Nonlinear Control of a Chemical Plant Employing a Combination of Fuzzy Logic and Particle Swarm Optimization Techniques

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ABSTRACT

Fuzzy logic control (FLC) systems have been tested in numerous practical and industrial applications as an important modeling tool that can cope with the uncertainties and nonlinearities of current control systems. The key shortcoming of the FLC approaches in the industrial environment is the number of tuning parameters to be chosen.

In this paper a technique has been offered for optimizing the membership functions of a fuzzy scheme using particle swarm optimization (PSO) algorithm. A mixture of fuzzy logic and PSO technique is employed to design a controller for a nonlinear chemical plant. To establish its efficiency, the proposed technique was employed to enhance the Gaussian membership functions of the fuzzy model of a nonlinear continuous stirred tank heater (CSTH); results show that the optimized membership functions (MFs) offered better performance than a fuzzy model for the same system when the MFs were heuristically described.

Keywords

Fuzzy logic control (FLC), Membership function (MF), Particle swarm optimization (PSO), Continuous stirred tank heater (CSTH).

1. INTRODUCTION

Using novel techniques for handling uncertain information is of fundamental significance. The broad framework of fuzzy reasoning allows handling much of this uncertainty, which characterizes uncertainty using numbers in the range [0, 1]. FLCs are established to employ human expert knowledge in designing control systems, particularly those imprecise and nonlinear systems.

Fuzzy systems are employed commonly, particularly on fuzzy control problems [5]. The goal of the fuzzy controllers in a CSTH is to drive the temperature to the anticipated set point using changes in the steam valve in the shortest time possible and to preserve the system at the required set point. To achieve this goal, the corresponding parameters of the MF of the FLC were optimized using PSO.

The PSO optimization method is a stochastic search through an n-dimensional problem space targeting the minimization (or maximization) of the objective function of the problem [2]. The PSO was constructed through the try to graphically mimic the choreography of a group of birds flying to resources. Later, searching for theoretical basics, studies were performed about the way individuals in groups interact, exchanging information and refining their adaptation to the situation. PSO produces faster convergence when compared to Genetic Algorithm, because of the balance between exploration and exploitation in the search space [13].

In this paper, we demonstrate a technique for constructing membership functions. The projected technique modifies membership function automatically based on Particle Swarm Optimization. The parameter values to be optimized are the mean value and standard deviation of each foot membership function. After particles attain the optimal result, the parameter value will be optimized by PSO and will be used to construct the whole new fuzzy membership functions.

2. PARTICLE SWARM OPTIMIZATION

A population-based optimization technique that discovers the optimal solution using a population of particles [1] is PSO. Every swarm of PSO is a solution in the solution space. PSO is basically developed through simulation of bird flocking. The PSO definition is presented as follows:

• Each distinct particle i has the following properties: A current position in search space, x_{id}, a current velocity, p_{id}, and a personal best position in search space, p_{id}.

• The personal best position, p_{id}, corresponds to the point in search space where particle i offers the smallest error as determined by the objective function f, assuming a minimization task.

• The global best position marked by represents the position producing the lowest error amongst all the p_{gd}.

During the iteration every particle in the swarm is updated using the following two equations:

$$V_{id}(t+1)=w*V_{id}(t)+c_1*r_1*(p_{id}-X_{id}(t))+c_2*r_2*(p_{gd}-X_{id}(t)) \quad (1)$$

$$x_{id}(t+1)=x_{id}(t)+v_{id}(t+1) \quad (2)$$

Where V_{id} (t+1) and V_{id} (t) are the updated and current particles velocities, respectively, $X_{id}(t+1)$ and $X_{id}(t)$ are the updated and current particles positions, respectively, c_1 and c_2 are two positive constants and r1 and r2 are normalized unit random numbers within the range [0,l]), and *w* is the inertia weight. The algorithm is illustrated in Figure 1.

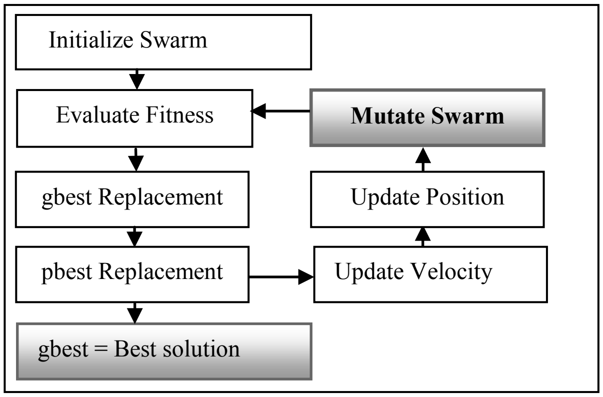

Fig 1: Flow chart depicting the general PSO algorithm.

3. OPTIMAL FLC DESIGN AND MODEL FORMULATIONS

FLCs are designed using expert knowledge that is in the form of rule-based behavior. In general the FLC rules are expressed in the form:

if input 1 is A and input 2 is B then output is C.

where antecedents A and B are declared by MFs [4]. A typical set of MFs are depicted in Figure 2.

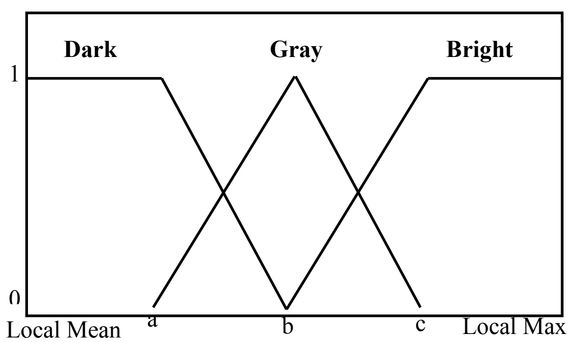

Fig 2: A typical set of MFs in an FLC.

There are two types of expressions for consequent C[7]. In Tagaki-Sugeno (TS)-type FLCs, the C is expressed as a linear combination of all inputs. On the other hand, if a Mamdani-type of FLC is used, C is expressed by a set of MFs. The process that is used to calculate the overall control action in FLC is determined by different type of defuzzification process. In general, a Centre of Area (CoA) method is commonly used, where the output u^* is calculated as[8]:

$$u^* = \frac{\int u m_o(u) du}{\int m_o(u) du} \tag{3}$$

The approach of using a PSO for MF tuning in FLC is shown in Figure 3. In the proposed PSO process, each particle is shaped to represent the MF parameters of the FLC's inputs and outputs. As the aim of the PSO is to minimize the control error of the FLC, the objective function of PSO is defined as:

$$f(x(k)) = \sum_{t=0}^{t_f} \varepsilon^2 \tag{4}$$

Where t_f is the total running time of the FLC, ε is the Control error.

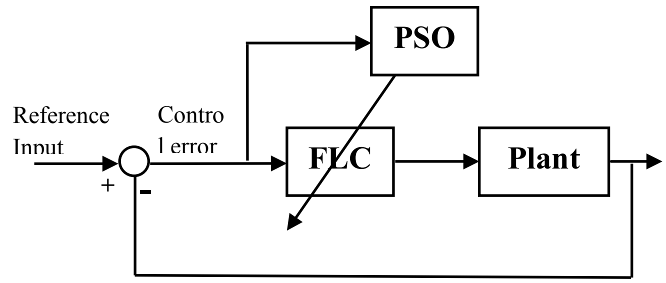

Fig 3: The PSO- FLC method.

The model consists of multi-input single-output (MISO) system with n number of inputs. The number of fuzzy sets for the inputs are m_1 , m_2 ,.., m_n.

There are some assumptions in the model formulation. These assumptions must be defined and available in advance as a basic integration of this hybrid algorithm. The assumptions are listed as below:

(i) Gaussian membership functions were used for input and output variables.

(ii) Complete rule-base was considered. A rule-base is considered complete when all possible combinations of input membership functions of all the input variables participate in fuzzy rule-base formation.

The integration between optimization algorithm and fuzzy logic problem is as follow:

(i) The parameters are the mean value and standard deviation of each fuzzy membership function.

(ii) These parameters act as particles and looking for the global best fitness.

(iii) It starts with an initial set of parameters.

(iv)After the parameters had been adjusted using optimization method, this parameter will be used to check the performance of the fuzzy logic.

(v) This process is repeated until the goal is achieved.

The optimization method as shown in Figure 4 starts with the initial set of parameters and employs the fitness function to obtain new values for the parameters of the membership function. These new values will be used in the case study considered in this paper.

These particle dimensions represent fuzzy membership function parameter values. The first column shows the input and output variables. All input and output MFs become different depending on their new position. The particle size for representing the Gaussian membership functions of input and output variables for a model is given by (5) and (6).

Particles dimension for input variables are:

$$\sum_{i=1}^{n} (2m_i) \tag{5}$$

where, n number of input variables and m number of fuzzy sets.

Particles dimension for output variable are:

$$\sum_{i=1}^{n} (2t) \tag{6}$$

where, n number of output variables and t number of fuzzy sets. The particle dimensions required for encoding the fuzzy model can be obtained in table 1.

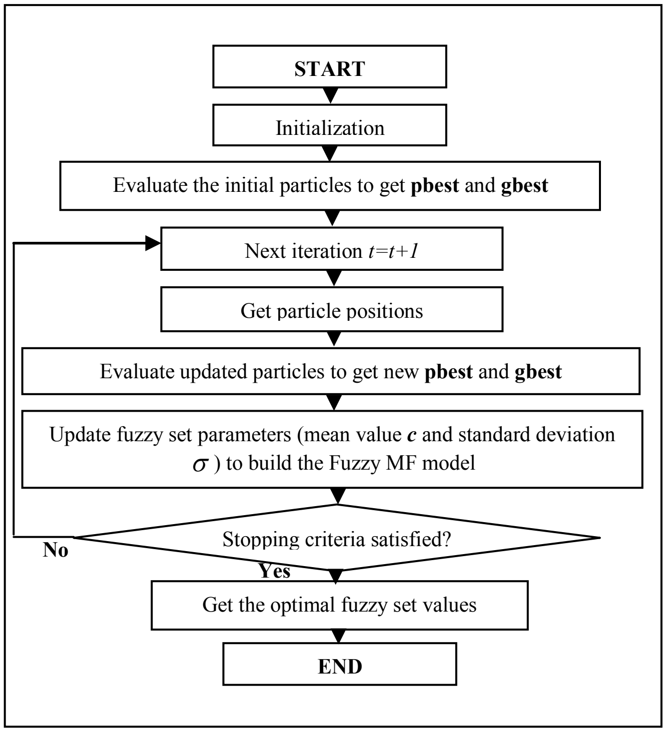

Fig 4: Flowchart of PSO to adjust fuzzy MFs.

Table 1. Particle dimension for representing fuzzy model.

	c	σ	c	σ	..	..	c	σ	
Input var #1	X11	X11	X12	X12		…	X1m	X1m	2m1
Input var #2	X21	X21	X22	X22	…	…	X2m	X2m	2m2
…	…	…	…	…	…	…	…	…	…
…	…	…	…	…	…	…	…	…	…
Input var #n	Xn1	Xn1	Xn2	Xn2	…	…	Xnm	Xnm	2mn
Output variable	Y1	Y1	Y2	Y2	…	…	Yt	Yt	2t

4. PROCESS DESCRIPTION MODEL

To demonstrate the effectiveness of the proposed PSO-MF tuning method, a nonlinear system is used in simulation. In particular, the case considered in this paper is the ~~No~~nlinear CSTH benchmark model, reported in [9]. is shown in Figure 5.

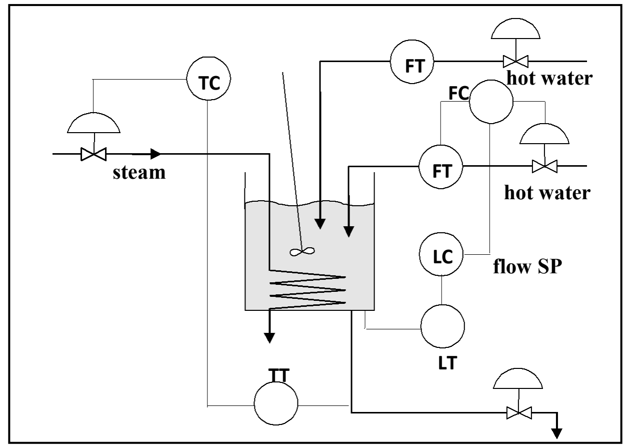

Fig 5:The schematic of CSTH.

The stirred tank heater model presented in this article is a hybrid simulation which uses measured data captured from a process to drive a first principles model. The noise and disturbances signals therefore have more complex and more realistic characteristics than if they were created by a random number generator. There are also experimentally measured data available for the purposes of identification.

The pilot plant in the Department of Chemical and Materials Engineering at the University of Alberta is a stirred tank experimental rig in which hot and cold water are mixed, heated further using steam through a heating coil and drained from the tank through a long pipe. The configuration is shown in Figure 5. The CSTH is well mixed and therefore the temperature in the tank is assumed the same as the outflow temperature. The tank has a circular cross section with a volume of 8l and height of 50 cm.

The cold and hot water (CW and HW) in the building are pressurized with a pump to 60 - 80 psi, and the hot water boiler is heated by the university campus steam supply. The steam to the plant comes from the same central campus source. Control valves in the CSTH plant have pneumatic actuators using 3 - 15 psi compressed air supply, the seat and stem sets being chosen to suit the range of control. Flow instruments are orifice plates with differential pressure transmitters giving a nominal 4-20 mA output. The level instrument is also a differential pressure measurement. Finally, the temperature instrument is a type J metal sheathed thermocouple inserted into the outflow pipe with a Swage lock T–fitting.

4.1 Volumetric and Heat Balance

The dynamic volumetric and heat balances are shown in the following equation:

$$\frac{dV(x)}{dt} = f_{cw} + f_{hw} - f_{out}(x) \tag{7}$$

$$\frac{dH}{dt} = W_{st} + h_{hw}\rho_{hw}f_{hw} + h_{cw}\rho_{cw}f_{cw} - h_{out}\rho_{out}f_{out}(x) \tag{8}$$

Where x is the level; V the volume of water; f_{hw} the hot water flow into the tank; f_{cw} the cold water flow into the tank; f_{out} the outflow from tank; H the total enthalpy in the tank; h_{hw} the specific enthalpy of hot water feed; h_{cw} the specific enthalpy of cold water feed; h_{out} the specific enthalpy of water leaving the tank; ρ_{cw} the density of incoming cold water; ρ_{hw} the density of incoming hot water; ρ_{out} the density of water leaving the tank; and W_{st} the heat inflow from steam.

The temperatures of the hot and cold water feeds were set to 50 °C and 24 °C respectively in the base case simulation. The inputs to the CSTH are electronic signals in the range 4-20 mA that go to the steam and cold water valves.

Table 2.Relationship between heat transfer rate and steam valve

Valve/mA	T/C°	H_{out} /kgm^{-1}	ρ_{out} /kgm^{-3}	W_{st}/kjs^{-1}
4	24	100.6	997.1	0
7.5	30	125.7	995.2	2.24
9	31	129.9	994.8	2.61
11	36.5	152.8	992.9	4.65
14	48	200.9	988.7	8.89
17	61	255.3	982.3	13.60
20	65	272.0	980.2	15.04

4.2 The simulink Platform

For numerical solution of the CSTH model equations its needed to an equation–based simulator and in this thesis the simulation was carried out in simulink. Figure 6 represents the CSTH simulated model implemented in MATLAB simulink environment.

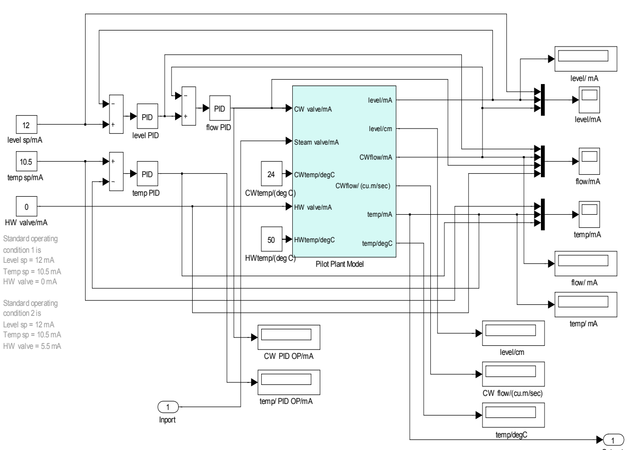

Fig 6: Simulink blocks diagram that represents the CSTH simulated model.

When the stirred tank heater operates with both hot and cold water feed the steady state valve positions and instrument conditions in the operating point shown in Table 3.

Table 3. Operating points for benchmark system.

Variable	Operating Point
Level/mA	12.00
Level/cm	20.48
CW flow/mA	7.33
CW flow/m^{3}s^{-1}	3.823*10^{-5}
CW vave/mA	7.704
Temperature/mA	10.50
Temperature/C°	45.52
Steam valve/mA	6.053
HWvave/mA	5.5
HW flow/m^{3}s^{-1}	5.512*10^{-5}

Fig 7 shows the feedback control system that was used to construct the control system. Here y(k) is the output signal of the plant, g(k) is the set point signal, and e(k) is the error. It was implemented in MATLAB where the controllers were designed independently to follow the input as closely as possible.

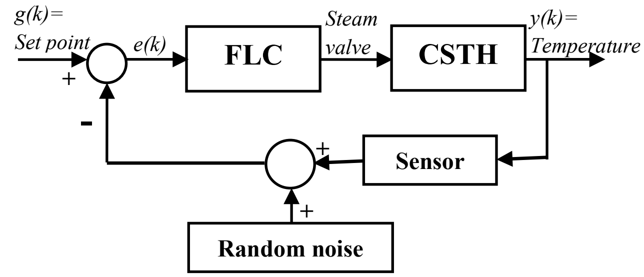

Fig 7: Block diagram of the fuzzy control systems.

In this case, as is shown in Figure 7, uncertainty is added to the system's output where it is simulated introducing random noise with normal distribution. The reference input is stable and noisy free but the feedback at the summing junction is noisy since we introduced deliberately noise for simulating the overall existing uncertainty in the system. In consequence, the controller's inputs e (error) contains uncertain data.

5. SIMULATION RESULTS

FLC output is the voltage change required to operate the valve change required to achieve desired concentration**.** In this section, two Fuzzy controllers (Conventional FLC, PSO tuned FLC) will be compared. For numerical solution of the CSTR model equations it's needed to an equation–based simulator and in this thesis the simulation was carried out in simulink.

In this case, the value of each process variable should be scaled properly to fit the specific interval. Furthermore, Gaussian shapes are considered for the membership functions. for input and output Seven such functions are used with the locations of their centers is as shown in Figure 8. Gaussian shape is selected because it is continuous function and can be easily coded in a digital computer. The number of fuzzy sets is chosen arbitrary, however increasing it will increase the number of control rules which has little benefit. The relative location of their center will be adjusted automatically using our proposed tuning method as discussed before.

5.1 Conventional FLC

The initial MFs for the inputs are shown in Figure 8. For the input of this FLC, seven fuzzy Gaussian MFs were defined: NB, NM, NS, ZE, PS, PM, and PB. The universe of discourse for these MFs is in the range[-3,3] and their initial mean is -3,-2,-1,0,1,1,and 3 respectively. The initial standard deviation for all MFs is 0.42. Figure 8 shows the input membership functions for the FLC and Fuzzy controllers have been designed and tested based on sugeno inference mechanism.

For the output of the FLC, centroids of FSs for consequent MFs were considered. There are seven consequent MFs, named, close_fast, close_smooth, close_slow, no_change, open_slow, open_smooth, and open_fast. They are on the interval [4,20] and their supports are 4,7,10,12,14,17,and 20 respectively.

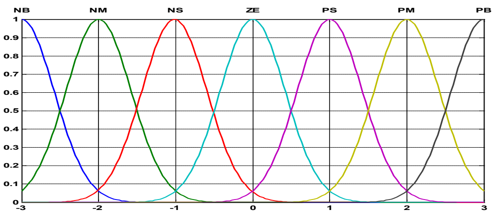

Fig 8: MFs for conventional FLC.

Using the fuzzy linguistic labels and their semantics described earlier, seven fuzzy rules have been considered to construct the fuzzy rule base. These rules are as follows:

1. If (e is NB) then (Steam valve is close_fast)
2. If (e is NM) then (Steam valve is close_smooth)
3. If (e is NS) then (Steam valve is close_slow)
4. If (e is ZE) then (Steam valve is no_change)
5. If (e is PS) then (Steam valve is open_slow)
6. If (e is PM) then (Steam valve is open_smooth)
7. If (e is PB) then (Steam valve is open_fast)

For FLC, the minimum operator is used as ~~the~~ tnorm, and centroid method for defuzzification.

To evaluate the merit of each fuzzy controller, Sum of Squared Error (SSE) that is given by Eq.(9) is used as performance criteria.

$$F = \sum_{j=1}^{N} \left[e(j) \right]^2 \qquad (9)$$

Where e the difference between the set point and the actual,which is output at the j_{th} sampling, and, N is the number of sampling instants.
Fig 9 represents the schematic of the CSTH simulated model implemented in the MATLAB/Simulink environment.

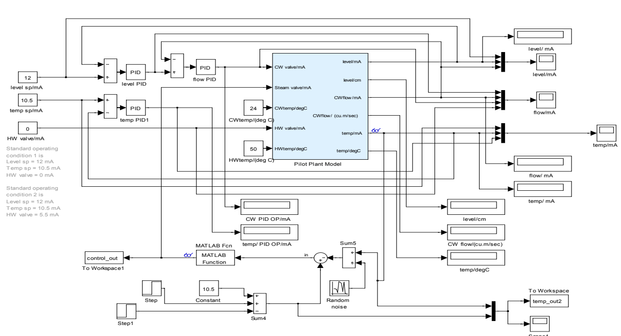

Fig 9:CSTH simulated model in Simulink with pso- FLC.

5.2 PSO tuned FLC

Gaussian forms are used in this FLC for all MFs. The parameters that define the MFs are the mean c and the deviation σ of each MF. The membership function is defined as:

$$f_{mf}(x) = e^{-(x-c)^2/(2\sigma^2)} \qquad (10)$$

Figure 10, show the optimized MFs of FLC respectively. This criterion is used by PSO to evaluate the fitness of each candidate solution. Since there are 7 input MFs, there are a total of 14 parameters that need to be tuned. Therefore, in the PSO, each particle must have 14 dimensions. This is a set which has 40 particles in the swarm and the total searching iterations are set to be equal to 250. The inertia factor w was set to be equal to 0.6 and weighting factors c_1 and c_2 were set to be 1.5 and 0.9, respectively. The objective function that evaluates the fitness of each particle was defined as (9). The PSO parameters were set as in Table 5.1.Therefore, after the proper tuning of the MFs, the FLC will have a minimized control error. Table 4 shows the MF parameters before and after the PSO tuning process.

Table 4 PSO Parameter for CSTH problem

Parameter	Value
C_1	1.5
C_2	0.9
Inertia w factor	0.6
Number of particle	40
Searching iterations	250
Fitness	SSE

Table 5. MF Parameters before and after the PSO

MF input	Before PSO Mean(c)	STD( )	After PSO Mean(c)	STD( )
NB	-3	0.42	-2.91	0.44
NM	-2	0.42	-1.29	0.53
NS	-1	0.42	-0.29	0.21
ZE	0	0.42	-0.02	0.03
PS	1	0.42	0.26	0.21
PM	2	0.42	1.68	0.53
PB	3	0.42	2.98	0.44

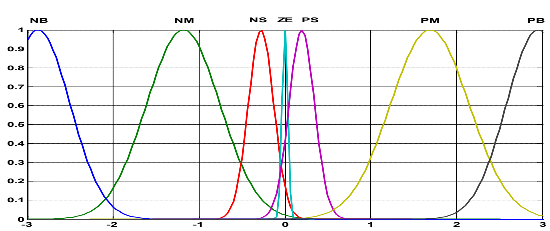

Fig 10: Optimized MFs for PSO-FLC.

Step response curves of the two FLCs are shown in Figure 11 and 12. Best SSE values for these two fuzzy controllers are summarized in table 6.

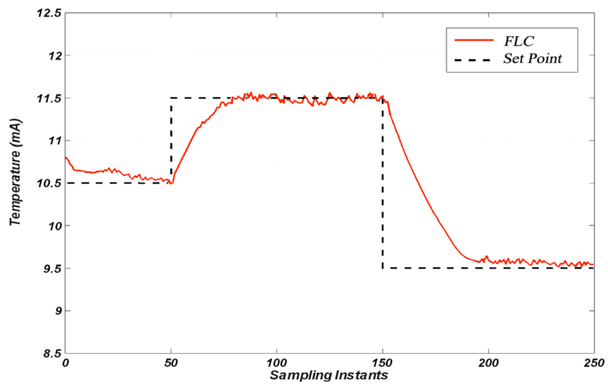

Fig 11: Step response for FLC.

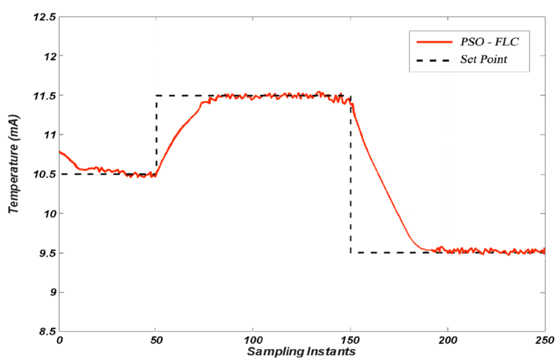

Fig 12: Step response for PSO-FLC.

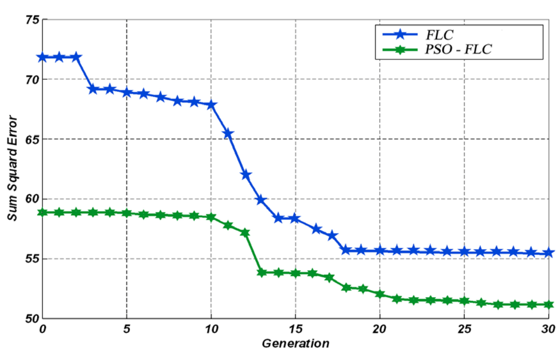

Fig 13: Relationship between generation and sum of squared error (SSE).

Table6.Comparison of the two FLC.

Control Structure	SSE
conventional FLC	56.25
tuned FLC (PSO-FLC)	51.71

Comparison between the control results obtained from FLC and PSO-FLC (in Figure 11 and 12 respectively) clearly shows that PSO-FLC gives more accurate and acceptable results rather than conventional FLC. Therefore, it is clear that the PSO-FLC control call achieve the desired output better than conventional FLC.

The superior of PSO-FLC over than FLC also can be seen in Table 6 and Figure 13 where the sum of square error (SSE) of PSO-FLC is less than conventional FLC.

6. CONCLUSIONS

Today, using fuzzy controllers is prevalent in controlling chemical plants. But the mere fuzzy controller has some disadvantages. The major disadvantage is lacking analytical design technique (the determination of parameters of MFs,..). In this paper, for resolving this problem, PSO is used. PSO determines the optimum fuzzy membership function which results in a high control performance. The new control strategy is applied on a model of CSTR, which have the inherent nonlinear characteristics.

The results show clearly that the optimized FLC has better performance in compare with a conventional controller in the presence of additive random noise. The concentration of a CSTR is controlled by means of two different fuzzy controllers. According to the results of the computer simulation, the FLC with PSO algorithm acts better than the conventional FLC without PSO algorithm.

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