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Fault Detection under Fuzzy Model Uncertainty

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Abstract: The paper tackles the problem of robust fault detection using Takagi-Sugeno fuzzy models. A model-based strategy is employed to generate residuals in order to make a decision about the state of the process. Unfortunately, such a method is corrupted by model uncertainty due to the fact that in real applications there exists a model-reality mismatch. In order to ensure reliable fault detection the adaptive threshold technique is used to deal with the mentioned problem. The paper focuses also on fuzzy model design procedure. The bounded-error approach is applied to generating the rules for the model using available measurements. The proposed approach is applied to fault detection in the DC laboratory engine.

Keywords: Fault diagnosis, fuzzy systems, uncertainty, noise.

1 Introduction

Nowadays, diagnostic systems are becoming an crucial element of technical and non-technical applications. Plants, medical problems are becoming more and more complicated and in the consequence require more sophisticated diagnostic systems. In the case of the simple technical systems, human inspection was enough but increased complexity of the industrial systems and high level of process quality, reliability and safety requirements force the automation of diagnosis in order to make it possible to determine the place, reason and time of the fault precisely[1−4]. The model based fault detection strategy is the subject of intensive researches in the area of diagnosis due to many important properties:

1) it can detect small scale faults

2) the solution is relatively cheap because sophisticated equipment is not required, suitable software and computer are usually enough

3) the installation of the fault diagnosis system usually does not require any intervention in the existing system; the installed sensors can usually be used for data acquisition.

Prompt fault detection requires accurate models of the processes and leads directly to the problem of the system identification[5]. Real processes are usually dynamic, nonlinear and stochastic and analytical approaches of identification are rarely suitable for them. An alternative approach proposes using artificial intelligence methods like neural networks, fuzzy systems, neuro-fuzzy systems and expert systems for this purpose[2, 6−10]. The paper focuses on Takagi-Sugeno fuzzy systems[11]. The attractiveness of the fuzzy approach arises from the fact that it can be applied even when phenomenological model of the system is unavailable. Qualitative and quantitative knowledge may be used to tune the model in this case[12−15]. Two types of fuzzy systems are commonly used for modelling purpose: Mamdani fuzzy system and Takagi-Sugeno fuzzy system. Generally, Takagi-Sugeno structures are frequently used if the knowledge can be extracted from raw data, and Mamadani systems are preferred when the knowledge is given by human experts in the form of the linguistic expressions. The main problem which arises during Takagi-Sugeno system design is the question of a suitable number of rules which should ensure the smallest modelling error. It is usually a trade off between the complexity of the system and its accuracy. The existing methods are usually time consuming i.e., genetic algorithms, clustering algorithms, partitioning algorithms and do not assure the accuracy of the model. A new method for structure design based on bounded-error approach (BEA) is developed in this work to overcome the discussed problem[16−18].

Another problem considered in this paper arises from model uncertainty. In real situations, regardless of the kind of identification method used, there is always a model-reality mismatch, which arises from wrong assumptions about the structure of the model or the type of disturbances which corrupt measurements. The uncertainty of the model can dramatically decrease the reliability of fault detection. Two main approaches can be used to overcome this problem: an active approach, which is based on robust observers[3, 8, 19], and a passive approach, which is based on the adaptive threshold technique[6, 20, 21]. Here the BEA technique is adapted and employed to build a robust model-based fault detection system. The main advantage of this approach is that it does not consider strong assumptions about the type of disturbances like, e.g., statistical methods[5]. It assumes only that bounds on the noise signal are available[17, 18]. Next, the method determines the feasible set of parameters that are consistent with the model, the measured data, and disturbance bounds.

The paper is organized as follows. In Section 2, the elementary information concerning model based fault detection using the Takagi-Sugeno fuzzy model is presented. Section 3 presents the algorithm for computing the adaptive threshold. Section 4 describes the algorithm proposed for tuning the structure of the fuzzy model. Section 5 contains experimental results obtained for fault detection and the last section is devoted to concluding remarks.

2 Fault detection using fuzzy model

The idea of model based fault detection assumes a comparison of the model output with real output values mea-

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sured from the process, thereby generating residuals[2, 22]. Residuals are usually generated as the difference between the model and system outputs. It means that the residual signal should be close to zero in the fault-free mode, otherwise, significantly different from zero. Ideally the residual signal should carry only information about faults but, practically, it also contains noise, which is the effect of model uncertainty. It is necessary in this case to establish thresholds on residuals to avoid false alarms. If the residual signal exceeds the range defined by the thresholds, the alarm is activated, otherwise the system is working in fault-free mode. The proposed fault detection approach utilizes Takagi-Sugeno fuzzy system to implement necessary models. The knowledge extracted from data is stored in the form of fuzzy rules:

$$R_i: \text{ IF } \boldsymbol{x} \text{ is } \boldsymbol{A}_i \text{ THEN } y_i = \boldsymbol{r}_i^{\mathrm{T}} \boldsymbol{p}_i \tag{1}$$

where $\boldsymbol{x}$ is the vector of the global network inputs, $\boldsymbol{A}_i$ is the multivariate fuzzy set, y_i is the output of the rule, $\boldsymbol{r}_i$ is the vector of the local linear model inputs, $\boldsymbol{p}_i$ is the vector of the local linear model parameters, and k is the index of the rule. Fuzzy sets have usually Gaussian membership functions and here such membership functions are considered. Global output of the fuzzy model is obtained using a defuzzification algorithm. The crisp value of the output can be viewed as a composition of the responses of all rules:

$$y = \frac{\sum_{i=1}^{n} \mu_k y_i}{\sum_{i=1}^{n} \mu_i} \tag{2}$$

where y is the global output of the network, μ_i is the membership degree achieved for i-th rule, y_i is the output of the i-th rule (local linear model), n is the number of rules. It is worth noticing that the number of rules determines the number of local linear models responsible for piecewise local linear approximation of the non-linear system. It is very important to include dynamics in the fuzzy models because the real processes are usually dynamic. It can be done by introducing into the input vector $\boldsymbol{r}_i$ the delayed inputs $\boldsymbol{u}_i$ of the local model and delayed output of the local output y_i, i.e., $r_i = [u_i(k), u_i(k-1), \dots, u_i(k-n_a), y_i(k-1), y_i(k-2), \dots, y_i(k-n_b)]$. The inference mechanism used in Takagi-Sugeno model is realized by the $SUP - T$ composition:

$$\mu_{B'}(y) = \sup_{\boldsymbol{x}} \{T_{\boldsymbol{x},y}[\mu_{A'}(\boldsymbol{x}), \mu_R(x,y)]\} \tag{3}$$

where $\mu_{B'}(y)$ is the singleton fuzzy set, $\mu_{A'}(\boldsymbol{x})$ is the singleton fuzzy set which represent crisp input values, $\mu_R(\boldsymbol{x}, y)$ is the fuzzy relation, which represents the rule base and $T_{\boldsymbol{x},y}$ is the T-norm defined as the algebraic product. The structure of the Takagi-Sugeno fuzzy model presented above is used in the considerations presented in the next points of this paper.

3 Uncertainty of the fuzzy model

Robust fault detection under the model uncertainty is the main requirement for modern fault detection systems. Robustness in this case is considered as the insensitivity of the fault detection system to model uncertainty. Methods like parity relations and observers with the unknown input ensure such requirement[3, 8, 19, 23]. The main idea behind these algorithms is a special design method which eliminates the influence of the unknown input (i.e. disturbances) on the residual signal, thus the fault detection system is robust against disturbances. Unfortunately, these methods are applicable to a narrow class of systems in the case of non-linear problems. The alternative passive approach is based on the adaptive threshold technique[6, 20, 21, 24]. The idea behind this approach is the acceptance of model imperfection and the examination of the influence of this fact on the residual signal. In order to avoid false alarms generated by disturbances or model uncertainty, thresholds are defined for the residual signal. The interval set by the thresholds defines the values of residuals that correspond to the fault-free mode. The adaptive threshold method is based on the assumption that the uncertainty of the model can be presented in the form of the confidence interval for the output of the model. The confidence interval is determined using the admissible set of parameters, which may be calculated using the statistical approach for parameters determined by the least square (LS) method[21]. Unfortunately, the usage of the method is restricted by the severe assumptions concerning the distribution and expectation of disturbances. These assumptions are rarely met in the reality (normal distribution and expectation equal to zero), and the application of the method without satisfied assumptions usually leads to a strongly inaccurate model, which in diagnosis is unacceptable. To overcome the mentioned problem an alternative approach in the form of the BEA method is adopted to calculate the admissible set of parameters. The method requires only information about the range of disturbances to work properly. However, it can be effectively applied only to LP systems[17]. The application of the BEA algorithm to computing the confidence interval of the Takagi-Sugeno fuzzy model output requires to establish some assumptions in order to view the model in the form of the LP system[25]. The main assumption is based on the fact that the parameters of membership functions of fuzzy sets are known. An appropriate selection of the values of these parameters has essential influence on the uncertainty of the whole fuzzy model. Wrong values of these parameters can significantly increase model uncertainty, thus the model can be unsuitable for diagnostic tasks. The problem of tuning these parameters is the main subject of the next section, where the details of the proposed algorithms are presented.

In order to present the method let us consider the following Takagi-Sugeno fuzzy model:

$$y(k) = \sum_{i=1}^{n} \phi_i(k) y_i(k) \tag{4}$$

where $y_i(k)$ is the output of the i-th rule and

$$\phi_i(k) = \frac{\mu_i(k)}{\sum_{j=1}^{n} \mu_j(k)}. \tag{5}$$

The model described by (4) can be viewed in the form of LP system:

$$y = \boldsymbol{x}^{\mathrm{T}}(k) \boldsymbol{p} \tag{6}$$

where

$$\boldsymbol{x}(k) = \begin{bmatrix} \phi_1(k)\boldsymbol{r}_1(k) \\ \phi_2(k)\boldsymbol{r}_2(k) \\ \vdots \\ \phi_n(k)\boldsymbol{r}_n(k) \end{bmatrix}, \boldsymbol{p} = \begin{bmatrix} \boldsymbol{p}_1 \\ \boldsymbol{p}_2 \\ \vdots \\ \boldsymbol{p}_n \end{bmatrix}$$

if parameters of the fuzzy sets are treated like constant values. The output error is given by the following formulae:

$$\varepsilon(k) = y'(k) - \boldsymbol{x}^{\mathrm{T}}(k)\boldsymbol{p} \tag{7}$$

where $e(k)$ is the error, and $y'(k)$ is the output of the system. The error is bounded by means of the following inequalities:

$$\varepsilon^{\min}(k) \le \varepsilon(k) \le \varepsilon^{\max}(k). \tag{8}$$

Thus the admissible set of parameters for N data points is given by the following expression (see Fig. 1):

$$\begin{aligned}\mathbb{P} =\{&\boldsymbol{p} \in \mathbb{R}^n \mid y'(k) - \varepsilon^{\max} \le \boldsymbol{x}^{\mathrm{T}}(k)\boldsymbol{p} \le \\ &y'(k) - \varepsilon^{\min}, k = 1, \dots, N\}\end{aligned} \tag{9}$$

and the confidence interval for the output of the system is described by means of the following inequalities:

$$\begin{aligned}&\boldsymbol{x}^{\mathrm{T}}(k)\boldsymbol{p}^{\min}(k) + \varepsilon^{\min} \le y'(k) \le \\ &\boldsymbol{x}^{\mathrm{T}}(k)\boldsymbol{p}^{\max}(k) + \varepsilon^{\max}\end{aligned} \tag{10}$$

where

$$\boldsymbol{p}^{\max}(k) = \arg\max_{\boldsymbol{p}\in\mathbb{W}} \boldsymbol{x}^{\mathrm{T}}(k)\boldsymbol{p} \tag{11}$$

$$\boldsymbol{p}^{\min}(k) = \arg\min_{\boldsymbol{p}\in\mathbb{W}} \boldsymbol{x}^{\mathrm{T}}(k)\boldsymbol{p}. \tag{12}$$

The minimum and maximum values for the following parameters are determined using the linear programming technique[18]. The confidence interval can be directly used to calculate adaptive threshold for residual signal:

$$e_r(k) = y'(k) - y(k). \tag{13}$$

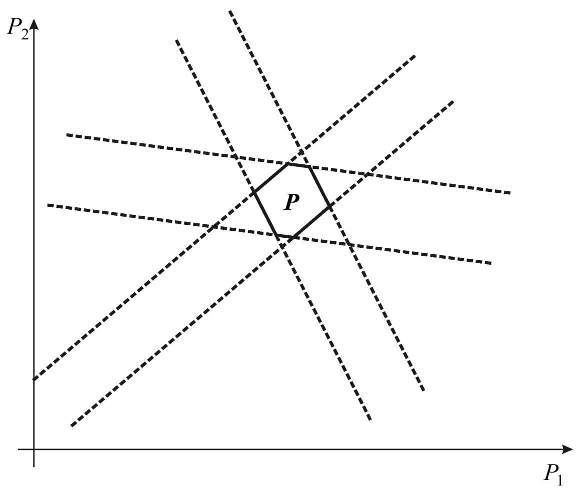

Fig. 1 Admissible set of parameters $\mathbb{P}$

Finally, adaptive threshold is described by the following inequalities:

$$\begin{aligned}&\boldsymbol{x}^{\mathrm{T}}(k)\boldsymbol{p}^{\min}(k) + \varepsilon^{\min}(k) - y(k) \le e_r(k) \le \\ &\boldsymbol{x}^{\mathrm{T}}(k)\boldsymbol{p}^{\max}(k) + \varepsilon^{\max}(k) - y(k).\end{aligned} \tag{14}$$

The presented approach does not take into account the fact that not only the output variable $y(k)$ is uncertain but also all input variables $\boldsymbol{x}(k)$ can be uncertain. Such situation is common due to the fact that input variables are usually measured so they can be known with the defined accuracy. If this fact is not considered the threshold computed for the output variable does not reflect the real model uncertainty so the false alarms can occur.

The problem of computing the feasible set of parameters when some or all explanatory variables, as well as the output, are uncertain is usually called error-in-variables (EIV) problem. The study of this problem can be found in [18]. In this work the EIV parameter-bounding algorithm is adapted for Takagi-Sugeno fuzzy model in order to compute the adaptive threshold. The real unknown input vector can be seen as the difference between the known values of inputs and their errors:

$$\boldsymbol{x}'(k) = \boldsymbol{x}(k) - \boldsymbol{\varepsilon}_{\boldsymbol{x}}(k). \tag{15}$$

Let us assume additionally that the error $\boldsymbol{\varepsilon}_{\boldsymbol{x}}(k)$ is bounded:

$$\varepsilon_x^{\min}(k) \le \varepsilon_x(k) \le \varepsilon_x^{\max}(k) \tag{16}$$

therefore, the admissible set of parameters $\mathbb{P}$ is given by the following inequalities:

$$\begin{aligned}\mathbb{P} =\{&\boldsymbol{p} \in \mathbb{R}^n \mid y'(k) - \varepsilon^{\max}(k) + {\boldsymbol{\varepsilon}_{\boldsymbol{x}}}^{\mathrm{T}}(k)\boldsymbol{p} \le \\ &\le \boldsymbol{x}^{\mathrm{T}}(k)\boldsymbol{p} \le y'(k) - \varepsilon^{\min}(k) + {\boldsymbol{\varepsilon}_{\boldsymbol{x}}}^{\mathrm{T}}(k)\boldsymbol{p} \\ &k = 1, \dots, N\}.\end{aligned} \tag{17}$$

Constraints that determine the admissible set of parameters depend upon the unknown vector of parameters $\mathbb{P}$, which makes it difficult to determine the estimates of these parameters. Nevertheless, from the practical point of view, the procedure for calculating the estimates requires only information about the sign of the expression ${\boldsymbol{\varepsilon}_{\boldsymbol{x}}}^{\mathrm{T}}(k)\boldsymbol{p}$. For this purpose each parameter is viewed in the form of the difference of two positive parameters:

$$p_i = p_i' - p_i'', \quad p_i', p_i'' \ge 0. \tag{18}$$

Such a modification of the task lets us replace the expression ${\boldsymbol{\varepsilon}_{\boldsymbol{x}}}^{\mathrm{T}}(k)\boldsymbol{p}$ with an expression that satisfies the following constraints:

$$\begin{aligned}&{\boldsymbol{\varepsilon}_{\boldsymbol{x}}}^{\mathrm{T}}(k)\boldsymbol{p} \le ({\boldsymbol{\varepsilon}_{\boldsymbol{x}}}^{\max}(k))^{\mathrm{T}}\boldsymbol{p}' - \\ &({\boldsymbol{\varepsilon}_{\boldsymbol{x}}}^{\min}(k))^{\mathrm{T}}\boldsymbol{p}''.\end{aligned} \tag{19}$$

From this modification there arises a new admissible set of parameters $\mathbb{P}$:

$$\begin{aligned}\mathbb{P} =\{&\boldsymbol{p} \in \mathbb{R}^n \mid y'(k) - \varepsilon^{\max}(k) - ({\boldsymbol{\varepsilon}_{\boldsymbol{x}}}^{\max}(k))^{\mathrm{T}}\boldsymbol{p}' + \\ &({\boldsymbol{\varepsilon}_{\boldsymbol{x}}}^{\min}(k))^{\mathrm{T}}\boldsymbol{p}'' \le \boldsymbol{x}^{\mathrm{T}}(k)(\boldsymbol{p}' - \boldsymbol{p}'') \le \\ &y'(k) - \varepsilon^{\min}(k) - ({\boldsymbol{\varepsilon}_{\boldsymbol{x}}}^{\max}(k))^{\mathrm{T}}\boldsymbol{p}' + \\ &({\boldsymbol{\varepsilon}_{\boldsymbol{x}}}^{\min}(k))^{\mathrm{T}}\boldsymbol{p}'', \, k = 1, \dots, N\}.\end{aligned} \tag{20}$$

For such an admissible set of parameters the linear programming technique can be employed analogously to approach with certain input variables. The difference is revealed only in constraints defined by measurements, which are not parallel hyperplanes now and each hyperplane must be considered separately. The admissible set of parameters $\mathbb{P}$ expressed by (20) allows determining the confidence interval for the output signal of the model in the form of the following inequalities:

$$\begin{aligned}&[\boldsymbol{x}(k)-\boldsymbol{\varepsilon_x}^{\max}(k)]^{\mathrm{T}}\boldsymbol{p}'^{\min}(k)-\\&[\boldsymbol{x}(k)-\boldsymbol{\varepsilon_x}^{\min}(k)]\boldsymbol{p}''^{\min}(k)\le(\boldsymbol{x}'(k))^{\mathrm{T}}\boldsymbol{p}\le\\&[\boldsymbol{x}(k)-\boldsymbol{\varepsilon_x}^{\min}(k)]^{\mathrm{T}}\boldsymbol{p}'^{\max}(k)-\\&[\boldsymbol{x}(k)-\boldsymbol{\varepsilon_x}^{\max}(k)]\boldsymbol{p}''^{\max}(k)\end{aligned}\tag{21}$$

where

$$\begin{aligned}&(\boldsymbol{p}'^{\min}(k),\boldsymbol{p}''^{\min}(k))=\\&\arg\min_{(\boldsymbol{p}',\boldsymbol{p}'')\in\mathbb{W}}\big([\boldsymbol{x}(k)-\boldsymbol{\varepsilon_x}^{\max}(k)]^{\mathrm{T}}\boldsymbol{p}'-\\&[\boldsymbol{x}(k)-\boldsymbol{\varepsilon_x}^{\min}(k)]\boldsymbol{p}''\big)\end{aligned}\tag{22}$$

$$\begin{aligned}&(\boldsymbol{p}'^{\max}(k),\boldsymbol{p}''^{\max}(k))=\\&\arg\max_{(\boldsymbol{p}',\boldsymbol{p}'')\in\mathbb{W}}\big([\boldsymbol{x}(k)-\boldsymbol{\varepsilon_x}^{\max}(k)]^{\mathrm{T}}\boldsymbol{p}'-\\&[\boldsymbol{x}(k)-\boldsymbol{\varepsilon_x}^{\min}(k)]\boldsymbol{p}''\big).\end{aligned}\tag{23}$$

The confidence interval for the output of the simulated system can be computed easily if the confidence interval for the output of the model is known:

$$\begin{aligned}&[\boldsymbol{x}(k)-\boldsymbol{\varepsilon_x}^{\max}(k)]^{\mathrm{T}}\boldsymbol{p}'^{\min}(k)-\\&[\boldsymbol{x}(k)-\boldsymbol{\varepsilon_x}^{\min}(k)]\boldsymbol{p}''^{\min}(k)+\varepsilon^{\min}(k)\le\\&y'(k)\le[\boldsymbol{x}(k)-\boldsymbol{\varepsilon_x}^{\min}(k)]^{\mathrm{T}}\boldsymbol{p}'^{\max}(k)-\\&[\boldsymbol{x}(k)-\boldsymbol{\varepsilon_x}^{\max}(k)]\boldsymbol{p}''^{\max}(k)+\varepsilon^{\max}(k).\end{aligned}\tag{24}$$

Finally, the adaptive threshold can be easily deduced from the uncertainty of the system output:

$$\begin{aligned}&[\boldsymbol{x}(k)-\boldsymbol{\varepsilon_x}^{\max}(k)]^{\mathrm{T}}\boldsymbol{p}'^{\min}(k)-\\&[\boldsymbol{x}(k)-\boldsymbol{\varepsilon_x}^{\min}(k)]\boldsymbol{p}''^{\min}(k)+\varepsilon^{\min}(k)-y(k)\le\\&e_r(k)\le[\boldsymbol{x}(k)-\boldsymbol{\varepsilon_x}^{\min}(k)]^{\mathrm{T}}\boldsymbol{p}'^{\max}(k)-\\&[\boldsymbol{x}(k)-\boldsymbol{\varepsilon_x}^{\max}(k)]\boldsymbol{p}''^{\max}(k)+\varepsilon^{\max}(k)-y(k).\end{aligned}\tag{25}$$

4 Takagi-Sugeno fuzzy model design procedure

The main problem of fuzzy model design is the choice of the significant number of rules that ensure the accuracy of the model. Let us consider that N input-output measurements which describes the behavior of the process are given. The idea of the proposed approach is to explore these data in order to find local approximately linear dependencies and next for each found dependence one linear model in the form of the fuzzy rule is generated. The algorithm requires the special evaluation function that decides if the set of the measurements compose the approximately linear dependence. For this purpose the algorithm based on BEA algorithm is developed. Let us consider the simplified situation, when one linear dependence must be found in the set of data points. First, the maximum acceptable error ε of the linear approximation must be given. Let us define the linear model:

$$y=\boldsymbol{r}^{\mathrm{T}}(k)\boldsymbol{p}.\tag{26}$$

The admissible set of parameters consistent with the measurements and chosen error can be defined by the following set:

$$\begin{aligned}\mathbb{P}=&\{\boldsymbol{p}\in\mathbb{R}^n\,|\,y'(k)+\varepsilon\le\boldsymbol{r}^{\mathrm{T}}(k)\boldsymbol{p}\le y'(k)-\varepsilon\\&k=1,\ldots,N\}.\end{aligned}\tag{27}$$

It is possible to generate for each single data point the admissible set of parameters $\mathbb{S}_k$, which has the form of the strip bounded by two parallel hyperplanes. The set of N data points may be defined as a local linear dependence if the generating data lay in the contiguity and the product of their admissible sets is not empty, otherwise data points are not consistent for the chosen error ε. The procedure is recurrent, and is repeated until the chosen data point passes the test of consistency with all previously tested points, otherwise the procedure is stopped. The set of all data points, which passes the test of consistency defines the local linear dependence. The parameters of this model can be calculated by determining the geometrical center of the admissible set of parameters. Four sample steps of the procedure are shown in Fig. 2. Three first data points are consistent each other but the fourth is not consistent with the previous data and can not be included to detect approximately linear dependence. In this case procedure stops and model is designed using only consistent measurements. Proposed algorithm is modified to find multiple approximately linear dependencies.

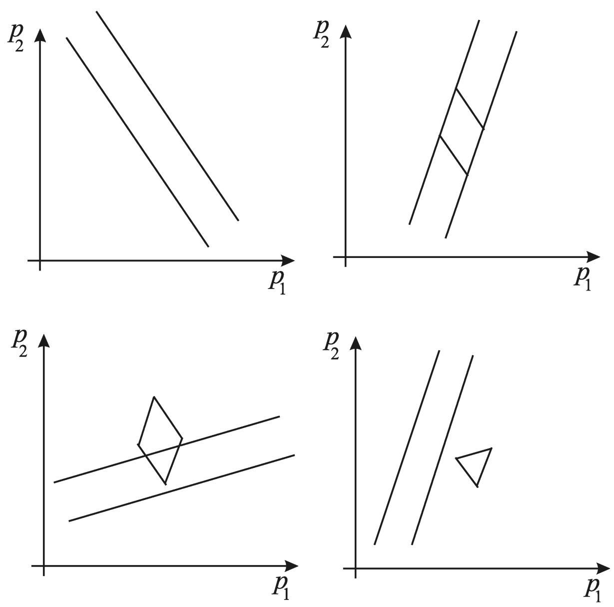

Fig. 2 Detection of linear dependencies in measurements (four sample steps)

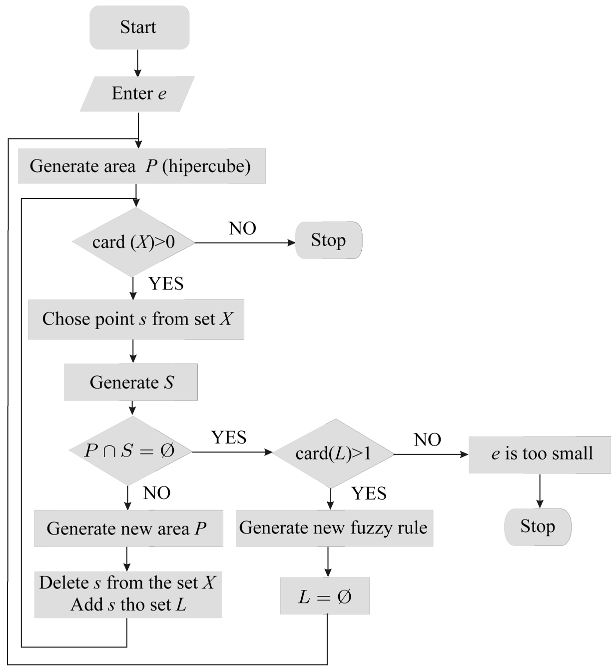

Fig. 3 Algorithm for detection of approximately linear dependencies

The steps of the modified algorithm are shown in Fig. 3, where the following notations are introduced: $\boldsymbol{X}$ is the set of all data points, $\boldsymbol{L}$ is the set of data points that compose the local linear dependence, s is a data point tested for the consistency with elements of the set $\boldsymbol{L}$, $\mathbb{P}$ is the admissible set of parameters generated by the data points from the set $\boldsymbol{L}$, $\mathbb{P}$ is the admissible set of parameters generated by measurement s. The process is repeated until the set $\boldsymbol{X}$ is empty or chosen data point is not consisted with any found linear dependence. The results of this procedure are as follows: the number of the local linear dependencies, ranges in the input-output space of the linear dependencies and the parameters of linear models that approximates these linear dependencies. Moreover, the ranges of the local linear dependencies are used to determine the centers and widths of Gaussian fuzzy sets thus algorithm can be used to determine the structure of Takagi-Sugeno fuzzy model and to estimate its parameters[21].

5 Experimental results

Electrical Direct Current (DC) engines are very often used in many industrial applications. The changing conditions of operation and intensive exploitation result in systematic wearing off of individual parts of engines. This phenomenon can be interpreted as an incipient fault, which in the final phase changes to an abrupt fault and causes big damages in the engine. It is very important in this case to detect the fault at an early stage and apply a special procedure to avoid the fault so that the worn off elements can be replaced. The faults considered manifest themselves at an early stage by a decreased efficiency, but finally, if the fault is not detected some parts of the engine can be damaged. Thus it is important to develop a reliable fault detection algorithm which should detect even small changes in system behavior.

The effectiveness of the robust fault detection method using the Takagi-Sugeno fuzzy models and adaptive thresholds has been examined using a laboratory stand. The laboratory stand is prepared to control the rotational speed of a DC engine with a changing load. It consists of five main elements: DC engine M_1, DC engine M_2, two engine-speed indicators, and clutch K. The shaft of the engine M_1 is connected with the identical engine M_2 by the clutch K and engine M_2 works in the generator mode. The fuzzy model of the engine M_1 was designed in order to build a fault detection system. Experiments with different structures of dynamic consequences show that the best results can be obtained using the following linear consequences for fuzzy rules:

$$y_i(k) = b_1u(k-1) + b_2u(k-2) + b_3u(k-3) \tag{28}$$

where $y_i(k)$ is the output of the ith rule, which should be interpreted as the rotational speed. The input variable $u(k)$ is a voltage responsible for controlling the rotational speed.

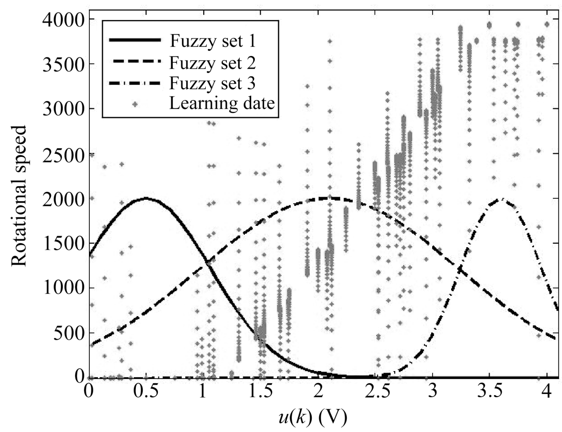

Fig. 4 Fuzzy sets after tuning procedure

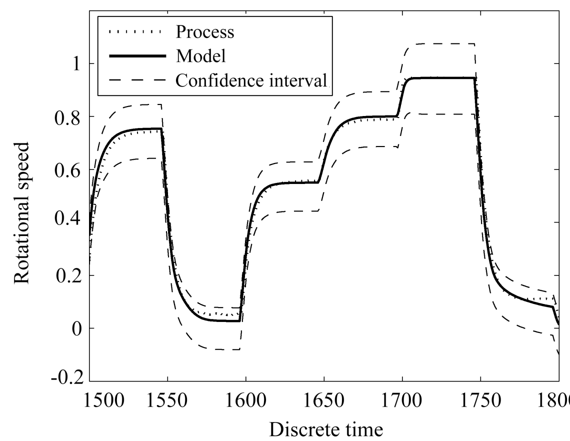

Fig. 5 Model and process outputs as well as corresponding confidence interval for fault-free mode

Table 1 Types of faults

No	Description	S	M	B	I
f_1	Tachometer fault	•	•	•	•
f_2	Mechanical fault of the engine	•	•		•

The fuzzy model built has only one global input variable $u(k)$. In order to identify the structure of the fuzzy model and its parameters, the input-output data were generated using the prepared input signal. The experiment was done using an open-loop control scheme. All variables were normalized to the range [-1,1]. The generated data were used to generate the structure of the model using the algorithm developed in Section 4. It was assumed that a single linear model that describes the consequence of the fuzzy rule can produce the maximum error on the level 0.04. For such a value of the error the algorithm generated 3 fuzzy rules, which were then included in the rule base (see Fig. 4). The behavior of the model was tested using the data that were not used during the design procedure. The model was tested in the open-loop control environment (see Fig. 5) and in the closed-loop control environment.

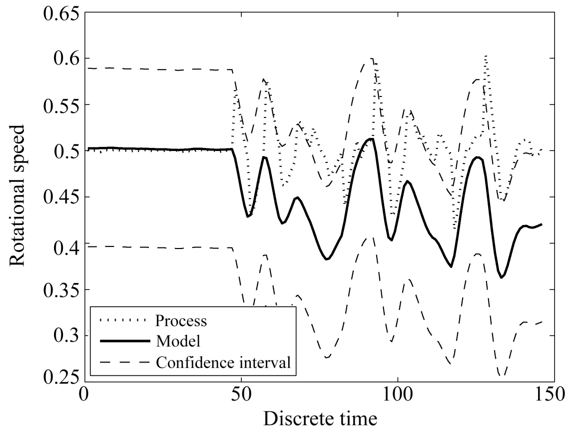

Fig. 6 Faulty scenario: small fault f_1 – process and model output

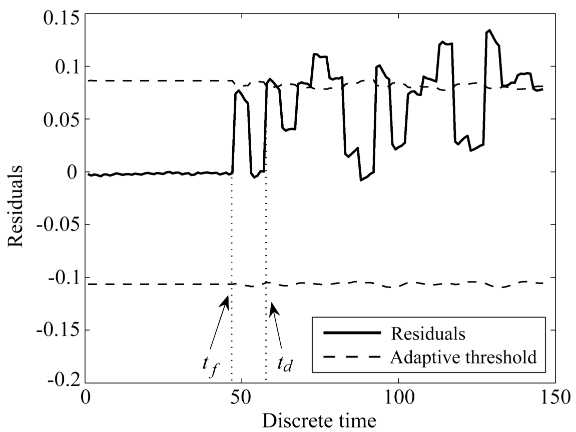

Fig. 7 Faulty scenario: small fault f_1 – residuals

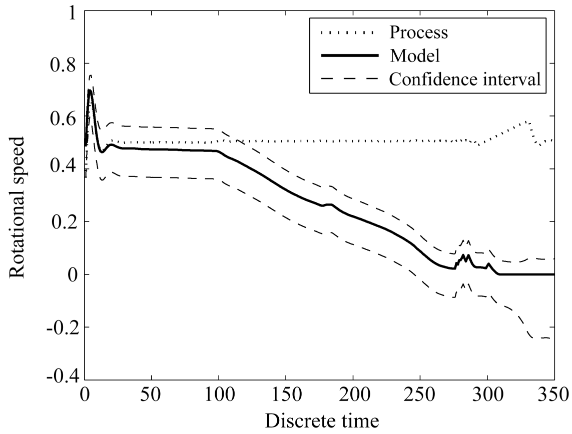

Fig. 8 Faulty scenario: incipient fault f_1 – process and model output

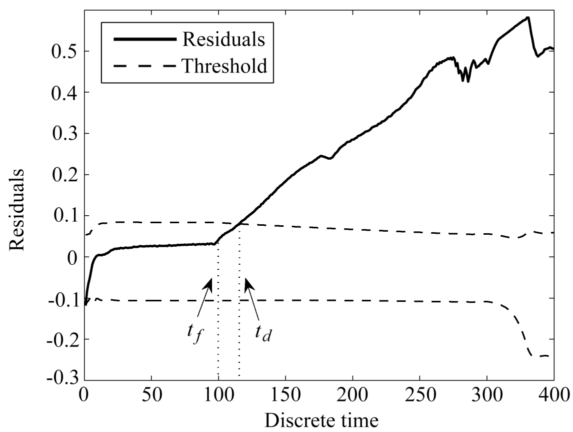

Fig. 9 Faulty scenario: incipient fault f_1 – residuals

A set of potential faults was defined for the engine in Table 1. It was assumed that faults can be incipient (I) or abrupt, and abrupt faults are divided into small (S), medium (M) and big (B) faults. The faults were simulated artificially using the elements of the laboratory system. It was impossible to generate real faults in the laboratory environment. The faults are divided into two groups: tachometer faults and mechanical faults of the engine M_1, which manifest themselves as a decreasing efficiency of the engine. Tachometer faults were simulated by disturbing its output signal using different types of noise. Such disturbed samples given by the tachometer were used to calculate the control signal in the closed-loop control scheme. In order to generate the second fault, the engine M_2 connected with the engine M_1 via the clutch K was used to simulate an additional faulty load. The aim of such an approach was to simulate the incipient mechanical fault in the engine M_1, i.e., a worn-off bearing. The effectiveness of the designed fault detection system was tested using data generated during fault simulations. Faulty data were prepared for all designed scenarios.

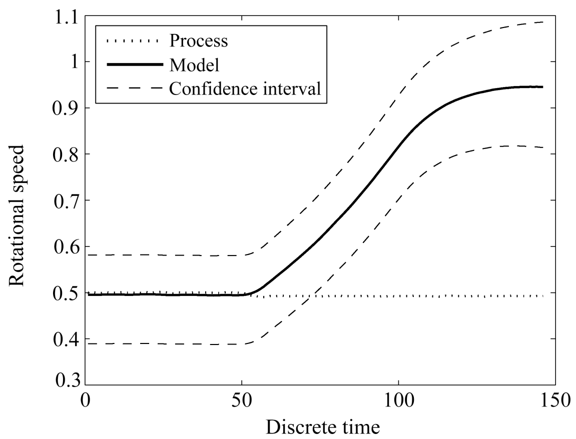

Fig. 10 Faulty scenario: incipient fault f_2 – process and model output

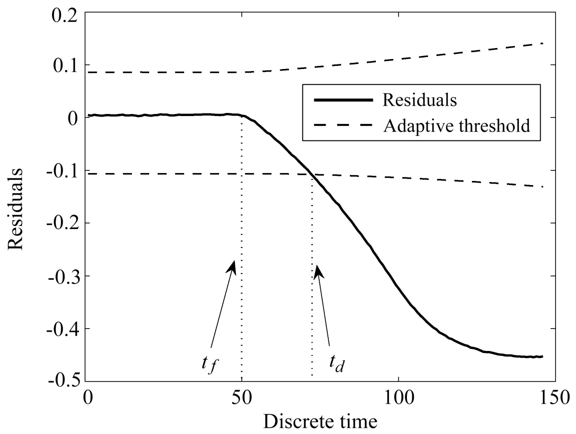

Fig. 11 Faulty scenario: incipient fault f_2 – residuals

The sample results, which present the output of the real object, model output and residuals, are presented in the figures. Sampling time equal to 1 s is used for all figures. The data for a small fault of the tachometer are presented in Figs. 6 and 7. The fault is simulated at the moment 45 (t_f), and is manifested as small random noise that corrupts the tachometer output. The fault is detected at the moment 58 (t_d)because the residual signal exceeds the interval determined by adaptive thresholds. It is important to detect not only abrupt and big faults, but also incipient fault from the point of view of effective diagnostics. Such faults are caused by the slow and progressive process of the wearing off of the parts of the engine so that faults are incipient and their scale is increasing with time, thus it is hard to detect them at an early stage. In order to illustrate the effectiveness of the developed methods for fault detection of incipient faults, experimental results obtained for the incipient fault f_1 are presented in Figs. 8 and 9. Fault detection of the incipient fault f_2 is illustrated by the data presented in Figs. 10 and 11. The fault detection system built is able to detect all simulated faults.

6 Concluding remarks

The main purpose of this paper was to develop robust fault detection scheme using the Takagi-Sugeno fuzzy models. This was achieved with the use of the adaptive threshold technique and BEA algorithm. Some assumptions were established to view the Takagi-Sugeno model in the form of LP system. Next BEA algorithm was applied to determination of admissible set of parameters for the fuzzy model. Unfortunately, the computations required to determine all vertices $\mathbb{W}$ of convex polyhedron are so time and memory consuming that it is hard to employ the classical BEA algorithm for complicated models. In this case the methods that approximate the actual set $\mathbb{P}$ by the area, which has the simplified shape, should be employed[17, 18]. It has to be also mentioned that the presented approach allows to determine real feasible set of parameters only in the static case or in the case of dynamic models, which do not have autoregressive part. The future work will concentrate on extension of the presented approach for Takagi-Sugeno fuzzy models with consequences in the form of ARX models.

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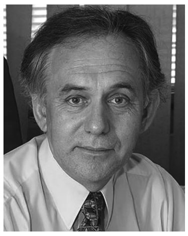

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