DESIGN OF FUZZY ESTIMATOR TO ASSIST FAULT RECOVERY IN A NON LINEAR SYSTEM

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ABSTRACT

In this paper, a fuzzy estimator to assist fault recovery in a nonlinear process plant is presented. The fuzzy estimator is designed by acquiring minimal information from a real time plant. The operational range of the plant with the fuzzy estimator is bound to increase. Experimental results show that the designed estimator is able to take care of feedback sensor failures over a sufficiently long period of time.

Keywords: Fault tolerant system, Fuzzy logic, nonlinear system, Estimator.

NOMENCLATURE

$f_{in}(k)$— inflow corresponding to k^{th} sample
$f_{out}(k)$ – outflow corresponding to k^{th} sample
y(k) – Plant output, level in cm.
vvf – very very fast
A – cross sectional area of tank
h – instantaneous height of conical portion of tank
H – total height of tank
t – total time constant
k – process gain
r – radius of conical tank
R - radius of cylindrical tank

1. INTRODUCTION

The construction of a parameter (or state) estimator can be considered as a function approximation problem. To design an estimator, at first it is necessary to obtain the training data set 'G' such that, this training data set contains as much information as possible about the system 'g'. The training data should be uniformly spread over the input space ensuring a regular spacing between points (avoiding local clustering). This is essential to get a good coverage of the whole input space. The information as to how the mapping 'g' is shaped in all regions should be implicitly present as much as possible in the training data set. Once trained properly, the estimator will adaptively follow the slope of 'g' at all times. In this paper the design of a fuzzy estimator to assist fault recovery in a non-linear process control system is presented. The work is organized as follows: section 2 describes the plant chosen for experimental study and the transfer function of the process is obtained. The extraction of the linguistic information and the design of fuzzy estimator is discussed in section 3. The fault tolerant plant model is presented in section 4 and the experimental results are presented in section 5. The conclusion is given in section 6.

2. PLANT DESCRIPTION

The prototype model constructed for experimental study consists of the non-linear process tank with the conical and cylindrical portion. The experimental model is to be used to study the performance of the proposed fuzzy estimator by obtaining the servo and regulatory response, in the presence of disturbances and feedback sensor failure. Suitable signals are given to a pneumatic operated control valve to regulate the manipulated variable inflow. A disturbance in the form of random variations in outflow (measurable) is considered to enter the process. The experimental set up is shown in Figure 11 (Appendix I). The process variable level is sensed by means of a level sensing probe and using suitable electronics circuitry, a voltage output is obtained. The analog voltage is converted into digital form using an 8- bit A/D converter. The inflow and outflow rates are measured using suitable flow sensors.

2.1 TRANSFER FUNCTION OF THE NONLINEAR PROCESS

The mathematical model of the chosen nonlinear process tank is obtained, by considering the process as a combination of (i) a cylindrical geometry and (ii) a conical geometry as shown in Figure 1.

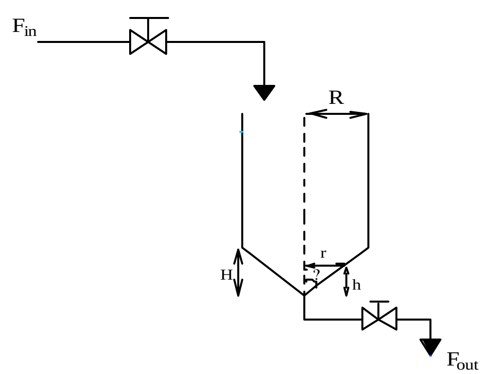

Figure 1 Geometrical cross-section of the tank

The plant transfer function is obtained in terms of the process characteristics namely the process gain and the process time constant. The dead time t_d is neglected.

2.1.1 MODELING FOR THE CYLINDRICAL PORTION

The cylindrical portion of the hopper type tank (Figure 1) is considered with outflow rate proportional to the square root of level. The mass balance equation governing the system dynamics is given by

$$\frac{dv}{dt} = F_{in} - F_{out} \qquad \text{-------} \quad (1)$$

$$A \frac{dh}{dt} = F_{in} - bh^{0.5} \qquad \text{------} \quad (2)$$

where A = ?R^2

The transfer function relating the height h and the inflow rate f_{in} with parameters (k, t) can be obtained as:

$$G(s) = \frac{H(s)}{F_{in}(s)} = \frac{k}{(1+s\,t)} \qquad \text{--------}(3)$$

where

$$k = \frac{2h}{U}; \quad t = \frac{2hA}{U}; \quad U = bh^{0.5};$$

The nominal transfer function

$$G_o(s) = \frac{k^o}{(1 + s\,t_o)} \qquad \text{-------} \quad (4)$$

where k^o and t^o are evaluated at a nominal height h_o.

2.1.2 MODELING FOR THE CONICAL PORTION

Similarly, the transfer function for the conical section can be obtained as

$$G_{con}(s) = \frac{k}{(1 + s\,t_{con})} \qquad \text{-------} \quad (5)$$

where

$$k = \frac{2h}{U}; \quad t_{con} = \frac{2hA(h)}{U}; \quad U = bh^{0.5};$$

Thus, the major difference in the model obtained for the two region is that the area A(h) is a function of the height h in the conical section.

3. FUZZY ESTIMATOR DESIGN

In the construction of a fuzzy state estimator for a single parameter in the plant 'g' random excitation inputs are chosen to form the training data set. Excitation with random inputs are chosen since it has a better tendency to place the data points over a whole range of locations and it is also difficult to choose other inputs 'u' that result in a better data set G. A set of experiments are conducted with system 'g' by varying the parameters inflow and outflow about their steady state values. The parameters are varied individually over a specified range of values to account for the possible failure scenarios the system might encounter. The parameters inflow and outflow ($f_{in}(k)$ and $f_{out}(k)$ respectively) are varied between –50% and +50% of its nominal value i.e. ? $f_{in}(k)$ and ? $f_{out}(k)$? [-0.5,+0.5], and the resultant variations of the plant output are recorded. The random variations in (inflow [-] outflow) and the resultant plant response obtained in shown for four sample cases in Figures 12 and 13 (Appendix-2). These plots are used to capture the time varying dynamics of the nonlinear process and design a suitable rule base.

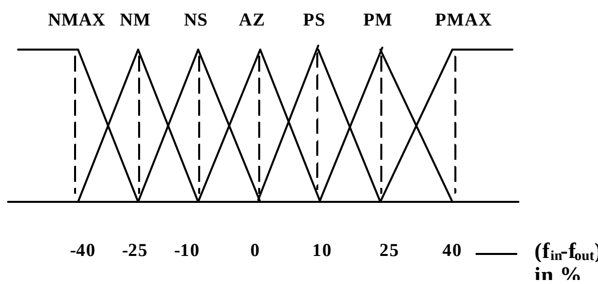

Figure 2 Membership function for (inflow-outflow)

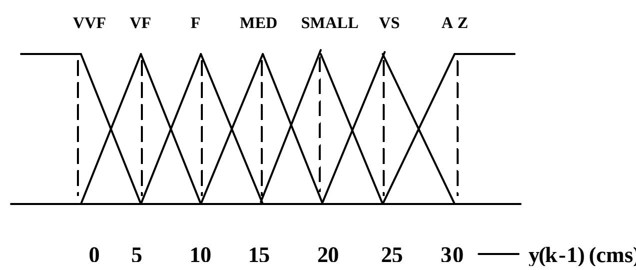

Figure 3 Membership function for y(k-1)

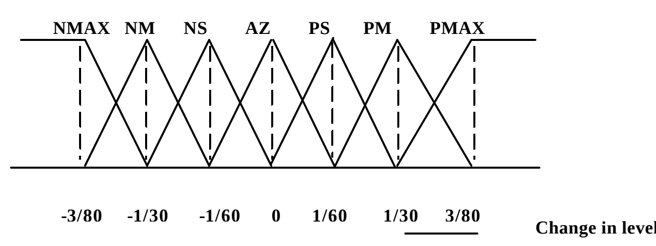

Figure 4 Membership function for change in level (in cms)

In the present work the fuzzy variables chosen are $f_{in}(k)$-$f_{out}(k)$, y(k-1) and the change in level. The membership function plots of these three variables are given in figures 2 to 4.

3.1 FUZZY ESTIMATOR- RULE BASE

Generally, the fuzzy logic rules are developed from operators experience or experimental data. In the present work, the rules are formed using the experimental response obtained. Each rule is a triplet (($f_{in}(k)$-$f_{out}(k)$), y(k-1),?y(k)).

The rule takes a given pair ($f_{in}(k)$- $f_{out}(k)$) ? [-50%,+50%] and y(k-1) ? [0,35] as inputs, and assigns an output ?y(k) ? [-1,+1]. The rule base for the fuzzy estimator is given in Table I.

Table I - Rule base

y(k-1) / f_{in}-f_{out}	*VVF*	*VF*	*F*	*MED*	*SMALL*	*VSMALL*	*AZ*
PMAX	PMAX	PMAX	PM	PM	PM	PS	PS
PM	PMAX	PM	PM	PM	PS	PS	AZ
PS	PM	PS	PS	AZ	AZ	AZ	AZ
AS	AZ	AZ	AZ	AZ	AZ	AZ	AZ
NS	NM	NM	NS	NS	AZ	AZ	AZ
NM	NMAX	NM	NM	NM	NS	NS	NS
NMAX	NMAX	NMAX	NM	NM	NM	NS	NS

4. FAULT TOLERANT PLANT MODEL

The fuzzy estimator with the membership functions of Figures 2 to 4 stored in the knowledge base and the rules stored in the rule base (Table 1) is incorporated into the existing plant model and is shown in Figure 5. The knowledge base and rule base are used by the fuzzy inference mechanism to fire the individual rules. The center of gravity method of defuzzification is used to obtain a crisp output.

4.1 FAULT TOLERANT CONTROL ALGORITHM

Repeat steps (i) to (iv) for n=1,2,3 ……..

(i) read level y(k) from level sensor

(ii)read inflow $f_{in}(k)$ and outflow $f_{out}(k)$ from flow sensors

(iii) calculate fuzzy estimator output y(k) with ($f_{in}(k)$ – $f_{out}(k)$) and y(k-1) as the fuzzy inputs.

(iv) if **[abs(y(k) - y(k))]** > a predefined threshold value

{

assign controller input = estimator output

and

assign y(k-1)= y (k)

}

else

{

assign controller input = sensor output

and

assign y(k-1) = y(k)

}

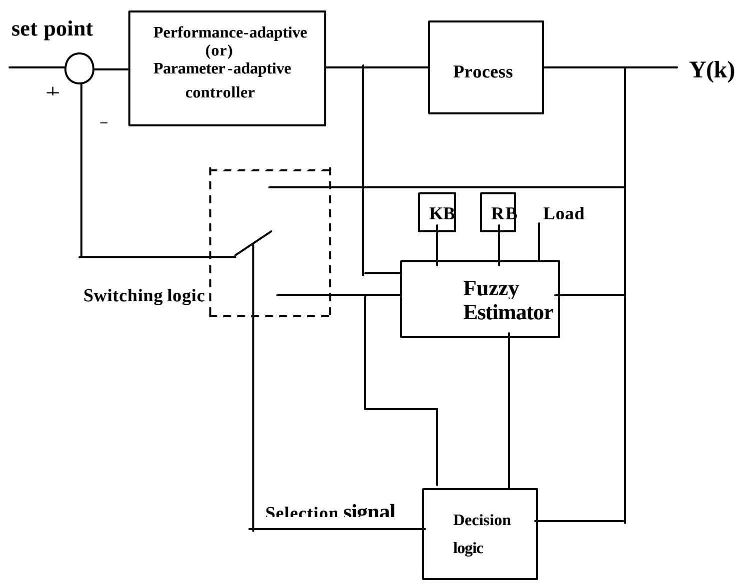

Figure 5 Plant model with the fuzzy estimator to take care of feedback sensor failure

5 EXPERIMENTAL RESULTS

The performance of the designed fuzzy estimator is tested on the nonlinear tank by introducing a feedback sensor failure at random time instants for a considerably long duration during the experimental run. The decision logic of Figure 5 selects the fuzzy estimator output as the feedback signal to the controller at those time instants when the deviation between the actual sensor value and the estimated value exceeds a set threshold.

The actual plant response obtained with a faultless sensor is compared with the estimator response (obtained during sensor failure) for different operating conditions such as variations in set point (servo tracking) and load variable (regulatory response) outflow.

5.1 SERVO TRACKING RESPONSE

In the servo tracking study on the real time plant, step signal with randomly varying magnitudes are used as the excitation inputs. The chosen variations of set point are shown in figure 6 for the actual (sensor normal) and fuzzy estimated response (during sensor failure) of the nonlinear plant is shown in figure 8. From the response, it can be observed that the designed estimator is able to adapt itself and follow the plant response during the time of feedback level sensor failure. The measured variations of $f_{in}(k)$ and $f_{out}(k)$ are shown in Figure 6 and 7.

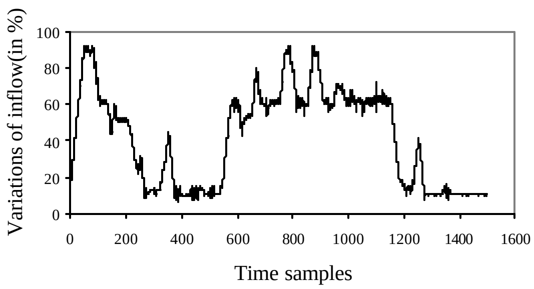

Figure 6 Measured variations of manipulated variable inflow

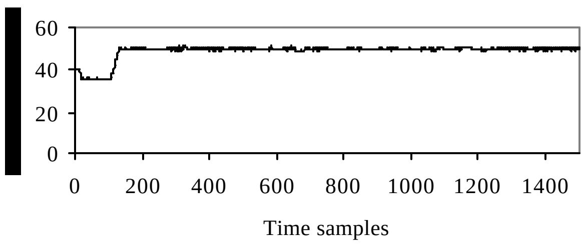

Figure 7 Measured variations of load variable outflow

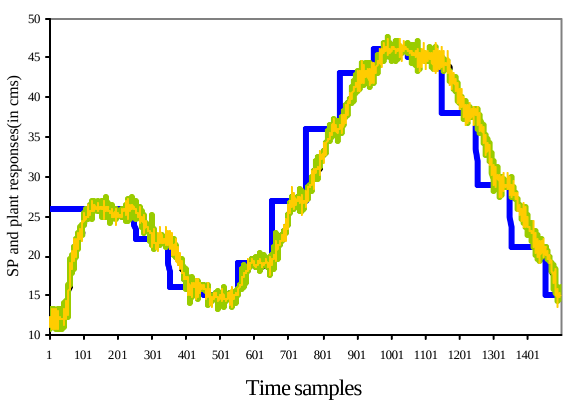

Figure 8 Measured and fuzzy estimated level variations of the real time plant in response to changes in set point.

A–Level variations during sensor normal (y ellow) B --Level variations estimated by fuzzy estimator (during sensor failure) (green) C---Set point(blue)

5.2 REGULATORY RESPONSE

This response is obtained to observe the effect of load variations on the performance of the dynamic fuzzy estimator. The chosen variations in load variable outflow about its steady state value of 50% are shown in Figure 9. The nominal operating point is set at 26 cms. The measured variations of $f_{in}(k)$ is shown in Figure 10.

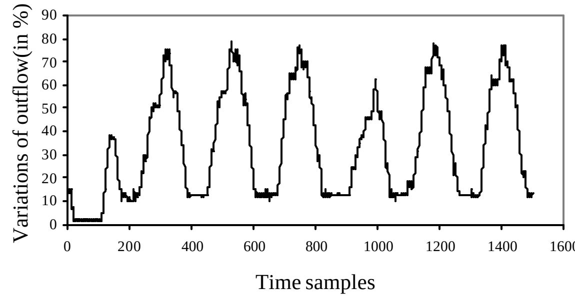

Figure 9 Random perturbations in the load variable outflow about its nominal value of 50%

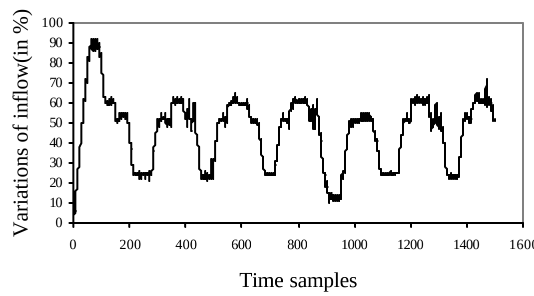

Figure 10 Measured variations of manipulated variable inflow

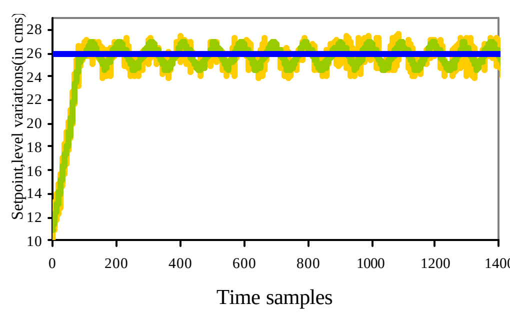

Figure 11 Measured and fuzzy estimated level variations of the real time plant in response to perturbations in load variable outflow.

A--Level variations during sensor normal (yellow) B --Level variations estimated by fuzzy estimator (during sensor failure) (green) C---Set point (blue)

The response of the fuzzy estimator and the actual plant output (if the sensor is normal) is shown in Figure 11.

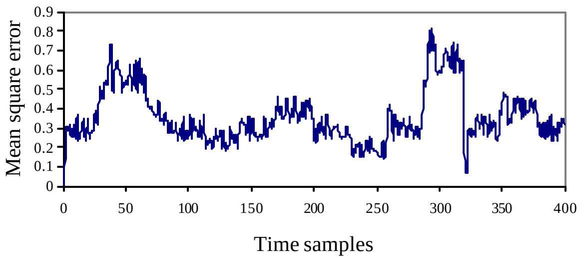

Figure 12 MSE plot for the servo tracking

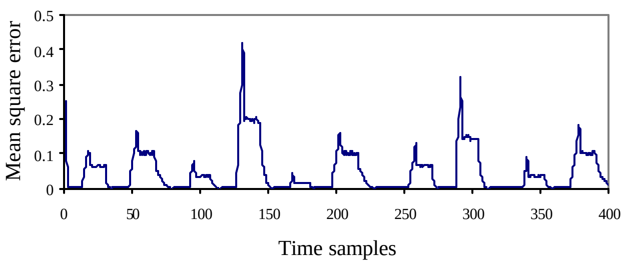

Figure 13 MSE plot for the regulatory control

The performance of the designed estimator is measured by calculating the MSE for the above 2 cases. The MSE is obtained as 1/N S $[(y(k) - y(k)]^2$ The mean square error is calculated for each case. The MSE plot corresponding to the servo tracking and regulatory control is shown in figures 12 and 13 respectively and is observed to be within acceptable limits.

6. CONCLUSION

In this paper, a novel fuzzy estimator based fault tolerant system has been designed and tested for satisfactory performance on a real time nonlinear process control plant. Future direction of study shall include extension of fault tolerant approach to take care of multiple sensor failures and also on embedding the estimator on-chip.

7. REFERENCES

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8.Biographies

1. K. Suresh is presently a research scholar in the faculty of Elec.Engg at Anna University, Chennai. His areas of interest include fault tolerant system design, Evolvable hardware, process control etc.

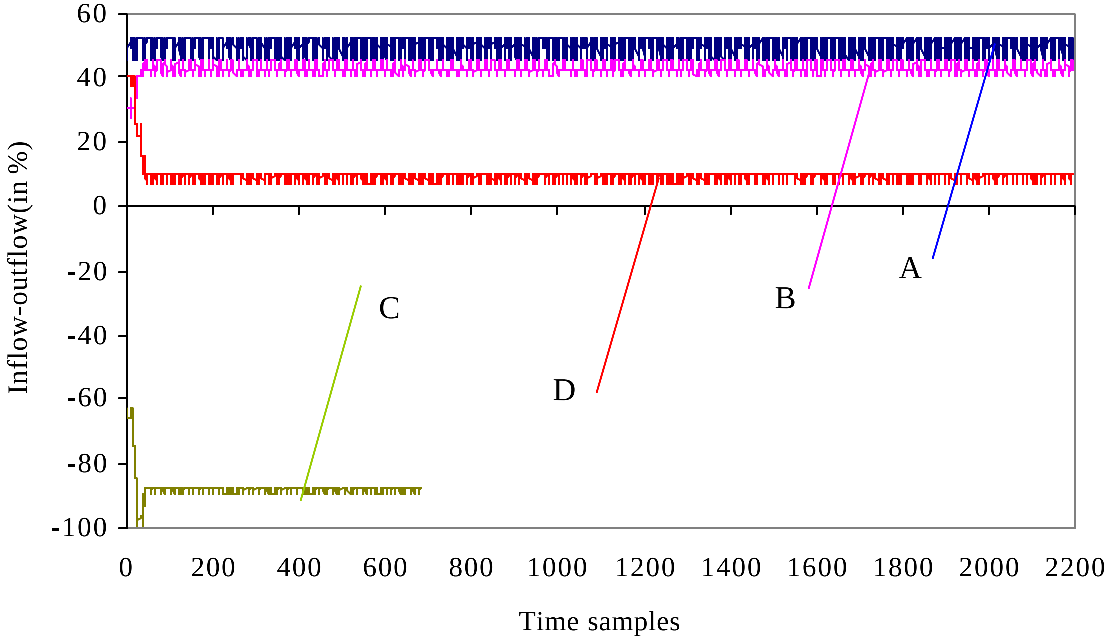
2. K. Balu is presently working as Prof. & Dean, A.C. College of Technology, Chennai. He completed his doctorate from IIT Madras. His areas of interest include mathematical modeling, Evolvable hardware, process control etc.

APPENDIX – I

Process tank chosen for experimental study

Figure 11.Laboratory set up of the plant model

APPENDIX II



A—Inflow fluctuating between 90 to 100% and out flow fluctuating between 40 to 50% after 50 Samples
B—Inflow Fluctuating between 90 to 100% and out flow fluctuating between 50 to 60% after 50 Samples
C – Inflow fluctuating between 0 to 10% and out flow fluctuating between 70 to 80% after 50 Samples
D–- Inflow fluctuating between 90 to 100% and out flow fluctuating between 90 to100% after 50 Samples

Figure 12 Combined plot of (inflow-outflow) for four different experimental conditions.

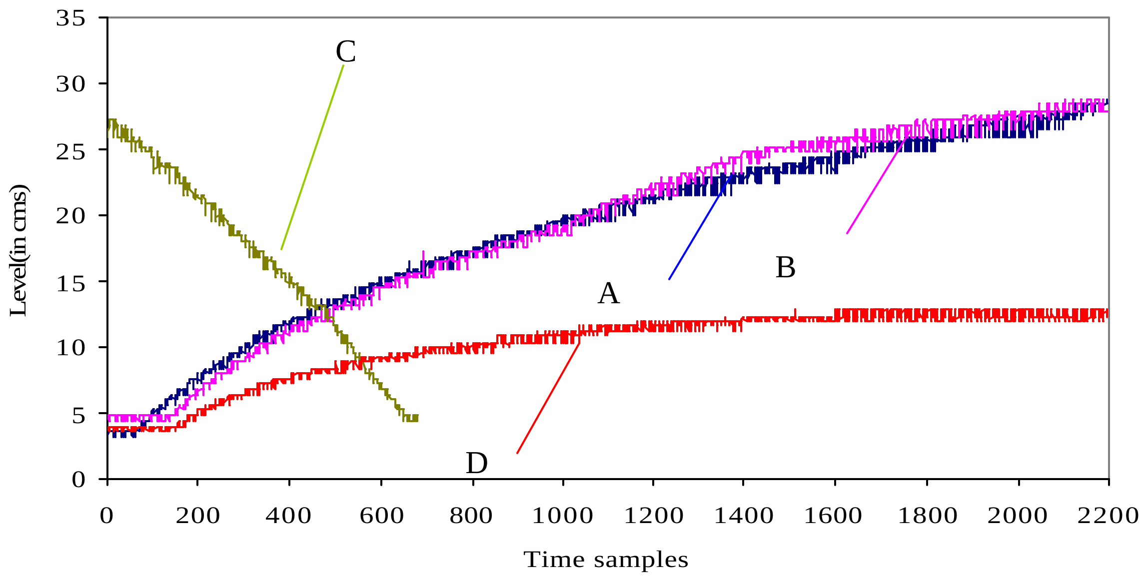


Figure 13 Combined plot of resultant level response corresponding to the case A, B, C, D of Figure 12