FUZZY-LOGIC FAULT ISOLATION IN LARGE-SCALE SYSTEMS

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Application of fuzzy logic in fault isolation is proposed. The introduced methods assume the industrial requirements such as integration of different detection algorithms, system complexity, data and knowledge uncertainties. Algorithms of decreasing the calculation expenditures for diagnosing large-scale systems are also introduced. An example of the application is also shown. The proposed technique is a development of the Dynamic State Tables method.

Keywords: diagnostics, fuzzy logic, fault isolation, large-scale systems.

1. Introduction

Diagnosing complex technical installations (large-scale systems) poses serious problems. Such systems contain hundreds and even thousands components, and the number of possible faults can be much higher. For their detection, many detection algorithms which apply process variable measurements as their input signals must be realised. The number of signals equals likewise hundreds or thousands, and since measuring paths can in turn have faults of their own, the set of possible faults also contains these elements.

Calculation expenditures required for realisation of diagnostic functions are therefore very high. Despite decomposition of diagnostic tasks and diagnosing in decentralised structures (Kościelny, 1999a), it is vital to limit calculation expenditures needed for formulation of diagnoses in each subsystem.

Algorithms of diagnosing for complex plants and fundamental problems that exist in diagnosing such systems have been presented by Kościelny (1994; 1995). One of them consists in taking uncertainties of symptoms into account. The problem has been solved in this paper by application of fuzzy logic in evaluation of the symptom values and in formulation of diagnoses. The presented diagnosing method called F-DTS is on that score a development of the DTS algorithm (Kościelny, 1995).

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2. Residual Generation

For every system it is possible to define the set of possible faults:

$$F = \{f_k : k = 1, 2, \ldots, K\} \tag{1}$$

It contains faults of instruments, actuators and components. The set of residuals is generated for the needs of fault detection and it is of the form

$$R = \{r_j : j = 1, 2, \ldots, J\} \tag{2}$$

The residuals are calculated on the basis of defined process variable values with the help of models connecting the variables. Such models are created for elementary parts of the installation, provided that they do not have any faults.

The residual values are evaluated and the results are symptoms S, based on which one performs isolation of faults

$$S = \{s_j : j = 1, 2, \ldots, J\} \tag{3}$$

The diagram of the residual generation and evaluation is presented in Fig. 1.

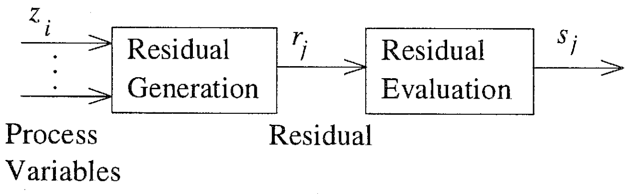

Fig. 1. Diagram of the residual generation and evaluation.

Possible symptom values s_j are described by the corresponding linguistic variables V_j,

$$V_j = \{v_i : i = 1, 2, \ldots, I\} \tag{4}$$

It is assumed that the set of values for each symptom can be an individual one. In each case, the set contains a positive value and one or more negative values.

The residuals in the diagnosis of complex technical installations (large-scale systems) should be generated based on partial models obtained for elementary parts of the installation. The set of models should cover the whole system. Such an approach offers the following advantages:

- the models applied are of lower orders, and therefore their identification is less difficult;
- the time of the symptoms appearing after the occurrence of faults is in this case the shortest;

- the susceptibility of a residual to particular faults can be easily defined without the necessity of modelling their influences.

The residuals can be generated by various methods:

- with the use of physical equations (e.g. balance ones) (Kościelny, 1999b);
- with the use of parity equations (input/output-type models) (Gertler, 1991; 1995; 1998; Patton and Chen, 1991);
- based on local state observers (Clark, 1978; Frank, 1987; 1990; Patton, 1994; Patton *et al.*, 1989);
- based on current identification of the process model parameters (Iserman, 1984; 1991; 1994);
- with the use of fuzzy models (Frank, 1994; Kościelny *et al.*, 1999);
- based on neural models (Koivo, 1994; Korbicz, 1997; Sorsa *et al.*, 1991; 1993);
- with the use of fuzzy neural networks (Garcia *et al.*, 1997; Zhang *et al.*, 1996).

In the diagnosing method presented in this paper, it is assumed that application of all the above-mentioned methods for residual generation is possible.

3. Fuzzy Residual Evaluation

The calculated value of a residual is evaluated (Fig. 1) in order to ascertain the existence of a fault in the controlled part of the diagnosing system. In the simplest case, a threshold test is applied (Frank, 1987; Garcia *et al.*, 1997; Kościelny, 1994; 1995). If admissible limits are exceeded, one acknowledges that a fault occurred. In the presence of measurement noise and inaccuracy of modelling, two-state evaluation of a residual performed based on a threshold test can be deceptive and can lead to inconsistent reasoning or erroneous diagnoses. Application of fuzzy logic makes it possible to take symptom uncertainties into account. Fuzzy evaluation called fuzzification of the residuals has been applied by Sędziak (1996), Theilliol *et al.*, (1997) and Kościelny (1999b).

The values taken by a linguistic variable are fuzzy sets. The general equation defining the value of the j-th symptom is of the form

$$s_j = \{\mu_{ji} : v_i \in V_j\} \tag{5}$$

where μ_{ji} is the grade of the membership of the j-th symptom to the fuzzy set v_i. The symptom values are defined by the grades of the membership of the residual value to particular fuzzy sets. In the simplest case, the set V_j of symptom values consists of two results: 'positive' and 'negative' (Fig. 2):

$$V_j = \{\mathrm{P}, \mathrm{N}\} \tag{6}$$

The symptom value is therefore defined by the grades of membership to a particular fuzzy set:

$$s_j = \{\mu_{ji} : v_i = \mathrm{P}, \mathrm{N}\} = \{\mu_{j\mathrm{P}}, \mu_{j\mathrm{N}}\} \tag{7}$$

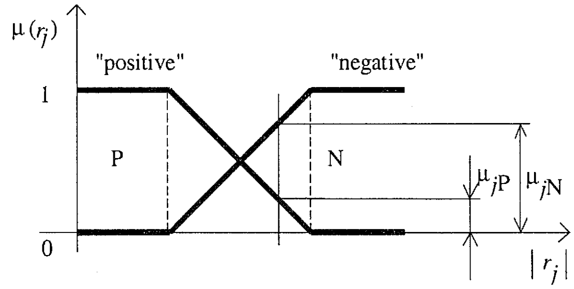

Fig. 2. Two-valued residual evaluation.

One can also apply multi-valued residual evaluation. For instance, three-valued evaluation takes into account the size of the residual value, as well as its sign ('positive', 'negative–', 'negative+'),

$$V_j = \{\mathrm{P}, \mathrm{N}-, \mathrm{N}+\} \tag{8}$$

to which correspond grades of the membership to a particular fuzzy set:

$$s_j = \{\mu_{ji} : v_i = \mathrm{P}, \mathrm{N}-, \mathrm{N}+\} = \{\mu_{j\mathrm{P}}, \mu_{j\mathrm{N}-}, \mu_{j\mathrm{N}+}\} \tag{9}$$

A three-valued partition of test results is shown in Fig. 3.

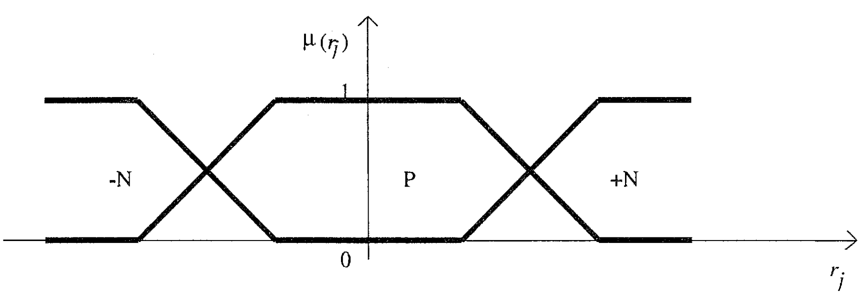

Fig. 3. Three-valued residual evaluation.

Let us consider the following division of a symptom value into partitions as an example of a different multi-valued evaluation:

$$V_j = \{\mathrm{P}, \mathrm{NM}-, \mathrm{NS}-, \mathrm{ND}-, \mathrm{NM}+, \mathrm{NS}+, \mathrm{ND}+\} \tag{10}$$

where P stands for a positive test result; NS–, NM–, NB– denote negative results having small, average and high negative values, respectively; NS+, NM+, NB+ signify negative results having small, average and high positive values, respectively.

4. Fault Isolation System

Fault isolation requires specification of an appropriate relation between detected symptoms (test results) and faults. Let us define the Fault Isolation System (FIS) as the following quadruple:

$$\mathrm{FIS} = \langle F, S, V, \phi \rangle \tag{11}$$

where F is the set of faults and S denotes the set of symptoms—they are defined by eqns. (1) and (3), respectively. Furthermore, V is the set of symptom values defined by

$$V = \bigcup_{s_j \in S} V_j \tag{12}$$

The function Φ is defined on the Cartesian product of sets F and S and it attributes subsets of values taken from the set V to pairs $\langle f, s \rangle$,

$$\Phi : F \times S \rightarrow \phi(V) \tag{13}$$

and

$$\Phi(f_k, s_j) = V_{kj} = \{v_{ji} \in V_j\} \subset V_j \tag{14}$$

The FIS is therefore the table which attributes a value or a subset of symptom values to each pair fault-symptom. It defines pattern symptom results for particular faults. Table 1 shows an example of FIS.

Table 1. An example of FIS.

F/S	f_1	$\dots$	f_k	$\dots$	f_K	V_j
s_1	N		P		N	$V_1 = \{$P,N$\}$
$\dots$						$\dots$
s_j	P		N−, N+		N−	$V_j = \{$P,N−,N+$\}$
						$\dots$
s_J	NS−, NB−		P		NS−, NS+	$V_J = \{$P,NS−,NB−, NS+,NB+$\}$

Declaration of two or more symptom values for a fault may:

- result from the nature of the fault (e.g. measuring a path's parametric fault can cause both an increase and a decrease in the measured signal value and thus in the residual value), or
- express an uncertainty concerning the symptom value caused by the fault.

5. Diagnostic Fuzzy Inference

The FIS defines pattern symptoms for particular single faults. Each column of the diagnostic table describes therefore the signature of a particular fault. On the other hand, the fault signature defines a rule of reasoning about the fault. For instance, the rule for a fault f_1 can be of the form

$$\text{IF } s_1 = \text{N and } \cdots \text{ and } s_j = \text{P and } (s_K = \text{NM}- \text{ or } s_K = \text{NM}+) \\ \text{THEN fault } f_1 \tag{15}$$

Note that the following rule corresponds to the state of full efficiency of the system:

$$\text{IF } s_1 = P \text{ and } \cdots \text{ and } s_j = \text{P and } s_K = \text{P} \\ \text{THEN the state of full efficiency} \tag{16}$$

The relation symptoms-faults can be written directly as a set of rules IF-THEN, but the notation in the form of FIS has a clear advantage: it simplifies appreciation of fault isolation. Each column of the table corresponds to a fault signature. If the signatures of different faults are identical, then the faults are not isolated.

The higher the rule's firing strength, the higher the degree of certainty that the fault shown in the conclusion did occur. By comparison of real and pattern symptom values, it is possible to define a degree of the attachment of a symptom to pattern ones described by the FIS, and hence to define the rule's firing degree.

Let us define the degree of an agreement between the j-th symptom and its pattern value obtained for the k-th fault:

$$\sigma_{kj} = \max\left\{\mu_{ji} \in s_j : v_i \in V_{kj}\right\} \tag{17}$$

The rule's firing degree can be calculated from the following quotient of products:

$$\delta_k = \frac{\prod_{j=1,\dots,J} \sigma_{kj}}{\sum_{n=1,\dots,K} \prod_{j=1,\dots,J} \sigma_{nj} + \prod_{j=1,\dots,J} \mu_{j\text{P}}} \tag{18}$$

The first component in the denominator corresponds to the fault set and the second component to the state of full efficiency. The index of firing for the rule defining the efficiency state is calculated from the equation:

$$\delta_0 = \frac{\prod_{j=1,\dots,J} \mu_{j\text{P}}}{\sum_{n=1,\dots,K} \prod_{j=1,\dots,J} \sigma_{nj} + \prod_{j=1,\dots,J} \mu_{j\text{P}}} \tag{19}$$

The diagnosis consists of the faults $f_k \in F$ for which the firing strength of a rule is the highest:

$$\text{DGN} = \left\{f_k : \delta_k = \max \quad \text{for} \quad k = 0, 1, \dots, K\right\} \tag{20}$$

6. Example of Diagnosis Formulation

The object of diagnosis considered in the paper is a three-tank system with the inflow forced by a pump and controlled by a valve (Fig. 4). The diagnosis is performed based on the following signals: water levels L_1, L_2 and L_3 in the tanks, the flow Q and a control signal U. The set of possible faults contains faults of instruments, actuators and components. The list of these faults is shown in Table 2. The faults should be detected and isolated in the diagnosing system.

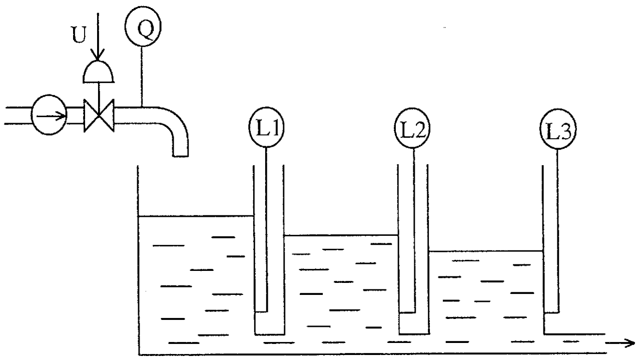

Fig. 4. A three-tank system.

Table 2. The set of faults F.

F	Description
f_1	Fault of the level sensor L_1
f_2	Fault of the level sensor L_2
f_3	Fault of the level sensor $L3$
f_4	Fault of the flow sensor Q
f_5	Fault of the actuator
f_6	Partial clogging of the channel between Tanks 1 and 2
f_7	Partial clogging of the channel between Tanks 2 and 3
f_8	Partial clogging of the outlet
f_9	Leakage from Tank 1
f_{10}	Leakage from Tank 2
f_{11}	Leakage from Tank 3

Residual r_1 denotes working characteristics of the actuator, residuals r_2, r_3 and r_4 use balance connections for particular tanks, and residual r_5 corresponds to the balance of the flows in the whole installation. The sensitivity of residuals to particular faults results in this case directly from the form of equations, which simplifies considerations concerning fault isolation.

Table 3. Residuals generated for the three-tank system.

R	Detection algorithm
r_1	$r_1 = Q - \hat{Q} = Q - f(U)$
r_2	$r_2 = Q - \alpha_{12}S_{12}\sqrt{2g(L_1 - L_2)} - A_1\dfrac{\mathrm{d}L_1}{\mathrm{d}t}$
r_3	$r_3 = \alpha_{12}S_{12}\sqrt{2g(L_1 - L_2)} - \alpha_{23}S_{23}\sqrt{2g(L_2 - L_3)} - A_2\dfrac{\mathrm{d}L_2}{\mathrm{d}t}$
r_4	$r_3 = \alpha_{23}S_{23}\sqrt{2g(L_2 - L_3)} - \alpha_3 S_3\sqrt{2gL_3} - A_3\dfrac{\mathrm{d}L_3}{\mathrm{d}t}$
r_5	$r_5 = Q - \alpha_3 S_3\sqrt{2gL_3} - A_1\dfrac{\mathrm{d}L_1}{\mathrm{d}t} - A_2\dfrac{\mathrm{d}L_2}{\mathrm{d}t} - A_3\dfrac{\mathrm{d}L_3}{\mathrm{d}t}$

Table 4. Fault isolation system having two- and three-valued residual evaluation.

F/S	f_1	f_2	f_3	f_4	f_5	f_6	f_7	f_8	f_9	f_{10}	f_{11}	V_j
s_1	P	P	P	N	N	P	P	P	P	P	P	P, N
s_2	N−, N+	N−, N+	P	N−, N+	P	N+	P	P	N−	P	P	P, N−, N+
s_3	N−, N+	N−, N+	N−, N+	P	P	N−	N+	P	P	N−	P	P, N−, N+
s_4	P	N−, N+	N−, N+	P	P	P	N−	N+	P	P	N−	P, N−, N+
s_5	N−, N+	N−, N+	N−, N+	N−, N+	P	P	P	N+	N−	N−	N−	P, N−, N+

The relation symptoms-faults defined by the FIS can be deduced by modelling the effect of faults on residual values. In the case of the three-tank set it is simple, but for complex technological installations it can be very difficult and costly. In such cases, the relation symptoms-faults is defined by an expert on the basis of his knowledge about the object of diagnosing and fault symptoms.

Let us consider an example of diagnostic reasoning based on the following symptoms:

$$s_1 = \{\mu_{j\mathrm{P}} = 1, \mu_{j\mathrm{N}} = 0\}$$

$$s_2 = \{\mu_{j\mathrm{P}} = 0.1, \mu_{j\mathrm{N}-} = 0, \mu_{j\mathrm{N}+} = 0.9\}$$

$$s_3 = \{\mu_{j\mathrm{P}} = 0.2, \mu_{j\mathrm{N}-} = 0.8, \mu_{j\mathrm{N}+} = 0\}$$

$$s_4 = \{\mu_{j\mathrm{P}} = 0.7, \mu_{j\mathrm{N}-} = 0.3, \mu_{j\mathrm{N}+} = 0\}$$

$$s_5 = \{\mu_{j\mathrm{P}} = 0.9, \mu_{j\mathrm{N}-} = 0, \mu_{j\mathrm{N}+} = 0.1\}$$

Table 5 shows the values of δ_{kj} which is the function of the membership of real symptoms to symptom sets being patterns of particular faults. The last row shows the calculated values of the firing strength of the rules for all the faults.

Table 5. The membership function of real symptoms to symptom sets which are patterns for particular faults.

F/S	f_0	f_1	f_2	f_3	f_4	f_5	f_6	f_7	f_8	f_9	f_{10}	f_{11}
s_1	1.0	1.0	1.0	1.0	0.0	0.0	1.0	1.0	1.0	1.0	1.0	1.0
s_2	0.1	0.9	0.9	0.1	0.9	0.1	0.9	0.1	0.1	0	0.1	0.1
s_3	0.2	0.8	0.8	0.8	0.2	0.2	0.8	0.0	0.2	0.2	0.8	0.2
s_4	0.7	0.7	0.3	0.3	0.7	0.7	0.7	0.3	0.0	0.7	0.7	0.3
s_5	0.9	0.1	0.1	0.1	0.1	0.9	0.9	0.9	0.1	0.0	0.0	0.0
δ_k	0.02	0.09	0.04	0.00	0.00	0.00	**0.84**	0.00	0.00	0.00	0.00	0.00

In the case under consideration, the diagnosis

$$\mathrm{DGN} = f_6$$

reveals a partial clogging of the channel between Tanks 1 and 2.

7. Algorithm of Diagnosing by the F-DTS Method for Complex Technical Installations

For complex technical installations, the power of the sets of faults and symptoms is very high. Diagnostic reasoning in such systems is associated with high calculation expenditures. In order to identify a particular faulty situation, it is not necessary to analyse all the symptoms. The problem can be solved by dynamic definition of a subset of possible faults F^* and a subset of symptoms S^* that are useful for identification of the faults (Kościelny, 1995; Sędziak, 1996), including a subset of symptoms S^*_{N} having negative values. This means that an appropriate subset FIS is considered at each stage of diagnosing.

The algorithm of diagnosing by the F-DTS method includes therefore three phases:

- cyclic testing of the symptom values in order to identify a faulty situation,
- creating of the subset FIS* which includes the faulty situation that is currently identified,
- reasoning on the basis of the FIS*.

1. Cyclic testing of symptom values

The cyclic testing of symptom values should detect symptoms of a faulty situation. Detection of the first symptom s_j^0 having the grade of membership to any negative value greater than a certain threshold value (e.g. $M = 0.6$) launches the process of fault isolation:

$$\exists\, s_j^0 \in S : v_i \neq \mathrm{P} \wedge \mu_{ji} > M \tag{21}$$

At the beginning of reasoning ($m = 0$ in the iteration), it is assumed that

$$S^* = S^*_{\mathrm{N}}(m = 0) = s_j^0 \tag{22}$$

$$F^* = \emptyset \tag{23}$$

2. Creating FIS which includes the fault that is currently identified*

Creation of FIS* is an iterative process which should define the smallest possible subset of the FIS necessary for the diagnosis formulation. The iteration number is denoted by the symbol m.

2.1. Creation of the set of possible faults F^*

The set of possible faults F^* includes the faults belonging to F that can be detected with the help of symptoms belonging to the set $S^*_{\mathrm{N}}(m)$. Creation of the set F^* is performed according to the following equation:

$$F^* = \{f_k \in F : \exists\, s_j \in S^*_{\mathrm{N}}(m) \cap \Phi(f_k, s_j) \neq \mathrm{P}\} \tag{24}$$

2.2. Creation of the set of symptoms S^* useful for identification of the faults belonging to the set F^*

The set S^* is created on the basis of the following equation:

$$S^* = \{s_j \in S : \exists\, f_k \in F^* \cap \Phi(f_k, s_j) \neq \mathrm{P}\} \tag{25}$$

2.3. Creation of the set of symptoms $S^*_\mathrm{N}(m)$ useful for identification of the faults belonging to the set F^* and having negative values

The set $S^*_\mathrm{N}(m)$ is created by the symptoms belonging to S^* and fulfilling the following equation:

$$S^*_\mathrm{N}(m) = \{s_j \in S^* : v_i \neq \mathrm{P} \wedge \mu_{ji} > M\} \tag{26}$$

2.4. Verification of the requirements for the end of dynamic FIS definition*

if $S^*_\mathrm{N}(m) \neq S^*_\mathrm{N}(m-1)$ then
    $m = m + 1$
    goto 2.1
else
    $F^* = F^* + f_0$
    $\mathrm{FIS}^* = \langle F^*, S^*, V, \phi^* \rangle$
endif

*3. Reasoning based on FIS**

Reasoning is performed according to the rules presented in Section 5. The first step consists in the definition of the rule's firing degree for particular faults belonging to the set F^*, see eqn. (24). Then the diagnosis is formulated according to eqn. (20).

8. Example of a Fault Diagnosis by the F-DTS Method

To clarify the essence of the F-DTS algorithm, two examples of diagnostic reasoning will be presented. The first one refers to the three-tank station (Section 6).

Example 1.

Stage 1. Let us assume that the diagnostic process was initiated by a symptom s_2 for which we have

$$\mu_{2\mathrm{N}+} = 0.9, \qquad F^* = \emptyset, \qquad S^* = \emptyset, \qquad S^*_\mathrm{N}(0) = s_2$$

Stage 2.

Step 1.

$$F^* = \{f_1, f_2, f_4, f_6, f_9\}$$

$$S^* = \{s_1, s_2, s_3, s_4, s_5\}$$

$$S^*_\mathrm{N}(1) = \{s_2, s_3\}$$

$$S^*_\mathrm{N}(1) \neq S^*_\mathrm{N}(0)$$

Step 2.

$$F^* = \{f_1, f_2, f_3, f_4, f_6, f_7, f_9, f_{10}\}$$

$$S^* = \{s_1, s_2, s_3, s_4, s_5\}$$

$$S^*_{\mathrm{N}}(2) = \{s_2, s_3\}$$

$$S^*_{\mathrm{N}}(2) \neq S^*_{\mathrm{N}}(1)$$

Step 3.

$$F^* = \{f_1, f_2, f_3, f_4, f_6, f_7, f_9, f_{10}\}$$

$$S^* = \{s_1, s_2, s_3, s_4, s_5\}$$

$$S^*_{\mathrm{N}}(3) = \{s_2, s_3\}$$

$$S^*_{\mathrm{N}}(3) \neq S^*_{\mathrm{N}}(2)$$

Stage 3.

$$F^* = \{f_0, f_1, f_2, f_3, f_4, f_6, f_7, f_9, f_{10}\}$$

$$S^* = \{s_1, s_2, s_3, s_4, s_5\}$$

Table 6. The membership function of actual symptoms to symptom sets which are patterns for particular faults.

F/S	f_0	f_1	f_2	f_3	f_4	f_6	f_7	f_9	f_{10}
s_1	1.0	1.0	1.0	1.0	0.0	1.0	1.0	1.0	1.0
s_2	0.1	0.9	0.9	0.1	0.9	0.9	0.1	0.0	0.1
s_3	0.2	0.8	0.8	0.8	0.2	0.8	0.0	0.2	0.8
s_4	0.7	0.7	0.3	0.3	0.7	0.7	0.3	0.7	0.7
s_5	0.9	0.1	0.1	0.1	0.1	0.9	0.9	0.0	0.0
δ_k	0.02	0.09	0.04	0.00	0.00	**0.84**	0.00	0.00	0.00

Based on Table 6, it can be seen that the set of faults under consideration was limited. The diagnosis formulated by the F-DTS method is the same as that obtained from direct reasoning presented in Section 6. ♦

Example 2.

Table 7. Fault isolation system having two-valued residuals evaluation (empty items denote P-type values).

F/S	f_1	f_2	f_3	f_4	f_5	f_6	f_7	f_8	f_9	f_{10}	f_{11}	f_{12}	f_{13}	f_{14}	f_{15}	f_{16}	f_{17}	f_{18}	f_{19}	f_{20}	f_{21}	f_{22}	V_j
s_1		N		N																			P, N
s_2			N			N																	P, N
s_3				N		N																	P, N
s_4	N				N	N																	P, N
s_5					N		N		N														P, N
s_6							N						N										P, N
s_7										N		N											P, N
s_8									N				N	N									P, N
s_9								N	N		N			N									P, N
s_{10}											N				N			N					P, N
s_{11}														N		N				N			P, N
s_{12}																	N		N				P, N
s_{13}																		N			N		P, N
s_{14}																		N		N	N		P, N
s_{15}																			N			N	P, N
s_{16}																	N					N	P, N

Table 8. Exemplary actual values of the symptoms for the fault f_9.

J	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
$\mu_{j\mathrm{P}}$	1.0	0.9	0.7	0.8	0.2	0.5	0.8	0.3	0.4	1.0	0.9	0.9	0.8	0.7	0.6	1.0
$\mu_{j\mathrm{N}}$	0.0	0.1	0.3	0.2	0.8	0.5	0.2	0.7	0.6	0.0	0.1	0.1	0.1	0.3	0.1	0.0

Table 9. A subset of the FIS obtained according to the F-DTS algorithm for the data from Table 8.

F/S	f_0	f_5	f_7	f_8	f_9	f_{11}	f_{13}	f_{14}
s_4	0.8	0.2	0.8	0.8	0.8	0.8	0.8	0.8
s_5	0.2	0.8	0.8	0.2	0.8	0.2	0.2	0.2
s_6	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5
s_8	0.3	0.3	0.3	0.3	0.7	0.3	0.7	0.7
s_9	0.4	0.4	0.4	0.6	0.6	0.6	0.4	0.6
s_{10}	1.0	1.0	1.0	1.0	1.0	0.0	1.0	1.0
s_{11}	0.9	0.9	0.9	0.9	0.9	0.9	0.9	0.1
δ_k	0.04	0.04	0.17	0.06	**0.58**	0.00	0.10	0.02

The above example proves that the number of faults under consideration can be much reduced during reasoning in comparison with the complete set of faults. Similarly, the number of symptoms analysed is relatively small when compared with the number of all the symptoms. ♦

9. Summary

A formalized description of the fault isolation system called FIS has been introduced. The paper describes application of fuzzy logic for residual evaluation and fault isolation. Fuzzy interpretation of residuals allows us to take the main uncertainty occuring in the process of diagnostic reasoning into account, i.e. the uncertainty of symptoms. Such an uncertainty results from existing disturbances, measurement noise and inaccuracies of modelling.

The presented F-DTS method of diagnostic reasoning is adopted for diagnosing complex systems. Appropriate subsets of possible faults and symptoms necessary for their isolation are created at each stage of the diagnosis formulation. Such an approach offers the following advantages:

- lower calculation expenditures needed for the diagnosis formulation;
- robustness to signal changes, i.e. changes of the detection algorithm during diagnosing;
- formulation of correct diagnoses also in the cases of multiple faults without the need for taking states with these faults into account.

A computer implementation of the suggested reasoning process is very simple. The most characteristic feature is the lack of the defuzzification phase (as opposed to fuzzy regulation). The diagnosis indicates the faults for which the degree of the rule ignition is the highest.

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References

Clark R.N. (1978): *Instrument fault detection.* — IEEE Trans. Aerospace and Electronic Syst., Vol.14, No.3, pp.456–465.

Frank P.M. (1987): *Fault diagnosis in dynamic systems via state estimation—A survey,* In: System Fault Diagnosis, Reliability and Related Knowledge-Based Approaches (Tzafestas *et al.*, Eds.). — Vol.1, Dordrecht: Dr. Reidel, pp.35–98.

Frank P.M. (1990): *Fault diagnosis in dynamic systems using analytical and knowledge-based redundancy—A survey and some new results.* — Automatica, Vol.26, No.3, pp.459–474.

Frank P.M. (1994): *Fuzzy supervision. Application of fuzzy logic to process supervision and fault diagnosis.* — Proc. Int. Workshop *Fuzzy Duisburg'94*, Duisburg, Germany, pp.36–59.

Garcia F.J., Izquierdo V. de Miguel L. and Peran J. (1997): *Fuzzy identification of systems and its applications to fault diagnosis systems.* — Proc. IFAC Symp. *Fault Detection Supervision and Safety for Technical Processes SAFEPROCESS'97*, Kingston Upon Hull, G.B., Vol.2, pp.705–712.

Gertler J. (1991): *Analitical redunduncy methods in fault detection and isolation.* — IFAC Symp. *Fault Detection, Supervision and Safety for Technical Processes SAFEPROCESS*, Baden-Baden, Germany, Vol.1, pp.9–21.

Gertler J. (1995): *Generating directional residuals with dynamic parity relations.* — Automatica, Vol.31, No.4, pp.627–635.

Gertler J. (1998): *Fault Detection and Diagnosis in Engineering Systems.* — New York: Marcel Dekker.

Isermann R. (1984): *Process fault detection based on modelling and estimation methods—A survey.* — Automatica, Vol.20, No.4, pp.387–404.

Isermann R. (1991): *Fault diagnosis of machines via parameter estimation and knowledge processing.* — Proc. IFAC Symp. *Fault Detection, Supervision and Safety for Technical Processes SAFEPROCESS*, Baden-Baden, Germany, pp.121–133.

Isermann R. (1994): *On the applicability of model-based fault detection for technical processes.* — Contr. Eng. Practice, Vol.2, No.3, pp.439–450.

Koivo H.N. (1994): *Artificial neural networks in fault diagnosis and control.* — Contr. Eng. Practice, Vol.2, No.7, pp.89–101.

Korbicz J. (1997): *Neural networks and their application in fault detection and diagnosis.* — Proc. IFAC Symp. *Fault Detection Supervision and Safety for Technical Processes SAFEPROCESS'97*, Kingston Upon Hull, G.B., Vol.2, pp.377–382.

Kościelny J.M. and Pieniążek A. (1994): *Algorithm of fault detection and isolation applied for evaporation unit in sugar factory.* — Contr. Eng. Practice, Vol.2, No.4, pp.649–657.

Kościelny J.M. (1995): *Fault isolation in industrial processes by the dynamic table of states method.* — Automatica, Vol.31, No.5, pp.747–753.

Kościelny J.M. (1999a): *Diagnostics of processes in decentralized structures.* — Arch. Contr. Sci., (in print).

Kościelny J.M. (1999b): *Application of fuzzy logic for fault isolation in a three-tank system.* — Proc. 14th IFAC World Congress, Beijing, China, pp.73–78.

Kościelny J.M., Syfert M. and Bartyś M. (1999): *Fuzzy logic fault diagnosis of industrial process actuators.* — Appl. Math. Comp. Sci., (in this issue).

Patton R.J. (1994): *Robust model-based fault diagnosis. The state of the art.* — proc. IFAC Symp. *Fault Detection, Supervision and Safety for Technical Processes, SAFEPROCESS'94*, Espoo, Finland, Vol.1, pp.1–24.

Patton R., Frank P. and Clark R. (Ed.) (1989): *Fault Diagnosis in Dynamic Systems. Theory and Applications.* — Englewood Cliffs: Prentice Hall.

Patton R.J. and Chen J. (1991): *A review of parity space approaches to fault diagnosis.* — Proc. IFAC Symp. *Fault Detection, Supervision and Safety for Technical Processes SAFEPROCESS*, Baden-Baden, Germany, Vol.1, pp.239–255.

Sędziak D. (1996): *F-DTS method of fault identification in industrial processes.* — Prep. 1st Nat. Conf. *Diagnostic of Industrial Processes*, Podkowa Leśna, Poland, pp.68–71, (in Polish).

Sorsa T., Koivo H. and Koivisto H. (1991): *Neural networks in process fault diagnosis.* — IEEE Trans. Syst. Man Cybern., Vol.1, No.4, pp.815–825.

Sorsa T. and Koivo H.N. (1993): *Application of artificial neural networks in process fault diagnosis.* — Automatica, Vol.29, No.4, pp.843–849

Theilliol D., Sauter D. and Vela Valdes L.G. (1997): *Integration of qualitative and quantitative methods for fault detection isolation.* — Proc. IFAC Symp. *Fault Detection Supervision and Safety for Technical Processes SAFEPROCESS'97*, Kingston Upon Hull, G.B., Vol.2. pp.687–692.

Zhang J., Morris A.J. and Martin E.B. (1996): *Robust process fault detection and diagnosis using neuro-fuzzy networks.* — Proc. 13th Triennial IFAC World Congress, San Francisco, 7f–05, pp.169–174.

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