International Research Journal of Engineering and Technology (IRJET) e-ISSN: 2395-0056
Volume: 02 Issue: 09 | Dec 2015 www.irjet.net p-ISSN: 2395-0072

Enhanced Fuzzy Model Reference Learning Control for Shell and Tube Heat Exchanger process

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Abstract - *Enhanced Fuzzy Model Reference Learning Control (EFMRLC) 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 EFMRLC in a closed loop. A similar test runs are also carried out with Neural Network based IMC PI and conventional ZN based PI-mode for comparison analysis. The results clearly indicate that the incorporation of EFMRLC in the control loop in spherical tank system provides a good tracking performance than the NNIMC and conventional PID mode.*

Key word: EFMRLC, FOPDT,NNIMC , PID

1. INTRODUCTION

Control of non linear process is main criteria in the process control industries. These 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 [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.

Recent years, neural network (NN) had been adopted in nonlinear IMC design due to its good ability of approximate arbitrarily nonlinear vector functions [5][6]. For some complex processes, however, when the work condition of system varies, the process characteristic changes drastically and falls outside training region. Even though the NN model is available, it is difficult to design the NN inverse controller unless the model is open-loop stable[7]. 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 trounce these problems, in this paper a "learning" control algorithm is presented which helps to resolve some of the issues of fuzzy controller design and NN inverse model. 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][10].

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 EFMRLC and NNIMC , section 5 presents the results and discussion and finally the conclusions are presented in section 6.

2. MATHEMATICAL MODELING OF (STHE)

Fig.ure.1 shows the two different heat exchanger sections namely shell and tube[11][12]. These sections are further divided into control volumes.

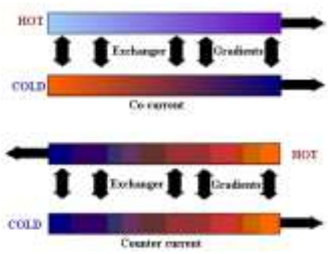


Figure.1 Flow arrangements of Shell and Tube Heat Exchanger (STHE)

The following assumptions were made while designing the mathematical model of shell and tube heat exchanger.

1. The control volumes are small and assumed to have a constant temperature.

2. The heat exchanger is insulated and there is no heat loss from the heat exchanger to the surrounding.

Shell Control Volume (CV) Energy Balance

The convection term in heat exchanger is divided into a number of sections called the control volume. The final equation for the energy balance on the shell control volume given in eqn. (1) is equal to the energy gained due to change in temperature plus energy gained by convection.

$$\frac{\rho_s c_s v_s}{N} * \frac{dT_{co}}{dt} = \dot{m}_s c_s (T_{ci} - T_{co}) + \frac{h_s A_s}{N}(T_{ho} - T_{co}) \quad (1)$$

Tube Control Volume Energy Balance

The energy balance on the tube control volume is analogous to the energy balance on the shell control volume. The energy balance equation is developed in the same manner as the equation developed for the shell control volume. The final differential equation for the rate of energy stored in the tube control volume is given by

$$\frac{\rho_t c_t v_t}{N} * \frac{dT_{ho}}{dt} = \dot{m}_t c_t (T_{hi} - T_{ho}) + \frac{h_t A_t}{N}(T_{co} - T_{ho}) \quad (2)$$

The eqns. (1) and (2) are referred as mathematical model of shell and tube heat exchanger and they are solved to get hot water outlet temperature (T_{ho}) by applying cold water inflow rate $\dot{m}_s$ (C_{in}). C_{in} is the volumetric flow rate in LPS.

3. ENHANCED FUZZY MODEL REFERENCE LEARNING CONTROL (FMRLC)

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

I. Direct fuzzy control
II. Adaptive fuzzy control

3.1Direct 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) (3)

c(kT) = (e(kT) - e(kT-T)) / T (4)

and the output variable is

u(kT) =cold water inflow rate in LPS (5)

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 1), meaning that only 4 (=2^2) rules at most can be active at any given time.

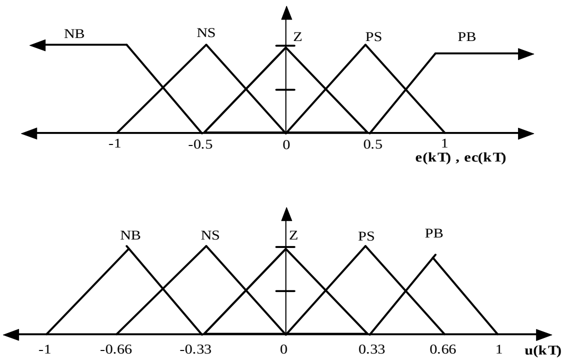


Figure 2 Membership functions for the fuzzy controller.

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 Positive big (PB)

This rule quantifies the situation where the STHE is far to minimum hot water temperature outlet to maximum temperature hence the cold water inflow rate changes from room temperature to 60^0C so that it control the particular operating point of the STHE. 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	PB	PB	PB	PS	Z
	NS	PB	PB	PS	Z	NS
	Z	PB	PS	Z	NS	NB
	PS	PS	Z	NS	NB	NB
	PB	Z	NS	NB	NB	NB

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.

3.2. Adaptive Fuzzy Control

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

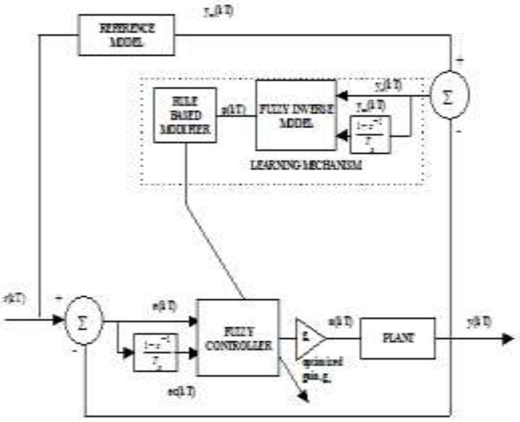


Figure 3. Enhanced Fuzzy Model Reference Learning Control

Figure 3 shows the EFMRLC as applied to the STHE process. The FMRLC uses a (*learning mechanism* that emphasizes

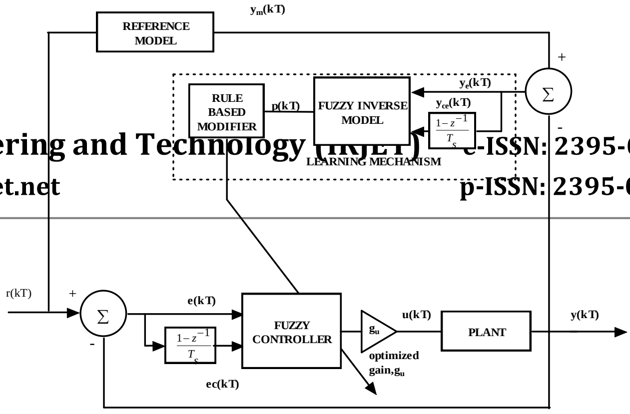
a) Observes data from a fuzzy control system (i.e. *r(kT)* and *y(kT)*)

b) Characterizes its current 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) (6)

yc(kT) = (ye(kT) – ye(KT-T)) / T (7)

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

$$\mu_i^e(e(kT-T))>0,\ i=\overline{1,n} \qquad (8)$$

$$\mu_j^c(c(kT-T))>0,\ j=\overline{1,m}$$

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*) (9)

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.

4. OPTIMIZATION GAIN (g_u)

Here scaling gain g_u is identified using an optimization technique by considering Integral Square Error as an objective function. In proposed EFMRLC, for a small number of output membership functions a small value of the gain g_u $(0 < g_u < 1)$ is sufficient for quick adaptation. In addition to that the small value of g_u decreases risk of instability of the adaptation mechanism.

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.

5. RESULTS AND DISCUSSION

In this section, To examine the performance of proposed EFMRLC at 44-45°C, it is realized from the Figure. **4** and Table 2 that the EFMRLC enhances the performances as well as reduces the ISE value to minimum of 1.544 after 37 sec.

Table 2. Performance indices in term of ISE and settling time(t_s) for servo response

	PID		NNIMC		EFMRLC	
	ISE	t_s	ISE	t_s	ISE	t_s
44-45°C	46.6	380	3.16	85	1.544	37
45-46°C	28.4	240	3.23	78	1.487	51
46-47°C	19.2	144	3.85	76	1.485	41
47-48°C	14.0	159	3.59	79	1.459	10
48-49°C	10.7	115	3.91	82	1.041	08

At the same time, the other two controller strategies reflect the poor performance (Figure. 4). The NNIMCand PID in STHE are capable of bringing the error to value of 3.16 & 46.67 respectively.

In the case of variations in different regions (45 - 49°C), the proposed EFMRLC behaves in the same trend of performance and brings minimum ISE error values as given in same Table 2. At the same time, other controllers give slow performance under all other conditions. The calculated ISE values as given in Table clearly indicate that the performance of NNIMC is moderate and PID is poor when compared to proposed EFMRLC.

Table 3. Performance indices in term of ISE and settling time(t_s) for servo regulatory response

	PID		NNIMC		EFMRLC	
	ISE	t_s	ISE	t_s	ISE	t_s
44-45°C	39.6	299	2.16	77	1.71	24
45-46°C	27.6	221	2.23	82	1.49	31
46-47°C	16	131	2.85	85	1.50	39
47-48°C	10.0	112	2.71	87	1.47	20
48-49°C	8.43	95	2.94	89	1.43	22

From the Figure. 5, in the adaptability test also EFMRLC gives satisfied performance and fetches minimum ISE error values. But the other controllers show their sluggishness in performance index as tabulated in Table 3 The results predict that a conventional PID and NNIMC exposes deficient performance as compared to EFMRLC.

6. CONCLUSION

This paper, a Enhanced Fuzzy Model Reference Learning Control (EFMRLC) is applied in to a non linear spherical tank system. Simulation runs are carried out by considering the EFMRLC algorithm, NNIMC and conventional PID-mode in a closed loop. The results clearly indicate that the incorporation of

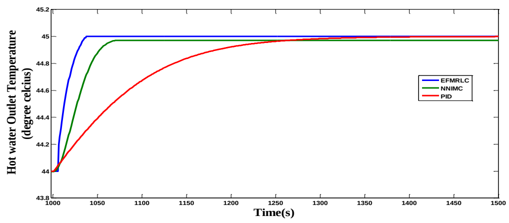


Figure.4 Servo Response of STHE at 44-45°C operation point

FMRLC in the control loop in spherical tank system provides a superior tracking performance than the NNIMC and conventional PI mode.

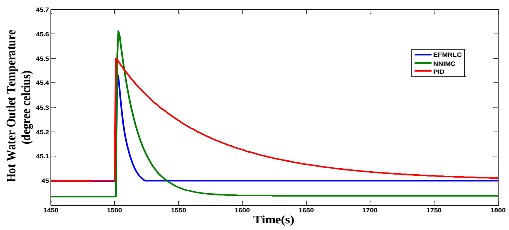


Figure.5 Regulatory Response of STHE at 45°C Operating point

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