ROBUST FAULT DETECTION USING NEURO-FUZZY NETWORKS

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Abstract: The paper focuses on the problem of robust fault detection using neuro-fuzzy model based strategies. The main objective of the work is to show how to employ bounding error approach to determine the uncertainty of the neuro-fuzzy model and next utilize this knowledge for robust fault detection. The paper presents also how to tackle the problem of choosing the right structure of the neuro-fuzzy models. Proposed algorithms are applied to fault detection in the valve that is the part of the technical installation at the Lublin sugar factory. Experimental results presented in the final part of the paper confirms the effectiveness of the proposed methods.

Keywords: fault detection, fuzzy modelling, uncertainty, bounded noise

1. INTRODUCTION

Reliability, safety and availability of the industrial plants play an important role during their operational use. It is important especially nowadays when industrial installations, control algorithms are becoming more and more sophisticated and economics pressures to reduce the costs, to reduce the downtime of plants and to shorten the time necessary to make product. The early detection of the faults could be achieved by the model based fault detection. The method is based on residual generation by comparaison of the estimates of the measured signals with their originals. The most common approach to form the residuals consider a difference between the estimate and original signal. Next residual are employed to detect and isolate the faults. The model based strategy of fault detection has received much attention in last few decades due to i.e. the possibility of detecting incipient faults. The detection of incipient faults is so important because they affect the process behavior slowly and it may take a long time before being detected by simply method of fault detection rely on monitoring the level or trend of a particular signal. Usually incipient faults finish as abrupt faults and make huge damages so the early detection in the incipient phase can minimize drastically the destructive effects of such faults. The prompt detection requires accurate models of the processes and leads directly to the problem of the system identification. Real processes are usually dynamic, nonlinear and stochastic and analytical approaches of identification are not suitable for such systems. One way out of this problem is application of artificial intelligence methods like Neural Networks, Fuzzy Systems, Neuro-Fuzzy (N-F) Systems and Expert Systems (Korbicz *et al.*, 2004; Patton and Korbicz, 1999; Rutkowska and Zadeh, 2000). The paper focuses on N-F networks, which could be used to build the model necessary to form residuals. The attractiveness of N-F methods arises from the fact that they could be useful when there are no phenomenological model available. In such a case N-F models could be identified using simultaneously quantitative and qualitative knowledge i.e. human expert could code his knowledge in the fuzzy rules, which next are introduced into N-F system, N-F model could be also identified using available measurements and methods of learning known for neural networks like i.e. gradient descent methods (Rutkowska, 2002; Rutkowski, 2004), another approach consider the use of data mining methods like clustering algorithms to identify the N-F network (Babuska, 1998). Two types of the N-F networks are commonly used for modelling purpose: Mamdani N-F network and Takagi-Sugeno N-F network. Generally Takagi-Sugeno structures have a better performance in modelling than other structures due to their possibility to decomposition of non-linear systems into a collection of local linear models and thus the paper concentrate on such structure. The main problem, which arises during designing Takagi-Sugeno networks is the question about suitable number of rules, which ensure modelling accuracy. It is usually a trade off between the complexity of the network and its accuracy. Existed methods for determining the structure of N-F network are time consuming i.e. genetic algorithms (Kang *et al.*, 2000), clustering algorithms (Chiu, 1994), partitioning algorithms (Nelles, 2001) and do not assure the accuracy of designed model. In the paper new method for structure determination based on bounding-error approach is proposed. It helps designer in such a way that he must define only maximum acceptable modelling error for local linear models and next algorithm determines the number of the fuzzy rules that fulfill the assumption about maximum error or inform the designer that it is impossible to achieve model with such error.

Another problem considered in the paper arises from the fact of model uncertainty. In real situations no matter what kind of identification method is used there is always model-reality mismatch, which arises usually from bad assumption about the structure of the model or about the type of noise, which corrupt measurements. The uncertainty of the model could dramatically decrease the reliability of fault detection if it is not taken into consideration for such system. Two main approaches have been proposed to overcome described problem: active approach, which usually bases on robust observers and passive approach, which usually bases on adaptive threshold computed for the residual (Patton and Chen, 1999). In the work adaptive threshold technique is employed to implement robust neuro-fuzzy model based fault detection system. This technique bases on uncertainty of the model defined as a range of possible values for model output. Unfortunately do not exists effective methods that allow to determine uncertainty for non-linear systems. However exist methods for linear systems and it is shown in the work they could be applied to Takagi-Sugeno N-F systems if it is treated as system linear in parameters. In the paper the bounding-error approach is modified and adapted for N-F model. The main advantage of this approach is that it does not consider strong assumptions about type of the noise like i.e. statistical methods (Soderstrom and Stoica, 1994). It assumes only that bounds on the noise signal are available (Walter and Pronzato, 1997; Milanese *et al.*, 1996). Next the method determines the feasible set of parameters that are consistent with the model, the measured data, and noise bounds. Unfortunately, the set computed in such a way could be very complex and computations required to determine them are time consuming that limits the use of the method to simply structures of the N-F model. To overcome this problem the Outer Bounding Ellipsoid method (OBE) (Walter and Pronzato, 1997) that approximates the real feasible set of parameters using ellipsoid is adopted to determine the uncertainty of N-F model.

The paper is organized as follows. In Section 2, the elementary information concerning model based fault detection using N-F network are presented. Section 3 describes the idea of bounded error approach and algorithm proposed to determine the structure of N-F model. Section 4, presents the algorithm of adaptive threshold and describes how to obtain such threshold for N-F model using OBE method. Section 5 contains an experimental results obtained for fault detection. Last section is devoted to conclusions.

2. NEURO-FUZZY MODELLING AND FAULT DETECTION

The idea of model based fault detection consider the comparison of the model output with the real values measured from the process, thereby generating the residuals, which are the faults indicators (Patton and Korbicz, 1999). Usually residuals are generated as a difference between model and system outputs. It means that residual signal should be close to zero in the fault free mode, otherwise it should be significantly different from zero. Ideally residual signal should carry only information about faults but practically it also contains errors, which are the effects of model uncertainty. It is necessary in this case to establish thresholds on residuals to avoid false alarms. If residual signal exceeds range defined by thresholds the alarm is activated, otherwise system is working in fault free mode. The proposed fault detection approach utilizes Takagi-Sugeno N-F networks to implement necessary models. The structure of the Takagi-Sugeno system could be presented in the form of layered topology similar to the neural network (Fig. 1). However knowledge coded in this structure could be viewed in the form of fuzzy rules

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

where, $\boldsymbol{x}$ is the vector of the global network inputs, $\boldsymbol{A}_i$ is the multivariate fuzzy set, y_i is the scalar output of the rule, $\boldsymbol{r}_i$ is the vector of the local linear system inputs, $\boldsymbol{p}_i$ is the vector of the local linear system parameters, and k is the index of the rule. Fuzzy sets have usually Gaussian membership functions and in the work such membership functions are considered. Global output of the N-F network is a composition of 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 archived for i-th rule, y_i is the output of the i-th rule (local linear system), n is the number of rules. It is worth to notice that the number of rules determines the number of the local linear models, which are responsible for piecewise local linear approximation of the non-linear system. It could be shown that the number of rules has strong influence on accuracy of the global model and its complexity. The designer must find compromise between these two coefficients. It is very important to include dynamic in the N-F network because the real processes are usually dynamic. It could be done by introducing into input vector $\boldsymbol{r}_i$ delayed inputs $\boldsymbol{u}_i$ of the local model and delayed output of the local output y_i i.e. $r_i = [u_i(k), u_i(k-1), \ldots, u_i(k-n_a), y_i(k-1), y_i(k-2), \ldots, y_i(k-n_b)]$. The sample layered structure of Takagi-Sugeno system is presented in (Fig. 1). It consist of 5 layers. The elements of the first layer are responsible for realizing membership functions and each element of this layer include in the case of Gaussian membership function 2 parameters: c - center of the Gaussian function and w - width of the Gaussian function. The nodes in the second layer realize algebraic product in order to compute firing levels of the rules. The third layer is responsible for inference operation and usually it is realized by algebraic product. The fourth layer represents consequents of the fuzzy rules and each node of this layer include the vector of parameters $\boldsymbol{p}_i$. The fifth layer is responsible for composition of rule responses in order to compute the global response of the network.

3. DESIGNING THE STRUCTURE OF THE NEURO-FUZZY MODEL

As has been already mentioned one of the main problems in designing the structure of N-F model

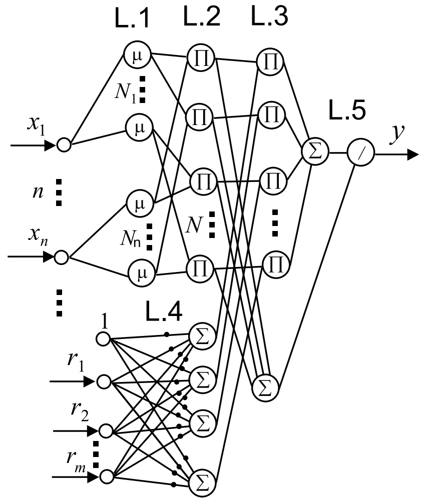

Fig. 1. Sample Takagi-Sugeno network

is the choice of the significant number of rules that ensure the accuracy of the model. Let us consider that N input-output measurements defining the characteristic 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 node generation of one rule. The measurements are explored in order to find local linear dependencies using the bounding-error approach. Let us consider simplified situation when one linear dependence must be found in the process characteristic. First the designer must define the maximum error ε that linear model (3) could made during the approximation of the linear dependence

$$y = \boldsymbol{r}^T(k)\boldsymbol{p}. \tag{3}$$

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

$$\begin{aligned} \mathbb{P} = \{ & \boldsymbol{p} \in \mathbb{R}^n \,|\, y'(k) + \varepsilon \le \boldsymbol{r}^T(k)\boldsymbol{p} \le y'(k) - \varepsilon \\ & k = 1, \ldots, N\}, \end{aligned} \tag{4}$$

where, $y'(k)$ is the output of the system. It is possible to generate for each measurement feasible set of parameters $\mathbb{S}_k$ separately and in this case it is a strip in parameter space, bounded by two parallel hyperplanes. The set of N measurement points could be viewed as a local linear dependence if they lay in the input-output space in the contiguity and the product of their feasible sets is not empty, otherwise measurements are not consistent for defined error ε. The procedure of looking for linear dependence is recurrent, and is repeated while the chosen measurement passes the test of consistency with all previously tested measurements, otherwise procedure is stopped. The set of all measurements that passed the test of consistency define the working ranges in the input-output space for the local linear model. The parameters of this model could be obtained by calculating the geometrical center of feasible set

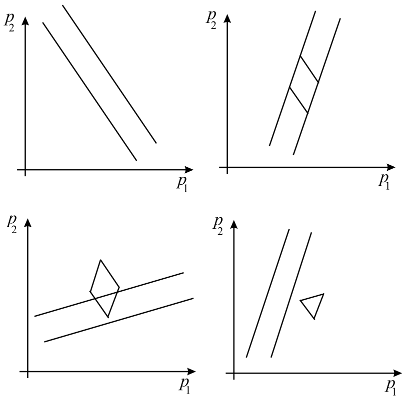

Fig. 2. Detection of linear dependencies in measurements (four sample steps)

of parameters generated by measurements that passed the test of consistency. Sample four steps of described procedure are shown in (Fig. 2) where the feasible sets for 4 measurements are shown. Three first measurements are consistent each other but fourth measurement is not consistent with the previous data and could not be used to generate local linear model. In this case procedure stops and model is designed using only consistent measurements. Proposed algorithm has been modified to find multiple approximately linear dependencies in process characteristic.

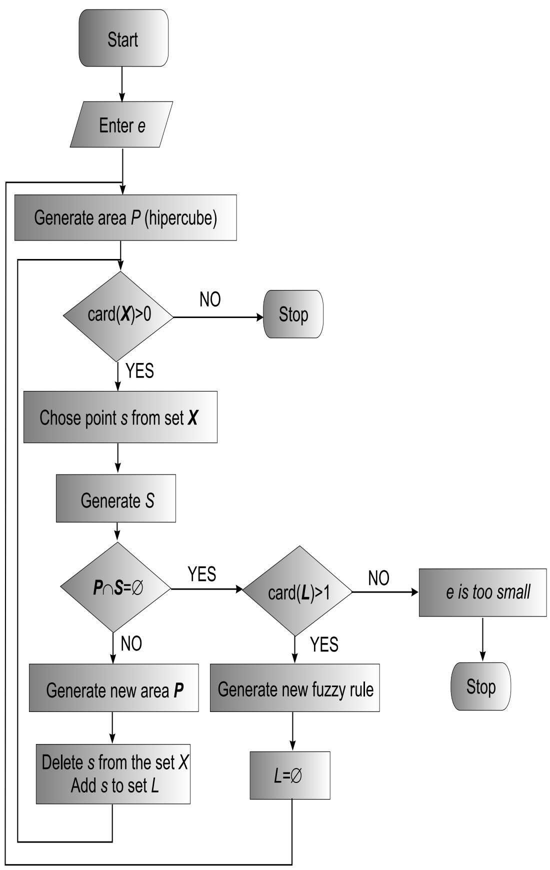

Fig. 3. Algorithm for detection local linear dependencies

The steps of modified algorithm are shown in (Fig. 3) where the following notations are introduced, $\boldsymbol{X}$ is the set of all measurements, $\boldsymbol{L}$ is the set of measurements creating local linear dependence, s is a measurement tested for the consistency with elements of the set $\boldsymbol{L}$, $\mathbb{P}$ is the feasible set of parameters generated by measurements from the set $\boldsymbol{L}$, $\mathbb{P}$ is feasible set of parameters generated by measurement s. The process is repeated until the set $\boldsymbol{X}$ will be empty or one measurement will not be consisted with any local 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 local linear dependencies could be used to determine the centers and widths of Gaussian fuzzy sets. Summing up, algorithm could be used to determine the structure of Takagi-Sugeno N-F network and to estimate its parameters.

4. ADAPTIVE THRESHOLD IN THE FAULT DETECTION

The adaptive threshold method bases on assumption that uncertainty of the model for each sample of data could be evaluated in order to compute thresholds for the residuals. In the proposed method the uncertainty of the model is characterized by feasible set of parameters determined by bounding error approach. Let us consider the following Takagi-Sugeno N-F model:

$$y(k) = \sum_{i=1}^{n} \phi_i(k) y_i(k), \tag{5}$$

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

$$\phi_i(k) = \frac{\mu_i(k)}{\sum_{j=1}^{n} \mu_j(k)}. \tag{6}$$

The model described by equation (5) could be viewed as system linear in parameters

$$y = \boldsymbol{x}^T(k)\boldsymbol{p}, \tag{7}$$

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. Let us define the output error

$$\varepsilon(k) = y'(k) - \boldsymbol{x}^T(k)\boldsymbol{p}, \tag{8}$$

where $e(k)$ is the error, and $y'(k)$ is the output of the system The usual statistical parameter estimation approaches assumes that the data are corrupted by the errors which can be modelled as realizations of independent random variables, with a known or parameterized distribution (Soderstrom and Stoica, 1994). Bounded error approach is more realistic because assumes that the errors lie between given priori bounds (Milanese *et al.*, 1996; Walter and Pronzato, 1997)

$$\varepsilon^{min}(k) \leq \varepsilon(k) \leq \varepsilon^{max}(k). \tag{9}$$

Let us assume that

$$\varepsilon^{max}(k) = \varepsilon,\ \varepsilon^{min}(k) = -\varepsilon. \tag{10}$$

Thus the feasible set of parameters for N data points is

$$\begin{aligned}\mathbb{P} =\{&\boldsymbol{p} \in \mathbb{R}^n \mid y'(k) + \varepsilon \leq \boldsymbol{x}^T(k)\boldsymbol{p} \leq y'(k) - \varepsilon \\ &k = 1, \ldots, N\}.\end{aligned} \tag{11}$$

and the confidence interval for output signal of the system is

$$\begin{aligned}&\boldsymbol{x}^T(k)\boldsymbol{p}^{min}(k) - \varepsilon \leq y'(k) \leq \\ &\leq \boldsymbol{x}^T(k)\boldsymbol{p}^{max}(k) + \varepsilon,\end{aligned} \tag{12}$$

where

$$\boldsymbol{p}^{max}(k) = \arg\max_{\boldsymbol{p}\in\mathbb{W}} \boldsymbol{x}^T(k)\boldsymbol{p}, \tag{13}$$

$$\boldsymbol{p}^{min}(k) = \arg\min_{\boldsymbol{p}\in\mathbb{W}} \boldsymbol{x}^T(k)\boldsymbol{p}. \tag{14}$$

The algorithm requires to determine the set of all vertices $\mathbb{W}$ of convex polyhedron $\mathbb{P}$. This process is so time consuming that it is hard to employ described algorithm for models with more then 6 parameters. Fortunately, recursive OBE algorithm is able to approximate the area $\mathbb{P}$ by enclosing it by ellipsoid $\mathbb{E}$ and is not so time consuming (Walter and Pronzato, 1997). The date in this algorithm are taken into account one after the other to construct succession of ellipsoids containing all values parameters consistent with all previous measurements. After the first k observations, the feasible set of parameters is described by the ellipsoid

$$\begin{aligned}\mathbb{E}(k) =\{&\boldsymbol{p} \in \mathbb{R}^n \mid (\boldsymbol{p} - \hat{\boldsymbol{p}}(k))^T\boldsymbol{M}^{-1}(k) \\ &(\boldsymbol{p} - \hat{\boldsymbol{p}}(k)) \leq \sigma^2(k)\},\end{aligned} \tag{15}$$

where $\hat{\boldsymbol{p}}(k)$ is the center of the ellipsoid, $\boldsymbol{M}(k)$ is the positive define matrix, which specifies the size and orientation of the ellipsoid, the coefficient $\sigma(k)$ has the influence on the size of the ellipsoid. By means of intersection of the above strip and the ellipsoid, we get region of possible parameter estimates. This region is overbounded, by new ellipsoid. The algorithm described below provides rules for computing $\hat{\boldsymbol{p}}(k+1)$, $\boldsymbol{M}(k+1)$ and $\sigma(k+1)$ in such a way that

$$\mathbb{E}(k) \cap \mathbb{U}(k+1) \subset \mathbb{E}(k+1). \tag{16}$$

The new $\mathbb{E}(k+1)$ ellipsoid is the smallest one in some sense. Detailed description of the algorithm could be found in (Milanese *et al.*, 1996). The last ellipsoid obtained from recursive algorithm is used to compute the confidence interval for the output signal of the system:

$$\begin{aligned}&\boldsymbol{x}^T(k)\hat{\boldsymbol{p}} - \sqrt{\boldsymbol{x}^T(k)\boldsymbol{M}\boldsymbol{x}(k)} - \varepsilon \leq y'(k) \leq \\ &\leq \boldsymbol{x}^T(k)\hat{\boldsymbol{p}} + \sqrt{\boldsymbol{x}^T(k)\boldsymbol{M}\boldsymbol{x}(k)} + \varepsilon\end{aligned} \tag{17}$$

The confidence interval could be directly applied to compute adaptive threshold for residual signal. Let us consider residual signal

$$e_r(k) = y'(k) - y(k). \tag{18}$$

Thus adaptive threshold can be put in the following form

$$\begin{aligned}&\boldsymbol{x}^T(k)\hat{\boldsymbol{p}} - \sqrt{\boldsymbol{x}^T(k)\boldsymbol{M}\boldsymbol{x}(k)} - \varepsilon - y(k) \leq e_r(k) \leq \\ &\leq \boldsymbol{x}^T(k)\hat{\boldsymbol{p}} + \sqrt{\boldsymbol{x}^T(k)\boldsymbol{M}\boldsymbol{x}(k)} + \varepsilon - y(k).\end{aligned} \tag{19}$$

It has to be pointed that presented method for computing the adaptive threshold for neuro-fuzzy model assumes that input vector $\boldsymbol{x}$ is not corrupted by errors. In real situations sometimes this assumption may be not fulfilled.

5. EXPERIMENTAL RESULTS

The proposed in this work methods have been applied to build fault detection system for valve. Based on the observations of the process variables and the knowledge about the process two neuro-fuzzy models have been designed

$$F = f_F(X, P_1, P_2, T_1) \tag{20}$$

$$X = f_X(C_V, P_1, P_2, T_1) \tag{21}$$

where F is the juice flow, X is the servomotor rod displacement, P_1 is the juice pressure (valve inlet), P_2 is the juice pressure (valve outlet), T_1 is the juice temperature (valve outlet) and C_V is the control value (controller output). The method for structure generation of N-F model presented in subsection 3 has been applied for models (20) and (21). The obtained structures are described in table 1. The parameters of fuzzy sets have been estimated from the results obtained during the structure generation and the parameters of the consequents have been estimated using the OBE algorithm. The priori known value of the error ε was 0.05. To demonstrate the effectiveness of the fault detection system 44 faulty scenarios were simulated using the model build within framework of the project DAMADICS.

Table 1. Neuro-fuzzy models

quantity	f_F	f_X
global inputs	X	C_V
local inputs	X, P_1, P_2, T_1	C_V, P_1, P_2, T_1
no. of rules	7	3

The faults have been divided into 2 main classes abrupt faults, and incipient faults, abrupt faults

Table 2. Fault detection results

No.	Desc.	S	M	B	A
	Control valve faults				
f_1	Valve clogging	Y	Y	Y	
f_2	Sedimentation			Y	Y
f_3	Seat erosion				Y
f_4	Bushing frictions				Y
f_5	External leakage				N
f_6	Internal leakage				Y
f_7	Medium evaporation	Y	Y	Y	
	Servo-motor faults				
f_8	Twisted piston rod	N	N	Y	
f_9	Housing				N
f_{10}	Diaphragm perforation	Y	Y	Y	
f_{11}	Spring fault			Y	Y
	Positioner faults				
f_{12}	E/P transducer fault	N	N	N	
f_{13}	Rod displ. sensor fault	Y	Y	Y	Y
f_{14}	Pressure sensor fault	N	N	N	
f_{15}	Feedback fault			Y	
	External faults				
f_{16}	Pressure drop	Y	Y	Y	
f_{17}	Unexpected pressure change			Y	Y
f_{18}	Opened bypass valves	Y	Y	Y	Y
f_{19}	Flow rate sensor fault F	Y	Y	Y	

are divided into 3 groups small, medium and big faults. Fault detection results obtained for all scenarios are shown in the table 2 where the following notations has been introduced Y indicates that fault was detected using designed N-F models, N indicates that fault was not detected by designed N-F models. The sample results obtained for the incipient fault are shown in Fig. 4.

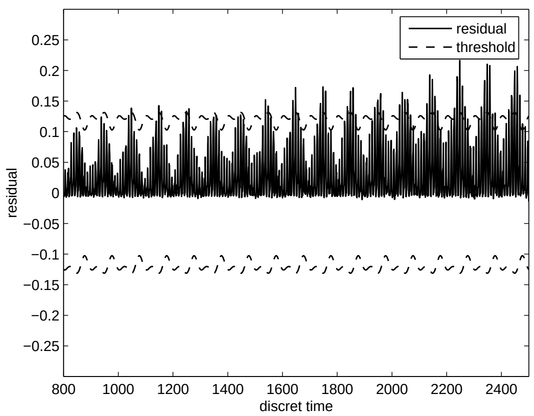

Fig. 4. Faulty scenario: adaptive threshold and residual signal

6. CONCLUDING REMARKS

The main purpose of this paper was to propose robust fault detection scheme using the N-F network. This was achieved with the use of the adaptive threshold technique for residual signal. The confidence interval for output signal had to be evaluated in order to determine the adaptive threshold. The Takagi-Sugeno N-F network was modified to obtain linear in parameters structure of N-F network and next OBE algorithm was applied to determine feasible set of parameters of the N-F model. Another objective of the work was to develop new method for designing the structure of N-F network. It has been proposed method based on bounding-error approach, which concentrate on detection of locally linear dependencies in the process characteristic in order to generate fuzzy rules. Experimental results confirm the effectiveness of the proposed solutions.

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