Fault Tolerant Control Using Evolving Fuzzy Modeling

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Abstract: *This article proposes a fault tolerant control approach using evolving fuzzy modeling. Load process faults, specifically variation in feed composition and change in heating (variation of re-boiler temperature), are considered, these faults can be abrupt or incipient. Such faults have the consequence of changing the operational ranges. The fault detection is made when the residual (difference between the process output and the model output) passes a certain threshold. To accommodate the faults effects, two different approaches are used, evolving fuzzy modeling [2, 1, 3] and adaptive fuzzy models [26, 4]. Both methods are performed on-line with current data (data with fault information). In evolving fuzzy modeling, according to certain conditions, new rules are added or the existing ones are updated. When new rules are added, their consequents are determined by using the recursive least square (RLS) method. In the adaptive fuzzy modeling approach, only the consequents are recursivelly updated by using RLS. Finally the proposed approaches are applied to fault tolerant control of a distillation column.*

Keywords: Fault tolerant control, fuzzy modeling, adaptive fuzzy models, evolving Takagi-Sugeno fuzzy models, model based predictive control, distillation column

1. INTRODUCTION

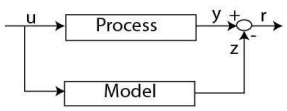
Fault tolerant control is a technique used to automatically monitor systems and in case of fault, they aim to reduce their effect or even eliminate it by using robust controllers or by reconfigurate the system. There are several approaches to deal with systems in presence of faults, including *fault tolerant control based on fuzzy models* [16], *geometric approach to nonlinear fault detection and isolation* [22], *fault tolerant model based predictive control using multiple takagi-Sugeno fuzzy models* [11], or *fault tolerant control using an admissible model matching approach* [27]. The main problem of some of these approaches is that they have to know the fault in advance, i.e, they have to characterize the fault in order to be able to handle it. This implies building controllers with enough robustness, or using fault information to select a model from a model data base created off-line. The main drawback of these controllers is when a non predicted fault occurs. In the aforementioned case, the operational range is completely different from the one for which the controller was built or prepared for. Thus, the controllers are not able to exactly characterize the fault, leading to wrong results in control strategy. Therefore, it is clear that arises the necessity of controllers that can continuously adapt themselves to different operational ranges, caused by faults or disturbances in the systems. In order to achieve this aim, this paper proposes a predictive fault tolerant control approach using evolving fuzzy modeling. The proposed approaches have the model based predictive control (MBPC) and the evolving fuzzy modeling (ETS) [2, 3], or the adaptive fuzzy models [26, 4], as framework. Evolving fuzzy modeling are models whose rule-base and parameters continuously evolve by adding new rules with more summarization and updating the existing rules and parameters. Differently, adaptive fuzzy models, keep the rule base and the structure fixed changing only the parameters of the consequents. By using these approaches, the models in MBPC are adapted at each time that the process operational range change due to faults or disturbances. That adaption allows the model to "know" the actual operational range, and consequently good predictions of the process behavior are achieved. Differently from the approach in [16] in which, the fault is detected, isolated (fault characterization) and then accommodated. The proposed approaches does not have the stage of isolation. The fault is detected when a residual passes a certain threshold. This residual threshold is defined, by knowing the system behavior. To set this value, one analyzes the free fault system output, and chooses a value bigger than this value, and use it as the residual threshold. When the fault is detected, the data with fault are gathered with a moving window, and when the moving window is full, the proposed fault tolerant control approaches are activated. The advantage of using one of these techniques is the fact that both have fuzzy logic as background, allowing them to deal with uncertain (data with fault and disturbances) information, resulting in a more effective control. The proposed approaches are applied to a distillation column, to accommodate faults that may occur in this equipment.

This paper is organized in five sections. In Section 2, an overview of fault tolerant control is made. Evolving fuzzy modeling is the issue of Section 3. This section is divided in three parts: 3.1 Takagi-Sugeno fuzzy models, 3.2 on-line adaption of the fuzzy models and in Section 3.3 evolving Takagi-sugeno fuzzy models are the issue. In Section 4, the evolving fuzzy models and the adaptive fuzy models are integrated in the model based predictive control scheme. The developed control approaches are applied to a distillation column in Section 5, and conclusions and the recommendations for future work are given in Section 6.

2. FAULT TOLERANT CONTROL

There are several processes that although one or more faults may occur within them, they must not stop working because of their impact in political, economical and social domains. Fault tolerant control (FTC), fault detection (FD) and fault isolation (FI) are research areas which aim to solve this problem. Those research areas, which have been developing since the 80th [20], are interested in studying methodologies for identifying and exactly characterizing possible faults that may occur in processes. When fault tolerant systems are used in control systems, it is possible to maintain the system working by accommodating the faults effects.The considered faults are, the abrupt faults and incipient faults. The abrupt fault is characterized by fast variations of the variables, giving rise to suddenly faults. Normally they are modelled as a step in the variable. The incipient one is characterized by slow variations of the variables, as depicted on the figure 1. The

Fig. 1. *Residual*



fault detection may be carried out by different ways such as *hardware redundancy* [14], which consists of comparing the outputs of identical hardware and performing consistence cross checks. This approach is not always feasible in practice due to the cost of a solution of this kind. *Analytical redundancy* [9] in an approach in which the FD can be accomplished using analytical and functional information about the system, using a mathematical model. There are two classes of model-based approaches. In the first class, quantitative models such as transfer functions, differential equations and state space models are used. These methods make use of theoretical tools such as parameter estimation techniques, state estimation techniques and parity space concepts. The *gold rule* for this approach is an a priori knowledge about the relationships between faults and changes in model parameters. The second approach is based on the use of artificial intelligence methods (*fuzzy logic* and *neural networks*), using qualitative reasoning and modeling. Qualitative models are used to predict the behavior of the system in nominal conditions and in different fault condition,and this detection and isolation of fault is performed by the residual analysis. Section 2.1 a decomposition in the fault tolerant control is made, and in Section 2.2 an overview in fault detection and isolation is made.

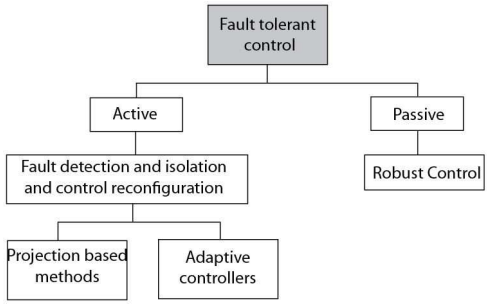
2.1 Passive and active fault tolerant control systems

In following Sections the decomposition of the FTC is presented, and Fig. 2 presents this decomposition [19].

Passive fault tolerant control system

Passive fault tolerant control is a method in which robust

Fig. 2. *Decomposition of fault tolerant control*



control is used [15]. These controllers are made to be fault insensitive and the process with fault remains working with the same controller and structure without losing performance. In general, the FTC architecture, and fault information and location is usually required before the controller react to the fault. In passive FTC systems, the controller is made robust to faults by assuming a restrictive kind of faults and the way they affect the controlled process. A priori knowlodge of the faults and their influence in the system are required for this types of controller.

Active fault tolerant control system

Differently from passive FTC, active systems are made to be fault sensitive. Therefore, when a fault occurrs the fault detection system is activated. Active FTC may be applied through reconfigurable control (reconfigurable control is an active FTC approach in which the parameters of the controller are adjusted to accommodate faults in the process)[5]. The reconfiguration is not applied only in the parameters, but the controller structure may also change. An active FTC system requires either a priori knowledge of expected faults or a mechanism for detecting and isolating anticipated faults. When the faults are detected, the decision concerning the location and nature of the faults are then used to reconfigure the control function. Active fault tolerant control is divided into two main fields, the *projection based methods* and the *adaptive controllers* as depicted in the Fig. 2. In projection based methods, one control law is selected in a pre-defined data base containing possibles control laws according to pre-defined faults and in adaptive controllers parameters of models are on-line reconfigured. In proposed FTC approaches the parameters and structure of the controller are reconfigured on-line.

2.2 Fault detection and Isolation

Since the $70's$, huge effort has been invested in fault detection and isolation (FDI) [30, 21]. In FDI, sevaral approaches have been developed, including *qualitative and quantitative model-based approaches*[29, 28], and *knowledge based approaches* [10]. The major task of FDI is to perform real time diagnostic of the plant, reading each

time the process variables and the model outputs and compute the residuals. In system failure-free (systems without fault) the residual should be close to zero. Many reconfigurable controllers use real time estimates of system parameters provided by parameter estimation based FDI methods[29, 18]. FDI based upon state estimation is said to be less accurate in providing information to the controller than the parameter estimation approach for on-line reconfiguration. However, in many applications it is extremelly difficult to get reasonably accurate parameters on-line. In order to overcome the disadvantages of using parameters estimation, different controllers reconfiguration have been developed. The FDI is expected to generate the residual, providing detailed information about faulty conditions and take the decision if a fault has occurred or not. In the proposed approaches the fault isolation is unnecessary once that the fault do not need to be characterized.
The fault tolerant control approaches that are going to be used, utilizes the fuzzy models as the framework. In the next Section the fuzzy models are going to be the issue.

3. EVOLVING FUZZY MODELING

3.1 Takagi-Sugeno fuzzy models

Takagi-Sugeno (TS) fuzzy models are models in which the consequents of the rules are mathematical functions

$$R\ :\mathbf{if}\ x\ is\ A\ \mathbf{then}\ \mathbf{y}\ =\ \mathbf{f}^k\left(x\right) \tag{1}$$

where R is the k rule, x are the antencedents , y are the consequents and A is the multidimensional antecedent fuzzy set of the kth rule. The multiple-input and multiple-output (*MIMO*) fuzzy model represented in (1), can be decomposed into a colletion of multiple-input and single-output (*MISO*) fuzzy models without loss of generality [26]. The most simple and widely used function is the affine linear form:

$$R:\ \mathbf{if}\ x\ is\ A\ \mathbf{then}\ y^k\ =\ \left(\mathbf{a}\right)^T x+\mathbf{b} \tag{2}$$

where $\mathbf{a}$ is a parameter vector and $\mathbf{b}$ is a scalar offset, the consequent of the affine TS model are hyperplanes in the product space of the inputs and outputs.
Before inferring the output the degree of fulfillment of the antecendents $\varphi_i\left(x\right)$ is computed. For rules with multivariate antecedents fuzzy sets, the degree of fulfillment is equal to the membership degree of the given input $\mathbf{x}$, i.e., $\varphi_i\ =\mu_i\left(x\right)$. In Takagi-Sugeno fuzzy models, the inference is reduced in the following equation:

$$y=\frac{\sum_{i=1}^K\varphi_i\left(x\right)y_i}{\sum_{i=1}^K\varphi_i\left(x\right)}. \tag{3}$$

When considering a fuzzy modeling approach, one has to choose the type of fuzzy model a priori, which depends on the particular application. TS fuzzy models are more suitable for identification for non-linear systems from the data, while linguistic fuzzy models give a more quantitative description of the system and can also be used when dealing with knowledge of the process. For that reason,Takagi-Sugeno fuzzy models are going to be used.

off-line identification

The off-line identification can be compressed in the following four steps:

- Construction of the regression data;
- Determination of the clusters corresponding to a set of local linear submodels;
- Determination of the antecedents membership function from clusters parameters;
- Estimation of the rules consequent parameters;

Regression data: available data samples are collected in matrix Z formed by concatenating the regression matrix Φ and the output vector
Υ:

$$\Phi=\begin{bmatrix} x\left(k_h\right)^T\\ \vdots\\ x\left(N-1\right)^T\end{bmatrix},\ \Upsilon=\begin{bmatrix} y\left(k_h+1\right)^T\\ \vdots\\ y\left(N\right)^T\end{bmatrix},\ \mathbf{Z}=\left[\Upsilon\,,\Phi\right]^T \tag{4}$$

where N is number of data samples.
Construction of the fuzzy clusters: data set Z is partitioned into K clusters, through the clustering. the result is a fuzzy set partition matrix $\mathbf{U}\ =\ \left[\mu_{kl}\right]^{K\times N_d}$, whose element $\mu_{kl}\ \in\ [0,1]$, represents the degree of fulfillment of the membership in cluster k, a prototype matrix $\mathbf{V}\ =\ [\mathbf{V}_1,\,\mathbf{V}_2\ \ldots,\mathbf{V}_K\,]$ and a set of covariance matrices $\mathbf{F}\ =\ [\mathbf{F}_1,\,\mathbf{F}_2\ \ldots,\mathbf{F}_K\,]$ are defined positive matrices.
Determination of antecedents membership function from clusters parameters: Gustafson-Kessel algorithm [4] is used to construct fuzzy clusters. Each cluster represents one TS fuzzy rule. The multidimensional membership functions A^k are given analytically by computing the distance of $x(k)$ from projection of cluster center $\mathbf{v}_k$ onto X, and then computing the membership degree in an inverse proportion to the distance. Denote with $\mathbf{F}_k^x\ =\ [f_{jl}]\ 1\ \leq\ j,l\ \leq\ n$, the submatrix of $\mathbf{F}_k^x$. This matrix describes the form of the cluster in the antecedent space X. Let $\mathbf{F}_k^x\ =\ [v_{1k},\ldots,v_{nk}]^T$ denote the projection of the cluster center onto the antecedent space X, the inner-product distance norm is given by:

$$d_{kl}=\left(\mathbf{x}\left(k\right)-\mathbf{v}_k^x\right)^T\left|\left(\mathbf{F}_k^x\right)\right|^{1/n}\left(\mathbf{F}_k^x\right)^{-1}\left(\mathbf{x}\left(k\right)-\mathbf{v}_k^x\right) \tag{5}$$

which is converted into the membership function degree by

$$\mu_{A^k}\left(\mathbf{x}\left(k\right)\right)=\frac{1}{\sum_{j=1}^K\left(d_{kl}/d_{jl}\right)^{2/(q-1)}} \tag{6}$$

where q is the fuzziness parameter of GK algorithm.
Estimation of the rules consequent parameters: optimal consequent parameters are estimated by the least square method. Let $\left(\theta^k\right)^T\ =\ \left[\left(a^k\right)^T,b^k\right]$, let $\mathbf{\Phi}_e$ denote the matrix $[\mathbf{\Phi}_e,\,\mathbf{1}]$, and let $\mathbf{\Gamma}^k$ denote a diagonal matrix in $\mathbb{R}^{(N_d)\times(N_d)}$ having the membership degree $\mu_{A^k}\left(\mathbf{x}\left(k\right)\right)$ as its lth diagonal element. Let $\mathbf{\Phi}'$ denote the matrix in $\mathbb{R}^{N_d\times K(n+1)}$ composed from matrices $\mathbf{\Gamma}^k$ and $\mathbf{\Phi}_e$ as follows

$$\mathbf{\Phi}'\ =\ \left[\left(\mathbf{\Gamma}^1\mathbf{\Phi}_e\right),\left(\mathbf{\Gamma}^2\mathbf{\Phi}_e\right),\ldots,\left(\mathbf{\Gamma}^{\mathbf{K}}\mathbf{\Phi}_e\right)\right]. \tag{7}$$

denote θ' the vector in $\mathbb{R}^{K(n+1)}$ given by

$$\theta'\ =\ \left[\left(\theta^1\right)^T,\left(\theta^2\right)^T,\ldots\left(\theta^K\right)^T\right]^T. \tag{8}$$

The resulting least square problem, $\Upsilon = \mathbf{\Phi}'\theta' + \epsilon$ has the solution

$$\theta' = \left[(\mathbf{\Phi}')^T \mathbf{\Phi}'\right]^{-1} (\mathbf{\Phi}')^T \Upsilon. \tag{9}$$

The optimal parameters $\mathbf{a}^k$ and b^k are given by

$$\begin{aligned} \mathbf{a}^k &= \left[\theta'_{s+1}, \theta'_{s+2}, \ldots, \theta'_{s+n}\right]^T \\ b^k &= \left[\theta'_{s+n+1}\right] \end{aligned} \tag{10}$$

where $s = (k-1)(n+1)$. With the determination of the parameters $\mathbf{a}^k$ and b^k, the fuzzy model identification procedure is completed.

3.2 On-line adaption of the fuzzy models

Changes in the operating condictions due to disturbances or faults, often occur in many industrial processes. To assure the desired product quality, the process control system have to deal with these changes. There are several adaptive control structures in fuzzy control literature among then: self-learning fuzzy control based on reinforcement learning [6], classical self-organizing linguistic controller [23] and neuro-fuzzy controller with temporal backpropagation learning [13]. The commom feature of these approaches is that the controller is adapted directly without identifiying the process model. Diferently from those approaches, an approach consisting of adapting the fuzzy model, using the exact inversion of the model to derive the control input is proposed in [25]. In this article, the adaptation is performed directly in the consequent parameters of the fuzzy models. It is assumed that the antecedent partition is derived off-line and remains valid. Since the antecedent parameters are determined and fixed as in 5 and 6, the model is linear in consequents and recursive least square can be used to estimate the consequents. The rule consequents are adapted by

$$\theta_j(k) = \theta_j(k-1) + \gamma_j(k)\left(y(k) - \mathbf{x}^T(k)\,\theta_j(k-1)\right) \tag{11}$$

where $\theta_j(k)$ is the vector of consequent parameters and γ is an intermediate variable without a specific physic meaning. θ and λ are initialized as following $\theta_{init} = FM.th$ and $\lambda = \lambda_{init}$

$$\gamma_j(k) = \frac{\mathbf{P}_j(k-1)\,\mathbf{x}(k)}{\mathbf{x}^T(k)\,\mathbf{P}_j(k-1)\,\mathbf{x}(k) + \lambda/\mu_{A^k}(x)} \tag{12}$$

where λ is the forgetting factor that implements forgetting of the old measurements and $\mathbf{P}_j$ is a matrix of adaptation gain initialized as $\mathbf{P}_{init} = FM.p1$.

$$\mathbf{P}_j(k) = \frac{1}{\lambda}\left[I - \gamma_j \mathbf{x}^T(k)\right]\mathbf{P}_j(k-1) \tag{13}$$

$FM.th$ is the value of the consequent parameters obtained offline, λ_{init} and $\mathbf{P}_{init}$ are values solved by a trial and error process.The presented Takagi-Sugeno fuzzy models are constant in structure, next Section the evolving fuzzy modeling are presented, in the fuzzy models the structure evolves continuously.

3.3 Evolving Takagi-Sugeno fuzzy modeling

Evolving Takagi-Sugeno (ETS) [2, 1, 3], are fuzzy model whose rule-base and parameters continually evolve by adding new rules with more summarization power and by modifying the existing rules and parameters. The algorithm continuously evaluates the Scatter or the Potential contained in the new data (both the scatter and the potential are seen as measures of average distance from a data sample to other data sample) and dynamically updates the number of rules and their antecedent parameters, combining that process with a recursive update of the consequence parameters. The ETS, ensures that high control performance can be achieved even with time variant process behaviour. Although the ETS entails two approaches, namely, the potential based approach and the scatter based approach, in this article one is going to present only the scatter based approach.Basically, the on-line learning of ETS entails the following stages:

(1) Initialization of the rule-base structure (antecedent part of the rule);
(2) Reading the next data sample at the next time step;
(3) Recursive calculation of the scatter od the new data.;
(4) Recursively update the scatter at the focal point (rule center) of the existing clusters;
(5) Possible modification or rule-base up-grade based on the scatter of the new data in comparison to scatter of the existing rule;
(6) Recursive calculation of the consequent parameters;
(7) Prediction of the model output of the next time step;

For on-line clustering first we normalize the data, solving recursivelly the mean $\bar{z}_j(k)$ and the variance $\sigma_j^2(k)$ for each element z_j of the input/output vector z

$$\bar{z}_j(k) = \frac{k-1}{k} z_j(k-1) + \frac{1}{k} z_j(k) \tag{14}$$

$$\sigma_j^2(k) = \frac{k-1}{k}\sigma_j^2(k-1) + \frac{1}{k-1}\left(z_j(k) - \bar{z}_j(k)\right)^2 \tag{15}$$

The data normalization is given by

$$z_{st}(k) = \frac{\left(z_j(k) - \bar{z}_j(k)\right)}{\sigma_j(k)} \tag{16}$$

With first normalized data that establish the focal point of the first cluster ($i = 1$), the scatter of the afforementioned focal point is assumed to be $S = 0$

$$R = 1; x^{1*} = x(k); S_1\left(z^{1*}\right) = 0; \tag{17}$$

where z^{1*} is the center of the first cluster ; x^{1*} is the focal point (projection of z^{1*} in the x axis).
The global scatter of the new data is solved by (18), which is the distance from a data sample to all other data samples.

$$S_k^G(z(k)) = \frac{1}{(N)(n+m)} \sum_{l=1}^{N} \sum_{j=1}^{n+m} \left(z_j(l) - z_j(k)\right)^2 \tag{18}$$

The values of $S_k^G(z(k))$ have the range [0, 1], with 0 meaning all of the data sample coincide (which is extremelly improbable) and 1 meaning all of the data are on the vertices of the hypercube formed as a result of data the normalization.
Recursivelly the equation (18) is given by:

$$S_k(z(k)) = \frac{1}{(k-1)(n+m)} \left((k-1) \sum_{j=1}^{n+m} z_j^2(k) - 2 \sum_{j=1}^{n+m} z(k) b_j(k) + h(k) \right) \quad (19)$$

where $b_j(k) = \sum_{j=1}^{k-1} z_j(l)$ and $h(k) = \sum_{l=1}^{k-1} \sum_{j=1}^{n+m} z_j^2(l)$.
The parameters $b_j(k)$ and $h(k)$ are recursively updated by

$$b_j(k) = b_j(k-1) + z_j(k-1) \quad (20)$$

$$h(k) = h(k-1) + \sum_{j=1}^{n+m} z_j^2(k-1) \quad (21)$$

The new data influence the scatter at the centers of the clusters$\left(z^{i*}, i = 1, 2, \ldots, R\right)$. The reason is that by definition, the global scatter depends on the distance to all points, including the new ones.
After the scatter of the existing clusters is updated, a comparison between the scatter of two consecutive steps, $k-1$ and k is made:

$$S_{k-1}\left(z^{i*}\right) = \frac{1}{(k-2)(n+m)} \sum_{l=1}^{k-2} \sum_{j=1}^{n+m} \left(z_j(l) - z_j(k-1)\right)^2 \quad (22)$$

$$S_k\left(z^{i*}\right) = \frac{1}{(k-1)(n+m)} \sum_{l=1}^{k-1} \sum_{j=1}^{n+m} \left(z_j(l) - z_j(k)\right)^2 \quad (23)$$

simplifying and comparing (22) and (23) the recusive equation is then obtained:

$$S_k\left(z^{i*}\right) = \frac{k-2}{k-1} S_{k-1}\left(z^{i*}\right) + \sum_{j=1}^{n+m} \left(z_j(k) - z_j(k-1)\right)^2 \quad (24)$$

The scatter of the new data sample is compared to the updated scatter of the centers of the existing clusters. The decision whether to modify or upgrade is taken based on the following rule:
IF

$$\left[S_k(z(k)) < \min_{i=1}^{R} S_k\left(z^{i*}\right)\right] OR \left[S_k(z(k)) > \max_{i=1}^{R} S_k\left(z^{i*}\right)\right] \quad (25)$$

and $z(k)$ is close to an existing rule center given by

$$\delta_{\min}(k) < 0.5r \quad (26)$$

where $\delta_{\min}(k) = \min_{i=1}^{R} \left\|x(k) - x^{i*}\right\|^2$ denotes the distance from the new data point to the closest of the existing rule centers.
Then the new data point $z(k)$ replaces this center

$$x^{i*} = x(k); S_k\left(z^{i*}\right) = S_k(z(k))$$
$$N^l(k) = N^l(k) + 1; \; ASI^l(k) = ASI^l(k) + k \quad (27)$$

ELSEIF equation (25) is satisfied and equation (26) is not.
The new data is added to the rule base, new focal point and new rule cluster is formed

$$R = R + 1; N^l(k) = 1; x^{R*} = x(k)$$
$$S_k\left(z^{R*}\right) = S_k(z(k)) \quad (28)$$

ELSEIF equation (26) is not satisfied
The data sample is assigned to the nearest existing cluster/focal point of the rule

$$ASI^l(k) = ASI^l(k) + k; N^l(k) = N^l(k) + 1$$
$$i = \arg\min_{i=1}^{R} \left\|x(k) - x^{i*}\right\|^2 \quad (29)$$

It should be noted that the distance $\delta_{\min}$ is calculated over the input only, disallowing rules with similar antecedents to co-exist.Once antecedents are determined and fixed, model is linear in parameters, and recursive least square (RLS).

ASI means assignation of data to an existing cluster. The fuzzy models presented here, are going to be used in model based predictive control (MBPC). In the next section the usage of the evolving fuzzy modeling in predictive fault tolerant control is done.

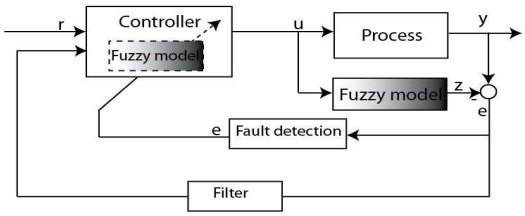
4. PREDICTIVE FAULT TOLERANT CONTROL USING EVOLVING FUZZY MODELING

The concept of using the model based predictive control (MBPC) with evolving Takagi-Sugeno fuzzy modeling (ETS) [2, 1, 3] is proposed in this article. Model based predictive control is a control technique which use the process model to predict future outputs. Using MBPC in fault tolerant control (FTC) can allows to use different control specifications in faulty conditions. The backbone of MBPC techniques is the accuracy of the models, used to predict future outputs. Even using modeling techniques such as neural networks [12], fuzzy logic [24] or neuro-fuzzy [13], the mismatch between the obtained models and the processes are not completely eliminated. What if one could have the guarantee that the mismatches between the models and the processes could be reduced?
The answer for the last question in the fuzzy logic field arises with adaptive fuzzy models and evolving Takagi-Sugeno fuzzy models [2, 1, 3]. These techniques aim to increase the accuracy of model, by reducing the mismatch between the model and the process. This increment in performance is done with recursive update of the model parameters. The difference between the adaptive fuzzy model and ETS is that in adaptive fuzzy models the number of rules is constant, the clusters centers are not updated and only the parameters of the consequents are recursively updated. Contrarily, in ETS according to certain conditions, new rules are added, the clusters centers are constantly updated and the consequents parameters are also recursively updated. Should be noted that, although one speak about adaptive and evolving, the evolving can be seen as a kind of adaptive and both names are used to distinguish the classical adaptation to the new one the evolving.
In fault conditions or "heavy" disturbances in the process, ETS seems to be more realist, because the addiction of new rules allows to increase the operational ranges (space created by the faults or disturbances) of the model. As

the new rules are going to be created in these spaces, their firing strength in these spaces are bigger than the existing ones.

Figure 3 depicts the proposed FTC scheme, both fuzzy

Fig. 3. *Evolving Takagi-Sugeno in the predictive fault tolerant control*



models depicted in that figure are equal. The fault is detected by comparing the residual (difference between the process output and the model output) with certain threshold. A moving window (MW) is used gather the data to be use in the FTC approach, it size is defined by a trial and error process. When its full, the collected data are used in the FTC in order to adapt the controller parameters. The residual is computed again and, if the fault is not accommodate the procedure is repeated. The presented control scheme are going to be used to a distillation column and, it is done in the next section.

5. APPLICATION ON THE DISTILLATION COLUMN

In chemical industry and petroleum refineries the distillation column is the most important tool to perform the separation of components into more or less pure product streams. This separation is based in difference of volatility among the components. The more volatiles are removed from top of the column and less volatiles are removed from botton part of column.

As the distillation column is a large scale process, and regarded as (MIMO) system [7]. Our interest is the control of the re-boiler temperature and, as the system has multiple inputs, the control problem is going to be a (MISO), with the following variables:

Inputs:

- Feed flow rate (F0)
- Fraction of feed liquid (q0)
- Reflux valve (frefluxo)
- Molar feed fraction of ethanol (xF0)
- Re-boiler heat (QR)

Output:

- Re-boiler composition (xB)

In order to control the temperature in the re-boiler, the composition must be transformed in temperature [17].

$$T_{reboiler} = -111.42x_{xB} + 96.217 \qquad (30)$$

The fault in distillation column [8] may be characterized as:

Process loads: these disturbances consists of change in

- Feed flow rate
- Feed composition
- Top-product flow rate
- Base-product flow rate

Changes in heating and cooling: changes in heat input to re-boiler and changes in heat output from condenser.

Equipment failing:heat equipment fails with extensive use. Since controller parameters are typicall functions of process parameter, and since failing can cause the change of these parameters, the performance of the control system associated with these devices can deteriorate with time if the controllers are not updated with the failing effects.

For the case study the considered faults are going to be:

- Variation in the feed composition;
- Variation in the re-boiler temperature;

5.1 Evolving fuzzy modeling in the fault tolerant control

The adaptive fuzzy modeling, potential based approach and scatter based approach are used to accommodate the aforesaid faults. Before moving directly till there, some parameters such as the matrix of adaptive gain ($\mathbf{P}$) and the forgetting factor (λ), whose the performance of any of these approaches depends are going to be introduced.

There is not a specific rule to select these values. According to [26] the initial values for the matrix of adaptive gain is a big value, and they have presented an example using 100, and in the example presented by [2, 3] they used 750. For our case study it shown to be completely different. The problem in hand, that one has is to simultaneously determine the matrix of adaptive gain and the forgetting factor, and to do so one fixed the forgetting factor to 0.99, and tried different values for the matrix of adaptive gain, as shown on the figures 4, 5 and 6.

Fig. 4. *Matrix of adaptive gain initialized with* 0.006

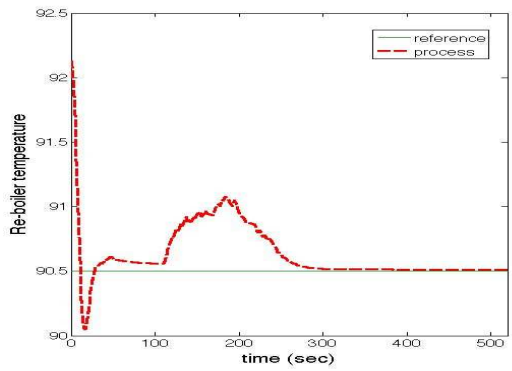


Fig. 5. *Matrix of adaptive gain initialized with* 0.17

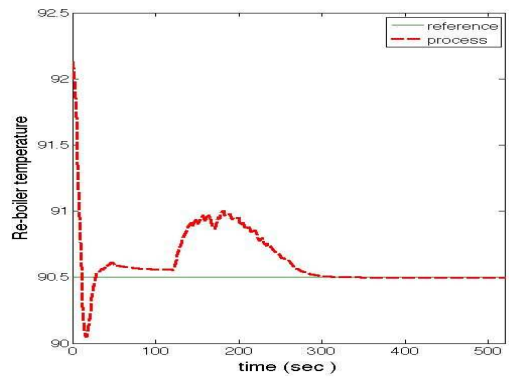
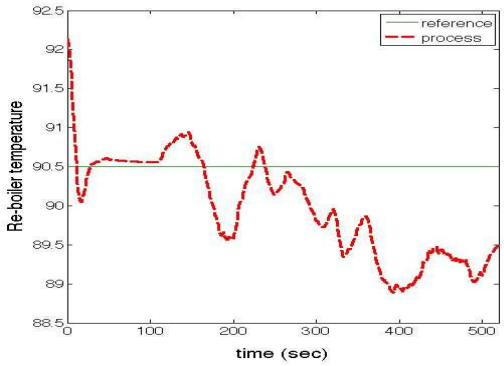


Fig. 6. *Matrix of adaptive gain initialized with* 10



Figures 7 and 8, show the controller behavior for a fixed value for the matrix of adaptive gain and different values for the forgetting factor. Table 1 presents the values that are going to be used in FTC approaches. Note that these values were set by a trial and error process.

Fig. 7. *Forgetting factor* 0.90

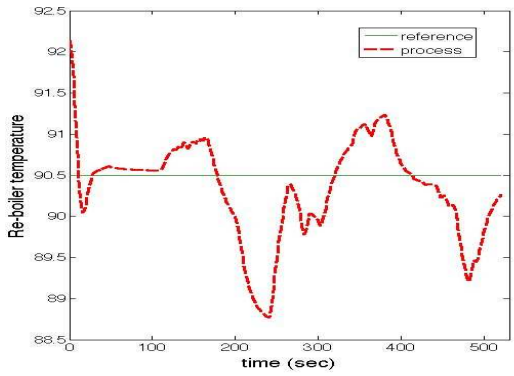
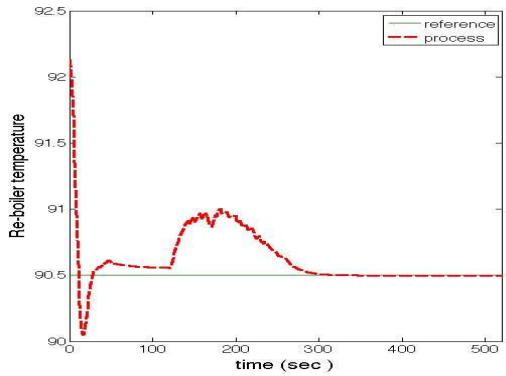


Fig. 8. *Forgetting factor* 0.99



Two faults are considered, a process load fault (variation in feed composition), where the feed composition is characterized by the percentage of ethanol in the composition. Initially the percentage of ethanol in the feed is 9% and the fault is made by decreasing this value to 8%. The second fault is a change in the heating (a variation in the re-boiler temperature). The power in the re-boiler heat is a value with the range $[0.25 - 0.29] * 4000$W and to simulate a fault in this variable the initial value 0.27 is going to be reduced to 0.25. Although in both faults, the value of the variables were decreased, one could do the inverse process (increasing these values). The reason to present as fault, the decreasing of both variables, is that decreasing the feed composition has the effect of change operational range of the distillation column to high temperatures, and decreasing the re-boiler heat has the effect of change the operational range of the distillation column to lower values. These faults can be seen as actuators malfunctioning. In both cases, incipient and abrupt faults are considered. The fault intensity for both faults (abrupt and incipient) are the same, the rising time for incipient fault, was considered 240 s. in all cases. To evaluate the controller performance two performance indices are used, the RMS presented in 31 and the Non-Dimensional Error Index (NDEI) presented in 32.

$$RMS = \sqrt{\frac{\sum_{i=1}^{N} (y_i - \hat{y}_i)^2}{N}} \tag{31}$$

$$NDEI = \frac{RMS}{std\,(y)} \tag{32}$$

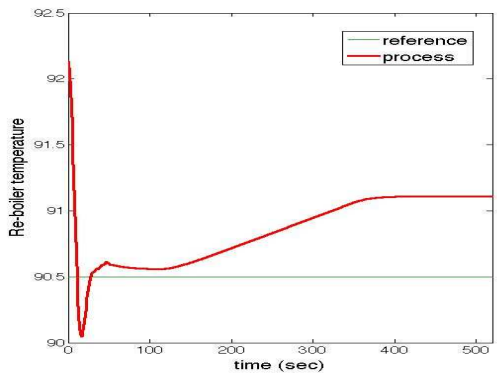
where y_i is the system output and $\hat{y}_i$ is the predicted output, $\bar{y} = \frac{1}{n}\sum_{i=1}^{n} y_i$, $\bar{y}$ is the mean of the output value, RMS is the root mean square error and std is the standard deviation of the system output.

Due to pages limitations, only the incipient fault in feed composition and abrupt fault in re-boiler temperature are presented. However tables containing the percentage of improvement for all considered faults (feed composition, re-boiler temperature in both incipient and abrupt faults)are shown. To present the results, the following procedure is going to be followed: a figure of the process with fault is depicted. Then, FTC approaches are applied to the process to accommodate faults, with following order: adaptive fuzzy models, potential based approach and scatter based approach. The improvement is given by the ratio:

$$\left[1 - \left(\frac{RMS_{without fault}}{RMS_{with FTC approach}}\right)\right] * 100 \tag{33}$$

Where $RMS_{without fault}$ is the RMS of the process without fault and $RMS_{with FTC approach}$ is the RMS of the process using any of the FTC approaches.From now on FTC approaches are going to be applied to the distillation column. An incipient fault was applied to the distillation

Fig. 9. *Process with incipient fault in feed composition*



column as depicted in the figure 9. The fault starts at time 120 s. and raised in 240 s. It can be seen in this

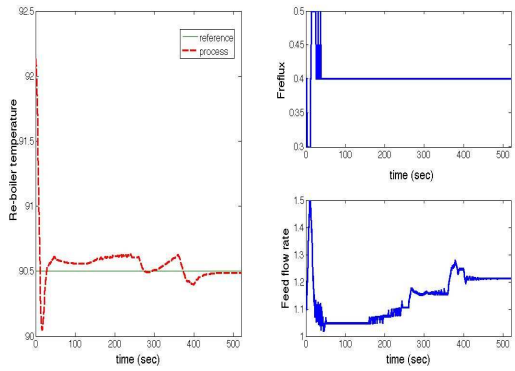
Table 1. *Adaptive gain matrix and forgetting factor values*

	fault in feed composition		fault in re-boiler temperature	
	Incipient	Abrupt	Incipient	Abrupt
	forgetting factor 0.99			
Adaptive fuzzy modeling	0.006	0.006	0.006	0.006
Pontential based approach	0.06	0.06	0.01	0.01
Scatter based approach	0.19	0.32	0.06	0.009

figure that the operational range of the distillation column has changed. Applying the adaptive fuzzy modeling FTC approach on the aforementioned situation, the results are presented in the figures 10, 13, and 14. From the figure **??** one may see that the controller adjusted five times the parameters of the consequents until it achieved constant values. However, these adjustment were not done in all parameters. The first adjustment of the consequents happened in the time 160 s. The reason to happen in that time is, as the fault is incipient, it takes too long until the residual passes the residual threshold, and the FTC, become activated.

Figure 10 show that, although the variations on the

Fig. 10. *Using adaptive fuzzy models to accommodate Incipient faults in the feed composition*



parameters of the consequents, the reflux variable does no change. However, the feed flow rate changed it value, from the moment which happens the first change in the parameters of the consequents, until constant parameters were achieved. The tables 2, 3, 4 and 5, presents the RMS, the $NDEI$ and the the percentage of improvement.As a conclusion one may say that the proposed FTC approach accommodates the presented fault.

Fig. 11. *Changes in the parameters of the consequents of the first rule*

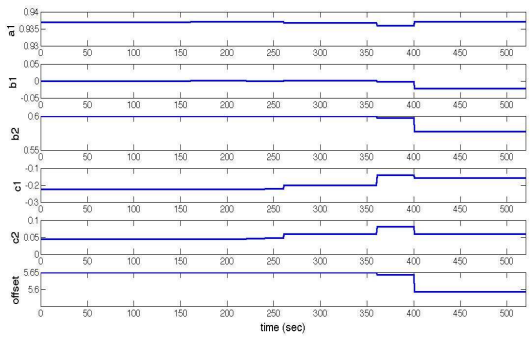


Fig. 12. *Changes in the parameter of the consequents of the second rule*

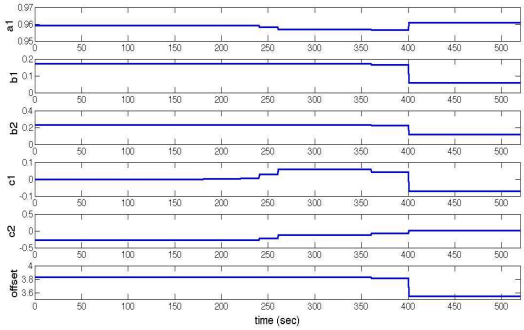


Fig. 13. *Using potential based approach to accommodate Incipient faults in the feed composition*

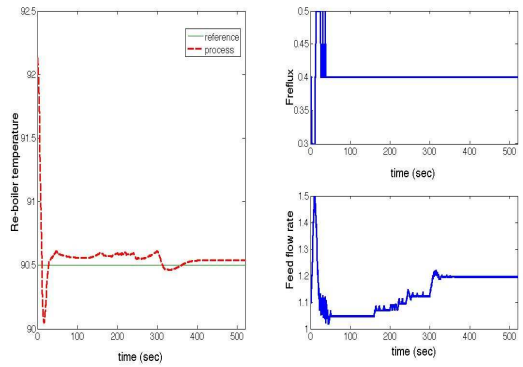
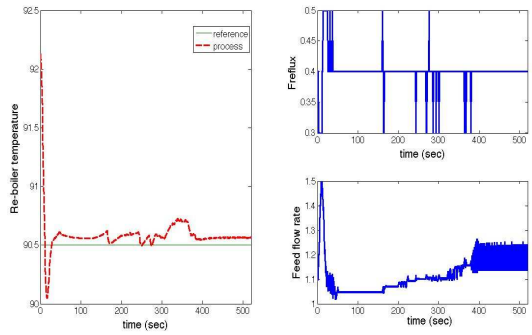


Fig. 14. *Using scatter based approach to accommodate Incipient faults in the feed composition*



6. CONCLUSIONS

6.1 Fault tolerant control approaches

This article proposed the use of adaptive and evolving fuzzy modeling approaches to fault tolerant control, and from the results presented we conclude that the main objective was achieved.

Table 2. *Comparison of the RMS and NDEI for the three approaches in presence of incipient fault in feed composition*

	RMS	NDEI	PI RMS	New rule
Process without fault	0.1705	1.0830		
Process with fault	0.4328	1.6162	61%	
Using the adaptive fuzzy modeling	0.1756	1.0428	3%	0
Using the potential based approach	0.1715	1.0663	0.6%	0
Using the scatter based approach	0.1834	1.1303	7%	1

Table 3. *Comparison of the RMS and NDEI for the three approaches in presence of abrupt fault in feed composition*

	RMS	NDEI	PI RMS	New rule
Process without fault	0.1705	1.0830		
Process with fault	0.5406	2.0179	68.5%	
Using the adaptive fuzzy modeling	0.2161	1.0359	21%	0
Using the potential based approach	0.2478	1.1332	31%	0
Using the scatter based approach	0.2036	1.0520	16%	1

Table 4. *Comparison of the RMS and NDEI for the three approaches in presence of incipient fault in the re-boiler temperature*

	RMSE	NDEI	PI RMS	New rule
Process without fault	0.1705	1.0830		
Process with fault	0.2293	1.0913	26%	
Using the adaptive fuzzy modeling	0.1753	1.0076	3%	0
Using the potential based approach	0.1714	1.0019	0.5%	0
Using the scatter based approach	0.1721	1.0019	0.9%	1

Table 5. *Comparison of the RMS and NDEI for the three approaches in presence of abrupt fault in the re-boiler temperature*

	RMSE	NDEI	PI RMS	New rule
Process without fault	0.1705	1.0830		
Process with fault	0.2725	1.2654	37%	
Using the adaptive fuzzy modeling	0.1828	1.0216	7%	0
Using the potential based approach	0.1779	1.0160	4%	0
Using the scatter based approach	0.1847	1.0112	8%	1

Fig. 15. *Process with abrupt fault in re-boiler temperature*

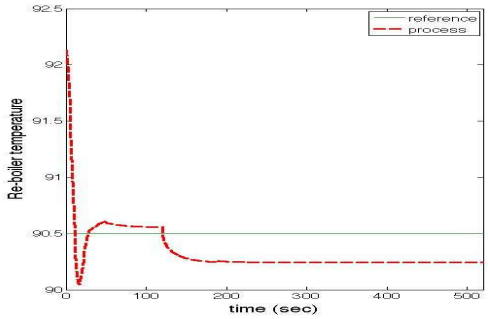


Fig. 16. *Using adaptive fuzzy models to solve abrupt fault in re-boiler temperature*

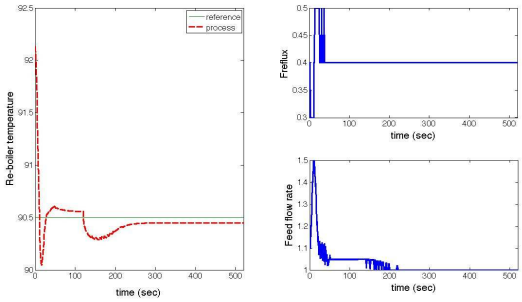
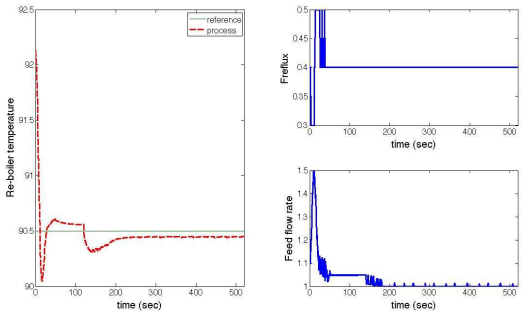
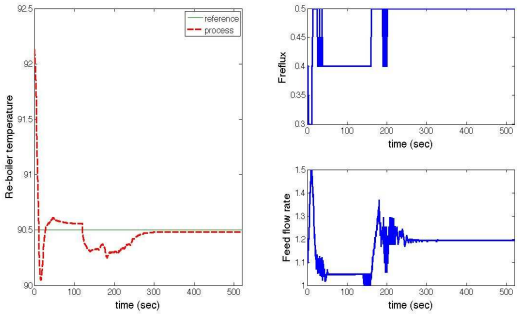


Fig. 17. *Using potential based approach to solve abrupt fault in re-boiler temperature*



The adaptive fuzzy modeling was easier to be used because the values of the matrix of adaptive gain were the same in all cases.The potential based approach, one variant of evolving Takagi-Sugeno fuzzy models, showed to accommodate the faults without having to add new rules, and from the results, one may conclude that, in general, this approach led to best control results. The scatter based approach, the other variant of the evolving Takagi-Sugeno fuzzy models, leaded also to good control performance. However, this approach shown to be more sensitive to new data than the potential based approach, and in all cases in which it was used, new rules were added.

Fig. 18. *Using scatter based approach to solve abrupt fault in the feed composition*



6.2 Influence of the adaptive gain matrix and the forgetting factor

Both the adaptive gain matrix and the forgetting factor have important roles in the controller. Adaptive fuzzy modeling, used the same values for the matrix of adaptive gain. The potential approach used the same values for the matrix of adaptive gain for each fault. However, in the scatter approach the values for the matrix of adaptive gain were different. For all the approaches, the value for the forgetting factor was the same. However, we believe that this value might vary slightly.

Despite the results presented by the scatter based approach, we believe that these results can be improved. This improvement can be made by searching better values for the matrix of adaptive gain and for the forgetting factor. In order to search for better values for these parameters, optimization algorithms such as genetic algorithms, ant colony and swarm optimization could be useful. Unfortunately, the fault tolerant controller presented here was not applied to real distillation column. Efforts have been doing in order to make it possible. The proposed FTC approaches were only applied to two different faults. However, other faults may be considered. The control performance can be tested in the future in faults as the ones described in Section 5.

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