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# Fuzzy logic application for fault isolation of actuators

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This paper is focused particularly on application of fuzzy logic approach for solving fault isolation problem of some class of industrial actuators described in the benchmark actuator definition [1]. Particular attention was paid for searching of applicable and acceptable solutions in terms of industrial implementations. The rational solution of the problem of setting fuzzy partitions for residual evaluation was proposed. The industrial benchmark study was applied for evaluating of proposed approach by means of the real process data acquired in normal and abnormal process states. The chosen examples of achieved results concerning fault isolability issues are presented.

**Keywords:** fault detection and isolation, industrial actuators, benchmark study, modelling, diagnosis

## 1. Introduction

Control tasks of technological processes can be generally defined in terms of acting on the energy and mass flows. Actuators (final control elements) are applied to real-time acting on these flows. Faults or malfunctions of final control elements (e.g. control valves, servo-motors, positioners) appear relatively often in the industrial practice. The actuators are installed mainly in harsh environment: high temperature, high pressure, low or high humidity, dusty pollutants, chemical solvents, aggressive media, vibrations, etc. This has the crucial influence on the final control element predicted lifetime. The malfunction or failures cause long-term process disturbs or even sometimes forces the installation shut down. Moreover, final control elements faults may vary final product quality and may cause also reasonable economic losses. The on-line diagnostics of final control elements have been applied in industrial practice to ensure proper fault prevention or early stage fault prediction tasks. Permanent or occasionally performed diagnosis of actuators significantly cuts the installation maintenance costs.

The diagnosis of actuators has been considered in many contributions [6, 7, 11, 23]. There were developed approaches, methods and algorithms for the fault detection and isolation of actuators: parity equation [20, 21], unknown input observer [24], extended Kalman filter, signal analysis, fuzzy logic [2, 5, 10, 14, 15], b-spline, spectral analysis [25], pattern recognition, structural analysis [4, 9], timed automata [19], statistical methods e.t.c. There were also developed intelligent positioners supporting auto-diagnostic and auto-validation functions [12, 22, 26, 27]. The decomposition of the diagnostic tasks in the complex systems and the concept of intelligent actuators providing diagnostic features were also presented in papers [3, 16, 17].

Fuzzy logic has been approved as an efficient technique of processing of uncertain and imprecise information. This is typical to the most of the information being acquired in the industrial practice. Therefore, the models of the systems, based on the uncertain data are also uncertain and imprecise. In consequence, residual values and fault symptoms obtained from the models are uncertain and imprecise. Fuzzy logic has build-in inherent mechanisms enabling handling the uncertain quantities. Therefore, it takes some advantages in applications of diagnostic algorithms [8, 10, 13, 15, 17, 18].

## 2. Fault detection

After detailed analysis of the structure and principles of operation of benchmark electro-pneumatic actuator [1], there were applied and tested 5 different partial models of liquid flow rate $F$. These models bring a possibility of defining of a set of five residuals (1..5). Residuals $r_1$ and $r_4$ are based on the simplified model of servo-motor stem displacement $Z$. Residual $r_2$ is based on the simplified model of flow controlled by control system by means of process control value $CV$ and pressure difference across the valve $(P_1 - P_2)$. Residuals: $r_3$ and $r_5$ are based on the general model of the actuator. Models were tuned by means of archive data acquired from fault free operation of technological installation in one of the sugar factories.

$$r_1 = Z - \hat{Z}(CV), \tag{1}$$

$$r_2 = F - \hat{F}(Z, \sqrt{P_1 - P_2}), \tag{2}$$

$$r_3 = F - \hat{F}(CV, \sqrt{P_1 - P_2}), \tag{3}$$

$$r_4 = F - \hat{F}(Z), \tag{4}$$

$$r_5 = F - \hat{F}(CV). \tag{5}$$

In fact, while considering practical applications, a problem of building of suitable process models arises. Following factors should be taken into consideration: variety of actuator and control valve types, huge amount of manpower needed for development of models and parameter identification, necessity of making simplifications, lack of engineering knowledge *etc.* In fact, data based modelling seems to be applicable. Multi-layer feed forward perceptron neural networks (MLP) were applied in detection phase of fault detection and isolation (FDI) approach presented below. Those networks take advantages of learning from experimental data.

The scheme of one of applied MLP networks is presented in Fig. 1. Moving Average (MA) models were principally applied. Moving average models are conceptually a linear regression of the current value of the data series against the white noise or random disturbs of one or more prior values of the series. In general, MA models have abilities of easy learning. Moreover, achieved modelling quality factors are acceptable. For example, MA mean square error value does not exceed 0.28% in model (3). Low values of model mean square residual errors are highly acceptable when considering practical applications (Fig. 2, Fig. 3). Care must be taken when choosing learning data sets. Particularly, if the span of magnitudes of learning data is too narrow in respect to spans of data values magnitudes in faulty states, the false or unlikely diagnosis can be generated. This case is exemplified and commented in Sec. 6. The investigations with the autoregressive moving average (ARMA) models (with additional input from the real output) show, that there is no significant improvement of values of modelling quality factors. Moreover, this class of ARMA models is not suitable for fault detection because of fault learning abilities.

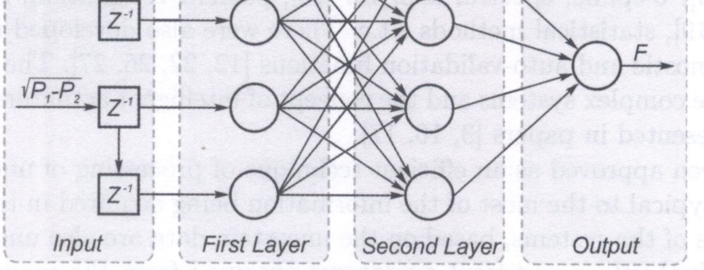


**Fig. 1.** Example of multilayer feed-forward perceptron neural network used for modelling of actuator

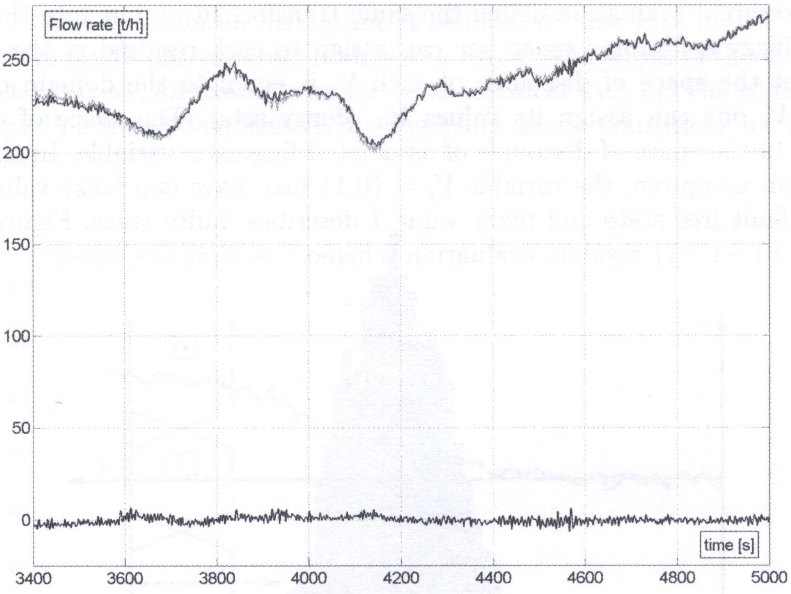


**Fig. 2.** Example of flow rate model (3) output in fault free state (normal process state). Flow rate (in technical units [t/h]) versus time (in [s]) is shown. Significant (ca. 50%) flow drop was observed. Modelled and measured flow rates are overlapping each other and both signals are practically indistinguishable. Residual is given also in the lower part of chart. One can observe that residual is practically not sensitive to the flow changes

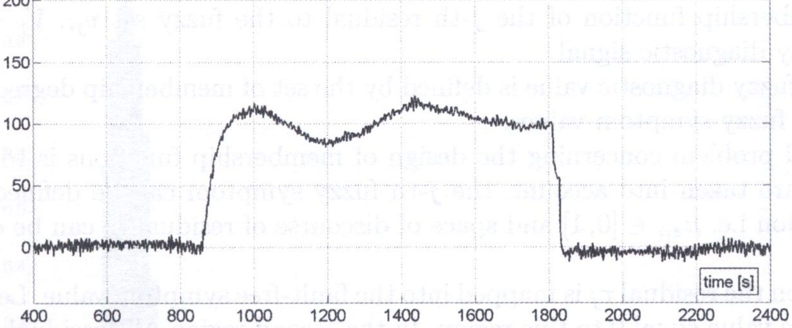


**Fig. 3.** Illustration of fault sensitivity of the flow rate model (3)

## 3. Idea of fuzzy residual evaluation

Constant or adaptive bi-valued residual threshold evaluation techniques possess many substantial drawbacks. There is a problem of defining the threshold values either theoretically or experimentally. The residual evaluation based on the threshold passing tests may fail particularly in case of uncertain signals, and in a consequence, may induce contradictory conclusions or false diagnosis. Application of fuzzy logic may be useful to overcome the diagnosis "flickering effects" in case of uncertain diagnostic signals. The main idea is based on the introduction of fuzzy residual threshold – thus softening the diagnostic transitions from faultless to faulty states.

The residual evaluation is defined as the operation that maps the residual space into the symptom space. The fuzzy residual evaluation define the same transformation but into the fuzzy symptoms space. To obtain fuzzy symptoms space one can assign to each residual $r_j$ the linguistic variable (symptom) $V_j$. Let the space of discourse of each $V_j$ is equal to the domain of the residual $r_j$. To each variable $V_j$ one can assign its values $V_{jk}$ (fuzzy sets). The space of discourse of fuzzy values is identical to the space of discourse of associated linguistic variable. In the simplest case of fuzzy bi-valued fault symptom, the variable $V_j = \{0,1\}$ may have two fuzzy values 0 and 1. Fuzzy value **0** describes fault free state and fuzzy value 1 describes faulty state. Figure 4 presents fuzzy three-valued $V_j = \{0,-1,+1\}$ residual evaluation scheme.

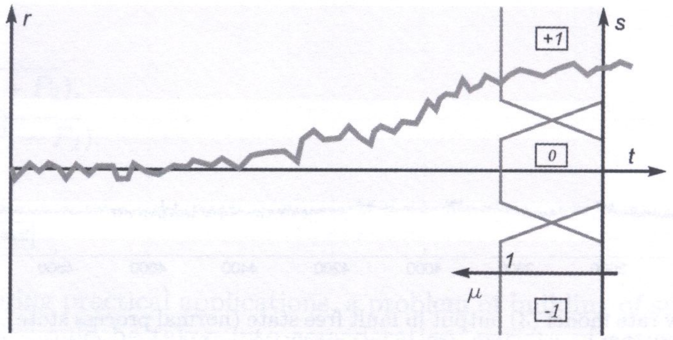


**Fig. 4.** Illustration of three-valued fuzzy residual evaluation technique

**Definition.** *Fuzzy fault symptom is defined as the k-dimensional fuzzy set such that for each residual $r_j$ assign k-tuplets.*

$$r_j \Rightarrow \{< v_{j1}, v_{j2} \ldots v_{jk} >: \ v_{jk} \in V_j\} . \tag{6}$$

The general expression for the fuzzy multiple-valued symptom is as follows.

$$v_j = \{v_{ji}, \mu_{ji} >: v_{ji} \in V_j\} \tag{7}$$

where: $\mu_{ji}$ – membership function of the $j$-th residual to the fuzzy set $v_{ji}$. $V_j$ – the set of fuzzy values of $j$-th fuzzy diagnostic signal.

Therefore, the fuzzy diagnostic value is defined by the set of membership degrees of crisp residual to the pre-defined fuzzy symptom values.

The substantial problem concerning the design of membership functions is to be considered. If practical aspects are taken into account, the $j$-th fuzzy symptom can be defined as a normalised membership function i.e. $\mu_{s_{ji}} \in [0, 1]$ and space of discourse of residual $r_j$ can be divided into three regions.

In the first region the residual $r_j$ is mapped into the fault-free symptom value. Let assign symptom membership degree value equal 0 to this region. In the second region, the residual $r_j$ is mapped into the fault symptom value – let assign symptom membership degree value equal 1 to this region. In the third region there is transition of $j$-th fuzzy symptom membership function from 0 to 1 value. The shape of this transition function and width of this region is to be defined in practical applications. The starting point and width of third region is related to the residual uncertainty. On the other hand, the residual uncertainty is a complex function of system model and measurement uncertainties. In general, those uncertainties are difficult to determine. Therefore, following practicable procedure is suggested for determining the starting point and width of the third region for model based FDI.

In the first step the statistical parameters of residual are determined. In the second step the starting point of third region on residual scale is determined as $b_3 = 3\sigma$, where $\sigma$ – residual standard deviation. The hypothesis of Gaussian residual distribution is allowable taking into account physical nature of measurement uncertainties and large number of influencing variables. An example of experimental histogram of residual of flow rate model of control valve in the normal system state is shown in Fig. 5. The experimental histogram of residual of flow rate model of control valve of actuator benchmark in faulty process state is shown in Fig. 6. The width of the third region of fuzzy symptom can be set arbitrary, for example on the value identical with $b_3$. The width should be tuned experimentally according to residual sensitivity. Typically, linear transitions for fuzzy membership functions are applied.

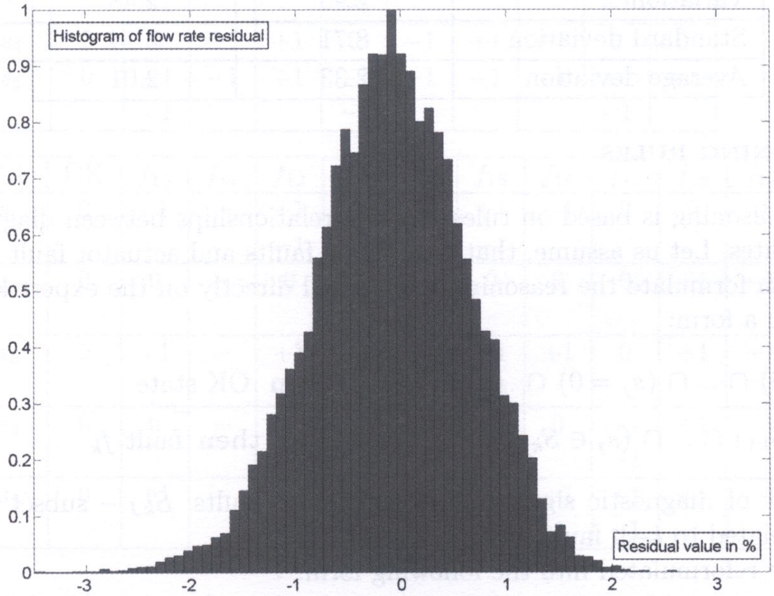


**Fig. 5.** Example of experimental histogram of residual of flow rate model of control valve

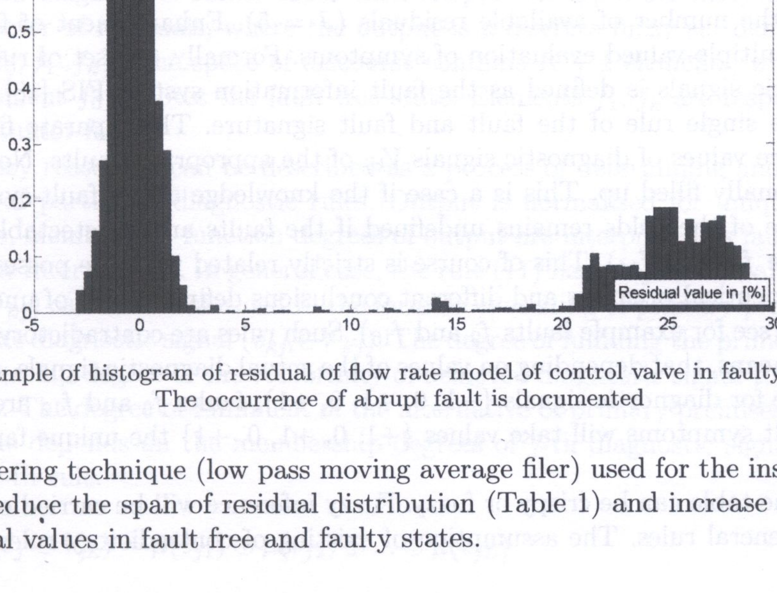


**Fig. 6.** Example of histogram of residual of flow rate model of control valve in faulty process state. The occurrence of abrupt fault is documented

Additional filtering technique (low pass moving average filer) used for the instrumentation measurements may reduce the span of residual distribution (Table 1) and increase separation between neighbour residual values in fault free and faulty states.

**Table 1.** Statistical evaluation of influence of filtering of input signals (model 5). Parameters are normalised

| Statistical parameter | Before filtering | After filtering |
|---|---|---|
| Mean value (absolute) | −0.38 | −0.38 |
| Residual minimum | −17.04 | −12.91 |
| Residual maximum | 10.45 | 7.55 |
| Variation | 2.95 | 2.48 |
| Standard deviation | 8.71 | 6.14 |
| Average deviation | 2.33 | 2.01 |

## 4. Fuzzy reasoning rules

Fuzzy diagnostic reasoning is based on rules defining relationships between diagnostic signals and faults or system states. Let us assume, that only single faults and actuator fault free states will be considered. One can formulate the reasoning rules based directly on the expert knowledge. In this case, the rules have a form:

$$R_0 : \textbf{If} \quad (s_1 = 0) \cap ... \cap (s_j = 0) \cap ... \cap (s_J = 0) \quad \textbf{then} \quad \text{OK state} \tag{8}$$

$$R_k : \textbf{If} \quad (s_1 \in S_{k1}) \cap ... \cap (s_j \in S_{kj}) \cap ... \cap (s_J \in S_{kJ}) \quad \textbf{then} \quad \text{fault } f_k \tag{9}$$

where: $J$ – number of diagnostic signals, $K$ – number of faults, $S_{kJ}$ – subset of values of $J$-th diagnostic signal related to $k$-th fault.

Rules (9) can be reformulated into the following form:

$$R_k : \textbf{If} \quad [(s_1 = s_a) \cup ... \cup (s_1 = s_c)] \cap ... \cap [(s_J = s_b) \cup ... \cup (s_J = s_e)] \quad \textbf{then} \quad \text{fault } f_k. \tag{10}$$

For example, the rule for the fault $f_1$ have following form:

$$R_1 : \textbf{If} \quad [(s_1 = +1) \cup (s_1 = -1)] \cap [(s_2 = 0)] \cap [(s_3 = +1) \cup (s_3 = -1)] \\ \cap [(s_4 = 0)] \cap [(s_4 = 0)] \cap [(s_5 = +1) \cup (s_5 = -1)] \quad \textbf{then} \quad \text{fault } f_1. \tag{11}$$

The knowledge of the fault-symptoms relation can be comprehensively shown in the matrix form. Table 2 contains the set of all reference fault signatures associated with each actuator fault ($K = 19$) defined in the benchmark definition [1]. The OK state is defined as the fault free state. Signature of this state consists exclusively from zero symptom values. The dimension of signature vector is equal to the number of available residuals ($J = 5$). Enhancement of fault isolability is achieved here by multiple-valued evaluation of symptoms. Formally, the set of rules for all defined faults and diagnostic signals is defined as the fault information system FIS [18]. Each column of the FIS defines the single rule of the fault and fault signature. The separate fields of the table contain the reference values of diagnostic signals $V_{kj}$ of the appropriate faults. Not all fields of FIS must be unconditionally filled up. This is a case if the knowledge about fault-symptoms relations is incomplete. Some of the fields remains undefined if the faults are undetectable by given set of diagnostic tests (see $f_{11}$ and $f_{14}$). This of course is strictly related with the possessed knowledge.

The rules with identical premises and different conclusions define the set of unconditional indistinguishable faults (see for example faults $f_9$ and $f_{16}$). Such rules are contradictory. The conditional distinguishability means, that depending on values of the actual diagnostic signals, faults are isolable or not. For instance for diagnostic signals $\{-1, 0, +1, 0, +1\}$, faults $f_9$ and $f_{12}$ are not distinguishable, but if the fault symptoms will take values $\{+1, 0, +1, 0, +1\}$ the unique fault $f_{12}$ is pointed out.

The entries in the table can be crispy or fuzzy. Fuzzy inference will be carried out on base of the above mentioned general rules. The assumption of existing of contradictory rules is admissible. If

**Table 2.** Reference values of diagnostic signals used for fault reasoning

| F/S | OK | $f_1$ | $f_2$ | $f_3$ | $f_4$ | $f_5$ | $f_6$ | $f_7$ | $f_8$ | $f_9$ |
|---|---|---|---|---|---|---|---|---|---|---|
| $s_1$ | 0 | +1<br>−1 | 0 | 0 | +1<br>−1 | 0 | 0 | −1 | +1<br>−1 | −1 |
| $s_2$ | 0 | 0 | −1 | +1 | 0 | −1 | +1 | +1 | 0 | 0 |
| $s_3$ | 0 | +1<br>−1 | −1 | +1 | +1<br>−1 | −1 | +1 | +1 | +1<br>−1 | +1 |
| $s_4$ | 0 | 0 | −1 | +1 | 0 | −1 | +1 | +1 | 0 | 0 |
| $s_5$ | 0 | +1<br>−1 | −1 | +1 | +1<br>−1 | −1 | +1 | +1 | +1<br>−1 | +1 |

| F/S | OK | $f_{10}$ | $f_{11}$ | $f_{12}$ | $f_{13}$ | $f_{14}$ | $f_{15}$ | $f_{16}$ | $f_{17}$ | $f_{18}$ | $f_{19}$ |
|---|---|---|---|---|---|---|---|---|---|---|---|
| $s_1$ | 0 | −1 | – | +1<br>−1 | 0 | – | +1<br>−1 | −1 | 0 | 0 | 0 |
| $s_2$ | 0 | 0 | – | 0 | +1<br>−1 | – | 0 | 0 | 0 | +1 | −1 |
| $s_3$ | 0 | +1 | – | +1<br>−1 | +1<br>−1 | – | +1<br>−1 | +1 | 0 | +1 | −1 |
| $s_4$ | 0 | 0 | – | 0 | +1<br>−1 | – | 0 | 0 | +1<br>−1 | +1 | −1 |
| $s_5$ | 0 | +1 | – | +1<br>−1 | +1<br>−1 | – | +1<br>−1 | +1 | +1<br>−1 | +1 | −1 |

the base of rules is build-up based on the expert knowledge one should assume its incompleteness. On the other hand, the incompleteness of the base of rules results from the fact, that there is a lack of the rules for all combinations of diagnostic signals.

## 5. Fault isolation algorithm

The classical fuzzy inferring system [28] consists of three processing stages: fuzzyfication, inference and defuzzyfication. Inputs and outputs are crispy signals. This is typical for fuzzy modelling and fuzzy control. In case of fuzzy fault isolation the structure of the inferring system (Fig. 7) is more comprehensive – consists only of two processing stages: fuzzyfication and inference machine. Therefore, the generated diagnosis is rather fuzzy then crispy. The input for fuzzy diagnostic system is $J$-dimensional vector of residuals, where the output is a discrete fuzzy set defined in the space of discourse $F = \{f_0, f_1..f_k\}$. The space of discourse contains $K+1$ elements, where $K$ is a number of faults. The element $f_0$ denotes the fault free state. Elements $f_1..f_k$ are respectively assigned to the particular actuator faults.

Diagnostic fuzzy reasoning can be described as a process of determining and aggregation of the activation levels of particular diagnostic rules. Output is normalised for unique interpretation of results. Therefore, membership function degrees of output are interpreted as fault certainty degrees and belongs to the interval [0,1]. In general case, the rule (11) has conjunction-alternative form. The expression $(s_j \in V_{kj})$ can be transformed to the formula consisting of primary premises $(s_j = v_{kji})$ of all the values of the diagnostic signal $(v_{kji} \in V_{kj})$. The degree of fulfilling the primary premise $\mu_i(v_{kji})$ equals the membership degree of the conformity of achieved diagnostic signal to the reference value stated in the rule. The degree of fulfilment of the alternative of primary premises for $j$-th diagnostic signal in $k$-th rule depends on the membership degrees of $j$-th diagnostic signal to the fuzzy sets depicted in the $k$-th rule.

$$\mu(f_k, s_j) = \mu(s_j \in V_{jk}) = \mu(v_{j1}) \oplus \mu(v_{j2}) \oplus ... \oplus \mu(v_{jL}) \qquad (12)$$

where: $\oplus$ – general operator of fuzzy alternative, $L$ – number of values of reference diagnostic signals $s_j$ in the $k$-th rule pointing out fault $f_k$, $V_{kj}$ – subset of values of reference signals $s_j$ signalling fault $f_k$.

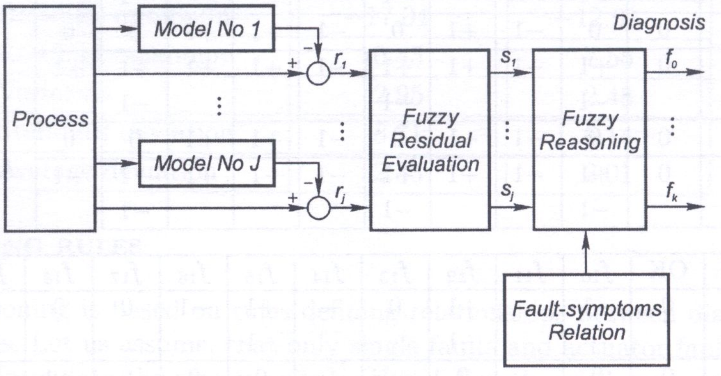


**Fig. 7.** The general fuzzy diagnostics scheme

Typically S-norm operators replace general fuzzy alternative operators in formula (12). If the fuzzy sum MAX operator will be applied, then the degree of fulfilment of alternative premise for the $j$-th diagnostic signal is equal to the maximal value of the membership degree of the $j$-th diagnostic signal to the fuzzy sets with linguistic terms pointed out in the $k$-th rule.

$$\mu(f_k, s_j) = \text{MAX}\,\{\mu(v_{jk1}, \mu(v_{jk2}), ..., \mu(v_{jkL})\}. \tag{13}$$

The degree of activation of the rule calculated from the conjunction of premises is determined according to:

$$\mu(f_k) = \mu(f_k, s_1) \otimes \mu(f_k, s_2) \otimes ... \otimes \mu(f_k, s_J), \tag{14}$$

where: $f_0$ – fault free state, $f_k$ – $k$-th fault, $J$ – number of diagnostic signals.

Typically, T-norm operators are used for determining the degree of fulfilling conjunction of premises (e.g. MIN or PROD). Formulas (15) and (16) define the values of fulfilment degrees of primary premises respectively for PROD and MIN operators.

$$\mu(f_k)_{\text{PROD}} = \mu(f_k, s_1) \cdot \mu(f_k, s_2) \cdot ... \cdot \mu(f_k, s_j), \tag{15}$$

$$\mu(f_k)_{\text{MIN}} = \text{MIN}\{\mu(f_k, s_1), \mu(f_k, s_2), ..., \mu(f_k, s_j)\}. \tag{16}$$

Activation levels of rules (15) and (16) for $k = 1, ..., K$ are interpreted as certainty degrees of particular faults. Activation level of the rule (8) is interpreted as the certainty degree of fault absence. This constitutes the fuzzy diagnosis produced as a output of the fuzzy fault isolation system. The diagnosis is a fuzzy set consisting of set of pairs: fault, fault certainty degree. Formally, fault certainty degrees are identical with membership degrees of fuzzy diagnosis.

$$\text{DGN} = \{< f_k, \mu(f_k) >: \mu(f_k) > 0\} \quad \text{for } k = 0, 1, ..., K. \tag{17}$$

The unisolable faults have equal or close certainty degrees. Diagnosis achieved is easy to interpret and what is practicable, easy for graphical presentation. Diagnosis may be shown for example in the form of bar graph charts.

*Example 1: Theoretical*

a) Consider that following set of diagnostic signals is available in the time moment $t_0$:

$$s_1 = \{ <0, 0.0>, <+1, 0.0>, <-1, 1.0> \},$$
$$s_2 = \{ <0, 0.4>, <+1, 0.0>, <-1, 0.6> \},$$
$$s_3 = \{ <0, 0.2>, <+1, 0.0>, <-1, 0.8> \},$$
$$s_4 = \{ <0, 0.1>, <+1, 0.0>, <-1, 0.9> \},$$
$$s_5 = \{ <0, 0.0>, <+1, 1.0>, <-1, 0.0> \}.$$

The conformity of membership degrees of symptoms $s_1..s_5$ with the reference symptoms (Table 2) are given in the Table 3. The level of rule activation was determined with application of operator PROD/$\Sigma$. Following diagnosis is obtained from Table 3:

$$\text{DGN} = \{ < f_1, 0.2 >, < f_4, 0.2 >, < f_8, 0.2 >, < f_{12}, 0.2 >, < f_{15}, 0.2 > \}.$$

**Table 3.** Table of conformity degrees of actual symptoms $s_1..s_5$ with the reference symptoms given in Table 2

| F/S | OK | $f_1$ | $f_2$ | $f_3$ | $f_4$ | $f_5$ | $f_6$ | $f_7$ | $f_8$ | $f_9$ | $f_{10}$ | $f_{11}$ | $f_{12}$ | $f_{13}$ | $f_{14}$ | $f_{15}$ | $f_{16}$ | $f_{17}$ | $f_{18}$ | $f_{19}$ |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| $s_1$ | 0 | 1 | 0 | 0 | 1 | 0 | 0 | 1 | 1 | 1 | 1 | – | 1 | 0 | – | 1 | 1 | 0 | 0 | 0 |
| $s_2$ | 0.4 | 0.4 | 0.6 | 0 | 0.4 | 0.6 | 0 | 0 | 0.4 | 0.4 | 0.4 | – | 0.4 | 0.4 | – | 0.4 | 0.4 | 0.4 | 0 | 0.6 |
| $s_3$ | 0.2 | 0.8 | 0.8 | 0 | 0.8 | 0.8 | 0 | 0 | 0.8 | 0 | 0 | – | 0.8 | 0.8 | – | 0.8 | 0 | 0.2 | 0 | 0.8 |
| $s_4$ | 0.1 | 0.1 | 0.9 | 0 | 0.1 | 0.9 | 0 | 0 | 0.1 | 0.1 | 0.1 | – | 0.1 | 0.9 | – | 0.1 | 0.1 | 0.9 | 0 | 0.9 |
| $s_5$ | 0 | 1 | 0 | 1 | 1 | 0 | 1 | 1 | 1 | 1 | 1 | – | 1 | 1 | – | 1 | 1 | 1 | 1 | 0 |
| **D** | **0** | **0.2** | **0** | **0** | **0.2** | **0** | **0** | **0** | **0.2** | **0** | **0** | – | **0.2** | **0** | – | **0.2** | **0** | **0** | **0** | **0** |

b) Let us consider case of unique symptoms i.e. symptoms assigned to one and only one fuzzy set. For example, if following symptoms appear:

$$s_1 = \{ <0, 1.0>, <+1, 0.0>, <-1, 0.0> \},$$
$$s_2 = \{ <0, 0.0>, <+1, 0.0>, <-1, 1.0> \},$$
$$s_3 = \{ <0, 0.0>, <+1, 1.0>, <-1, 0.0> \},$$
$$s_4 = \{ <0, 0.0>, <+1, 0.0>, <-1, 1.0> \},$$
$$s_5 = \{ <0, 0.0>, <+1, 1.0>, <-1, 0.0> \},$$

then following diagnosis will be generated:

DGN=$\{<f_{13}, 0.5>, <f_{18}, 0.5>\}$ pointing out on the same certainty degrees for both indistinguishable faults. From the other hand, both faults are distinguishable in case if for example $s_5 = \{< 0, 0.0 >, < +1, 0.0 >, < -1, 1.0 >\}$. The diagnosis will point out fault $f_{13}$. This illustrates the advantage of multiple-valued FIS system (Table 2) when considering fault distinguishablity problem.

*Example 2: Practical*

Single fault occurs in the system ($f_{16}$ – see Sec. 6). In time moment $t = 57400$ s the following set of diagnostic signals is available in diagnostic system:

$$s_1 = \{ <0, 0.35>, <+1, 0.00>, <-1, 0.65> \},$$
$$s_2 = \{ <0, 0.97>, <+1, 0.03>, <-1, 0.00> \},$$
$$s_3 = \{ <0, 0.18>, <+1, 0.82>, <-1, 0.00> \},$$
$$s_4 = \{ <0, 0.95>, <+1, 0.05>, <-1, 0.00> \},$$
$$s_5 = \{ <0, 0.02>, <+1, 0.98>, <-1, 0.00> \}.$$

The conformity degrees of symptoms $s_1..s_5$ with the reference symptoms (Table 2) are given in the Table 4. By neglecting close to zero fault certainty factors, the following diagnosis is obtained:

$$\mathrm{DGN} = \{< f_{16}, 0.12 >, < f_{15}, 0.12 >, < f_{12}, 0.12 >, < f_{10}, 0.12 >,$$
$$< f_9, 0.12 >, < f_8, 0.12 >, < f_4, 0.12 >, < f_1, 0.12 >\}.$$

The rule activation levels were determined with application of operator PROD/$\Sigma$. The diagnosis points out eight indistinguishable faults. Fault $f_{16}$ is properly identified however it is not isolable from other faults. Isolability would be better in case if additional measurements will be available (for example air pressure in servomotor chamber). Please note, non-critical selection of parameters of fuzzy terms in case of $f_{16}$. If instead of $s_1 = \{<0, 0.35>, <+1, 0.00>, <-1, 0.65>\}$, appears $s_1 = \{< 0, 0.00 >, < +1, 0.00 >, < -1, 1.00 >\}$ then the diagnosis will be identical.

**Table 4.** Table of conformity degrees of actual symptoms $s_1..s_5$ with the reference symptoms given in Table 2.

| F/S | OK | $f_1$ | $f_2$ | $f_3$ | $f_4$ | $f_5$ | $f_6$ | $f_7$ | $f_8$ | $f_9$ | $f_{10}$ | $f_{11}$ | $f_{12}$ | $f_{13}$ | $f_{14}$ | $f_{15}$ | $f_{16}$ | $f_{17}$ | $f_{18}$ | $f_{19}$ |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| $s_1$ | .35 | .65 | .35 | .35 | .65 | .35 | .35 | .65 | .65 | .65 | .65 | – | .65 | .35 | – | .65 | .65 | .35 | .35 | .35 |
| $s_2$ | .97 | .97 | 0 | .03 | .97 | 0 | .03 | .03 | .97 | .97 | .97 | – | .97 | .03 | – | .97 | .97 | .97 | .03 | 0 |
| $s_3$ | .18 | .82 | 0 | .82 | .82 | 0 | .82 | .82 | .82 | .82 | .82 | – | .82 | .82 | – | .82 | .82 | .18 | .82 | 0 |
| $s_4$ | .95 | .95 | 0 | .05 | .95 | 0 | .05 | .05 | .95 | .95 | .95 | – | .95 | .05 | – | .95 | .95 | .95 | .05 | 0 |
| $s_5$ | .02 | .98 | 0 | .98 | .98 | 0 | .98 | .98 | .98 | .98 | .98 | – | .98 | .98 | – | .98 | .98 | .98 | .98 | 0 |
| **D** | **.00** | **.12** | **0** | **.00** | **.12** | **0** | **0** | **.00** | **.12** | **.12** | **.12** | – | **.12** | **.00** | – | **.12** | **.12** | **.04** | **.00** | **0** |

## 6. Industrial benchmark problem. Practical results

Industrial benchmark, denoted as a benchmark step III [1], is intended as a last stage of testing of the FDI algorithms prior to industrial implementation. This implies the availability of exclusively real process value measurements for the benchmark. This fact has a crucial meaning when addressing fault detectability and isolability problems. This allows also to rank suitability of developed FDI methods for application to particular industrial cases. This section will illustrate the chosen results obtained by application of fuzzy approaches for fault isolation of industrial actuator.

Fuzzy FDI reasoning approach described in the paper was applied to fault isolation of actuator described in the benchmark problem definition. The MLP models, given in Sec. 3, were used for residual generation. Models were tuned by means of the data acquired from real process during fault free operation of actuators. Afterwards, the learning data were replaced by the data from faulty actuator operation. The data were acquired after artificial injecting single faults into actuating system.

Two faults are considered in this section: $f_{16}$ – denoting drop of air pressure in positioner supply line and fault $f_{18}$ denoting misuse of actuator's bypass valve. Physically, fault $f_{16}$ was introduced by artificial throttling actuator supply pressure. Fault $f_{18}$ was introduced twice by artificially partly opening and afterwards closing by-pass valve in the technological installation in sugar factory.

Models (1..5) were used for fault detection purposes. Fault isolation was based on fuzzy approach by means of FIS fault-symptoms relations (Table 2). It is clear that by available set of measurements not all faults are isolable. Set of seven elementary diagnoses was defined to fulfil benchmark requirements (Table 5). This allows calculation of FDI performance indices (PI) given in Table 6. The exemplary results of actuator fault isolation process are given in Fig. 8 and Fig. 9.

Very interesting is behaviour of fault isolation certainty degree shown in Fig. 8g. Short unexpected peak (false diagnosis) is clearly seen in the middle of the chart. This phenomenon can be explained as follows: Strength of fault $f_{16}$ is very high. This makes unusable model (4) because this model was

**Table 5.** Fault classification into elementary fault clusters

| Elementary diagnosis | Diagnosis members |
|---|---|
| $DGN_0$ [1] | OK [2], $f_{11}$, $f_{14}$ |
| $DGN_1$ | $f_1$, $f_4$, $f_8$, $f_{12}$, $f_{15}$ |
| $DGN_2$ | $f_1$, $f_4$, $f_8$, $f_9$, $f_{10}$, $f_{12}$, $f_{15}$, $f_{16}$ |
| $DGN_3$ | $f_2$, $f_5$, $f_{13}$, $f_{19}$ |
| $DGN_4$ | $f_3$, $f_6$, $f_{13}$, $f_{18}$ |
| $DGN_5$ | $f_7$ |
| $DGN_6$ | $f_{17}$ |

[1] $DGN_0$ denotes undetectable faults and fault free system state

[2] OK denotes the fault free state

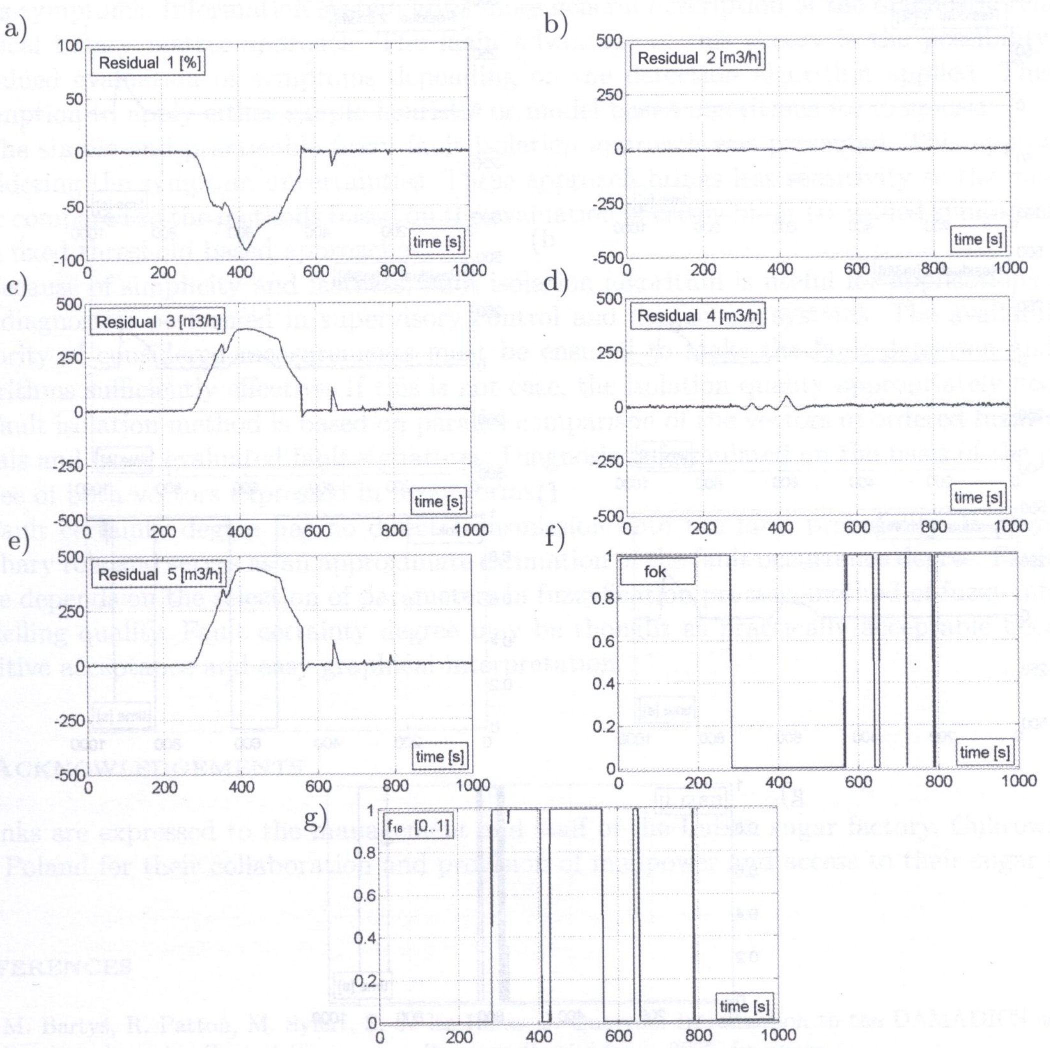


**Fig. 8.** a)..e) Time series of residuals generated by models (1)..(5) by appearance of drop of air pressure supplying positioner of actuator. Chart f) shows the development of signal denoting the OK state of actuator, whilst chart g) shows faulty actuator behaviour due to fault $f_{16}$. Data were registered at November 9, 2001 in sugar factory Lublin. The faulty system state is correctly diagnosed although partly non likely diagnosis is achieved

**Table 6.** Summary of experimental FDI performance indices obtained in industrial benchmark

| Fault | Elementary diagnosis | $t_{dt}$ [s] | $r_{td}$ | $r_{fd}$ | $t_{dm}$ [s] | $t_{drt}$ [s] | $t_{it}$ [s] | $r_{fi}$ | $r_{ti}$ | $t_{im}$ [s] | $t_{irt}$ [s] |
|---|---|---|---|---|---|---|---|---|---|---|---|
| $f_{16}$ | $DGN_2$ | 3 | 0.99 | 0 | 57283 | 8 | 6 | 0 | 0.91 | 57286 | 3 |
| $f_{18}$ | $DGN_4$ | 4 | 0.97 | 0 | 58529 | 3 | 44 | 0 | 0.62 | 58569 | 0 |
| $f_{18}$ | $DGN_4$ | 5 | 0.95 | 0 | 58835 | 5 | 27 | 0 | 0.68 | 58857 | 0 |

Remarks:

1. detection moment was captured when OK state certainty degree drop down below 0.75
2. Isolation moment was captured when fault certainty degree rise above 0.25

Notion:

$t_{dt}$ – detection time, $t_{drt}$ – fault detection recovery time, $r_{ti}$ – true isolation rate,
$r_{fd}$ – false detection rate, $t_{it}$ – isolation time, $t_{im}$ – isolation moment,
$r_{fi}$ – detection moment, $t_{dm}$ – fault detection moment, $t_{irt}$ – fault isolation recovery time.

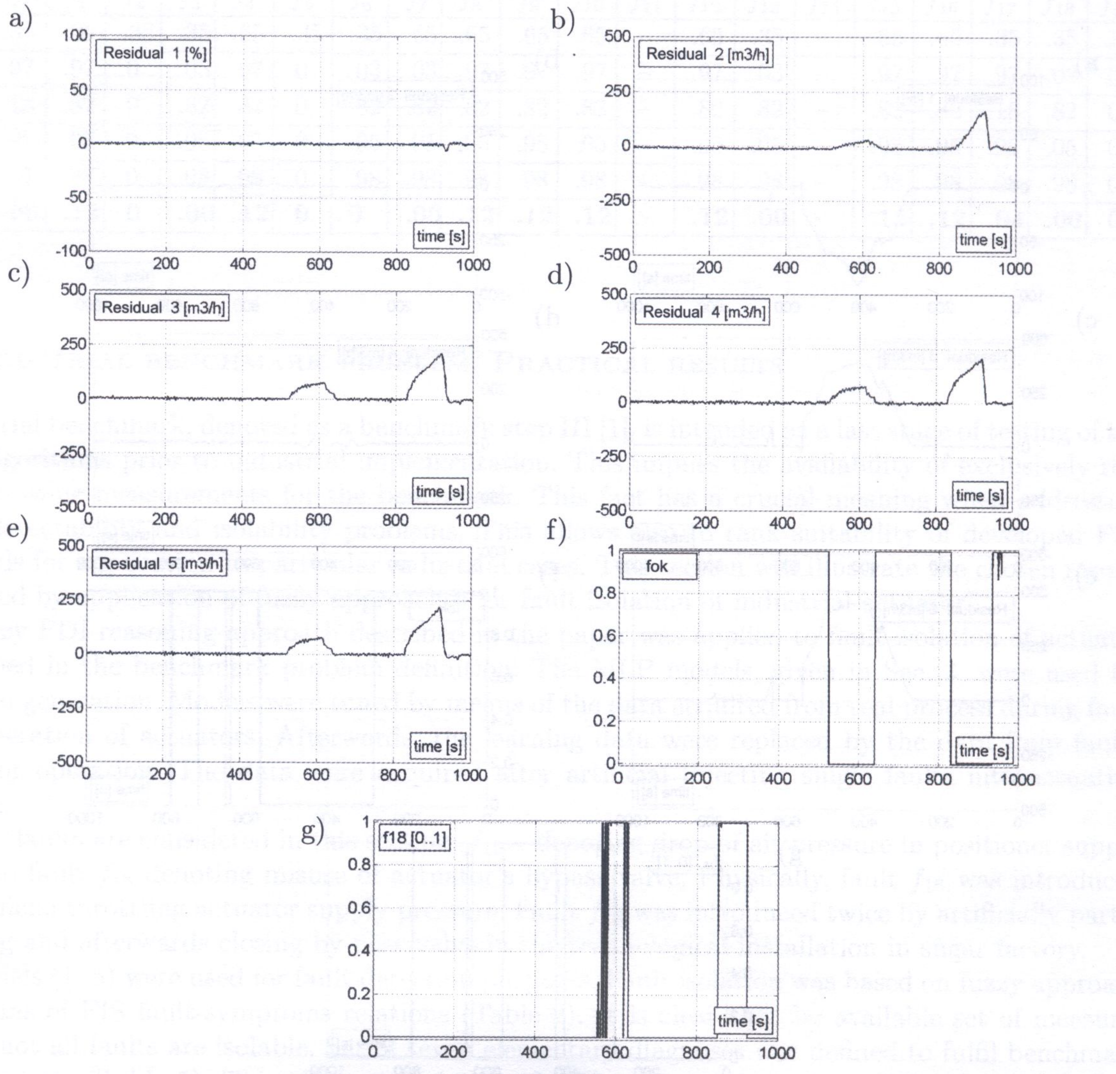


**Fig. 9.** a)..e) Time series of residuals generated by models (1)..(5) by repeated (twice) opening and afterwards closing cut-off bypass valve. Chart f) shows the development of signal denoting the OK state of actuator, whilst chart g) shows faulty actuator behaviour due to fault $f_{18}$. Data were registered at November 9, 2001 in sugar factory Lublin. Fault $f_{18}$ is detected correctly, although is not isolable from the faults with identical signatures (please refer to Table 2 and Table 5)

learned by means of data sets with values varying only about ±15% around operating point. Changes of measurements exceed significantly this range. Model lost its generalising features. Therefore, diagnosis is not likely.

Discussing values of FDI performance indices of algorithm applied, one can underline very good results of achieved false detection and isolation rates. Values of fault detection, isolation and recovery times are short (drops into the 10 seconds process data sampling intervals). This meets most of contemporary industrial requirements. High values of true detection rates are indirect acknowledgements of the quality of models applied. Isolation rates are not so high in case of fault $f_{18}$. This is caused in part by sufficiently small fault strength and its quasi-incipient development. In contrast to constant or adaptive threshold techniques, introduction of fuzzy residual reasoning allows obtaining of additional rough information about fault development (see Fig. 9g).

## 7. Final remarks

In the paper the practicable approach of diagnostic reasoning of actuators with application of fuzzy set theory was presented. The information system was applied for the description of relation faults-symptoms. Information system gives more general description of the diagnostic relation than classical binary matrix approach. The main advantage of this theory is the possibility of bi- or tri-valued evaluation of symptoms depending on the detection algorithm applied. This gives an assumption to apply either simple heuristic or model based algorithms for diagnosis.

The simple and practicable fuzzy fault isolation approach was presented. This approach allows considering the symptom uncertainties. These approach brings less sensitivity to the measurement noise compared to the methods based on the evaluation of crispy bi- or tri-valued symptoms achieved from fixed threshold based approaches.

Because of simplicity and fastness, fault isolation algorithm is useful for applications in the on-line diagnostics performed in supervisory control and diagnosing systems. The availability of the majority of considered measurements must be ensured to make the fault detection and isolation algorithms sufficiently effective. If this is not case, the isolation quality appropriately decreases.

Fault isolation method is based on parallel comparison of the vectors of ordered fuzzy diagnostic signals and fuzzy evaluated fault signatures. Diagnosis is formulated on the basis of the conformity degree of both vectors expressed in fuzzy terms.

Fault certainty degree has no direct transmission onto the fault probability. It plays only the auxiliary role and serves as an approximate estimation of the fault occurrence degree. Fault certainty value depends on the selection of parameters in fuzzyfication process, method of fuzzy inferring and modelling quality. Fault certainty degree may be thought as practically acceptable because of its intuitive acceptance and easy graphical interpretation.

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