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Fuzzy Model Based Learning Control for Spherical Tank Process

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ABSTRACT
Fuzzy Model Reference Learning Control (FMRLC) is an efficient technique for the control of non linear process. In this paper, a FMRLC is applied in to a non linear spherical tank system. First, the mathematical model of the spherical tank level system is derived and simulation runs are carried out by considering the FMRLC in a closed loop. A similar test runs are also carried out with hybrid fuzzy P+ID Controller and conventional fuzzy controller for comparison and analysis. The results clearly indicate that the incorporation of FMRLC in the control loop for spherical tank system provides a good tracking performance than the hybrid fuzzy P+ID and conventional fuzzy controller.
***Keywords* -** Fmrlc, Hybrid Fuzzy, Fuzzy

I. INTRODUCTION

Control of non linear process is obscure task in the process control industries. This kind of nonlinear process exhibit many not easy control problems due to their non linear dynamic behavior, uncertain and time varying parameters. Especially, control of a level in a spherical tank is vital, because the change in shape gives rise to the non linear characteristics. An evaluation of a controller using variable transformation proposed by Anathanatrajan et.al [1] on hemi-spherical tank which shows a better response than PI controller. A simple PI controller design method has been proposed by Wang and Shao [2] that achieves high performance for a wide range of linear self regulating processes. Later in this research field, Fuzzy control is a practical alternative for a variety of challenging control applications, since it provides a convenient method for constructing nonlinear controllers via the use of heuristic information. Procyk and Mamdani [3] have discussed the advantage of Fuzzy Logic Controllers (FLC) is that it can be applied to plants that are difficult to get the mathematical model. Recently, Fuzzy logic and conventional control design methods have been combined to design a Proportional Integral Fuzzy Logic Controller (PI - FLC). Tang and Mulholland [4] have discussed about the comparison of fuzzy logic with conventional controller.

Wei Li [5] has discussed the Fuzzy P+ID controller and analyze its stability. The main idea of the study is to use a conventional D controller to stabilize a controlled object and the fuzzy proportional (P) controller to improve control performance. According to the stability condition [6], modify the Ziegler and Nichols' approach to design of the fuzzyP+ID controller since this approach is used in industrial control of a plant with unknown structure or with nonlinear dynamics. When the process is unstable in local region, the controller based on a fixed model will be unreliable and thus the system performance is affected seriously.

To overcome these problems, in this paper a "learning" control algorithm is presented which helps to resolve some of the issues of conventional fuzzy and hybrid fuzzy controller design. This algorithm employs a reference model (a model of how you would like the plant to behave) to provide closed-loop performance feedback for synthesizing and tuning a fuzzy controller's knowledge-base. Consequently, this algorithm is referred to as a "Fuzzy Model Reference Learning Controller" (FMRLC) [8][9].

The paper is divided as follows: Section 2 presents a brief description of the mathematical model of Spherical tank system, section 3 and 4 shows the methodology, algorithms of FMRLC and hybrid fuzzy P+ID , section 5 presents the results and discussion and finally the conclusions are presented in section 6.

II. DYNAMIC MODEL OF THE SPHERICAL TANK LEVEL SYSTEM

The spherical tank level system[10] is shown in Figure 1. Here the control input f_{in} is being the input flow rate (m^3/s) and the output is x which is the fluid level (m) in the spherical tank

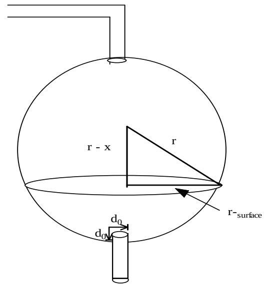


Figure.1. Spherical Tank System

Let, r = radius of tank

d_0 = thickness (diameter) of pipe (m) and initial height

$r_{surface}$ = radius on the surface of the fluid varies according to the level (height) of fluid in the tank.

Dynamic model of tank is given as

$$\frac{\delta}{\delta t}\left[\int_0^{x_1} A(\mathrm{x})\delta \mathrm{x}\right] = f_{in}(t) - a\sqrt{2gx} \quad (1)$$

Where

$A(\mathrm{x})$ = area of cross section of tank

$$= \pi\,(2\mathrm{rx} - x^2) \quad (2)$$

a = area of cross section of pipe

$$= \pi\left(\frac{d_0}{2}\right)^2 \quad (3)$$

Re write of dynamic model of tank at time t+ δt,

$$\mathrm{A(x)}\ \delta\mathrm{x} = f_{in}\ \delta t - a\sqrt{2g(x - d_0)}\ \delta t \quad (4)$$

By combining equation (1) to (4) we have

$$\frac{\delta \mathrm{x}}{\delta t} = \frac{\mathrm{fin}\ \delta t - \frac{\pi . d_0^2}{4}\sqrt{2g(\mathrm{x}-d_0)}}{\pi\,(2\mathrm{rx}-x^2))} \quad (5)$$

$$lim_{d\rightarrow 0}\ \frac{\delta \mathrm{x}}{\delta t} = \frac{d\mathrm{x}}{dt}$$

Therefore

$$\frac{d\mathrm{x}}{dt} = \frac{\mathrm{fin}\ \delta t - \frac{\pi . d_0^2}{4}\sqrt{2g(\mathrm{x}-d_0)}}{\pi\,(2\mathrm{rx}-x^2))} \quad (6)$$

Equation (6) shows the dynamic model of the spherical tank system

III. FUZZY MODEL REFERENCE LEARNING CONTROL (FMRLC)

This section discusses the design and development of the FMRLC and it is applied to the spherical tank level system. The following steps are considered for the design of FMRLC.

I. Direct fuzzy control
II. Adaptive fuzzy control

1. DIRECT FUZZY CONTROL

The rule base, the inference engine, the fuzzification and the defuzzification interfaces are the our major components to design the direct fuzzy controller [8].

Consider the inputs to the fuzzy system: the error and change in error is given by

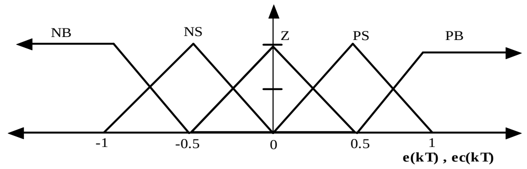
e(kT)=r(kT) – y(kT) (7)

c(kT) = (e(kT) - e(kT-T)) / T (8)

and the output variable is

u(kT) = Flow(control valve) (9)

The universe of discourse of the variables (that is, their domain) is normalized to cover a range of [-1, 1] and a standard choice for the membership functions is used with five membership functions for the three fuzzy variables (meaning 25 = 5^2 rules in the rule base) and symmetric, 50% overlapping triangular shaped membership functions (Figure 2), meaning that only 4 (=2^2) rules at most can be active at any given time.



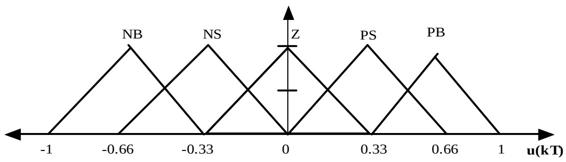


Figure 2. Membership functions for the fuzzy controller.

The fuzzy controller implements a rule base made of a set of IF-THEN type of rules. These rules were determined heuristically based on the knowledge of the plant. An example of IF THEN rules is the following

IF e is negative big (NB) and ce is negative big (NB) THEN u is Negative big (NB)

This rule quantifies the situation where the spherical tank system is far to minimum level to maximum level hence the control valve needed to open from 100% to 0% so that it control the particular operating point of the liquid level system. The resulting rule table is shown in the Table 1.

Table 1: Rule base for the fuzzy controller

"Level" u		"Change in error" ce				
		NB	NS	Z	PS	PB
"Error" e	NB	NB	NB	NB	NS	Z
	NS	NB	NB	NS	Z	PS
	Z	NB	NS	Z	PS	PB
	PS	NS	Z	PS	PB	PB
	PB	Z	PS	PB	PB	PB

Here min-max inference engine is selected, utilizes minimum for the AND operator and maximum for the OR operator. The end of each rule, introduced by THEN, is also done by minimum. The final conclusion for the active rules is obtained by the maximum of the considered fuzzy sets. To obtain the crisp output, the centre of gravity (COG) defuzzification method is used. This crisp value is the resulting controller output.

2. ADAPTIVE FUZZY CONTROL

In this section, design and development of a FMRLC, which will adaptively tune on-line the centers of the output membership functions of the fuzzy controller determined earlier.

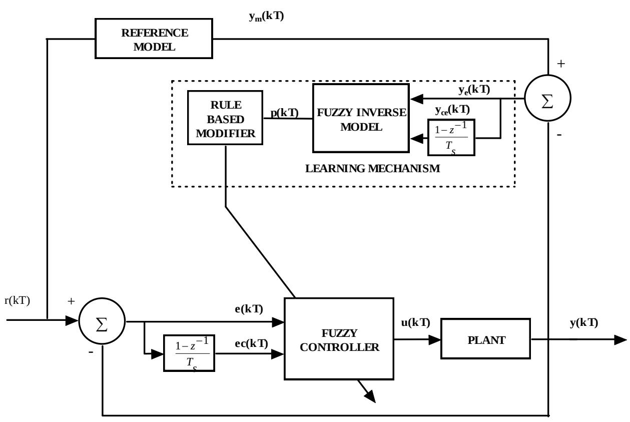


Figure 3. Fuzzy Model Reference Learning Control

Figure 3 shows the FMRLC as applied to the spherical tank level system. The FMRLC uses a *learning mechanism* that emphasizes
a) Observes data from a fuzzy control system (i.e. *r(kT)* and *y(kT)*.
b) Characterizes its present performance, and
c) automatically synthesizes and/or adjusts the fuzzy controller using rule base modifier so that some pre-specified performance objectives are satisfied.

In general, the *reference model*, which characterizes the desired performance of the system, can take any form (linear or nonlinear equations, transfer functions, numerical values etc.). In the case of the level process reference model is shown in the figure.3.

An additional fuzzy system is developed called *"fuzzy inverse model"* which adjusts the centers of the output membership functions of the fuzzy controller, which still controls the process, This fuzzy system acts like a second controller, which updates the rule base of the fuzzy controller by acting upon the output variable (its membership functions centers). The output of the inverse fuzzy model is an adaptation factor *p(kT)* which is used by the rule base modifier to adjust the centers of the output membership functions of the fuzzy controller. The adaptation is stopped when *p(kT)* gets very small and the changes made to the rule base are no longer significant. The fuzzy controller used by the FMRLC structure is the same as the one developed in the previous section.

The *fuzzy inverse model* has a similar structure to that of the controller (the same rule base, membership functions, inference engine, fuzzification and defuzzification interfaces. See section 3.1).

The inputs of the fuzzy inverse model are

$$ye(kT) = ym(kT) - y(kT) \qquad (10)$$

$$yc(kT) = (\, ye(kT) - ye(KT\text{-}T)\,) / T \qquad (11)$$

and the output variable is the adaptation factor *p(kT)*.

The *rule base modifier* adjusts the centers of the output membership functions in two stages

1. The active set of rules for the fuzzy controller at time *(k-1)T* is first determined

$$\mu_i^e\big(e(kT-T)\big) > 0,\ i = \overline{1,n}$$
$$\mu_j^c\big(c(kT-T)\big) > 0,\ j = \overline{1,m} \qquad (12)$$

The pair *(i, j)* will determine the activated rule. We denoted by *i* and *j* the i-th, respectively the *j*-th membership function for the input fuzzy variables error and change in error.

2. The centers of the output membership functions, which were found in the active set of rules determined earlier, are adjusted. The centers of these membership functions (*bl*) at time *kT* will have the following value

b (*kT*) =*b* (*kT*- *T*) +*p*(*kT*) (13)

We denoted by *l* the consequence of the rule introduced by the pair *(i, j)*.

The centers of the output membership functions, which are not found in the active set of rules *(i, j)*, will not be updated. This ensures that only those rules that actually contributed to the current output *y(kT)* were modified. We can easily notice that only local changes are made to the controller's rule base.

For better learning control a larger number of output membership functions (a separate one for each input combination) would be required. This way a larger memory would be available to store information. Since the inverse model updates only the output centers of the rules which apply at that time instant and does not change the outcome of the other rules, a larger number of output membership functions would mean a better capacity to map different working the adjustments it made in the past for a wider range of specific conditions. This represents an advantage for this method since time consuming re-learning is avoided. At the same time this is one of the characteristics that differences learning control from the more conventional adaptive control.

IV. HYBRID FUZZY P+ID CONTROLLER

For implementing the block diagram of fuzzy P+ID controller referred Figure 4 only one supplementary parameter has to be attuned. Consequently, the physical tuning time of the controller can be greatly reduced in comparison with a conventional fuzzy logic controller.

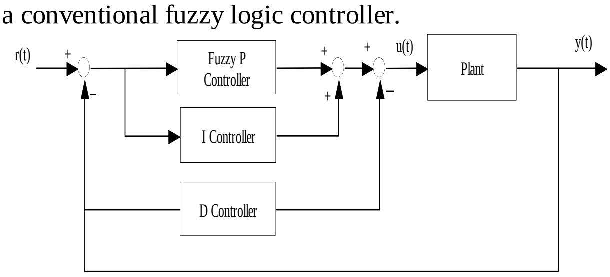


Figure 4 Block diagram of hybrid fuzzy P+ID controller

1. DESIGN OF HYBRID FUZZY P+ID CONTROLLER

Design of fuzzy P+ID controller is constructed by replacing the conventional proportional term with the fuzzy one, we propose the following formula:

$$K_P = 0.6 K_P(crit) \tag{14}$$

$$K_I = \frac{2K_P}{T(crit)} \tag{15}$$

$$K_D = (T+2)K_P + K_I T^2 \tag{16}$$

For determination of their parameters. We select the parameter K_D of the derivative controller by using the sufficient stability condition [5] instead of the Ziegler and Nichols' formula. This result implies that stability of a system does not change after the conventional PID controller is replaced by the fuzzy P+ID controller without modifying any PID-type controller parameter.

The selection of the sampling period T is made in two stages: 1) during the loop design and 2) during the controller design. The observed rule [6] suggests that the sampling frequency must be from 4 to 20 times the bandwidth of the closed-loop system. For the controller design, T should be enhanced to be greater than the sum of the error computation time, the digital analogue converter (DAC) and analogue digital converter (ADC) conversion times, and the zero-order hold delay time.

The necessary conditions for selection of T is given below,

1) if T is greater, the stability regions are smaller;
2) Large T implies small cost;
3) Large T results in large conversion times of the DAC's and ADC's (i.e., to smaller cost);
4) Small T allows good system performance in the presence of noise.

V. RESULTS AND DISCUSSION

In this section, the simulation results for Spherical tank level system are presented to illustrate the performance of the FMRLC control algorithm. The differential equation(6) is derived in the section 2 are considered for this simulation study. Here, simulations are analyzed in two cases. Initially, the spherical tank is maintained at 35 % of its maximum level and a 5% step signal is applied to the process with FMRLC control algorithm and the responses are recorded in Figure 5. Similarly, a same procedure is applied to hybrid fuzzy P+ID and Conventional fuzzy for the comparative analysis. The performance indices in terms of ISE and IAE are calculated and summarized in the table 2

In order to validate the FMRLC algorithm, the different operating points (50% and 60 %) are also considered and output responses are recorded in the Figure 6 and Figure 7 and their performance indices are given in the same table2.

To analyze the FMRLC controller for the both the cases, a performance analysis in terms of ISE, IAE is made and their values are tabulated in Table 2 and Table 3

Table 2. Performance index for servo response

	FMRLC		**Hyb-fuzzy**		**Conv-fuzzy**	
	ISE	**IAE**	**ISE**	**IAE**	**ISE**	**IAE**
35%	122.2	85.63	347.9	141.1	686.6	299.8
50%	143.3	94.59	344.1	144	701.3	310.3
60%	167.9	129.3	341.5	146.3	711	316.7

Secondly, a load disturbance is applied to the FMRLC algorithm under the same operating points and responses are traced in Figure 8 to figure 10. In the case of servo regulatory, the process is maintained at 35 % of its maximum level and 5% step signal is applied to the process and the disturbance is given at new steady state level (10% of given step change) disturbance at 700 sec instant.

Table 3.Performance index for servo regulatory response

	FMRLC		**Hyb-fuzzy**		**Conv-fuzzy**	
	ISE	**IAE**	**ISE**	**IAE**	**ISE**	**IAE**
35%	129.2	93.11	351.9	154.9	686.3	297
50%	153.8	118.8	348.5	157.5	700.6	306.6
60%	170.2	132.9	346.2	160.1	710.1	312.5

The performance indices for all the three controllers are computed and tabulated in the table 3. Also the different operating points (50% and 60 %) are also carried out and their performances indices are summarized in the same table 3.It is observed that, the FMRLC algorithm gives an excellent performance than the other two.

From the table 2 and 3, it is observed that FMRLC control algorithm provides satisfactory performance in the servo and servo regulatory cases than the other control strategies

VI. CONCLUSION

This paper, a Fuzzy Model Reference Learning Control (FMRLC) is applied in to a non linear spherical tank system. Simulation runs are carried out by considering the FMRLC algorithm, hybrid fuzzy and conventional fuzzy controller in a closed loop. The results clearly indicate that the incorporation of FMRLC in the control loop in spherical tank system provides a superior tracking performance than the hybrid fuzzy P+ID and conventional fuzzy controller.

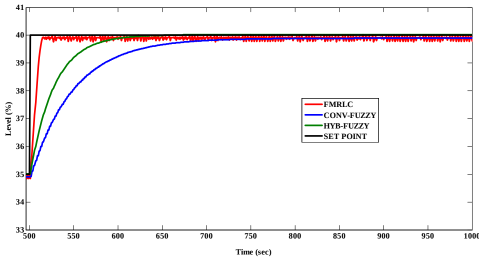


Figure 5. Servo Response of spherical tank at 35% operation point

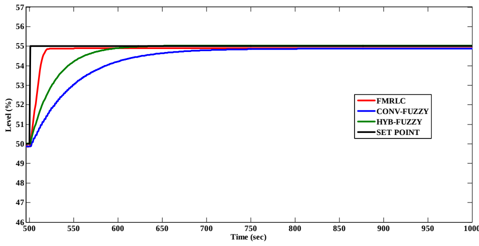


Figure 6. Servo Response of spherical tank at 50% operation point

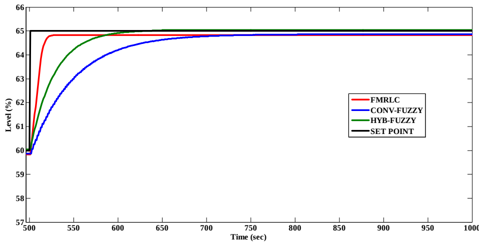


Figure 7.Servo Response of spherical tank at 60% operation point

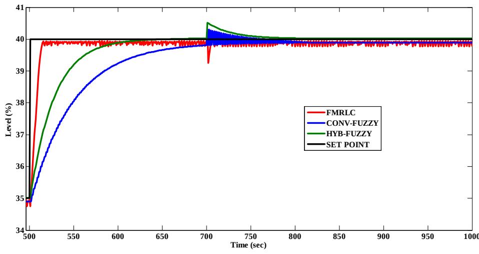


Figure 8. Regulatory Response of Spherical tank at 35% operating point

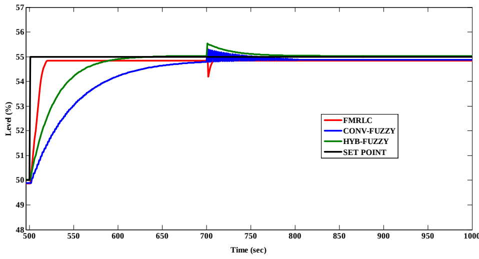


Figure 9. Regulatory Response of Spherical tank at 50% operating point

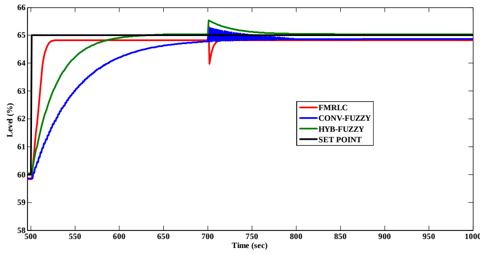


Figure 10. Regulatory Response of Spherical tank at 60% operating point

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