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Fault Tolerant Fuzzy Gain Scheduling Proportional-Integral-Derivative Controller for Continuous Stirred Tank Reactor

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ABSTRACT

In recent years, an adaptive PID controller is proposed for fault-tolerant control of process system in the presence of sensor and actuator faults. A fuzzy inference scheme (FIS) was used to tune in the controller gains depending upon the system dynamics. Errors and change in Error are inputs of fuzzy gain scheduler to make the system act faster and more effectively in the event of fault occurrence. Three fault scenarios were investigated: (i) +25% additive faults in sensor; and (ii) in actuator called single fault. And both sensor and actuator simultaneously faulty is also studied. The proposed Fault Tolerant Fuzzy Gain Scheduled PID (FT GS-PID) controller was studied through an experimental application to Continuous Stirred Tank Reactor (CSTR). The obtained results show the effectiveness of the proposed method.

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INTRODUCTION

About 95% of process control loops are of PID or PI type. Since its inception over eighty years ago, the proportional-integral-derivative (PID) control structure has remained the most commonly used single-input single-output (SISO) technique in industry, primarily because it is one of the simplest. PID control is often combined with other technologies to build the complex automation systems that are used in many industries. Chemical and petrochemical control strategies are often organized in a hierarchy of functions, with scheduling and optimization functions running on top of the hierarchy, multivariable predictive controllers in the middle and PID controllers at the lower level, directly sending control signals to actuators. One of our main objectives is to propose control methods that are effective, simple to implement for real-time applications and robust to model uncertainties and external disturbances including actuator faults. PID (Proportional - Integral - Derivative) controllers are the most well-known controller in the society of automation and control, due to their simple structure and wide variety of usage. These kinds of controllers are classified into two main categories in terms of parameters selection strategies. In the first group, controller gains are fixed during operation while in the second group, gains change based on the operating conditions. In the first group, gains are tuned by the designer and remain invariable during the operation. One of the most well-known methods for choosing control gains in this group is Ziegler-Nichols method which has been addressed in lots of research works (Ziegler and Nichols, 1942). Although this method is simple and straightforward, fine tuning is required for different applications. In most applications, due to structural changes the controlled system may lose its effectiveness, therefore the PID gains need to be continuously retuned during the system life span. To reduce the effort of retuning the gains and also in order to increase system's performance, in the second group of controllers, the gains are adapted online. Several methods have been proposed in the literature for PID gain scheduling. In Ng *et al*. (1997) a stable gain-scheduling PID controller is developed based on grid point concept for nonlinear systems, in which gains switch between some predefined values. Different gain scheduling methods were studied and compared in Karray *et al.* (2002). In Zhao *et al*. (1993) a new PID scheme is proposed in which the controller gains were scheduled by a fuzzy inference scheme. Many variations and improvements of this simple and effective method were followed by latter research works (Yu and Hsu, 2007; Zulfatman and Rahmat, 2009; Guo and Yang, 2010). A particle swarm optimization method is used in Yu and Hsu (2007) to design membership functions of fuzzy PID controller. In Yao and Lin (2005), an accumulated genetic algorithm is proposed which learns the parameters and number of fuzzy rules in the fuzzy PID controller. The GS-PID has been implemented for fault tolerant by properly tuning the PID controller gains for both normal and fault

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conditions. The switching from one PID to another is then based on the actuator's health status. It is worthy to note that the above method requires a Fault Detection and Diagnosis (FDD) scheme to provide the time of fault occurrence as well as the location and the magnitude of the fault. Motivated by this work and to eliminate the need for the FDD module, an adaptive PID controller is proposed in this paper for fault tolerant control of a CSTR system. A fuzzy inference scheme is used to tune in real-time the controller gains, where the error and the derivative error are used in this fuzzy scheduler to make the system act faster and more effectively in the fault-free case as well as in the event of fault occurrence. Three fault scenarios are investigated: (i) +25% faults in sensor, (ii) +25% Fault in actuator called single fault, and (iii) +25% faults in both sensor and actuator simultaneously are studied.

The reminder of this paper is as follows. Section 2 gives a description and the mathematical model of CSTR Plant. Section 3 discusses the proposed fuzzy gain-scheduled PID controller. Some experimental results are illustrated in Section 4 before giving the concluding remarks.

Model Identification Of Cstr:

System Identification means, to find a function that will map the input and output time series on to the parameter space such that some objective function$\in (y - \hat{y})$ is satisfied. The knowledge of the model is necessary for the design of soft sensing technique and model based control system. System identification is an experimental approach [13] for determining the dynamic model of a system. It includes four steps:

i. Input/output data acquisition under an experimentation protocol
ii. Selection or estimation of the “model” structure
iii. Estimation of the model parameters
iv. Validation of the identified model (structure and values of the parameters)

A complete identification operation must necessarily comprise the four stages indicated above. The specific methods used at each stage depend on the type of model desired (parametric or non-parametric, continuous-time or discrete-time) and on the experimental conditions (for example: hypothesis on the noise, open loop or closed loop identification). The validation is the mandatory step to decide if the identified model is acceptable or not. As there does not exist a unique parameter estimation algorithm and a unique experimental protocol that always lead to a good identified model, the models obtained may not always pass the validation test. In this case, it is necessary to reconsider the estimation algorithms, the model complexity or the experimental conditions. System identification should be then considered as an iterative procedure as illustrated in Figure 1.

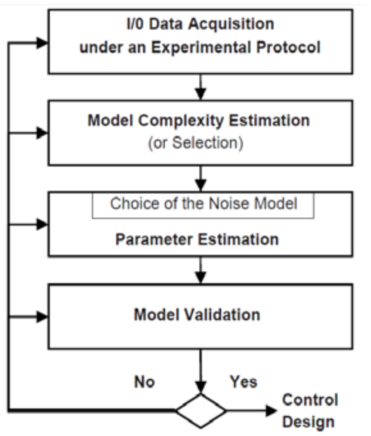

Fig. 1: Flow diagram of System Identification

The system shown in Figure 4 was taken for system identification. The inputs were feed water flow and coolant flow rate. The measured output variable is temperature of the reactor.

The Input and output data were collected for the above process using Compact RIO as shown in Figure 2. The average feed flow is maintained as constant value. The temperature data was collected till it reaches steady state. A step change was given in coolant flow rate and temperature was measured once again till it reaches steady state. All the values were obtained in terms of (1-5) Volts in order to normalize them within a single unit range.

The parametric model approach was used for system identification. 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 conditions. The Actual plant output vs. Identified Model response is shown in Figure 4.

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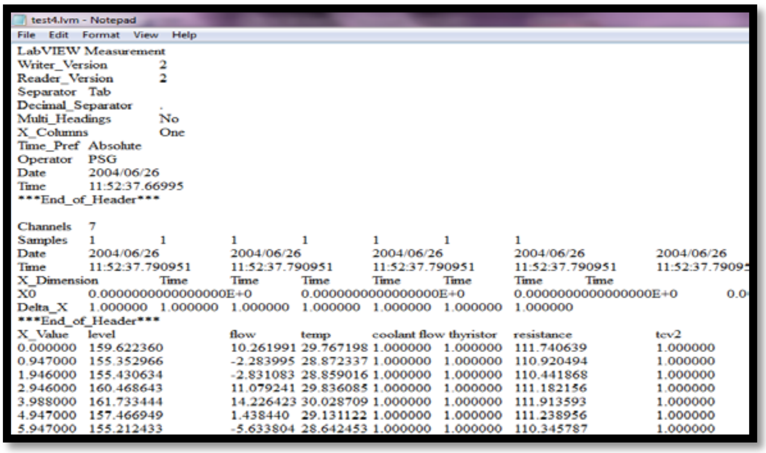
Fig. 1: CSTR process



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LabVIEW Measurement
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Reader_Version 2
Separator Tab
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Multi_Headings No
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Date 2004/06/26
Time 11:52:37.66995
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Channels 7
Samples 1 1 1 1 1 1 1
Date 2004/06/26 2004/06/26 2004/06/26 2004/06/26 2004/06/26
Time 11:52:37.790951 11:52:37.790951 11:52:37.790951 11:52:37.790951 11:52:37.7909
X_Dimension Time Time Time Time Time Time Time
X0 0.0000000000000000E+0 0.0000000000000000E+0 0.0000000000000000E+0 0.0
Delta_X 1.000000 1.000000 1.000000 1.000000 1.000000 1.000000 1.000000
End_of_Header

X_Value	level	flow	temp	coolant flow	thyristor	resistance	tcv2
0.000000	159.622360	10.261991	29.767198	1.000000	1.000000	111.740639	1.000000
0.947000	155.352966	-2.283995	28.872337	1.000000	1.000000	110.920494	1.000000
1.946000	155.430634	-2.831083	28.859016	1.000000	1.000000	110.441868	1.000000
2.946000	160.468643	11.079241	29.836085	1.000000	1.000000	111.182156	1.000000
3.988000	161.733444	14.226423	30.028709	1.000000	1.000000	111.913593	1.000000
4.947000	157.466949	1.438440	29.131122	1.000000	1.000000	111.238956	1.000000
5.947000	155.212433	-5.633804	28.642453	1.000000	1.000000	110.345787	1.000000

Fig. 2: Sample Data Collection Using Compact RIO

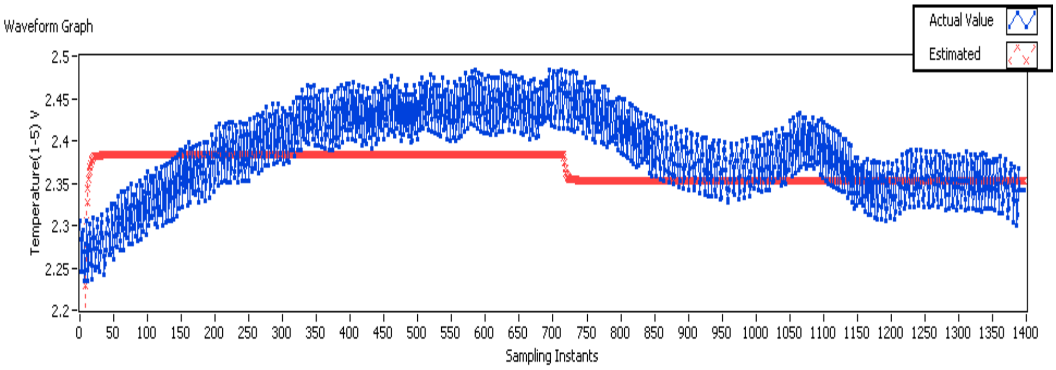

Fig. 3: Comparison of Open loop response of Actual plant and Identified Model

Thus the Mathematical model of CSTR real process was obtained in the form of discrete state space form and is shown here.

$$X(k+1) = \begin{bmatrix} 0.707895 & 2.77556E-17 \\ 1.66533E-16 & 0.273895 \end{bmatrix} X(k) + \begin{bmatrix} 0.000697335 & -0.143476 \\ -0.0110839 & -0.292452 \end{bmatrix} u(k) \tag{1}$$

$$Y(k+1) = \begin{bmatrix} 2.71197 & 0.172458 \end{bmatrix} X(k) + \begin{bmatrix} 0.00146101 & 0.354851 \end{bmatrix} u(k) \tag{2}$$

where, U(k):
U_1(k) is Coolant flow (manipulated variable)
U_2(k) is Feedwater Flow (treated as constant)
Y(k) is Temperature (output variable)

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Fault Tolerant Fuzzy Gs-Pid:

Conventional PID controllers are frequently and widely used in vast number of industrial applications. They are simple and easy to use due to the fact that they do not need any mathematical model of the controlled process or complicated theories. But one of the main drawbacks of these controllers is that there is no certain way for choosing the control parameters which guarantees good performance of the system.

The transfer function of a conventional PID controller is:

$$G(s) = K_p + \frac{K_i}{s} + K_d s \tag{3}$$

Where K_p ,K_i and K_d are the proportional, integral, and derivative gains respectively. Conventional PID controllers are frequently and widely used in vast number of industrial applications. They are simple and easy to use due to the fact that they do not need any mathematical model of the controlled process or complicated theories. But one of the main drawbacks of these controllers is that there is no certain way for choosing the control parameters which guarantees the good performance. Although PID controllers are robust against structural changes and uncertainties in the system parameters, their performance may be affected by such changes or may even lead to system instability. Therefore in real world applications these gains need to be fine-tuned to keep the required performance. To overcome this shortcoming, Fuzzy Logic Controller (FLC) is used to tune PID gains online where the tracking error and the change of the tracking error are used to determine control parameters.

Controller gains can be calculated through a simple linear transformation:

$$K_p = \left(K_{p,max} - K_{p,min}\right)K_p^{'} \tag{4}$$

$$K_i = (K_{i,max} - K_{i,min})K_i^{'} \tag{5}$$

$$K_d = (K_{d,max} - K_{d,min})K_d^{'} \tag{6}$$

With $[K_{p,min}, K_{p,max}]$, $[K_{i,min}, K_{i,max}]$ and $[K_{d,min}, K_{d,max}]$ are predefined ranges of K_p, K_i, and K_d respectively. A set of linguistic rules in the form of (5) is used in the Fuzzy Logic Controller structure to determine $K_p^{'}$, $K_i^{'}$ and $K_d^{'}$.

If $res(k)$ is A_i and $\Delta res(k)$ is B_i Then $K_p^{'}$ isC_i, $K_i^{'}$ is D_i and $K_d^{'}$ is E_i (7)

WhereA_i , B_i ,C_i D_i andE_i are fuzzy sets corresponding to $res(k), \Delta res(k), K_p^{'}, K_i^{'}$ and $K_d^{'}$ respectively. Three sets of 49 rules are used to determine controller gains. Tables 1-3 show the linguist rules used in the FLC. In these tables, VL, MH, H,Z, L, ML,VL represent Very High, Medium High, High ,Zero, Low, Medium Low, Very Low respectively. For example L means Low and so on.

Table 1: Fuzzy Tuning Rules for Kp

Δe(k)/ e(k)	VH	MH	H	Z	L	ML	VL
VS	H	H	H	H	H	H	H
MS	L	H	H	H	H	H	L
S	L	L	L	L	L	H	L
Z	L	B	L	H	L	H	H
PS	L	L	H	H	L	H	H
PM	L	H	H	H	L	H	H
PB	H	H	H	H	H	H	L

Table 2: Fuzzy Tuning Rules for Kd

Δe(k)/ e(k)	VH	MH	H	Z	L	ML	VL
VS	L	L	L	L	L	L	L
MS	H	L	L	H	H	L	L
S	H	H	L	H	L	L	L
Z	H	H	H	H	L	L	H
PS	H	L	H	H	L	H	H
PM	H	L	L	L	L	H	H
PB	L	L	L	L	H	H	H

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Table 3: Fuzzy Tuning Rules for Ki

Δe(k)/ e(k)	VH	MH	H	Z	L	ML	VL
VS	H	H	H	H	H	H	H
MS	M	M	H	H	H	M	M
S	L	M	M	M	Z	L	M
Z	Z	M	M	Z	L	M	Z
PS	L	Z	M	M	M	H	H
PM	M	M	M	M	M	H	H
PB	H	M	M	H	H	H	H

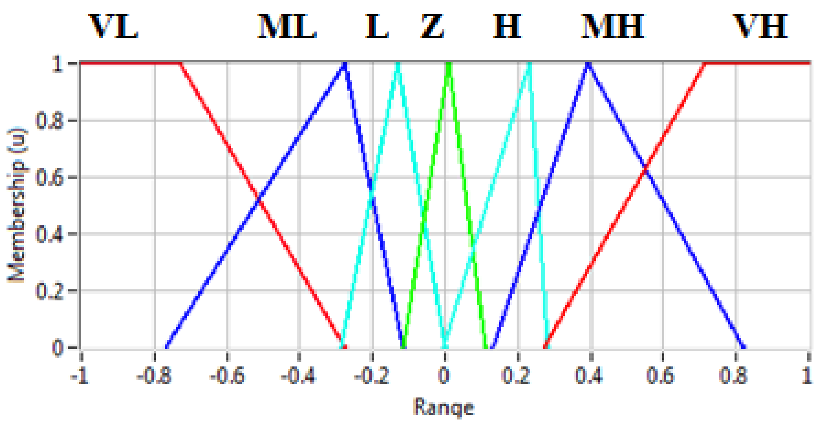


Fig. 4: Input Membership Function

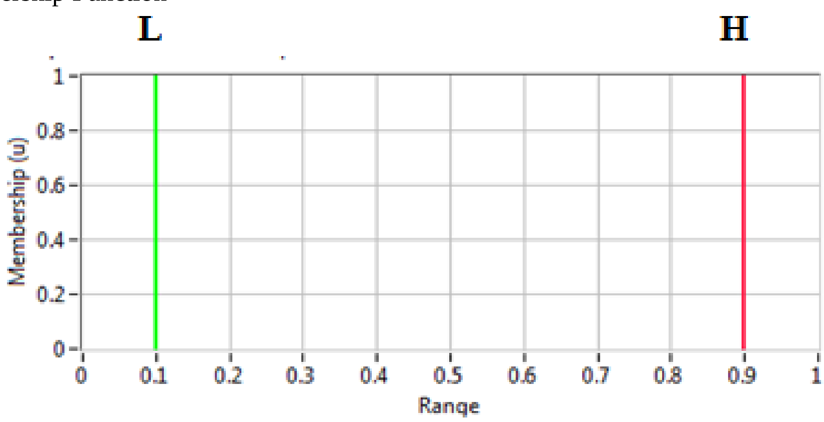


Fig. 5: Output Membership Function for K_p , K_d

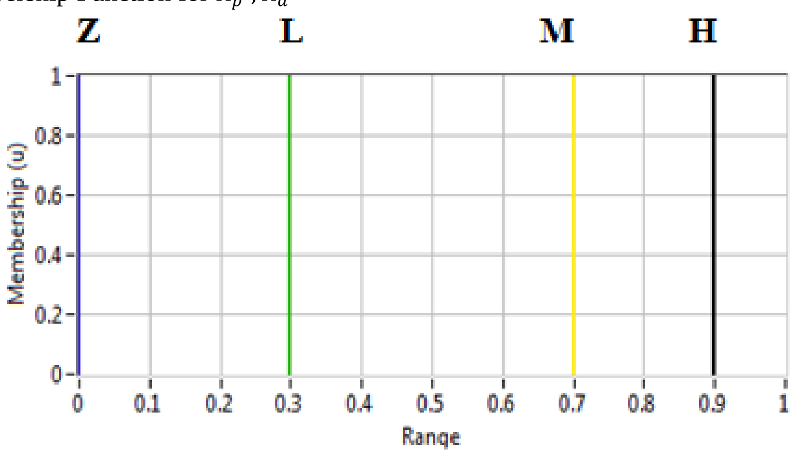


Fig. 6: Output Membership Function for K_i

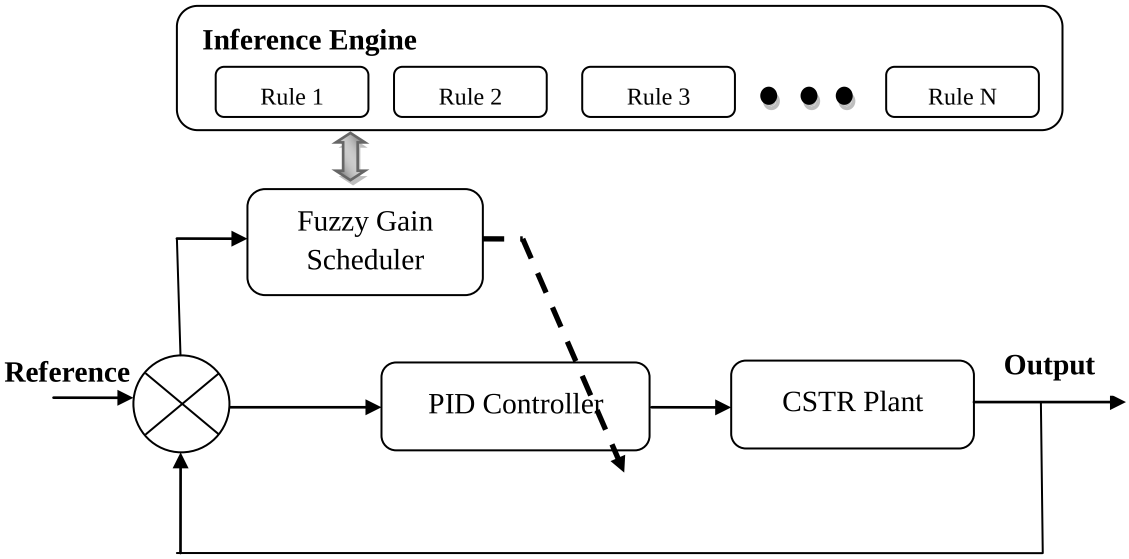
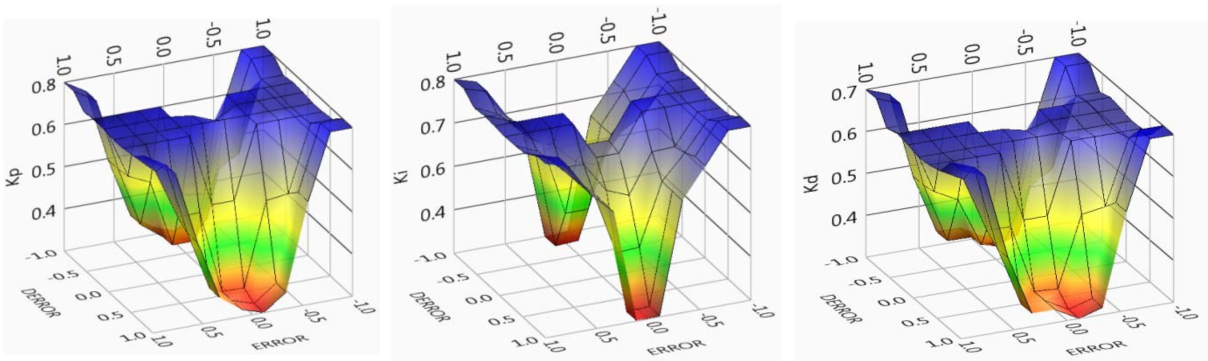


Fig. 7: Block Diagram for Fault Tolerant Fuzzy Gain Scheduled PID Controller

The membership functions for input variables are defined with triangular and trapezoidal shapes and those for output variables are singleton (Figures 4-6). All the fuzzy sets for input and output values are normalized for convenience.



(a) (b) (c)

Fig. 8: Surface Viewer for (a) K_p (b) K_i (c) K_d

Experimental Results And Discussions:

The fuzzy PID controller proposed in Section 3 has been experimentally tested on CSTR Plant. Three cases have been investigated such as (i) + 25% Sensor Fault, (ii) + 25% Actuator Fault (iii) + 25% Both Sensor and Actuator Fault.

Case (i): Sensor Fault:

In the first case, it is assumed that a loss of control effectiveness of 25% additive fault is taking place in the sensor. This kind of fault results in poor performance and does not really produce desired set point. The predefined ranges of Kp, Ti, and Td for the fuzzy gain-scheduled PID in the process control are Kp;min =41.80 Kp;max = 64.50, Ti;min = 2.50, Ti;max = 6.25, Td;min = 0.10, and Td;max = 0.50 and Sampling time = 1000ms. Figure 9 shows a closed loop response of fuzzy adaptive PID controllers for desired CSTR temperature. It is clear that the fuzzy adaptive PID controller reduces the fault effect on the system by reacting faster and returning the system quicker to its desired set point. The time evolutions of the fuzzy PID gains are illustrated in Figure 10. Unlike those of the conventional PID, the fuzzy gains are time-varying to adapt to uncertainties, disturbances and faults as can be clearly seen at t = 80 s.

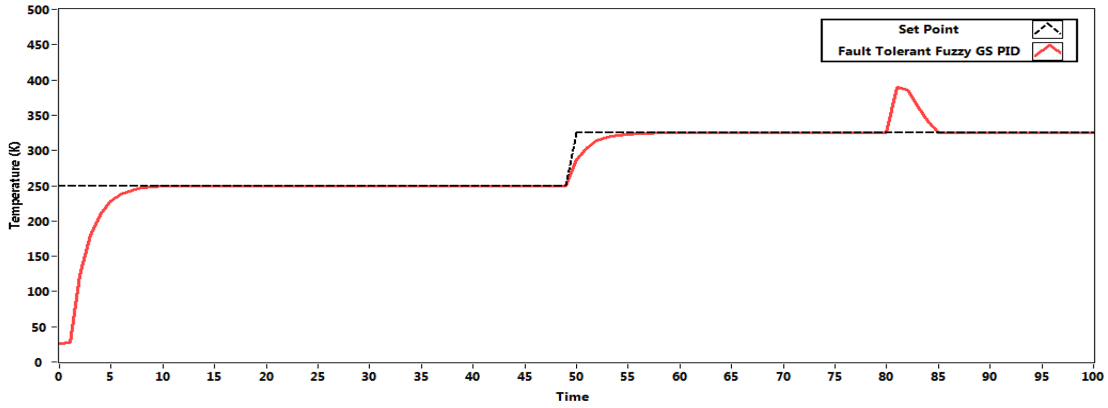


Fig. 9: Closed loop response of fuzzy adaptive PID controllers at Case (i)

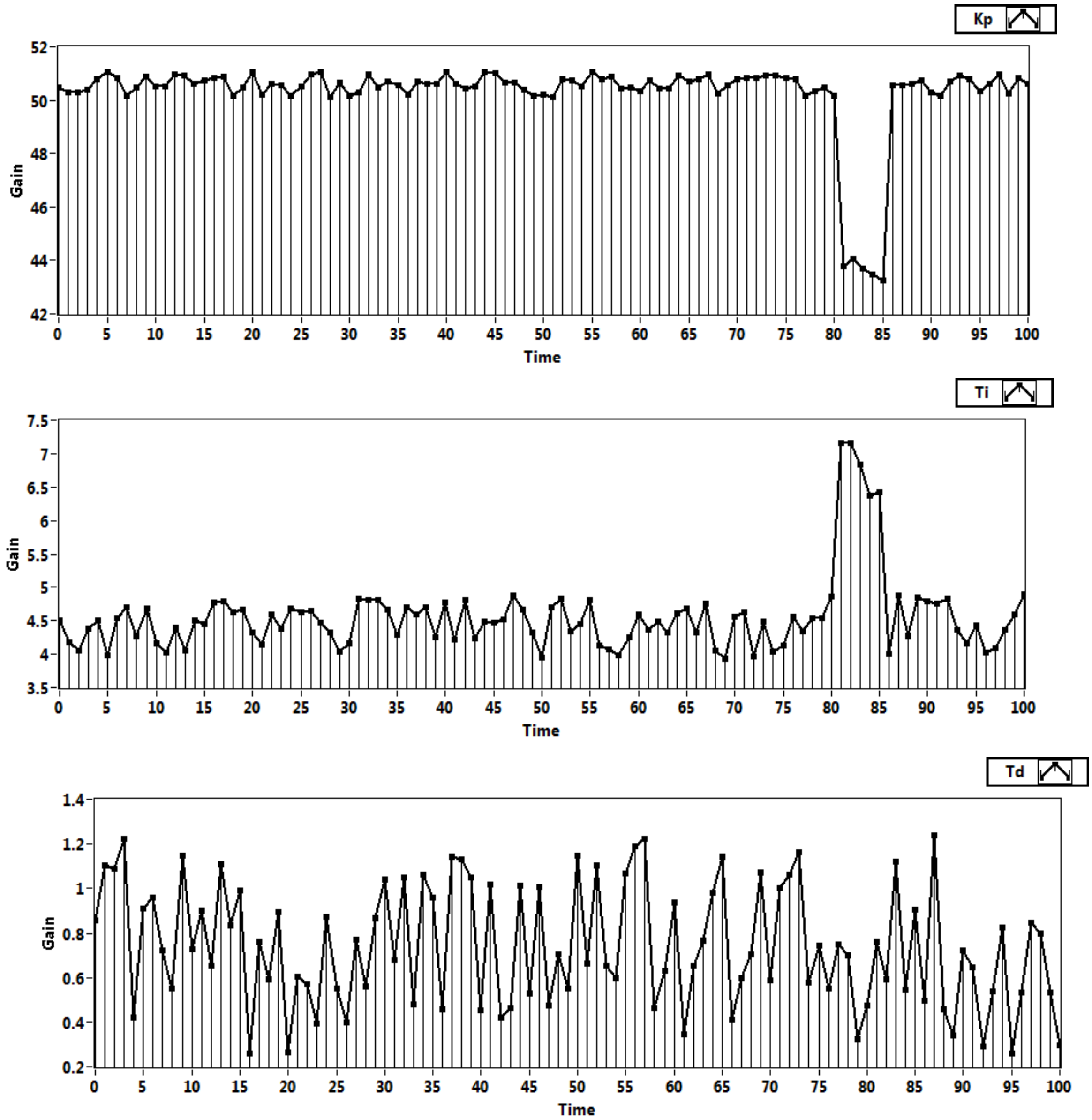


Fig. 10: Gains at fault case 1 (a) K_p (b) K_i (c) K_d

It can be seen in Figure 10 that after the fault occurs, Kp decreases to avoid system overshoot due to increase in error. The derivative gain Kd remains fixed with a high value to make a fast response to sudden changes in the error. When the system stops descending (loosing altitude) Kd decreases to let the system recovers faster and goes back to its desired position. After the fault, integrator gain Ki also increased to help the recovery process.

Case (ii): Actuator Fault:

In the second fault case, it is assumed that a loss of control effectiveness of 25% additive fault is taking place in the actuator. This kind of fault results in a loss of control action. The gains and predefined ranges for the PID controllers remain the same as given in the previous case discussed The predefined ranges of Kp, Ti, and Td for the fuzzy gain-scheduled PID in the process control are Kp;min =41.80 Kp;max = 64.50, Ti;min = 2.50, Ti;max = 6.25, Td;min = 0.10, and Td;max = 0.50 and Sampling time = 1000ms. Figure 11 shows a comparison between the conventional and the fuzzy PID controllers for CSTR Temperature loop. As in the first scenario, the fuzzy PID allows the system to react and return faster to its desired temperature. The time evolutions of the fuzzy PID gains are illustrated in Figure 12.

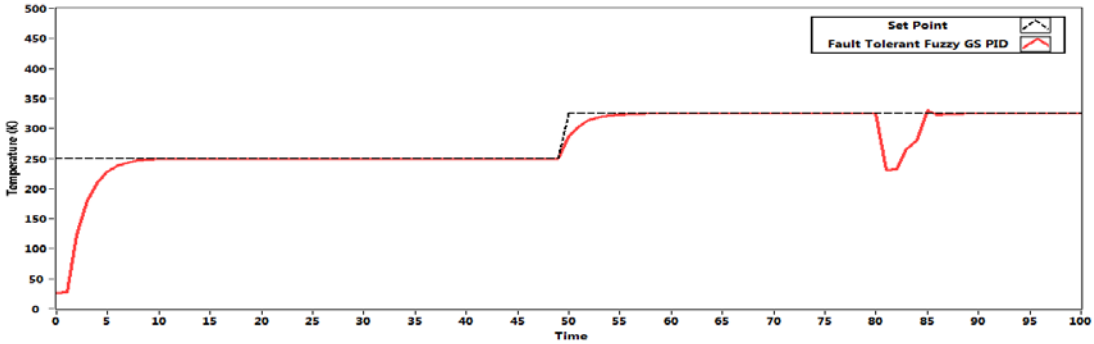


Fig. 11: Closed loop response of fuzzy adaptive PID controllers at Case (ii)

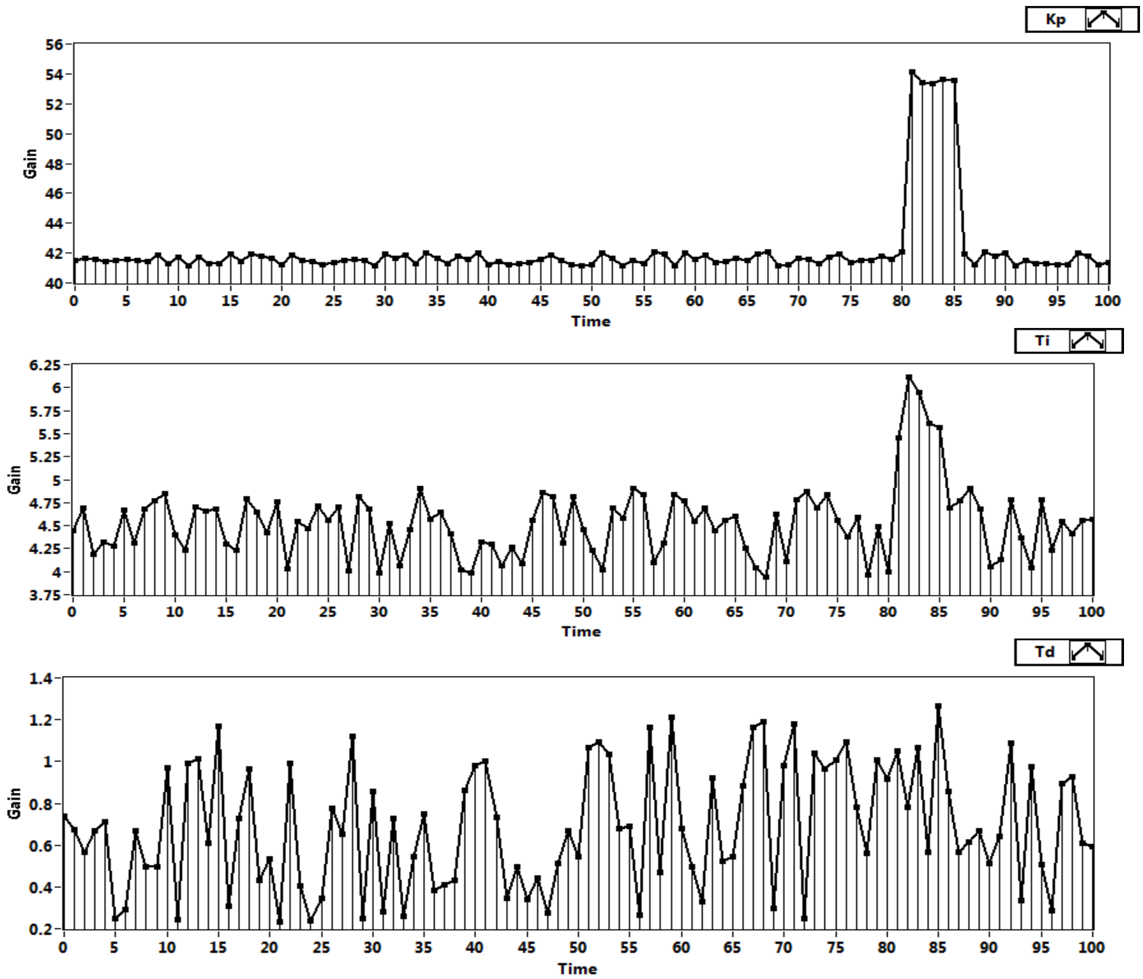


Fig. 12: Gains at fault case 2 (a) K_p (b) K_i (c) K_d

Case (ii): Sensor and Actuator Fault:

In the third fault case, it is assumed that a loss of control effectiveness of 25% additive fault is taking place in both sensor and actuator. The gains and predefined ranges for the PID controllers remain the same as given in the previous case discussed. Figure 13 shows a comparison between the conventional and the fuzzy PID controllers for CSTR Temperature loop. As in the first scenario, the fuzzy PID allows the system to react and return faster to its desired temperature. The time evolutions of the fuzzy PID gains are illustrated in Figure 14.

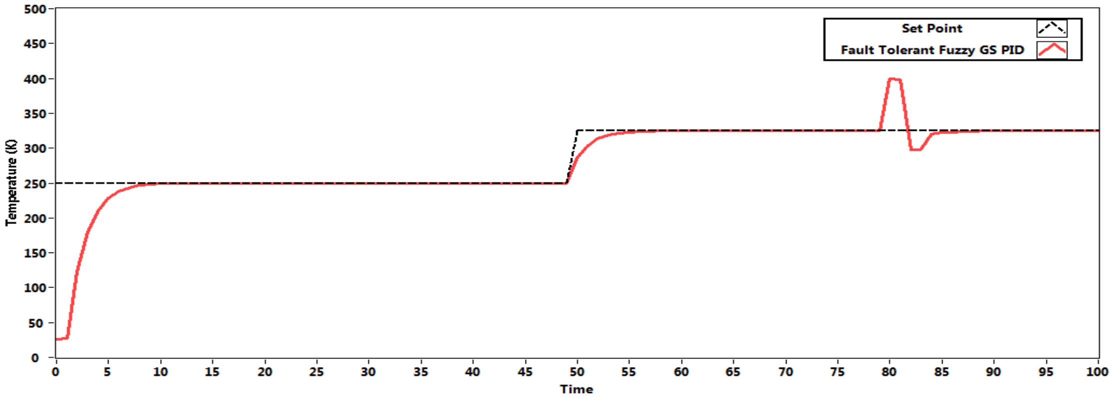


Fig. 13: Closed loop response of fuzzy adaptive PID controllers at Case (iii)

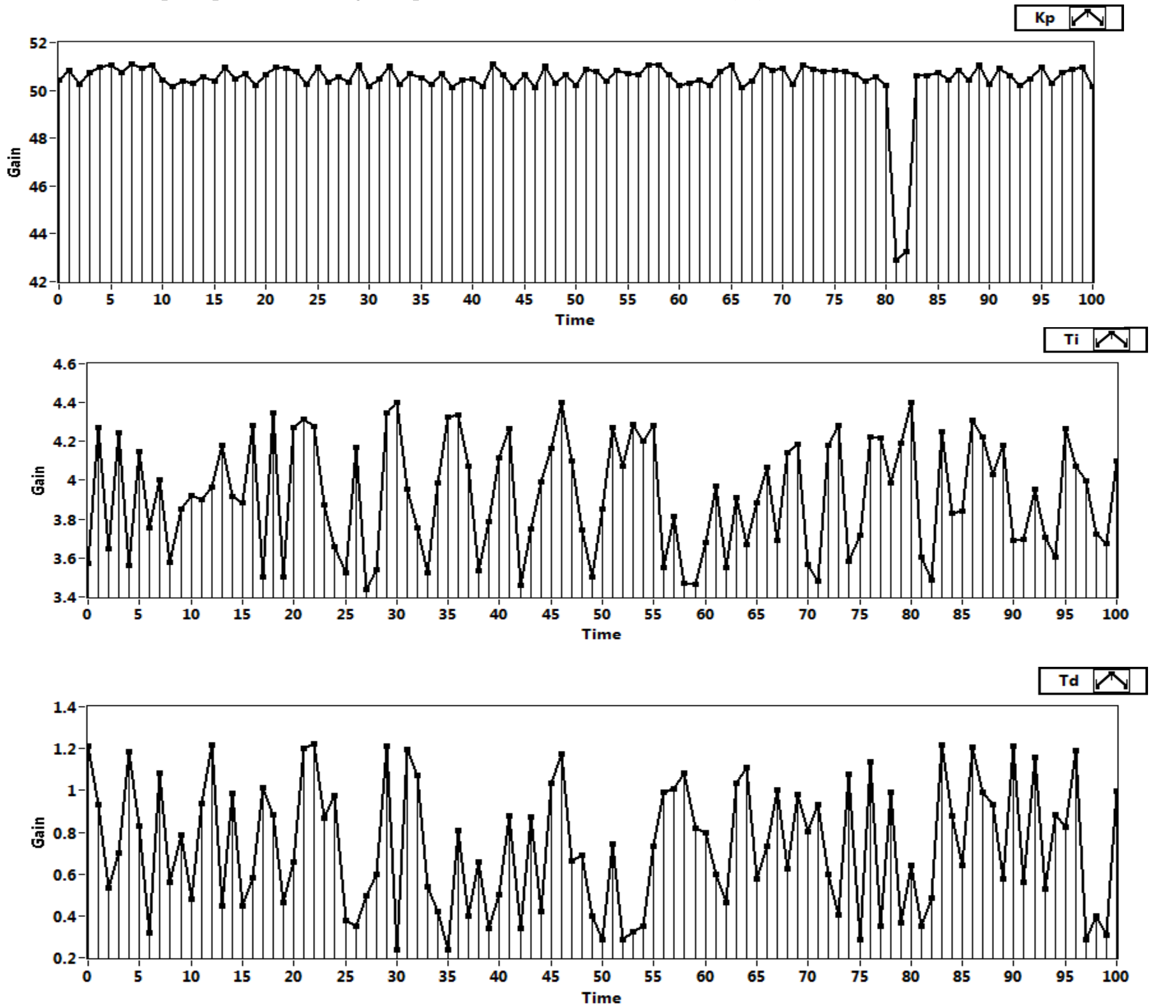


Fig. 14: Gains at fault case 3 (a) K_p (b) K_i (c) K_d

Conclusion:

This paper proposed an intelligent fuzzy approach to tolerate the sensor and actuator faults occurred in the CSTR plant. The proposed controller has been experimentally tested. The obtained results revealed the effectiveness of the proposed method and its ability to adapt in the presence of uncertainties and external disturbances.

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