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Weighted Fuzzy Fault Tolerant Model Predictive Control

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***Abstract* - This paper proposes a new active fault-tolerant control (FTC) using fuzzy predictive logic. The FTC approach is based on two steps, fault detection and isolation (FDI) and fault accommodation. The fault detection is performed by a model-based approach using fuzzy modeling and fault isolation uses a fuzzy decision making approach. The information obtained on the FDI step is used to select the model to be used in fault accommodation, in a model predictive control (MPC) scheme. The fault accommodation is performed with one fuzzy model for each identified fault. The FTC scheme is used to accommodate the faults of real-time CSTR level process. The fuzzy FTC scheme proposed in this paper was able to detect, isolate and accommodate correctly the considered faults of the system.**

Keywords: Fault tolerant Control, FDI, MPC, Fuzzy FTC.

I. INTRODUCTION

Industrial applications rely extensively on highly automated control system in order to deal with increasingly stringent requirements of safety, environmental sustainability, and profitability. Automation, however, adds a layer of complexity to a process that may lead to additional faults. The success of a Fault-Tolerant control (FTC) method requires efficient fault detection, control designs that account for the complex nonlinear dynamics and constraints, and a high-level supervisor that coordinates the overall plant response to achieve fault-tolerant control. The success of any fault-tolerant control method requires an integrated approach that brings together several essential elements, including: (1) the design of advanced feedback control algorithms that handle complex dynamics effectively, (2) the quick detection of process faults, and (3) the design of supervisory switching schemes that orchestrate the transition from the failed control configuration to available well-functioning fall back configurations to ensure fault-tolerance [1]. On line model based diagnosis of incipient faults is another area of research [2]. Soft faults such as biases or drifts in sensors and actuators are most commonly occurring faults in process operation. These faults should be detected in time and a corrective action should be done to avoid degradation in closed loop performance and endangering the safety, reliability and productivity of the plant. The existing techniques for fault detection and diagnosis could be divided into process history based and process model based methods. Each of these can further classified as quantitative and qualitative approaches. The qualitative approaches involve fuzzy logic [3], neural networks and expert systems [5]. The quantitative approaches are basically modeling, filtering and estimation methods where a wide variety of them have already been reviewed by [4]. FTC is the control loop that has the ability to fulfill the required system performances even if faults occur through utilizing the help provided by Fault detection mechanism called Supervision level. Approaches for synthesizing the FTC loop are classified as either a passive FTC (PFTC) or active FTC (AFTC).

AFTC relies on the detection of a fault case in the control process, in order to introduce a proper compensation to the feedback system (*active approach*) [7]. In this scheme, it is first necessary to detect a fault scenario, and next, to design an algorithm to identify the type fault occurred (fault isolation). Based on the fault isolation block, an external compensation signal for the nominal control signal is introduced, or the parameters of the controller are updated [8], [9]. Three main types of faults are recognized: actuator, sensor and plant faults [4], [10]. The first two are modelled as external signals that are added to the nominal ones (additive faults). Meanwhile, the plant faults are related to mechanical wear down of the plant elements, or intrinsically changes in the dynamics of the system. These faults are usually modelled as parameter variations in the mathematical model of the plant. The problem of additive faults will be addressed in this paper.

The use of model predictive control to deal with fault accommodation is relatively natural and straightforward, considering the representation of both faults and control objectives [12]. MPC with additional flexibility is obtained using fuzzy sets in the objective function. The fuzzy sets theory provides ways of representing and dealing with flexible or soft criteria.

The fuzzy objective function used in MPC includes goals and the constraints. The optimal trade-off amongst fuzzy goals and fuzzy constraints is determined by maximizing simultaneously the satisfaction of the optimization goals and the constraints [3].The FDI approach used in this paper uses one fuzzy model representing the normal state of the system and one fuzzy model for each fault that can occur in a given system. The faults are detected and isolated based on these fuzzy models. A fuzzy decision making (FDM) approach is used to isolate the faults. When a fault is isolated, fault accommodation is performed by using the respective faulty model. This paper proposes a fault tolerant control scheme, where the faulty model is used in a fuzzy MPC scheme. This control technique can be a highly efficient approach to perform fault accommodation [10, 12].

This paper is organized as follows. Next section presents fault tolerant control. The architecture for proposed fault tolerant control proposed in this paper is presented in Section 3. Predictive control is presented in Section 4. This paper presents an application example, CSTR real timer plant in Section 5. Finally, some conclusions are drawn in Section 6.

II. FAULT TOLERANT CONTROL

FTC can be motivated by different purposes, as the improvement of safety and efficiency in industrial processes. The main design challenges of FTC are: the number of possible faults and their diagnosability; the system reconfigurability, and the global stability of the system [5].

When MPC is used in FTC, some faults can be accommodating modifying the constraints in the MPC problem definition [7]. The use of MPC increases the degree of fault tolerance under certain conditions, when the fault is not detected.

Thus, MPC in fault tolerant control provides suitable implementation architecture and increases the system capability to accommodate the faults. In order to overcome the limitations of conventional control, new controllers are being used which are capable of tolerating component malfunctions. Complex control applications require a capability for accommodating faults in the controlled industrial process. Fault accommodation involves the detection and isolation of faults, and taking appropriate control actions that eliminate or reduce the effect of the faults and maintains the control. The method used in this paper is an active approach.

B. FDI in Fault Tolerant Control

A system that includes the capacity of detecting, isolating and identifying faults is called a fault diagnosis and isolation system [9]. During the years, many researchers have been carried out using analytical approaches, based on quantitative models. The idea is to generate signals that reflect inconsistencies between normal and faulty system operation, and detect and isolate the faults. Such signals, the residuals, are usually generated using analytical approaches, such as observers, parameter estimation or parity equations.

Early detection and isolation of abrupt and incipient faults can be achieved using a model-based approach, which processes all measured variables, using either qualitative or quantitative modeling. The use of fuzzy logic for fault detection and isolation in industrial processes is presented in [12]. Optimized fuzzy models have been used with success in model based FDI [10].

The use of FDI in fault tolerant control is very important in the active way of achieving fault-tolerance, by detect and isolate the faults. After the fault indication by FDI, the system can then be reconfigured or restructured. In some cases, a pre-calculated controller will be activated, or the parameters of the controller will be changed according the real time diagnostic provided by the FDI. Next section presents the architecture of FTC proposed in this paper.

III. PROPOSED FUZZY FTC

This paper proposes a simple architecture for fault tolerant control. This approach is based on two steps: the first performs fault detection and isolation, and the second performs fault accommodation. The two steps are depicted in Fig. 1, and are denoted as FDI and FTC.

A. Fault Detection and Isolation

The fault detection and isolation approach is showed in Fig. 1 in the block called FDI. In this FDI approach, the multidimensional input, u, of the system enters both the process and a model (observer) in normal operation. The vector of residuals e is defined as

$$\boldsymbol{\varepsilon} = \boldsymbol{Y} - \boldsymbol{\hat{Y}} \quad (1)$$

Where, Y is the output of the system and $\hat{Y}$ is the output of the model in normal operation. When any component of e is bigger than a certain threshold, the system detects faults. In this case, n observers (models), one for each fault, are activated, and n vectors of residuals are computed. Each residual i with $i = 1 \ldots\ldots, n$ is computed as

$$\boldsymbol{\varepsilon_{F_i}} = \boldsymbol{y} - \boldsymbol{\hat{y}_{F_i}} \quad (2)$$

Where $\hat{y}_{F_i}$is the output of the observer for the fault i. The residuals $\varepsilon_{F_1}, \ldots., \varepsilon_{F_n}$ are valuated, and the fault or faults detected are the outputs of the FDI system. The fault isolation is performed by evaluating fuzzy decision factors, which are built based on residuals. The fuzzy fault isolation used in this paper is based on fuzzy decision making (FDM) [2]. In this approach, a membership function $\mu_{\varepsilon_{ij}}$ is derived for each residual ε_{ij}. The membership functions used in this paper are trapezoidal because they revealed to be the most appropriate to describe the residuals in a simple and effective way. The membership functions spread are obtained experimentally based on the maximum and minimum variations of the residuals. The core of the membership functions indicates the possible isolation of a fault, i.e. if ε_{ij} is zero, then the membership degree $\mu_{\varepsilon_{ij}}$should be one. The core is also determined experimentally and is a small interval around zero in order to accommodate process noise, disturbances and model-plant mismatches. Note that this method to derive membership functions is common in various fuzzy approaches [4]. The m membership functions $\mu_{\varepsilon_{i1}}, \ldots\ldots, \mu_{\varepsilon_{im}}$must be aggregated using a conjunction operator, which assures that a fault is isolated only when all the residuals e_{ij} are close to zero. The aggregation can be given by

$\boldsymbol{\gamma_i} = \left(\boldsymbol{\mu_{\varepsilon_{i1}}}, \dots\dots, \boldsymbol{\mu_{\varepsilon_{im}}}\right)$ (3)

Where, t is a triangular norm, as e.g. the minimum operator. An example of γ_i for two outputs is shown in Fig. 2. Let $\boldsymbol{\gamma_i}(k) \in [0,1]$, i=1,…..,n, be called a fuzzy decision factor. These values are computed at each time instant k.

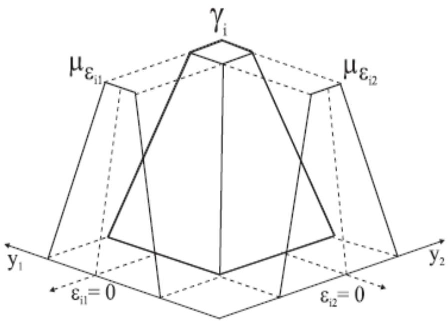

Fig.1. Residual evaluations of fuzzy model of fault i.

A vector of fuzzy decision factors can be computed as:

$\Gamma(k) = [\gamma_1(k)\gamma_2(k) \dots\dots \gamma_n(k)]$, (4)

i.e. one fuzzy decision factor for each fault. A fuzzy decision factor $\gamma_i(k)$ is high only if all the residuals are close to zero.In order to isolate a fault i, the value of $\gamma_i(k)$ must be higher than a threshold T, which must be close to one. Note that the threshold T is equal for all the faults, because the fuzzy decision factors are already normalized in the interval [0, 1]. The threshold is obtained experimentally and defines the regions of fault and no fault. Note that several $\gamma_i(k)$ can be above the threshold at a certain time k. Therefore, a fault$_i$ is isolated only when the remaining faults are below T. However, even if only one fault is above the threshold at a certain time instant, this can occur due to noise or model errors. Therefore, our approach considers that a fault $i \in \{1, \dots., n\}$ is only isolated when

$$\begin{cases} \gamma_i > T \\ \gamma_i < T \ \forall l \ \neq i \ \ for \ t_k \ for \ consecutive \ instants, \end{cases} \quad (5)$$

i.e., when γ_i is above the threshold T and the remaining γ_l decision factors are below the same threshold for t_k consecutive time instants. The fuzzy isolation scheme proposed in this paper is illustrated as flow chart in Fig.1.

B. Fuzzy Fault Tolerant Control

The FTC structure proposed in this paper was shown in Fig.2b.The presented architecture uses FDI and MPC. The FDI approach was presented in next Section. The MPC is very useful in FTC, because it allows a different control specification for the faulty models, in order to have minimal losses when the system is working in a faulty mode. Furthermore, the control action can take into account a time interval (prediction horizon). Also the receding horizon principle allows at each time instant to assess the situation by taking into account any change in the fault status to apply the best control action [3].The FTC scheme proposed in this paper uses a multiple model selection approach, where a fuzzy model for the process running in normal operation and one model for each one of the faults are used. The use of fuzzy set theory in MPC support the FTC proposed approach because sometimes, it is impossible to model nonlinear systems by analytical equations.

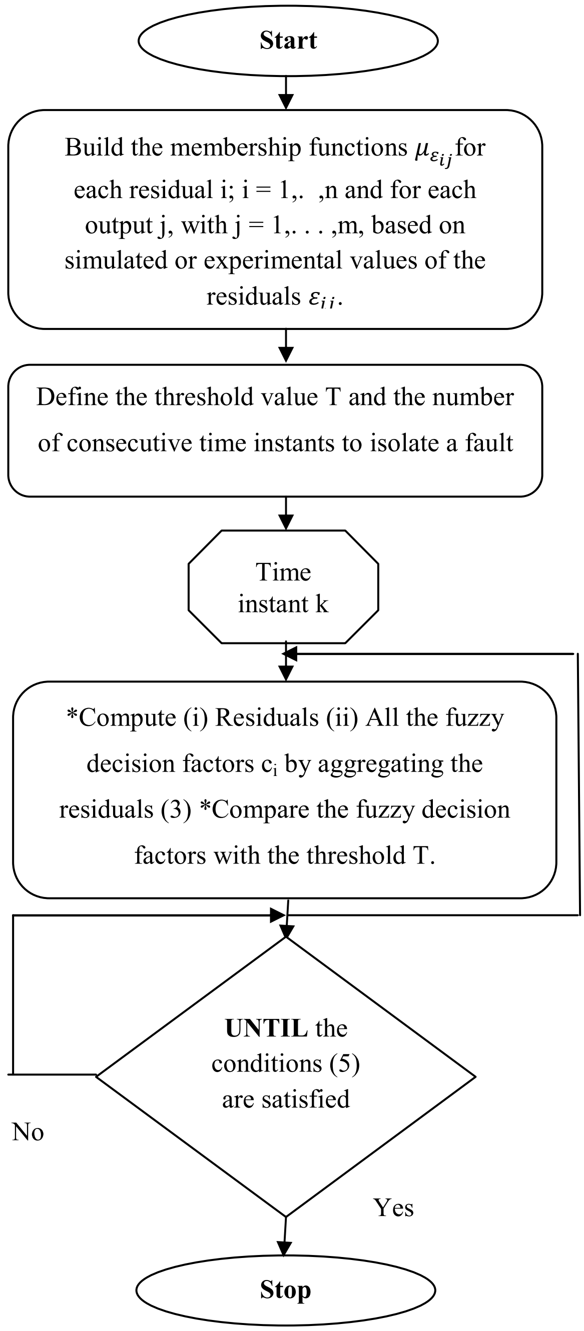

Fig.2a. Flow Chart - Fuzzy Fault Isolation Scheme

The uses of fuzzy models increase the capability of proposed FTC architecture to work with systems without complete information and noisy. The key advantage of fuzzy logic is that it enables the system behavior to be described by ''if-then'' relations.MPC has also been demonstrated as a highly efficient approach to failure accommodation [8]. The fault accommodation means to adapt the controller parameters to the dynamical properties of the faulty plant. A simple but well established way of fault accommodation is based on predesigned controllers, each of which has been selected off-line for a specific fault [2]. Next section presents some characteristics of MPC.

IV. Model Predictive Control

Predictive control is probably the advanced control scheme most frequently used in industry. Its advantages are the use of an objective function and the ability to control complicated processes. Predictive control is closely related to decision making. The objective function can be seen as the simultaneous satisfaction of (soft) goals and (soft) constraints in multistage decision making. This technique has been applied to control by several authors [11]. When a fuzzy criterion is used in the objective function, fuzzy optimization is the most obvious technique to deal with the optimization problem in fuzzy predictive control. Next section resents a brief description of classical predictive control and subsequently, fuzzy predictive control is presented.

A. Classical Objective Functions

In predictive control of multivariable systems, the output values $\hat{y}(k+1), i = 1 \ldots, H_p$, depend on the states of the process at the current time k and on the future control signals u(k + j),j = 1,. . . ,Hc, where Hc is the control horizon. For multivariable systems the objective function can be represented by

$$J = e^T Re + \Delta u^T Q \Delta u \qquad (6)$$

Where the first term in (6) accounts for the minimization of the output errors, the second term represents the minimization of the control effort, and R and Q are weighting matrices.

Note that these parameters have two functions: they normalize the different outputs and inputs of the system, and vary the importance of the two different terms in the objective function (6) over the time steps.

B. Fuzzy Objective Functions

One of the main issues in MPC is the optimization technique applied to derive the control actions. When fuzzy criteria are used in the objective function, the criteria have some flexibility that can be exploited for improving the optimization objective [5]. Predictive control using fuzzy goals and fuzzy constraints can be defined as a fuzzy decision making problem.

Let G_i, with i = 1,. . . ,q, be a fuzzy goal characterized by its membership function μ_{Gi}, which is a mapping from the space of the goal G_i to the interval [0, 1]. Let also C_l, l = 1,. . . , r be a fuzzy constraint characterized by its membership function μ_{G_l}, mapping the space of the constraint C_l to the same interval [0, 1].

The fuzzy goals G_i and the fuzzy constraints C_l can be defined for the domain of the control actions, system outputs, and state variables or for any other convenient domain. Each fuzzy goal Gi and each fuzzy constraint C_l constitute a decision criterion ζ_j, j = 1,. . . ,T, where T = q + r is the total number of goals and constraints. Each criterion is defined in the domain $\emptyset_j$,j = 1,. . . ,T, which can be any of the various domains used in control. In order to solve the optimization problem in low computational time, the optimization problem is defined in a discrete control space with a finite number of control alternatives.

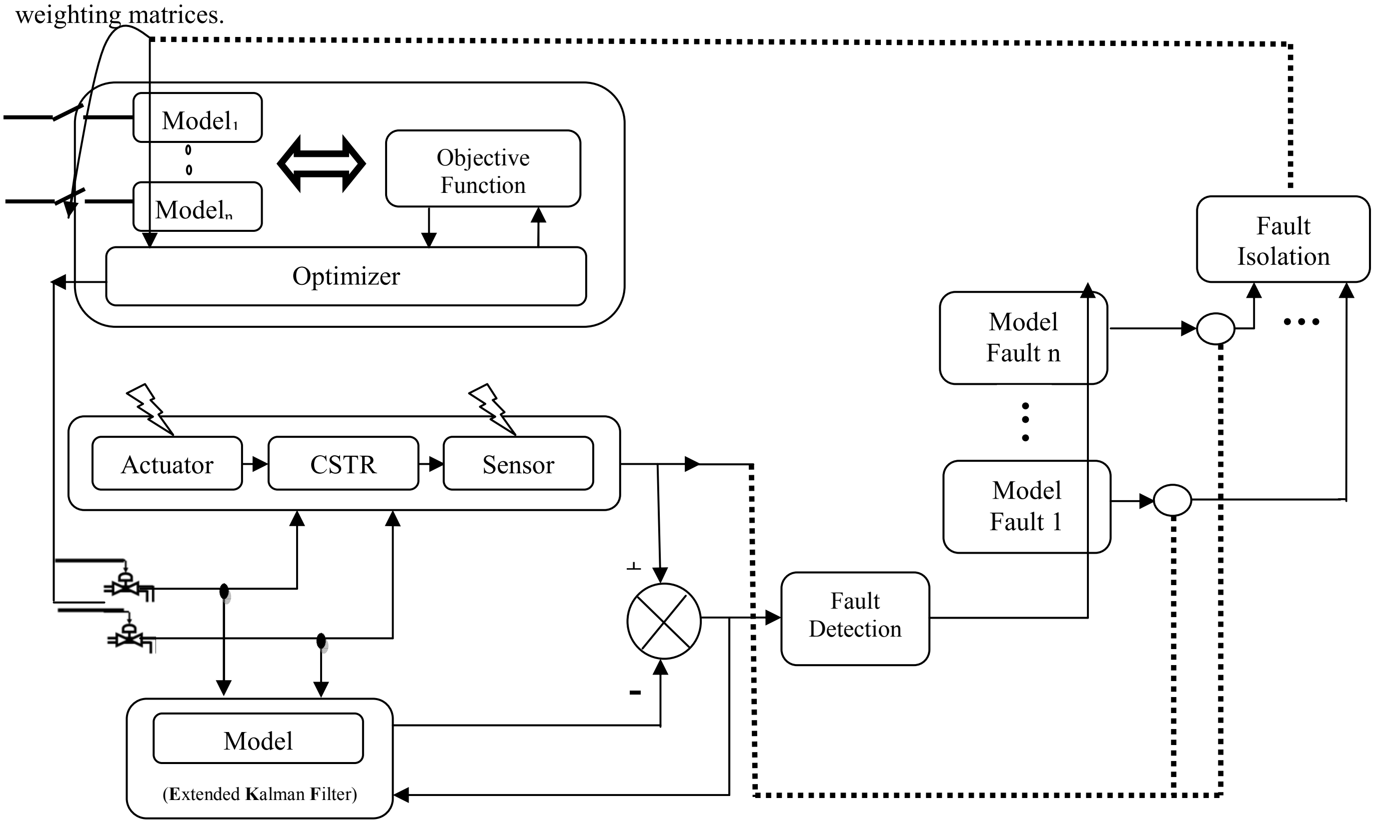

Fig.2b. Block Diagram of Proposed Weighted Fault Accommodation MPC

Fuzzy criteria are aggregated in the control environment. Assume that a policy π is defined as a sequence of control actions for the entire prediction horizon in MPC, Hp:

$$\pi = u(k), \dots, u(k + H_p - 1), \ \pi \in \Omega, \quad (7)$$

Where control actions belong to a set of alternatives Ω. In the general case, all the criteria must be applied at each time step$i$, with $i = 1, \dots, H_p$. Thus a criterion ζ_{ij} denotes that the criterion j is considered at time step $k + i$, with $i = 1, \dots, H_p$ and$j = 1, \dots, T$. Further, let $\mu_{\zeta_{ij}}$ denote the membership value that represents the satisfaction of this decision criterion after applying the control actions $u(k + i)$.The total number of decision criteria for the decision problem is$\tilde{T} = T \cdot H_p$.The confluence of goals and constraints is performed by aggregating the membership values$\mu_{\zeta_{ij}}$. The membership value l_p for the control sequenceπ is obtained using the aggregation operator □to combine the decision criteria, i.e.

$$\mu_{\pi} = \mu_{\zeta_{11}} \square \dots \square \ \mu_{\zeta_{11}} \square$$

$$\mu_{\zeta_{1(q+1)}} \square \dots \square \ \mu_{\zeta_{1T}} \square$$

.

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$$\mu_{\zeta_{H_p(q+1)}} = \mu_{\zeta_{11}} \square \dots \square \ \mu_{\zeta_{H_pT}} \square$$

In this equation, the aggregation operator combines the goals and the constraints. Various types of aggregation operations can be used as decision functions for expressing different decision strategies using the well-known properties of these operators. Parametric triangular norms can generalize a large number of t-norms, and can control the degree of compensation between the different goals and constraints. Usually, parametric t-norms depend only on one parameter, which makes them easier to tune when compared to weighted t-norms. On the other hand, they are not so general as the weighted approaches [5]. The translation of each goal and each constraint for a given policy π to a membership value avoids the specification of the criteria in a large dimensional space. The decision criteria in (8) should be satisfied as much as possible, which corresponds to the maximum value of the overall decision. Thus, the optimal sequence of control actions $\pi^*$is found bythe maximization ofμ_π:

$$\pi^* = \underset{u(k), \dots, u(k+H_{p-1})}{\text{argmax}} \ \mu_\pi \quad (8)$$

Because the membership functions for the fuzzy criteria can have an arbitrary shape, and because of the nonlinearity of the decision function, the optimization problem (9) is usually non-convex. To deal with the increasing complexity of the optimization problem, a proper optimization algorithm must be chosen. One possibility is to use, for instance, a branch-and-bound algorithm [9,12].This paper uses one approach where preference for different constraints and goals can be specified by the decision-maker and the difference in the preference for the constraints is represented by a set of associated weight factors as proposed in [5,7]. Next section presents the heuristic used to obtain the weight factors.

C. Weight Selection in Fuzzy Aggregation

The weight factors represent the relative importance of various constraints and objectives with respect to one another. The general assumption is that the higher the weight of a particular constraint, the larger its importance on the aggregation result. Hence, the final optimization result will be closer to the more important constraints. If the objective is more important, the constraints will be relaxed to a larger degree in order to increase the objective function. The user can specify preferences regarding the outcome of the optimization by changing the weight factors [10, 12]. Knowing how to combine the different weights in the weighted aggregation function, it is now very important to choose properly the values of the weights for each criterion. The used algorithm is summarized as follows:

(1) Initialize all the weight factors to one, and evaluate the control performance using the corresponding objective function.

(2) Decrease each of the $\tilde{T}$ weight factors to 0.5 one by one. Evaluate the performance, and order the criteria, where the first is the one that improved the performance of the system most. When the number of criteria $\tilde{T}$ is very high, a simplification can be made. In this case, reduce simultaneously a certain criterion for the entire prediction horizon Hp. This is similar to evaluate simultaneously each column in (8). The number of iterations is then reduced from $\tilde{T} = T \times H_p$to TThus, instead of evaluating each weight associated with the criterionζ_{ij},the same weight is assumed for the criterion ζ_j, i.e. the criterion is considered constant for the entire prediction horizon.

(3) For each criterion, ζ_{ij} or ζ_j depending on the choice in Step 2, reduce the weight factor to 0.25 and check if the control performance is better. If this is the case, reduce further the weight to 0.125. The weight that yields the best performance is chosen as the weight factor for that criterion.

(4) When all the criteria have been evaluated, the best combination of weight is determined, and should be used for the system.

V. PROCESS DESCRIPTION

A. Experimental setup

A real time experimental setup for highly nonlinear tank is constructed. The process control system is interfacing DAQ module to the Personal Computer (PC). The laboratory set up for this system is shown in Figure 1.It consists of a tank, a water reservoir, pump, rotameter, a differential pressure transmitter, an electro pneumatic converter (I/P converter), a pneumatic control valve, an interfacing DAQ module and a Personal Computer (PC).

The differential pressure transmitter output is interfaced with computer using DAQ module in the RS-232 port of the PC.

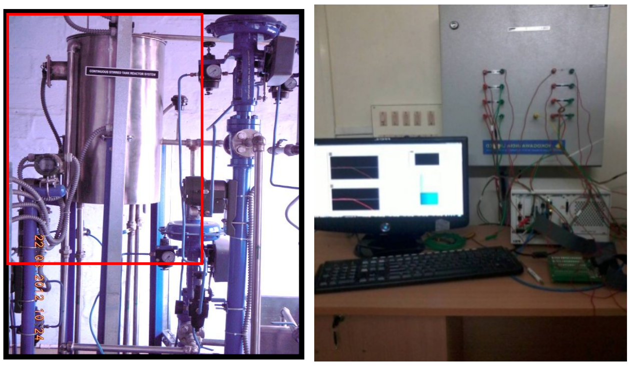

Fig.3. Experimental setup for liquid level control of a CSTR

After computing the control algorithm in the PC control signal is transmitted to the I/P converter in the form of current signal (4-20) mA, which passes the air signal to the pneumatic control valve. The pneumatic control valve is actuated by this signal to produce the required flow of water in and out of the tank.

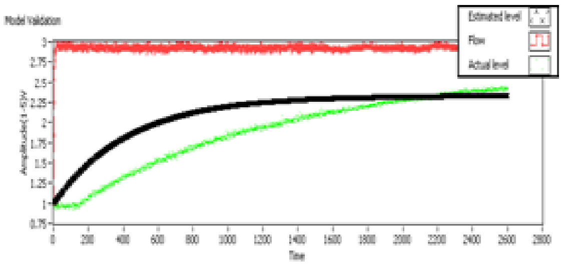

Fig. 4. Comparison of Open loop response of Actual plant and Identified Model

B. System identification

The parametric model approach was used. Recursive least square (RLS) method is used for estimating the parameters. After the completion of parameter estimation, results were validated against a new set of data for same operating condition. The actual plant output vs identified Model response is shown in Figure 4. The inputs are the feed water flow and the output variable is the level of the reactor. The average feed flow is maintained as constant value. The level data was collected till it reaches steady state. A step change was given in feed flow rate and again the level was measured till it reaches steady state. All the values were obtained in terms of (1-5) V in order to normalize them within a single unit range. Thus the Mathematical model of CSTR real process was obtained in the form of discrete state space form and is shown here

$$\mathbf{dx/dt} = \left[-0.00231489\right] \mathbf{x(t)} + \left[0.000184292\right] \mathbf{u(t)} \qquad (9)$$

$$\mathbf{y(t)} = \left[10.013\right] \mathbf{x(t)} + \left[0\right] \mathbf{u(t)}$$

Where, U(t) is feed water flow (input variable) and Y(t) is Level (output variable).

C. FDI results

The proposed fuzzy FTC scheme was applied to a model the process. Two faults are considered in this paper. Fault F1 is +50% Multiplicative faults in the Sensor. The result of this fault is a decrease in the liquid level of the tank T1. Further, another fault, F2, is +50% Multiplicative faults in the actuator. The faults intensities considered are 50% and 50%, because when small faults intensities are considered the system controller is able to accommodate the fault effects. The identification data used to build the valve model in normal operation contains 1500 samples.

The same number of samples was used to identify each considered fault. A fuzzy model was identified for the model in normal operation. This model has two inputs, which are the supply voltage of the pump. The outputs of the model are the liquid level of tank. Table 1 presents the modeling results when the process is without fault and with faults. The presented performance values are obtained for each one of the output variable h_1. In general, the fuzzy models present good accuracy when the system is with or without faults.

Table 1

Accuracy of fuzzy models for process without/with faults

	VAF	RMS
Faults	H_1	H_1
No fault	99.80	0.002
F1	99.40	0.002
F2	99.20	0.002

The FDI step is made considering the scheme presented in Fig. 2a. Faults F1 and F2 occur at 860s. The performance of fault detection and fault isolation is presented in Table 2. The indices, detection time t_{td} and isolation time t_{ti} are used to evaluate the performance of the proposed FDI architecture.

The two faults F1 and F2 are correctly detected and isolated. When the fault intensities are decreased, the detection time t_{td} and the isolation time t_{ti} increase for both faults. Note however, that the obtained values of t_{td} and t_{ti} remain small.

Table. 2

Detection and isolation performance

Faults	t_{td}(s)	t_{ti}(s)	Fault Intensity (%)
F1	9	9	25
F2	10	10	25

D. Fuzzy FTC results

The fault accommodation of the three tank process was performed using the classical MPC and the fuzzy FTC. The obtained results for the accommodation of faults F1 and F2 are presented in Section (a) and Section (b), respectively.

(a) Fuzzy FTC for fault F1

The fault accommodation is made considering the one output of process, h_1. The approach proposed in this paper with weighted fuzzy MPC was applied to the system. The weights w1 is for h_1, respectively. The control performance is measured using the normalized sum squared error between the references and the outputs of the system after fault isolation. Table 3 shows the control results when the faults F1 and F2 occur, using the algorithm for weight selection described in Section IV. The error using the classical predictive controller with weights $R_{h1}=1$ is taken as 1 (100%), and it serves as the normalization to be compared with the errors using the Yager t-norm with the weights presented in Table 7. The absolute error values obtained using the classical controller are $e_{h1}=1$ for the liquid level of tank. The best result is obtained at Step 5 of the weighted fuzzy predictive control for fault F1 and at step 4 for fault F2.The fuzzy FTC scheme proposed in this paper was able to detect, isolate and accommodate correctly the faults F1 and F2. The fault behavior of fault F1 and fault F2 can be observed in the liquid level of tank. Note that when one fault occurs, the fuzzy model in normal operation is substituted by the fuzzy model of the isolated fault. This faulty fuzzy model is used in the weighted fuzzy MPC scheme to derive the proper control actions. The experimental results for fault F1 using fuzzy predictive control (weights presented in Step 5, Table 3) are depicted in Fig. 5. The controller presents good control performance for the two controlled variables. The error in the liquid level of tank T1 and decrease when weighted fuzzy MPC is applied. The best values for controlled variable, is obtained with the weights w1 = 0.01. This experimental example shows clearly that the best results are obtained using a fuzzy objective function with different values for the weights.

(b) Fuzzy FTC for fault F2

Considering the fault F2 also the error using the classical predictive control, presented in Table 3 is taken as 1 (100%), and it serves as the normalization. The best results obtained with the classical controller are $e_{h1}= 1$ for the liquid level of tank with weights $R_{h1}= 1$ and $R_{h2}=1$. The best result is obtained at Step 4 with the weighted optimization. The experimental results using weighted fuzzy objective functions (weights presented in step 4, Table 3) are depicted in Fig. 6. The controller presents good control performance for the controlled variable. However, the error of h1 decreases when weighted fuzzy MPC is applied. Fig. 6 shows that the fault is isolated at 820s. At this time, the model used in MPC is replaced, and the system behavior improves clearly. The liquid level error reduces its value and it is close to zero. Concluding, the FTC system proposed in this paper was able to detect, isolate and accommodate the two faults considered.

VI. Conclusion

This paper proposes a weighted fuzzy FTC scheme to accommodate faults. The FTC approach is based on two steps: fault detection and isolation, and fault accommodation. In the first step, the FDI scheme is based on fuzzy models for both normal operation and faulty operation, and on a fuzzy decision making approach. The fault isolation is performed by evaluating fuzzy decision factors that are built based on residuals. In the second step, the fault accommodation is made using weighted fuzzy MPC. The fuzzy models that were identified for the FDI step are now used in the weighted fuzzy MPC control scheme. The proposed approach is applied to a real-time CSTR plant shown its ability to detect, isolate and accommodate the faults. Future research can consider the extension of the proposed FTC scheme to a larger number of faults, including incipient, intermittent or other types of faults.

Table 3

Normalized errors using Yager t-norm with various five combinations for the faults F1 and F2

		F1		F2
Class.	R_{h1}	e_{h1}	R_{h1}	e_{h1}
	1	1	1	1
Fuzzy	W_1	W_2	W_1	W_2
1	1.00	1.19	1.00	0.90
2	0.50	1.08	0.50	0.86
3	0.25	0.63	0.25	0.77
4	0.05	0.59	0.05	0.73
5	**0.01**	**0.55**	**0.01**	**0.71**

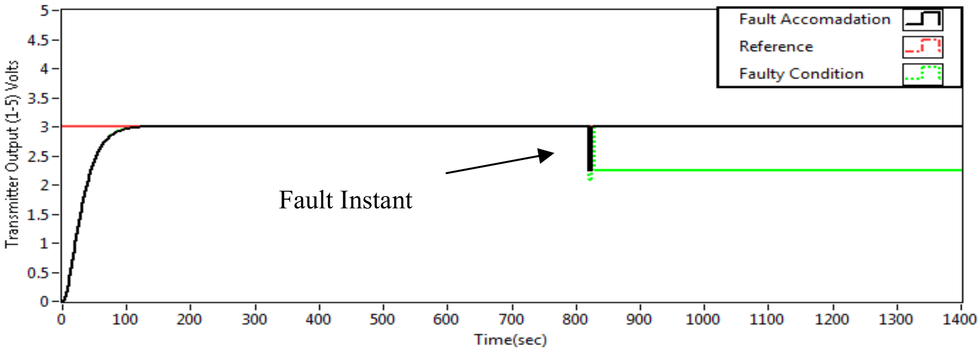

Fig.5. Fault F1 accommodation (weighted fuzzy objective function). (Black) - Fault with weighted accommodation, (Red) - Reference, (Green) - Fault without accommodation

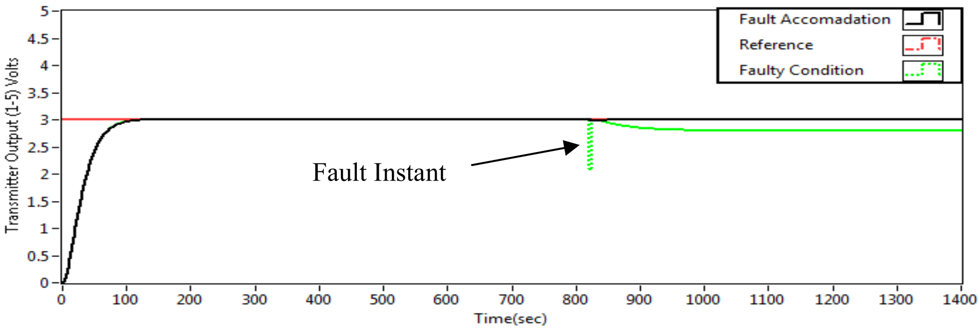

Fig.6. Fault F2 accommodation (weighted fuzzy objective function). (Black) - Fault with weighted accommodation, (Red) - Reference, (Green) - Fault without accommodation

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