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FUZZY-LOGIC FAULT DIAGNOSIS OF INDUSTRIAL PROCESS ACTUATORS

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The paper presents an idea of decomposition of diagnostic tasks in complex systems. Such decomposition consists in splitting basic diagnostic functions into lower-level units existing in decentralised structures of automatic control and supervision of the process. An example of a unit that realises this concept and includes a positioner that controls and diagnoses an assembly consisting of a servomotor and a pneumatic control valve is also given. An application of fuzzy logic to the actuator diagnosing algorithm is presented and results of the corresponding fault detection tests in an industrial environment are discussed.

Keywords: fault diagnosis, fuzzy logic, actuators, decentralised, diagnostic systems.

1. Introduction

Problems of diagnostics of industrial processes have been investigated for about thirty years. Many methods of early detection and investigation of faults have been developed. Such methods base most often on analytical models of processes (Clark, 1978; Frank, 1990; Gertler, 1995; Isermann, 1994, Patton, 1994) or apply artificial-intelligence techniques (Frank, 1994; Korbicz, 1997; Sorsa *et al.*, 1991; Kościelny and Bartyś, 1997). Expert diagnostic systems co-operating with automatic control systems have attracted attention only recently (Betz *et al.*, 1992; Kościelny and Zakroczymski, 1997).

Diagnostic functions of a process are usually realised in a centralised way. The paper presents a concept of local realisation of diagnostic functions for measurement instruments, actuators and other components of a technical installation by the lowest-level units existing in the automatic control structure. An example of a positioner is given that not only controls movements of a pneumatic servomotor's piston, but also makes a current diagnosis of the servomotor-control valve assembly.

We propose an application of fuzzy logic to the algorithm of diagnosing the assembly. A fuzzy model of the assembly operating in normal conditions is identified by means of a modified Wang-Mendel method (1992). The modification was introduced in order to meet some needs of industrial applications. Verification of such a method was performed in an industrial environment.

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2. Local and Distributed Realisations of Diagnostic Functions

Current diagnostics of measurement instruments, actuators and other components of an industrial installation is realised most often by special diagnostic systems existing in supervisory layers of complex automatic control and monitoring systems of the process under consideration , e.g.

- ABB's MODI expert system is an extension of Procontrol P or Advant OCS automatic control systems (Betz *et al.*, 1992),
- Siemens' KNOBOS expert system is a part of the Teleperm XP system,
- the DIAG diagnostic system developed at the Institute of Automatic Control and Robotics of the Warsaw University of Technology is designed to co-operate with many SCADA and DCS systems (Kościelny *et al.*, 1998).

Diagnostic systems should detect and isolate faults of measurement instruments, actuators and other technical devices. When only one diagnostic system is applied for a complex industrial installation, it should handle a very large number of fault combinations. In order to isolate faults, a relation between faults $e_k \in E$ and symptoms (test results) $d_j \in D$ has to be known (Kościelny, 1995). Such a relation can be represented by a diagnostic matrix (Table 1). The number of possible fault states is equal to $2^{|E|}$. It is easy to observe that differentiation of all faults is ensured when the signatures of particular faults (the corresponding column vectors of the diagnostic matrix) are different. In this context, the best diagnostics matrix structure exists when the diagnostic matrix is square and diagonal (Table 2). Such a form of the matrix means that for each fault a separate test is applied. The number of tests in such a case equals the number of faults. The set of the test results defines the state of the system since it indicates all the existing faults. In this case, all the states of the system can be easily distinguished, e.g. the state of complete efficiency, states with single faults and states with multiple faults. At the same time, the fault identification algorithm seems to be trivial. However, many different faults may act as sources of the same symptoms, and vice versa: each fault may cause many different symptoms (Table 1). In industrial processes, the number of possible faults is usually very high. The necessity of taking into account states with multiple faults complicates fault identification algorithms.

The above considerations show that one should strive to ensure a diagonal structure of the diagnostic matrix as shown in Table 2. A sub-optimal diagnostic structure (Table 3) can be realised in such a way that particular tests control tolerably small subsets of faults, and appropriate subsets of tests are attributed to specified devices of the system. It is therefore useful to perform a decomposition of the diagnostic system that consists of separate diagnosing subsystems. Each diagnosing unit detects and isolates a specified set of faults within this diagnosing subsystem. Such a situation corresponds to a sub-optimal structure of the diagnostic matrix (Table 3). Thus the number of considered states can be significantly reduced. Problems of decomposition of large-scale systems as well as decentralised diagnosing were studied in (Kościelny, 1991; 1999).

Table 1. An example of the diagnostic matrix.

D/E	e_1	e_2	e_3	e_4	e_5	e_6	e_7	e_8	e_9
d_1	1			1	1				
d_2	1	1		1		1			1
d_3			1		1		1		
d_4				1		1		1	
d_5	1	1	1	1				1	1
d_6			1			1	1		
d_7		1		1			1		
d_8					1			1	
d_9			1	1	1				1

Table 2. Optimal structure of the diagnostic matrix.

D/E	e_1	e_2	e_3	e_4	e_5	e_6	e_7	e_8	e_9
d_1	1								
d_2		1							
d_3			1						
d_4				1					
d_5					1				
d_6						1			
d_7							1		
d_8								1	
d_9									1

Table 3. A sub-optimal structure of the diagnostic matrix.

D/E	e_1	e_2	e_3	e_4	e_5	e_6	e_7	e_8	e_9
d_1	1		1						
d_2		1							
d_3		1	1						
d_4				1	1				
d_5					1	1			
d_6				1		1			
d_7							1	1	
d_8								1	1
d_9							1		1

Decentralisation of diagnostic tasks consists, among other things, in supplying automatic control and technical devices with autonomous diagnosing units. The functions of a central diagnosing system are in this case significantly reduced. This leads to:

- shortening the time needed to obtain the diagnosis because diagnostic functions are realised in parallel by many units,
- easy implementation in stages and extension of the diagnostic system,
- simplification of diagnostic conclusion algorithms,
- the possibility of applications of conclusion algorithms under the assumption of the existence of single faults,
- easy isolation of multiple faults,
- higher robustness of the diagnostic system due to the fact that the results of faults of particular diagnosing units have only a local meaning.

Realisation of decentralisation of diagnostic tasks in industrial processes requires the development of a new generation of automatic control and technical devices. The following devices can be proposed:

1. Intelligent measurement instruments that perform diagnostics of measurement loops. They should test the instrument efficiency, as well as the correctness and credibility of the output signal. Since such tests base only on an analysis of a single signal and do not comprise its connections with other process variables, parametric faults cannot be detected in this way.
2. Intelligent actuators equipped with auto-diagnostic functions. An example of such a device is described in detail in what follows.
3. Control units, e.g. programmable controllers equipped with auto-diagnostic software, as well as software that would allow for diagnostics of measurement loops with the use of relations existing between measurement signals. At present, auto-diagnostic functions are commonly realised by such devices, but advanced diagnostics of measurement loops is practically unattainable.
4. Analysers of the states of technical devices such as pumps, motors, etc.

3. Positioning Devices in Decentralised Diagnostic Systems

The basic function of the positioner (Fig. 1) is automatic control of the servomotor's piston displacement X. On the basis of the control error defined as the difference between a set point U and the process variable X, the positioner generates a control signal P_0 in order to reduce the control error. Application of the positioner renders it possible, among other things, to shape dynamic properties of the actuator (a servomotor A and a valve V), to reduce the hysteresis width of the servomotor's static characteristic and to improve the accuracy of positioning the piston at a steady state.

Due to realisation of diagnostic functions in decentralised structures, the positioner is supplied with a full duplex digital communication system (frequency FSK

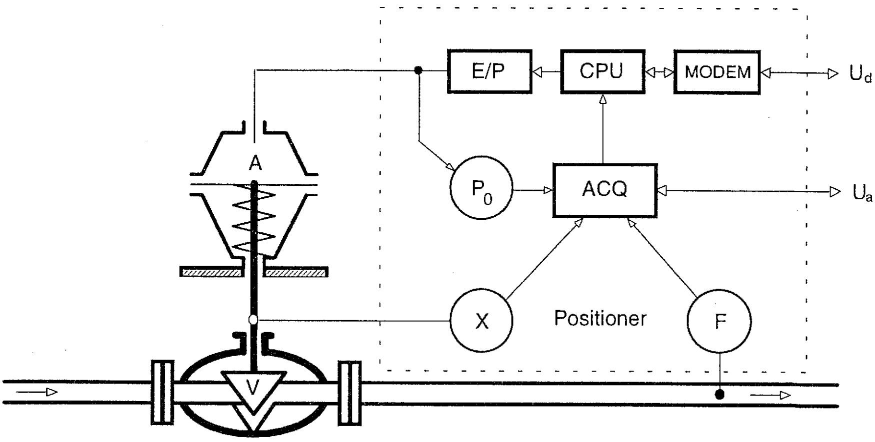

Fig. 1. The diagram of the positioner and servomotor-valve assembly (Notation: A – servomotor, V – valve, ACQ – data acquisition system, CPU – central control and diagnostic unit, E/P – electro-pneumatic transducer, MODEM – system for digital communication with external supervising control and diagnosing system, X – servomotor's piston displacement transducer, F – volume flow transducer, P_0 – output pressure of the E/P transducer, U_d – full duplex digital communication link, U_a – bi-directional analogue communication link).

modulation) and an additional analogue (4÷20 mA) system. Application of the communication standard HART makes it possible to couple both the kinds of systems in one analogue communication channel.

The positioner can also realise local control tasks, e.g. control of the volume flow F. A characteristic feature of the presented positioner is realisation of diagnostic tasks of the actuator consisting of the servomotor and control valve.

4. Fuzzy Models of the Servomotor-Valve Assembly

4.1. Wang-Mendel's Method

Wang-Mendel's identification method allows us to construct a fuzzy model of the system from numerical data. The main advantage of the method is the simplicity of the identification algorithm. This also means the time of training which is much shorter than e.g. in the case of neural networks. Much lower are also the necessary calculation expenditures. Such features mean that the method seems to be suitable for an intelligent positioner.

Application of fuzzy models to fault detection can be split into two stages. The first one consists in construction of a fuzzy model. The second one lies in generation of the so-called residuals (the differences between model outputs and real process values) on the basis of this model.

The process of identification in Wang-Mendel's method is performed in four steps:

Step 1. Definition of the input, output and corresponding fuzzy sets.

Step 2. Generation of a fuzzy rule base from experimental data. Each rule has the following form:

$$\text{IF } (x_1 = A^1) \text{ AND } \dots (x_k = A^k) \dots \text{ AND } (x_n = A^n) \text{ THEN } y = A^{n+1} \quad (1)$$

where x_k is the k-th input, y denotes the output, and A^k stands for a fuzzy set defined for x_k or y. It is created for a finite set of input-output data. The rule contains fuzzy sets $A_1, \dots, A^n$ and A^{n+1} for which the degree of the membership of $x_1, \dots, x_n$ and y to an appropriate fuzzy set is maximal.

Step 3. Assigning a weight to every rule. Since each pair of data generates one rule, it is highly probable that there will be some rules with the same premises but different conclusions, i.e. there will be conflicting (inconsistent) fuzzy rules. In order to reject such conflicting rules, each rule is fitted with a weight. It is calculated as a product of the degrees of membership of the rule's premises and that of the conclusion:

$$w_l = \mu_{A^{n+1}}(y) \prod_{k=1}^{n} \mu_{A^k}(x_k) \quad (2)$$

Step 4. Creation of the fuzzy rule base. Only the rule from the set of conflicting rules that has a maximal weight is accepted.

Some tests of the actuator valve assembly modelled by Wang-Mendel's method have been performed. They show that the method is sensitive to measurement disturbances.

4.2. Modified Wang-Mendel Method

Figure 2 shows the block diagram of a modified Wang-Mendel algorithm. The fuzzification block is responsible for the calculation of a fuzzy representation of variables. Successive input and output values of the modelled system obtained at successive time slices (on-line or off-line data from the training set) are fed to the input of that block. For a specified partitioning of particular variable ranges, the assignment of A_k (a fuzzy set) and μ_k (the value of the membership function) to a particular variable is performed according to the following equation:

$$\forall_k \ \mu_{A^k} = \max_i \left\{ \mu_{A_i^k}(x_k) \right\} \quad (3)$$

where x_k is the k-th input value and $\mu_{A_i^k}(x_k)$ stands for the value of the membership function of the k-th input to the i-th partition. The fuzzy rule

$$\text{IF } (x_1 = A^1) \text{ AND } \dots (x_k = A^k) \dots \text{ AND } (x_n = A^n) \text{ THEN } y = A^{n+1} \quad (4)$$

being actually calculated in the rule generation block is memorised in the rule base in an appropriate way. Partitions A_k defined for particular variables and denoted by R_i act as the rule premises.

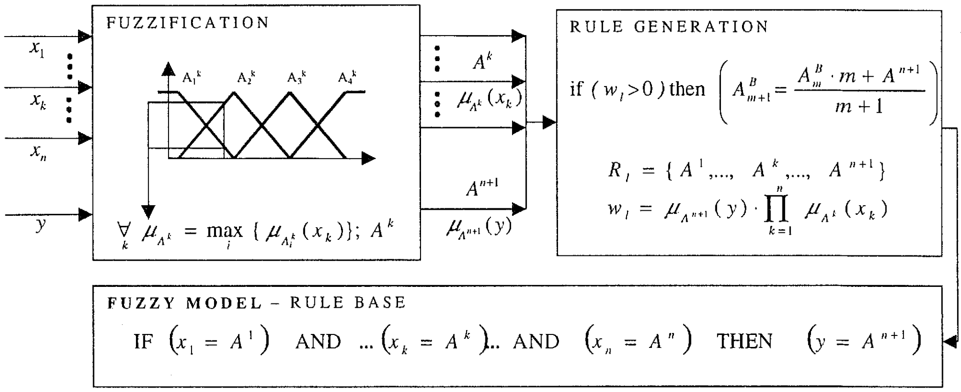

Fig. 2. Modified Wang-Mendel identification algorithm.

In the modified method, all of the rules having the same premises are memorised in such a way that the average value of conclusions is calculated as follows:

$$\text{IF} \quad (w_l > 0) \quad \text{THEN} \quad A^B_{m+1} = \frac{A^B_m m + A^{n+1}}{m+1} \tag{5}$$

where m is the number of rules having the same premises, A^B_m denotes the average value of the conclusions of n rules, and A^B_{m+1} stands for the updated value of the conclusion after addition of the next rule. During calculation of the average value, each of the conclusions is fitted with the coefficient equal to $1/n$.

The presented algorithm allows for creating models with many inputs and single output (MISO). Models with many inputs and many outputs (MIMO) are easy to obtain by putting several MISO-type models together with the help of an AND-type operator.

4.3. Residual Calculation on the Basis of a Fuzzy Model

The algorithm of the residual calculation based on the obtained fuzzy model is presented in Fig. 3. It corresponds to the well-known Mamdani's scheme. The model's output is compared with the real variable value, and the result is cast as the percentage value of the modelled span, according to the dependence

$$\text{Res} = \frac{(y - \hat{y})}{(y_{\max} - y_{\min})_{\text{nominal}}} 100\% \tag{6}$$

where Res is the value of the residual, y is the actual value of the modelled variable, $\hat{y}$ stands for the model output, and $(y_{\max} - y_{\min})_{\text{nominal}}$ signifies the nominal range of the modelled variable. During normal operation, the residual value should oscillate around zero. The appearance of a fault causes an adequate deviation of the residual value from zero.

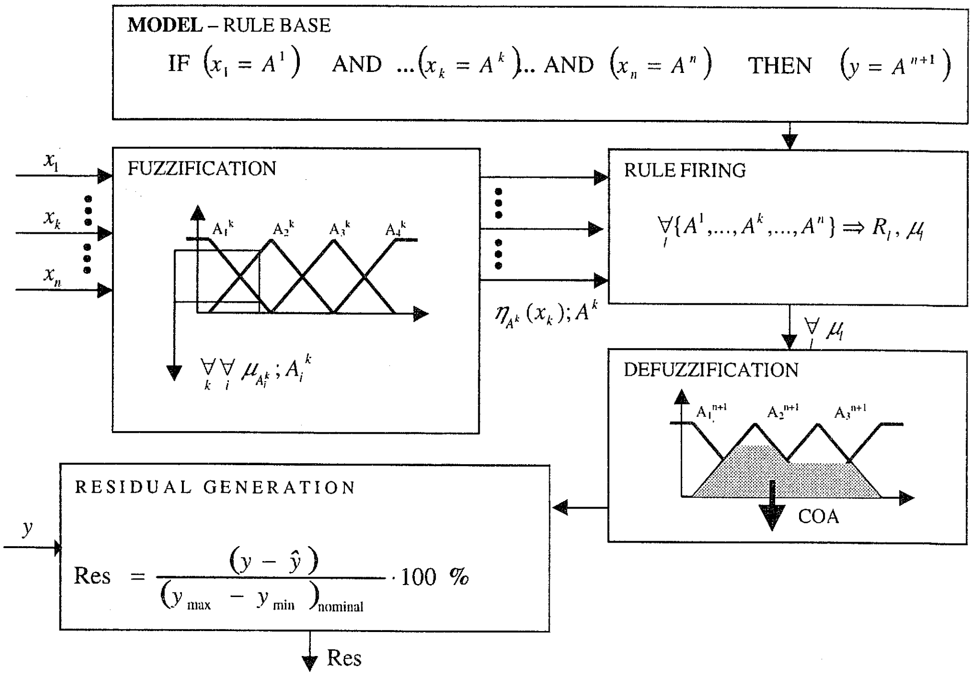

Fig. 3. Algorithm of the residual calculation on the basis of a fuzzy model.

The following parameters have an effect on the quality of modelling: the model's structure, the number of fuzzy sets into which particular inputs of the model and its output are divided, the shape of the membership function, and the 'quality' of the training set. These parameters can be defined according to the existing needs by taking into consideration experimental data.

In a laboratory, when several tests of the modelled assembly can be performed and when complete training data are easily attainable, precise fuzzy models of the servomotor-valve assembly can be obtained. It is possible to achieve the accuracy of modelling within the range of 1 to 2%, even while taking into account both the dynamics and static non-linearity of the system. Figure 4 shows exemplary changes for the modelled valve having a constant percentage characteristic. In this case, the static model with 31 fuzzy sets at its inputs and at the output was applied. The model had the following form:

$$\overline{F}_k = f(U_k) \tag{7}$$

where U_k and F_k denote respectively the control signal and flow values, both normalised to the (0,1) range.

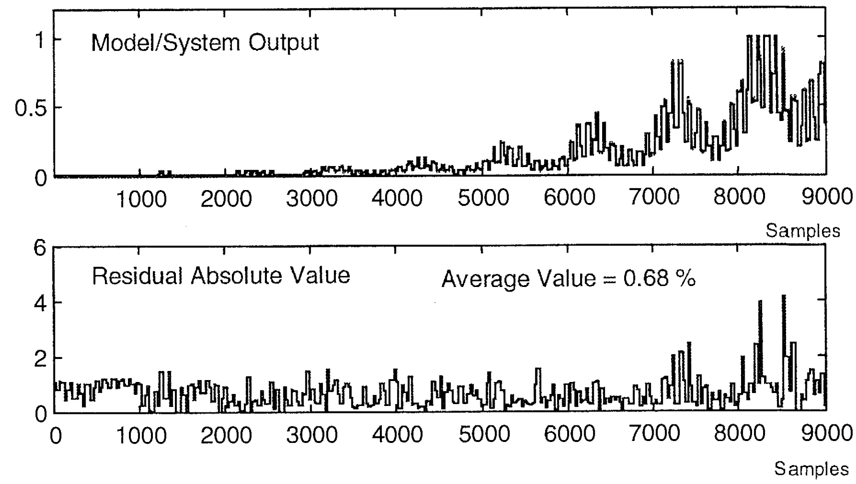

Fig. 4. An example of the servomotor-valve assembly modelled in a laboratory.

4.4. Tests Performed in an Industrial Environment

Fuzzy models for the servomotor-valve assembly were applied in the diagnostic system DIAG developed at the Lublin Sugar Factory (Lublin is a town in the south-eastern part of Poland). The assembly consisting of a pneumatic servomotor and a valve controlling the raw juice inflow to the first stage of the evaporation plant was modelled. In this case, three process variables related to the valve operation were attainable: flow F(F51_01), value of the control signal U(LC51_03.CV) and raw juice pressure P(P51_04). A part of the installation including the chosen valve is shown in Fig. 5. Data were collected with the sampling interval 10 s.

Based on an expert's knowledge, two models were proposed:

$$\text{Model A}: \quad \overline{F}_k = f(U_{k-1}, P_k) \tag{8}$$

$$\text{Model B}: \quad \overline{F}_k = f(U_{k-1}) \tag{9}$$

In both cases, the inputs and output of the model were divided into 31 uniformly distributed fuzzy sets having trapezoidal membership functions shapes. The extents of the inputs and output were defined by the corresponding ranges of the measurement transducers. A relatively large number of partitions was chosen because a sufficiently accurate modelling was required within the whole accepted input signal ranges. Fuzzy sets were uniformly distributed due to the lack of prior knowledge (e.g. provided by an expert).

The models were trained according to the modified Wang-Mendel algorithm presented in Section 4.2. This produces especially good results when applied during training with large data sets. Data obtained during half-a-year's measurements were used for training. Owing to calculation of the average value during memorisation of

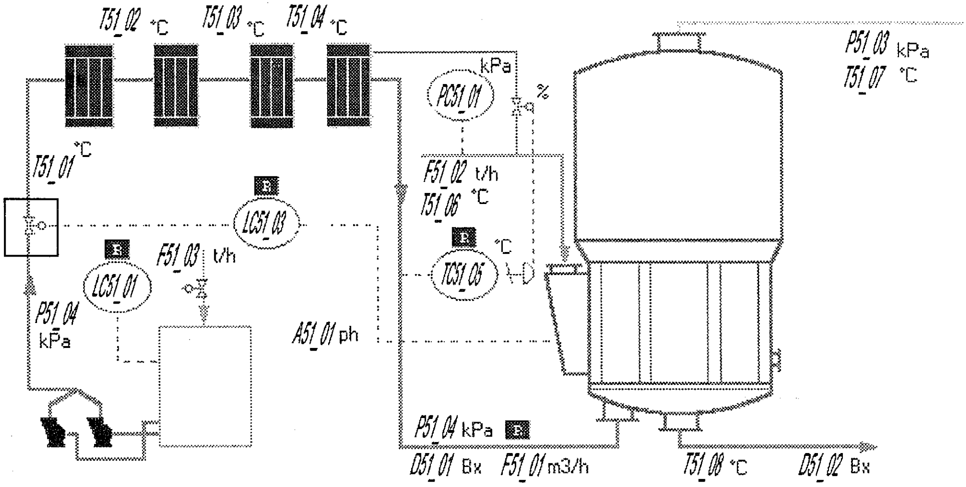

Fig. 5. Part of the installation at the Lublin Sugar Factory.

a rule, the method produced satisfactory results. In addition, modification of the model on the basis of the evaluation of the obtained rule base (fuzzy relations) by an expert can be performed after the training process is completed. As an example, Fig. 6 illustrates the rule base obtained for Model B. Version B.1 is the rule base obtained at the beginning, but after the training process via the modified algorithm was completed. Then, on the basis of an expert's evaluation, the model was modified into Model B.2 that was the final product of the identification process. Rule base B.2 was applied to generate residuals.

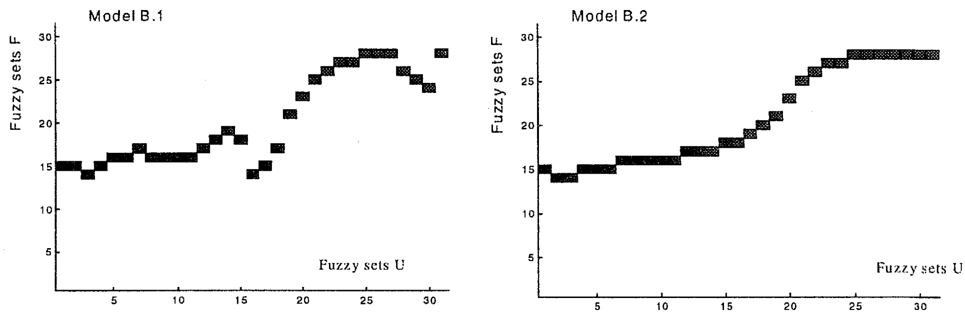

Fig. 6. A graphic interpretation of the rule bases for Model B.

Figure 7 presents exemplary changes in the residual values based on Models A and B.2 for normal operation conditions. Figure 8 shows the residual values obtained in the presence of faults.

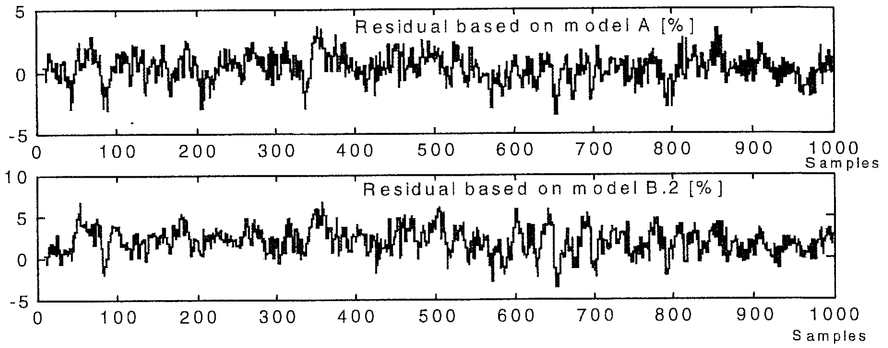

Fig. 7. Exemplary changes in the residual values based on fuzzy models.

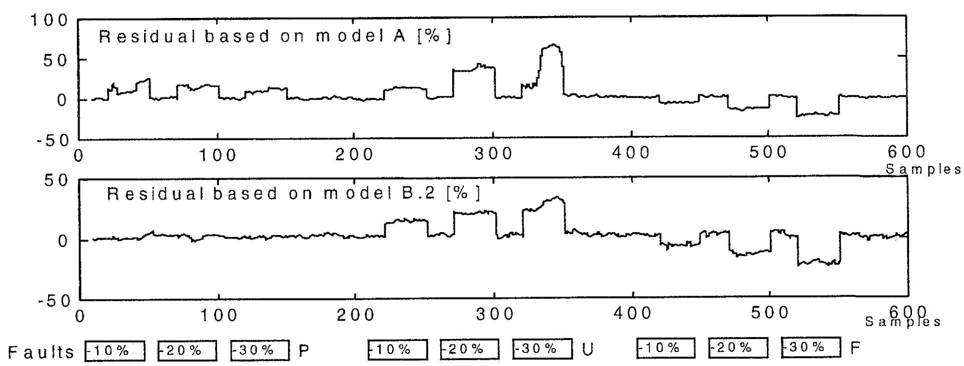

Fig. 8. Residual values obtained in the presence of faults.

Fuzzy models allowed for modelling with the accuracy of $\pm 5\,\%$. This permits detection of faults that cause relatively higher changes. Figure 8 shows the residual changes obtained in the presence of faults introduced as changes in individual signals by 10, 20, and 30 %. It can be seen that the residuals satisfactorily react to incorrect situations. It can also be seen that Model B does not detect the pressure changes, which is obvious since the value of F in this model is calculated based only on U.

5. Fault Isolation within the Servomotor-Valve Assembly

Fault isolation was performed on the basis of the following rules given by Kościelny and Bartyś (1997):

$$\text{IF}\ \ (r_1 = B)\ \ \text{AND}\ \ (r_2 = B)\ \ \text{AND}\ \ (r_3 = S)\ \ \text{AND}\ \ (r_4 = S)\ \ \text{THEN}\ \ e_1 = \text{N}\ \ \text{ELSE}\ \ e_1 = \text{P} \tag{10}$$

$$\text{IF } (r_1 = S) \text{ AND } (r_2 = B) \text{ AND } (r_3 = B) \text{ AND } (r_4 = S) \text{ THEN } e_2 = \text{N} \text{ ELSE } e_2 = \text{P} \tag{11}$$

$$\text{IF } (r_1 = B) \text{ AND } (r_2 = S) \text{ AND } (r_3 = B) \text{ AND } (r_4 = S) \text{ THEN } e_3 = \text{N} \text{ ELSE } e_3 = \text{P} \tag{12}$$

$$\text{IF } (r_1 = S) \text{ AND } (r_2 = S) \text{ AND } (r_3 = B) \text{ AND } (r_4 = B) \text{ THEN } e_4 = \text{N} \text{ ELSE } e_4 = \text{P} \tag{13}$$

$$\text{IF } (r_1 = B) \text{ AND } (r_2 = S) \text{ AND } (r_3 = S) \text{ AND } (r_4 = B) \text{ THEN } e_5 = \text{N} \text{ ELSE } e_5 = \text{P} \tag{14}$$

where $r_1 = F - \hat{F}(U)$, $r_2 = P_0 - \hat{P}_0(U)$, $r_3 = X - \hat{X}(P_0)$, $r_4 = F - \hat{F}(X)$, e_1 is the fault of the electropneumatic transducer E/P, e_2 denotes the fault of the pressure sensor P_0, e_3 stands for the fault of the servomotor A, e_4 means the fault of the piston displacement transducer X, e_5 signifies the fault of the valve V, and N, P, B, S denote 'negative', 'positive', 'big' and 'small', respectively. The above rules correspond to the diagnostic matrix obtained for the servomotor-valve assembly and shown in Table 4 with the assumption

$$d_j = \begin{cases} 0 & \text{when} \quad |r_j| \le K \\ 1 & \text{when} \quad |r_j| > K \end{cases}$$

where K is chosen threshold.

Note that the fuzzy inference procedure proposed in (Kościelny *et al.*, 1999) can also be applied to the process of diagnosing.

Table 4. The diagnostic matrix obtained for the servomotor-valve assembly.

D/E	e_1	e_2	e_3	e_4	e_5
d_1	1		1	0	1
d_2	1	1			
d_3		1	1	1	
d_4				1	1

6. Summary

The paper presents a fuzzy identification algorithm that is a modified version of the method developed by Wang and Mendel (1992). The modifications proposed in the paper ensure robustness of the algorithm to measurement disturbances. Some tests performed in a sugar factory show that the fuzzy models obtained can be applied for fault detection purposes.

A low computer power needed for the construction of the model and generation of residuals are advantages of this method. The algorithm can therefore be implemented in a microprocessor-based positioner that performs not only control of the servomotor's piston displacement, but also detects faults and performs diagnostic tasks of the pneumatic servomotor-valve assembly. Such an intelligent positioner acts as an example of the device that embodies the proposed concept of distribution of diagnostic tasks for complex systems into the lowest-level units existing in the automatic control structure. Such a concept offers many advantages that were stressed in Section 1. The performed tests were the initial phase needed for the application of the algorithm in the A785 MERA-PNEFAL positioner.

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