signal is sensitive to both measurement faults (f_1 and f_2).

Moreover, there is the question, which models should be used? One possibility is to use local models (LM), describing the smallest possible part of the process (one process component). Another solution is to use global models (GM), describing larger parts of the installation. Local models are sensitive to small sets of faults. Global models are sensitive to much larger sets of faults. All residuals in the example of the steam draught use local models. An example of a model describing a larger part of the system can be composed from residuals r_3 and r_4:

$$r_3 = F_W - \hat{F}_W \qquad \hat{F}_W = f(X, P_W - P_P), \tag{11}$$

$$r_4 = X - \hat{X} \qquad \hat{X} = f(U). \tag{12}$$

Substituting 12 in 11 we get:

$$r_6 = F_W - \hat{F}_W \qquad \hat{F}_W = f(U, P_W - P_P). \tag{13}$$

Residual r_6 describes the overall valve and is sensitive to both faults f_{10} and f_{11}. On the other hand, it does not use measurement of X, so it is not sensitive to fault f_8.

Therefore, using local models leads to a diagnostic matrix that contains minimal number of non-zero entries. After sorting, ones are grouped near the diagonal of the diagnostic matrix. The process of diagnosis with local models is an expression of the striving for a diagnostic matrix close to the diagonal matrix (Table 5). The example of such a solution is a diagnostic matrix for evaporation station in a sugar factory [7] shown in Table 6. This approach has the following advantages:

- LM has a much simpler structure than GM and has a lower rank.
- Times of fault detection depend on the transport delays and the rank of the process. They are shorter for smaller delays and lower ranks, which means LM.
- Computational expenditure on the identification of LM is smaller than on the identification of GM.
- Design expenditure related with obtaining the set of the structured residuals is lower for LM.
- Diagnostic systems based on LM are more robust in the case of changes of the set of sensor signals.
- Changes in the structure or parameters of the process make it necessary to design the whole set of residuals once again in the case of GM. With LM, only part of the residuals must be adjusted.

All the above arguments unambiguously point to the advantages of LM in the diagnostics of industrial processes. In some cases, it is justifiable to use selected models covering larger parts of the process because this can improve faults distinguishability.

To obtain structure of binary diagnostic matrix close to diagonal matrix:

- faults should be directly measured, or there should be measured variables sensitive to the fault and located near the place of the fault occurrence - such measurement will quickly detect the fault,
- process models for fault detection should be local and describing small part of the diagnosed process, the input and the outputs of the model should be measured.

Table 6. Part of binary diagnostic matrix for sugar factory.

1				1																	
				1	1																
		1	1																		
	1		1																		
			1		1																
			1			1															
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It is therefore appropriate to make direct measurements of faults occurring in the process. There are already existing solutions for many faults. The examples are: sensors for corrosion monitoring and gas or liquid leak detection. Optical vision systems can be used for assembly monitoring, bottle-filling monitoring, quality assessment, and the detection of blockages in conveyors. Thermovison is used for control of overheating machines like pumps, engines, compressors, and turbines and for detection of leaks and defects in thermal insulation. Wear of rotating parts of machines like engines, pumps, fans, and turbines is often monitored by vibration measurement. However, not each fault can be directly measured.

4 Conclusion

The possibility of separating the process diagnostics from the diagnostics of measuring instruments was analysed. It was shown that, in the general case, such separation is impossible. The separation of the diagnostics of measuring instruments from process diagnostics is possible only if all the measuring instruments are equipped with redundant sensors and a microprocessor unit, providing self-diagnostic functions. In this case, the diagnostic system has the structure of two diagonal binary diagnostic matrices, one for the measuring devices, and the second for the other faults. The self-diagnosable sensors of faults are future-proof, but they have their limitations. Not every fault can be directly measured.

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