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TEMPERATURE CONTROL OF A CONTINUOUS STIRRED TANK REACTOR BY MEANS OF TWO DIFFERENT INTELLIGENT STRATEGIES

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ABSTRACT- Continues Stirred Tank Reactor (CSTR) is an important subject in chemical process and offering a diverse range of researches in the area of the chemical and control engineering. Various control approaches have been applied on CSTR to control its parameters. This paper presents two different control strategies based on the combination of a novel socio-political optimization algorithm, called Imperialist Competitive Algorithm (ICA), and concept of the gain scheduling performed by means of the least square and fuzzy logic approaches. The goal is to control the temperature of the

CSTR in presence of the set point changes. The works followed with designing those controllers and simulating in MATLAB software. The performance of the proposed controllers have been consider based on the Sum of the Square Error (SSE) and Integral Absolute Error(IAE) Criteria. The results clearly indicate that both suggested control strategies offer an acceptable performance with respect to the functional changes of the process. In other word, robustness of the proposed methods in dealing uncertainties throughout the tracking of the reference signal take the highlighted point into account. Furthermore, fuzzy based structure strategy gives the more flexibility and precise behavior in control action in comparison to the least square based approach.

Index terms: CSTR, modeling, ICA, PI controller, gain scheduling, fuzzy controller

I. INTRODUCTION

The problem of controlling of CSTR is considered as an attractive and controversial issue, especially for control engineers, corresponding to its nonlinear dynamic. Most of the conventional controllers are restricted just for linear time invariant system applications. However, in real environment, the nonlinear characteristics of the systems and their functional parameters changes, due to wear and tear, cannot be neglected. Furthermore, dealing the systems with uncertainties in real applications, is the another subject which must be noticed. In this way, the role of the adaptive and intelligent controllers, by the capability of the overcoming the aforementioned points are of the importance.

One of the most popular controllers both in the realm of the academic and industrial application is PID. PID controller has been applied in feedback loop mechanism and extensively used in industrial process control since 1950s .Easy implementation of PID controller, made it more popular in system control applications. It tries to correct the error between the measured outputs and desired outputs of the process in order to improve the transient and steady state responses as much as possible. In one hand, PID controller appear to have an acceptable performance in the most of systems, but sometimes there are functional changes in system parameters that need an adaptive based method to achieve more accurate response. Several researches are available that combined the adaptive approaches on PID controller to increase its performance with respect to the system variations [1], [2]. In another hand, although PID controller is used widely in the area of both academic and industrial control applications, its tuning is still the controversial scope of investigation.

Limitations of traditional approaches in dealing with constraints are the main reasons for emerging the powerful and flexible methods. Bio- inspired intelligent computing has been successfully applied to solve the complex problem in recent years. Genetic algorithm, neural network and fuzzy logic expressed the high capability to overcome the aforementioned issues [3]. Success of the fuzzy logic, which is based on the approximate reasoning instead of crisp modeling assumption, remarks the robustness of this method in real environment application [4]. It can also observe the practical implementation of fuzzy logic, in fuzzy controller, due to employ as an intelligent controller in real control application. Fuzzy logic controller emulates the behavior of the experts in controlling the system. Not needing the precise mathematical modeling is a remarkable merit, causes fuzzy controller more flexible in dealing with complex nonlinear problem. Strictly depend to the expert knowledge, which make the rule bases, is one of the remarkable issues in designing the fuzzy controllers.

In both mentioned controllers, PID and fuzzy, the challenge is fine design and tuning in order to achieve accurate and acceptable results. In PID tuning, optimization algorithms such as GA, PSO, and ACO are drastically used to find the optimum values of PID parameters [5], [6] .In addition, these bio-inspired algorithms, can help individual to design desired fuzzy controller [7]. The strategy toward the optimum designation in this paper is employing a heuristic search algorithm, named ICA, which finally offers the parameters so that the criteria of the control scheme would be optimized. In order to accommodate the nonlinearity, and set point variations, a gain scheduled control scheme is investigated, as well. A gain scheduled control system consists of a family of controllers (Local Controllers) and a scheduler. The scheduler selects the controller depending on the operating region. In the first part, concept of the gain scheduling is applied to design the online PI controller based on the least square approach. ICA offers the optimum value of the PI throughout this strategy. Next, fuzzy gain scheduling is exploited as an intelligent method, by relying on ICA, to construct a fuzzy-PI controller with ability of online tuning with respect to the time. An analysis of the performance will be carried out to the both controllers, so that the best performance can be identified.

II. MATHEMATICAL MODELING OF THE CSTR

Chemical reactions in a reactor are either exothermic or endothermic and therefore require that energy either be removed or added to the reactor for a constant temperature to be maintained. Figure 1 illustrates the schematic of the CSTR process. In the proposed CSTR, an irreversible exothermic reaction takes place. The heat of the reaction is removed by a coolant medium that flows through a jacket around the reactor. A fluid stream A is fed to the reactor. A catalyst is placed inside the reactor. The fluid inside the reactor is perfectly mixed and sent out through the exit valve .The jacket surrounding the reactor also has feed and exit streams. The jacket is assumed to be perfectly mixed and at a lower temperature than the reactor [8], [9]. The mathematical model equations are obtained by a component mass balance (1) and energy balance principle (2) in the reactor.

(Accumulation of component Mass) = (component Mass) $_{in}$ - (component Mass) $_{out}$ + (generation of component Mass) (1)

(Accumulation U + PE + KE) = (H + PE + KE) $_{in}$ - (H+PE+KE) $_{out}$ + Q-Ws (2)

The dynamic equation of CSTR is [10], [11]:

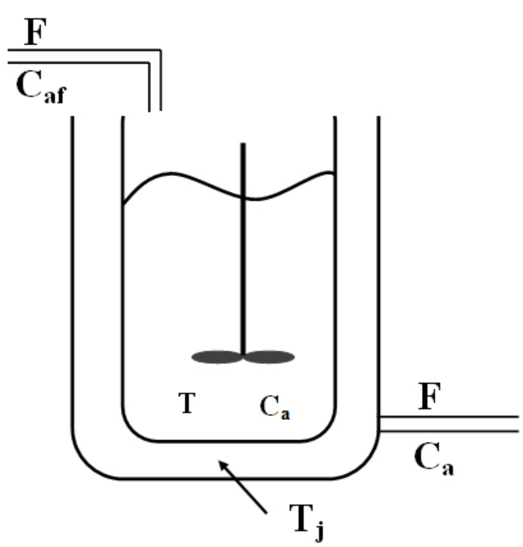

Figure 1. CSTR process

$$\frac{dc_a}{dt} = (\frac{F}{V}).(ca_f - c_a) - k_0.\exp\left[\frac{E}{R.(T+460)}\right].c_a \tag{3}$$

$$\frac{dT}{dt} = (\frac{F}{V}).(T_f - T) - \frac{\Delta H}{\rho.C_p}.\left[k_0.\exp[-\frac{E}{R.(T+460)}].c_a\right]$$
$$-(\frac{U.A}{\rho.C_p.V}).(T - T_j) \tag{4}$$

where T_j is the jacket temperature as the input, while C_a and T are concentration and temperature of reagent as the outputs respectively. It should be noted that the objective of control is to manipulate the jacket temperature T_j so it keeps the temperature of the system at the desired level. All parameters are shown as follows:

Table 1: Mathematical model parameters of CSTR

variables	**values**	**Unit**
Ca	na	lbmol/ft ^{3}
T	na	
Ea	32400	BTU/lbmol
K0	1.50E+13	Hr $^{-1}$
ΔH	-45000	BTU/lbmol
U	75	BTU/hr-ft^2 -of
ρ	53.25	BTU/ft ^{3}
R	1.987	BTU/lbmol-of
V	750	ft ^{3}
F	3000	ft^3 /hr
Ca_f	0.132	lbmol/ft^3
T_f	60	
A	1221	ft^2

III. GAIN SCHEDULING

Gain-scheduling is a well-known technique of industrial control and it is employed when a plant is subject to large changes in its operating state, a situation that is typical in industry. Large changes in the operating state lead to corresponding variations in the parameters of the linearized models of the plant about these operating states, it is well known that it is not possible therefore to design a controller to operate satisfactorily at one operating state and expect it to perform equally well elsewhere without re-tuning it. The performance of the system is degraded since the controller cannot track the changes in the operating states. Considerable effort has gone into developing controllers that can track the variations in plant parameters with a view to achieving invariant operation throughout the domain of operation of the plant. Adaptive controllers are one such approach, yet even these controllers do not always demonstrate satisfactory performance throughout the domain of operation of the plant and may, on occasion, lose control altogether. Robust controllers, another approach, also have their limitations since they must deal with system dynamics that vary over a wide range though using constant parameters only. Clearly this class of controllers can only operate satisfactorily over a limited domain [8], [9].

In this study, gain scheduling is utilized in two different structures. In the first strategy, it is applied to online tuning of the conventional PI controller, which has the obligation of controlling the temperature of CSTR in presence of set point changes. The model structure is offered based on least square method. The method of least squares is a standard approach in system identification for identifying the parameters. Least squares mean that the overall solution minimizes the sum of the squares of the errors made in solving every single equation [12]. It can be mentioned that data fitting is an important least square applications. The best fit corresponding to the least-squares need the accurate input and output data set. To gather the appropriate data, which is used to obtain the adaptive model, the original applied set point to the CSTR is divided into three parts. Figures 2, 3 illustrate the original set point, and its subdivisions. Least square method maps the set point information as the inputs to the proportional gain (K_P) and integral gain (K_I) as the outputs based on the second order equation.

$$K_I = a_0 + a_1 x + a_2 x^2 \qquad (5)$$

$$K_P = b_0 + b_1 x + b_2 x^2 \qquad (6)$$

$$\begin{bmatrix} K_{P1} \\ K_{P_2} \\ K_{P_3} \end{bmatrix} = \begin{bmatrix} 1 & x_1 & x_1^2 \\ 1 & x_2 & x_2^2 \\ 1 & x_3 & x_3^2 \end{bmatrix} \begin{bmatrix} a_0 \\ a_1 \\ a_2 \end{bmatrix} \qquad (7)$$

$$\begin{bmatrix} K_{I_1} \\ K_{I_2} \\ K_{I_3} \end{bmatrix} = \begin{bmatrix} 1 & x_1 & x_1^2 \\ 1 & x_2 & x_2^2 \\ 1 & x_3 & x_3^2 \end{bmatrix} \begin{bmatrix} b_0 \\ b_1 \\ b_2 \end{bmatrix} \qquad (8)$$

$$a_i , b_i = (F^T.F)^{-1}.F^T.Y \qquad (9)$$

where x_i for =1, 2, 3 indicate the set point information, K_{P_i} for = 1, 2, 3 and K_{I_j} for = 1,2,3 are the proportional and integral gains of the proposed PI controller ,related to the first, second, and third part of subdivision set point that individually applied to plant. In other word, three individual PI controllers are applied on the CSTR corresponding to divided set point so that the sum square error (SSE) is minimized. This way prepares the data set for K_P and K_I to substitute part of equations (7), (8).

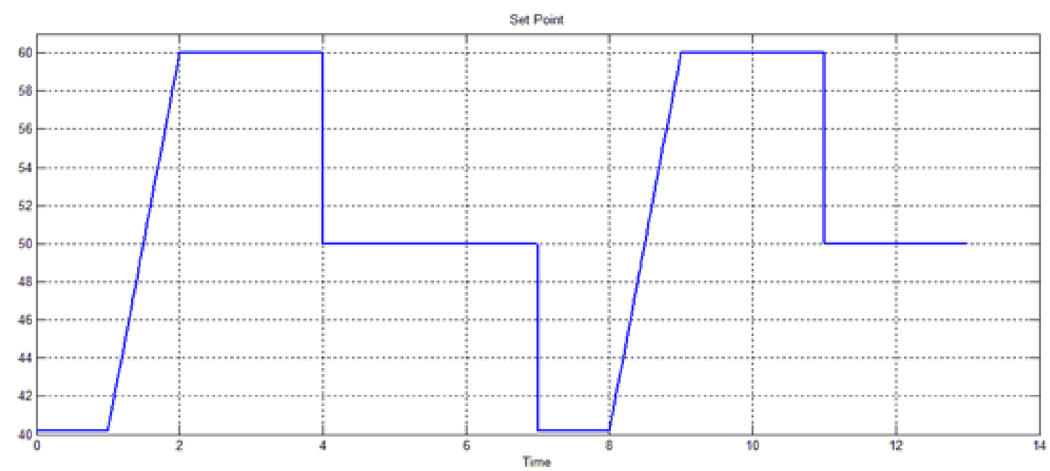

Figure 2. Original set point signal

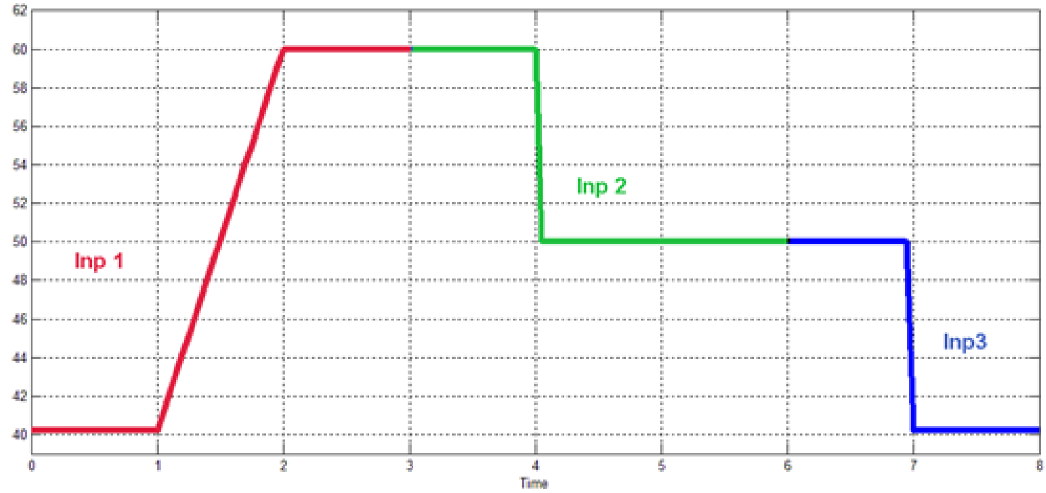

Figure 3. Subdivisions of set point signal

The controversial issue in data gathering is tuning the PI by optimum value of K_P and K_I in each part in order to have an accurate fitting model. There are several methods that result in optimum value of PI parameters. Successes of evolutionary algorithms such as GA, PSO, and ACO in the area of the optimization, problems inspire researchers to utilize these methods in overcoming their problems [5], [6]. PI controller parameters in this study are determined by ICA that is presented in the next part of this paper.

In the second strategy, gain scheduling approach is described based on fuzzy logic concept. It means that a fuzzy construction is playing the role of the critic to on line tuning of the PI parameter, and entirely form an intelligent fuzzy-PI. Regarding the control signal based on the PI structure shown in (10):

$$u_p(t) = k_p e(t) + k_i \int_0^t e(t)dt \qquad (10)$$

Fuzzy gain scheduling (FGS) structure includes e(t) and de(t),which are error and derivative of error as inputs, and K_p, K_i as outputs. The bound for the error is [-10 10] and for the derivative of error is [-192 56], depicted in Figure 5, 6, while the changes of K_P is done in the bound of [10 18] and for K_i these variations are in [50 73.48].The main role of FGS is online tuning of the proportional and integral gains based on the fuzzy computation. Figure 7 shows the graphic representation of FGS structure.

The proposed structure makes decision to set the value of the K_P, and K_i parameters automatically with respect to the time, based on the 9 rules determined by the expert. In Table 2, rules base corresponding to the changes in e(t) and de(t) are depicted.

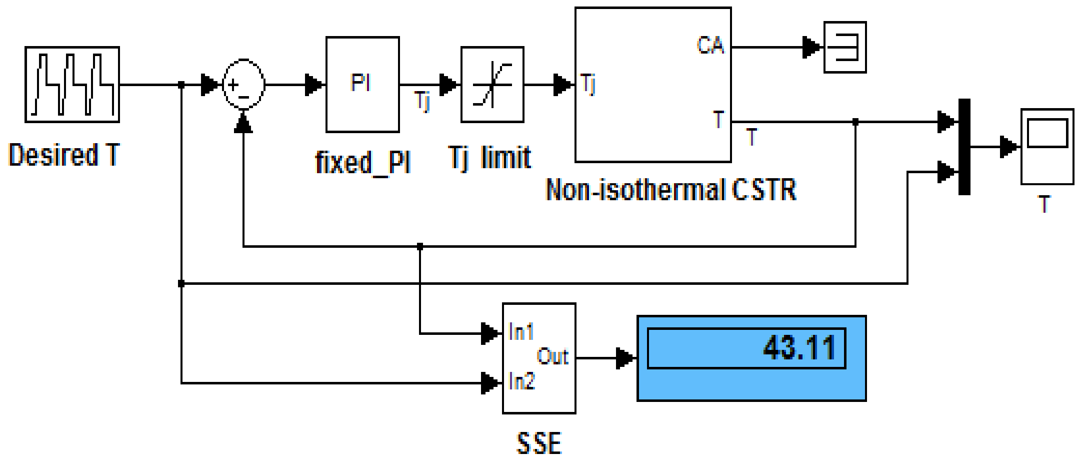

Figure 4. Closed loop configuration of the plant

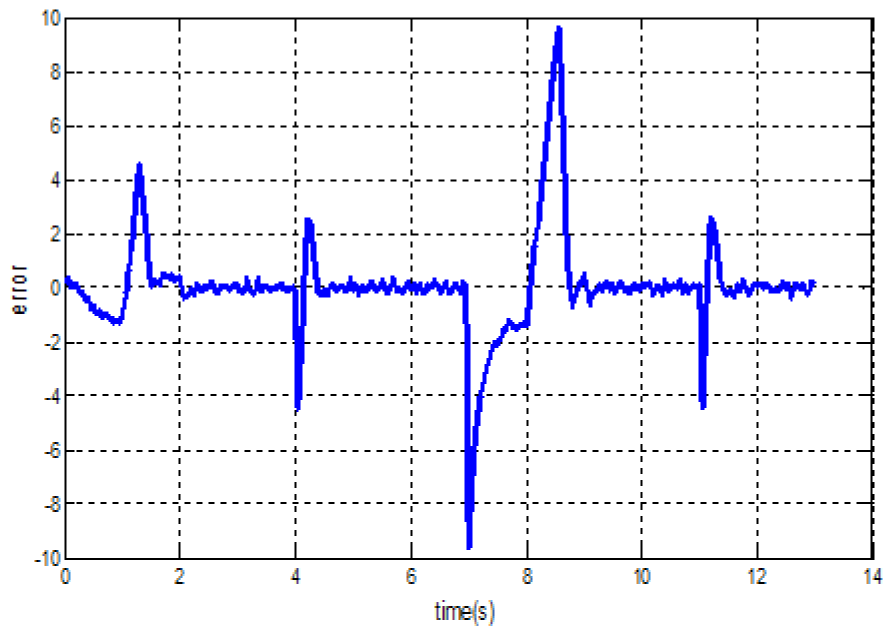

Figure 5. Bound of the error variations

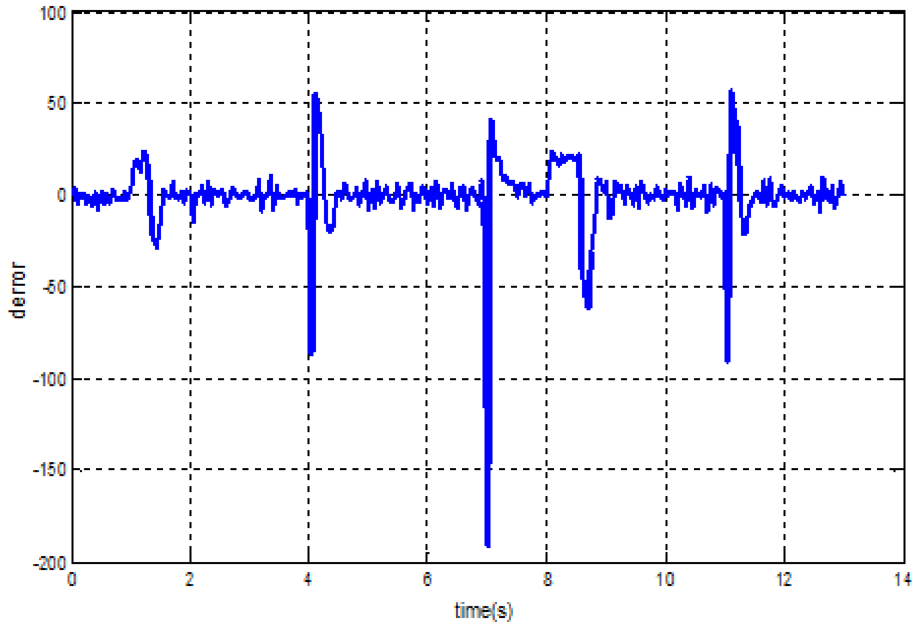

Figure 6. Bound of the derivative of error variations

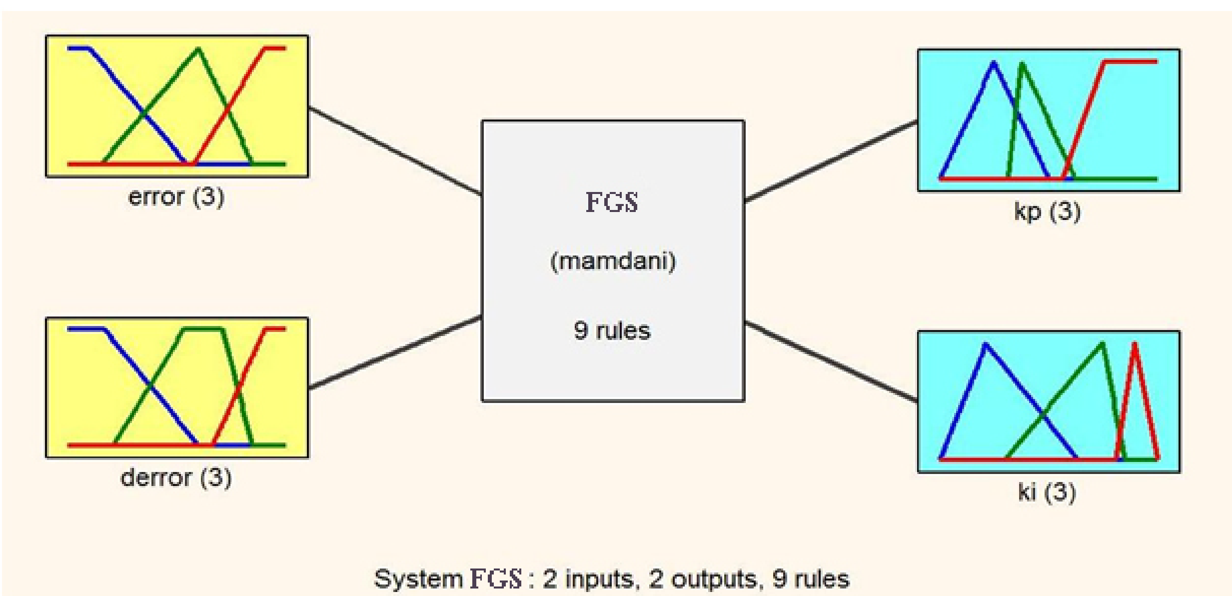

Figure 7. Graphical representation of fuzzy gain scheduling structure

Table 2. Rule base for fuzzy inference engine

derror / **error**	**Negative**	**Zero**	**Positive**
Negative	Negative	Negative	Positive
Zero	Negative	Zero	Positive
Positive	Negative	Positive	Positive

However, appropriate response of the plant to the various set point signals is directly related to the value of the parameters K_p, and K_i which are determined by FGS. To satisfy this issue, a novel strategy is needed to design more accurate membership function of inputs and outputs fuzzy sets. This strategy is introduced in the form of optimization problem. A global search algorithm called ICA was employed to find the appropriate membership function partitions. In the next part, this algorithm is introduced.

IV. Brief Description of Imperialist Competitive Algorithm

Imperialist competitive algorithm was introduced first time by E.A.Gargary and C.Lucas in 2007 [13]. It is a global heuristic search method that uses imperialism and imperialistic competition process as a source of inspiration.

This algorithm starts with some initial countries. Some of the best countries are selected to be the imperialist states and all the other countries form the colonies of these imperialists. The colonies are divided among the mentioned imperialists based on their power. After dividing all colonies among imperialists and creating the initial empires, these colonies start moving toward their relevant imperialist state. This movement is a simple model of assimilation policy. The algorithm can be described in the seven steps below [13]

Step 1: The initial population for each empire should be generated randomly.

Step 2: Move the colonies toward the irrelevant imperialist.

Step 3: Exchange the position of a colony and the imperialist if its cost is lower.

Step 4: Compute the objective function of all empires.

Step 5: Pick the weakest colony and give it to one of the best empires.

Step 6: Eliminate the powerless empires.

Step 7: If there is just one empire, stop, if not go to 2.

The movement of a colony towards the imperialist is shown in (11). Figure 8 also illustrates this structure. In this movement, θ and x are random numbers with uniform distribution and d is the distance between colony and the imperialist.

$$\begin{aligned} & x \sim (0, \beta \times d) \\ & \theta \sim U(-\gamma, \gamma) \end{aligned} \qquad (11)$$

where β and γ are arbitrary numbers that modify the area that colonies randomly search around the imperialist. β and γ are 2 and 0.5 (rad), in our implementation, respectively. The total power of an empire depends on both the power of the imperialist country and the power of its colonies. This fact is modeled by defining the total power of an empire by the power of imperialist state plus a percentage of the mean power of its colonies. In imperialistic competition, all empires try to take possession of colonies of other empires and control them. This competition gradually brings about a decrease in the power of weak empires and an increase in the power of more powerful ones. This competition is modeled by just picking some (usually one) of the weakest colonies of the weakest empires and making a competition among all empires to possess these (this) colonies. Figure 9 shows a big picture of the modeled imperialistic competition.

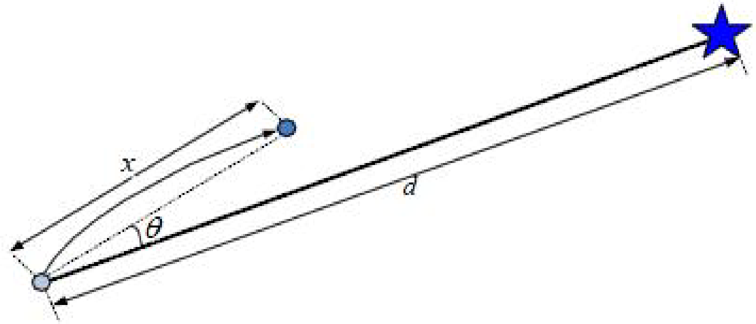

Figure 8. Movement of colonies toward their relevant imperialist in a randomly deviated direction

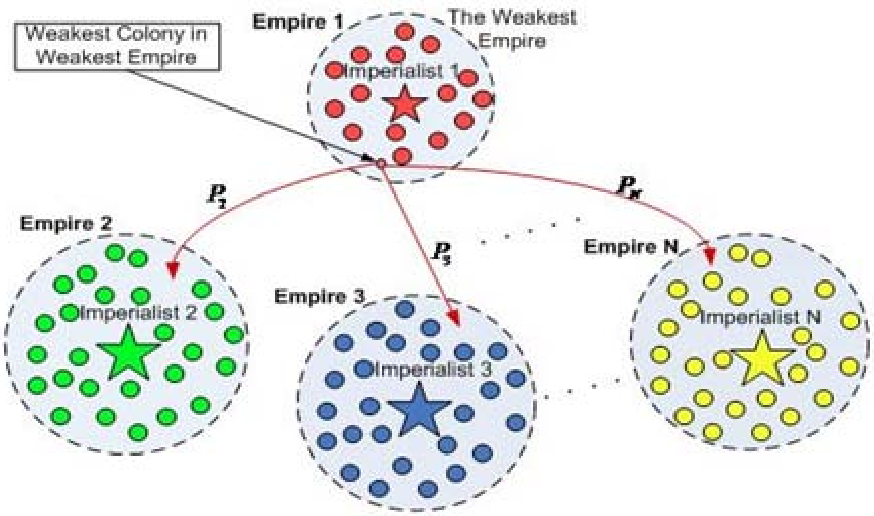

Figure 9. Imperialistic competition: The more powerful an empire is, the more likely it will possess the weakest colony of weakest empire

Based on their total power, in this competition, each of empires will have a likelihood of taking possession of the mentioned colonies. The more powerful an empire, the more likely it will possess these colonies. In other words these colonies will not be certainly possessed by the most powerful empires, but these empires will be more likely to possess them. Any empire that is not able to succeed in imperialist competition and cannot increase its power (or at least prevent decreasing its power) will be eliminated. The imperialistic competition will gradually result in an increase in the power of great empires and a decrease in the power of weaker ones. Weak empires will gradually lose their power and ultimately they will collapse.

The movement of colonies toward their relevant imperialists along with competition among empires and also collapse mechanism will hopefully cause all the countries to converge to a state in which there exist just one empire in the world and all the other countries are its colonies. In this ideal new world colonies have the same position and power as the imperialist [13], [14].

To exploit ICA in our designation, firstly, it is initialized by number of 80 countries and 8 empires, and selected 80 iterations, which lead to the optimum value for proposed PI parameters. Next, in the case of FGS, the algorithm is initialized by number of 120 countries, 10 empires, and 100 iterations, which result in optimum fuzzy membership functions. The revolution rate is equal to 0.5 and the cost function is defined as Sum of Square Error (SSE) for the both cases. ICA offers the optimum parameters and membership functions so that the SSE is minimized.

V. SIMULATION AND RESULT

a. PI gain scheduling

In this part, an adaptive PI controller is completed based on the second order model and ICA algorithm discussed in section III, and IV. The optimum K_P and K_I related to each part of the subdivision set point based on ICA are illustrated in Table 3.

Table 3. Optimum values for K_P, K_I

Signal Number	**K_P**	**K_I**
Input 1	10	50
Input 2	18.97	73.48
Input 3	17.75	50

Figures 10, 11, and 12 illustrate the response of non-isothermal reactor related to input signal mentioned previously, with respect to the optimum K_P, and K_I in PI controller.

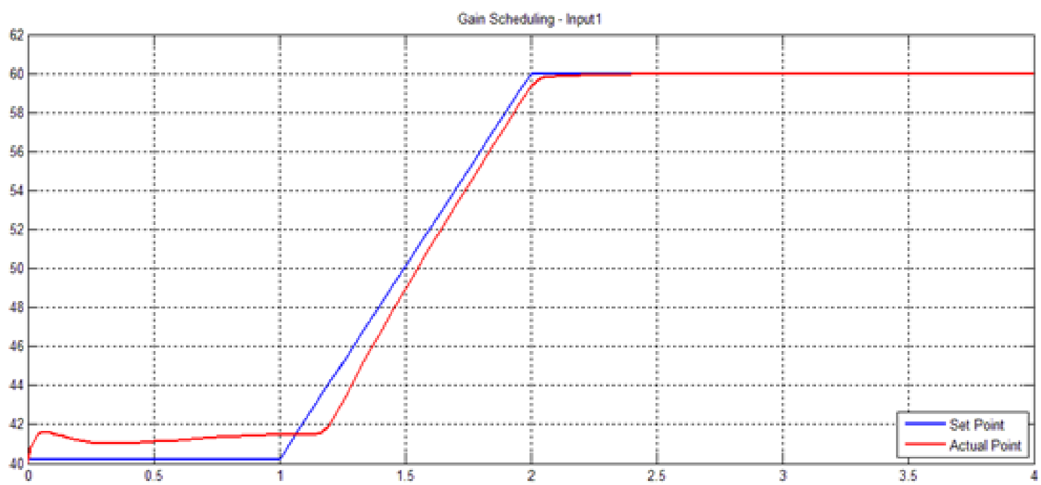

Figure 10. Plant's response to input 1, K_P = 10, K_I = 50.

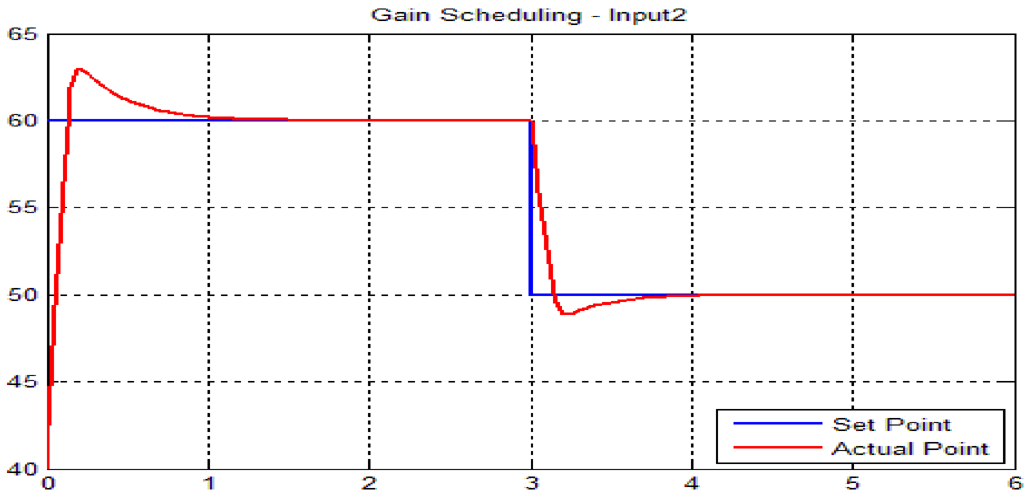

Figure 11. Plant's response to input 2, K_P = 18.97, K_I = 73.48.

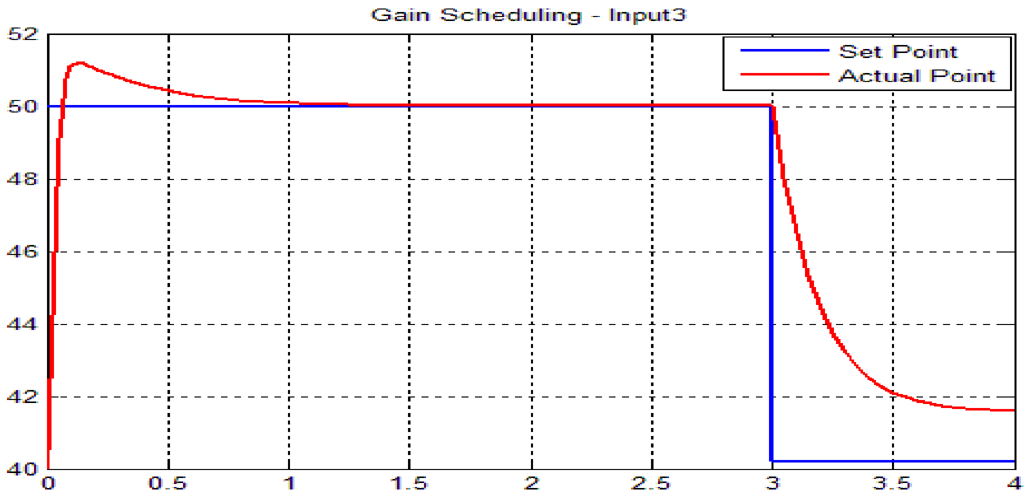

Figure 12. Plant's response to input 3, K_P = 17.75, K_I = 50.

By substituting the optimum value of K_P, and K_I in (7), (8), consequently, the obtained coefficient values are:

$$Y = \begin{bmatrix} 60 \\ 50 \\ 40.2 \end{bmatrix} \qquad F = \begin{bmatrix} 1 & 10 & 100 \\ 1 & 18.97 & 359.86 \\ 1 & 17.75 & 315.06 \end{bmatrix} \qquad K_P = \begin{bmatrix} 10 \\ 18.97 \\ 17.75 \end{bmatrix} \qquad (12)$$

$$Y = \begin{bmatrix} 60 \\ 50 \\ 40.2 \end{bmatrix} \qquad F = \begin{bmatrix} 1 & 50 & 2500 \\ 1 & 73.48 & 5399.31 \\ 1 & 50 & 2500 \end{bmatrix} \qquad K_I = \begin{bmatrix} 50 \\ 73.48 \\ 50 \end{bmatrix} \tag{13}$$

$$\begin{bmatrix} a_0 \\ a_1 \\ a_2 \end{bmatrix} = \begin{bmatrix} -90.9512 \\ 4.7779 \\ -0.0516 \end{bmatrix} \tag{14}$$

$$\begin{bmatrix} b_0 \\ b_1 \\ b_2 \end{bmatrix} = \begin{bmatrix} -527.8955 \\ 24.0071 \\ -0.2396 \end{bmatrix} \tag{15}$$

Based on above coefficients, the models are:

$$K_P = -90.9512 + 4.7779x + 0.0516x^2 \tag{16}$$

$$K_I = -527.8955 + 24.0071x + 0.2396x^2 \tag{17}$$

AS previously mentioned in Figure 4, the closed loop form of the process has been configured by fixed gain PI .The values of K_P, and K_I in this form are equal to K_P=6 and K_I= 110. It is replaced by the new designed adaptive controller to deliver the better performance.

Simulation result corresponding to fixed gain PI model, ICA based fixed gain PI , and ICA based Self –adaptive PI controller depict in Figure 13. It can be obviously seen that the SSE by the fixe gain PI equal to 43.11, is more than the two mentioned models. Although the optimized PI controller based on ICA offers lower error, an adaptive online PI gives the higher accuracy with the least SSE. The results of the three mentioned controllers are presented in Table 4 below.

Table 4. Comparing the result of three different controllers

MODEL	SSE
Self-adaptive PI controller	28.86
Optimized fixed gain PI controller	31.03
Fixed gain PI controller	43.11

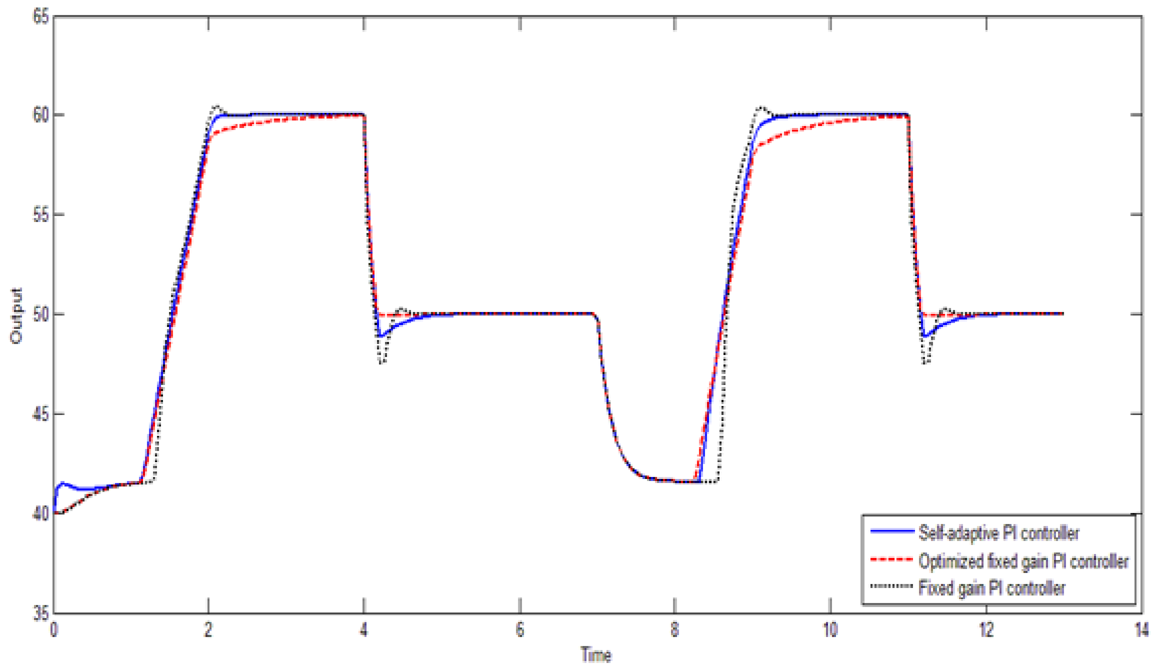

Figure 13. Response of the system for all three controllers

b. Fuzzy gain scheduling

In this part, ICA is applied to the fuzzy gain scheduling model to find the optimum membership functions both in inputs and outputs. To address these concerns, the parameters of the membership functions are coded to form the array country [15] and a cost function is defined in such a way that the design criteria are satisfied through minimizing it. Figures 14, 15 illustrate the typical membership functions of input variables error and derror in three relevant sets. Each set of the input membership function, comprises three parts, called Negative, Zero, and Positive .These sets in membership function of the first and second input can be specified by points P_i ($1 \le i \le 15$). Non-identical arranging the membership function's partitions results in more flexibility in designation.

The same procedure is done for the outputs. In Figures 16, 17 the membership function of the outputs are coded in points P_i ($16 \le i \le 29$).Therefore, the problem of finding the membership functions is related to the problem of determining 29 points. The 29 points are put together to form the array country. Sum of square error was selected as the cost function. The best solution leads to minimize the performance criterion.

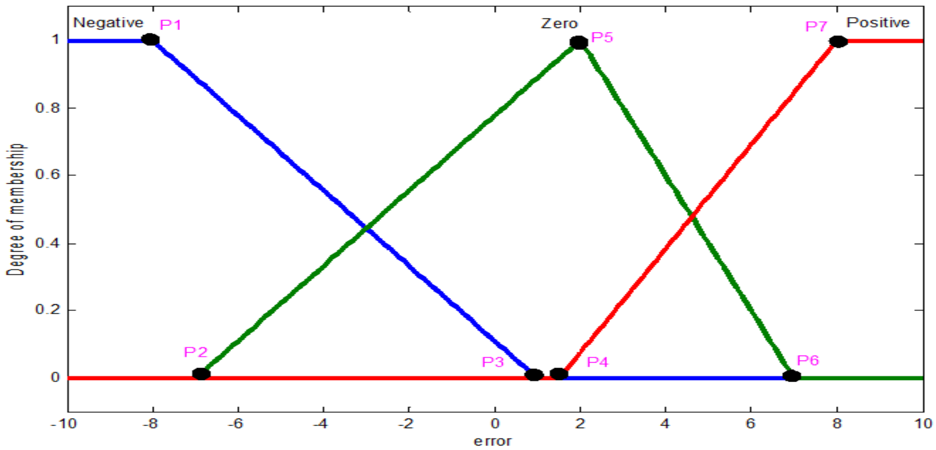

Figure 14. Membership function of input variable error

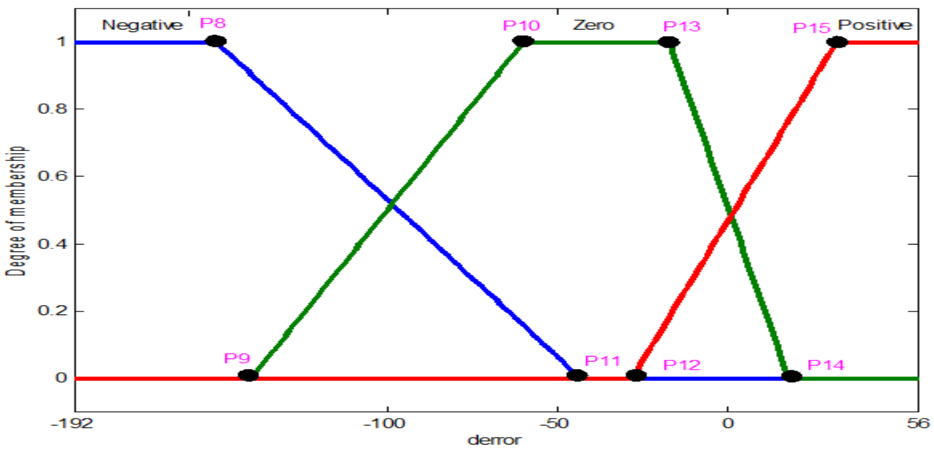

Figure 15. Membership function of input variable derror

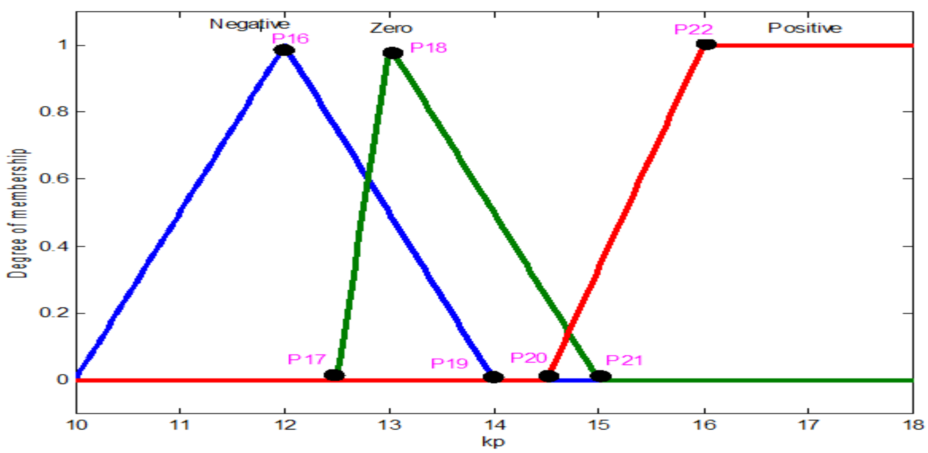

Figure 16. Membership function of output variable k_p

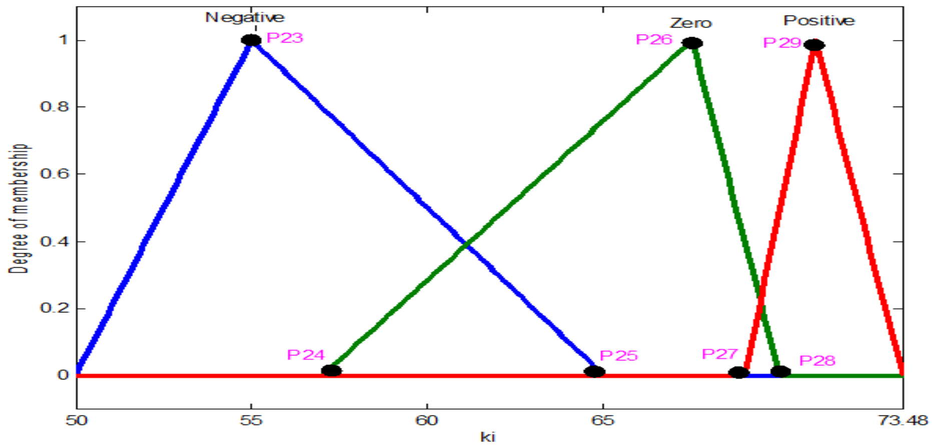

Figure 17. Membership function of output variable k_i

The fact is coded parameters in the form of the points that construct the country array lead to the best solution. Furthermore this technique is a new strategy that can be compared by expert. In the Figures 18, 19 modified membership functions of inputs, found by ICA, is illustrated. In the same way, ICA is also offered the optimum membership functions for the two outputs variable which are indicated in Figures 20, 21.

Now, the prepared intelligent controller is applied to non-isothermal reactor to control the temperature. Table 5 compares the performance of the proposed controller by other aforementioned types, based on the SSE.

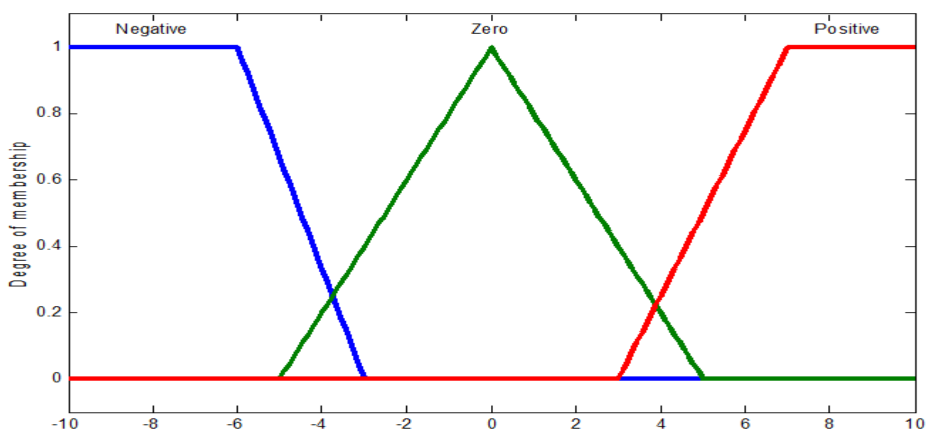

Figure 18. Modified membership function of input variable error by ICA

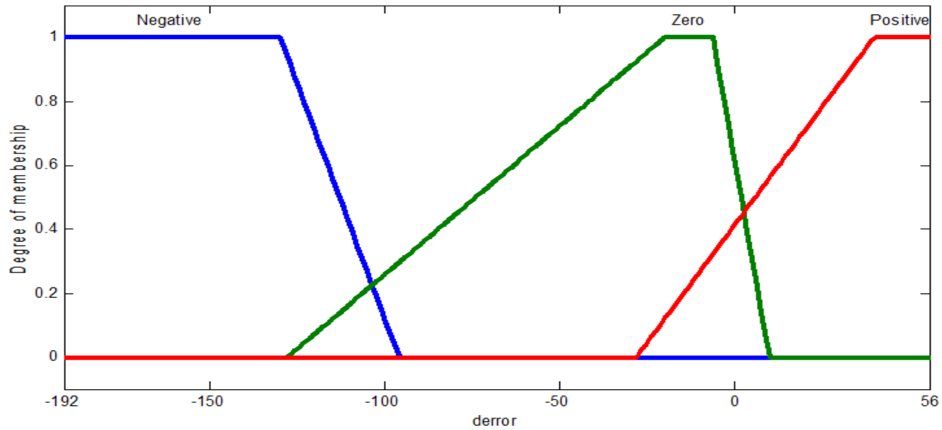

Figure 19. Modified membership function of input variable derror by ICA

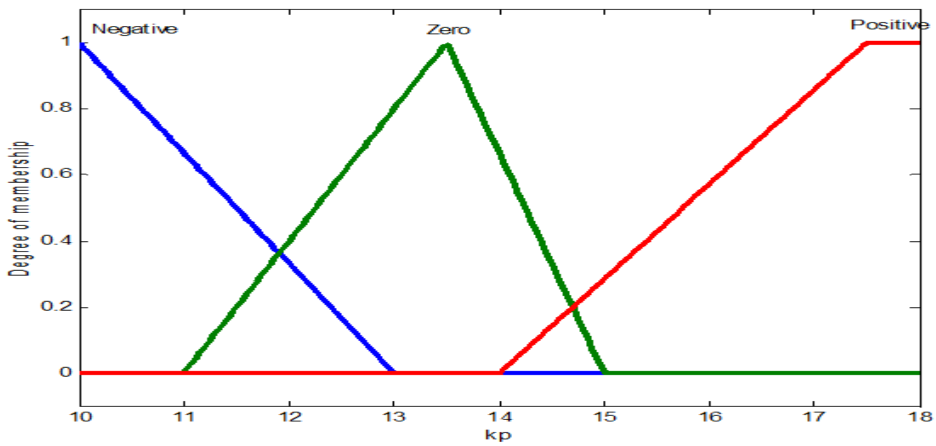

Figure 20. Modified membership function of output variable k_p by ICA

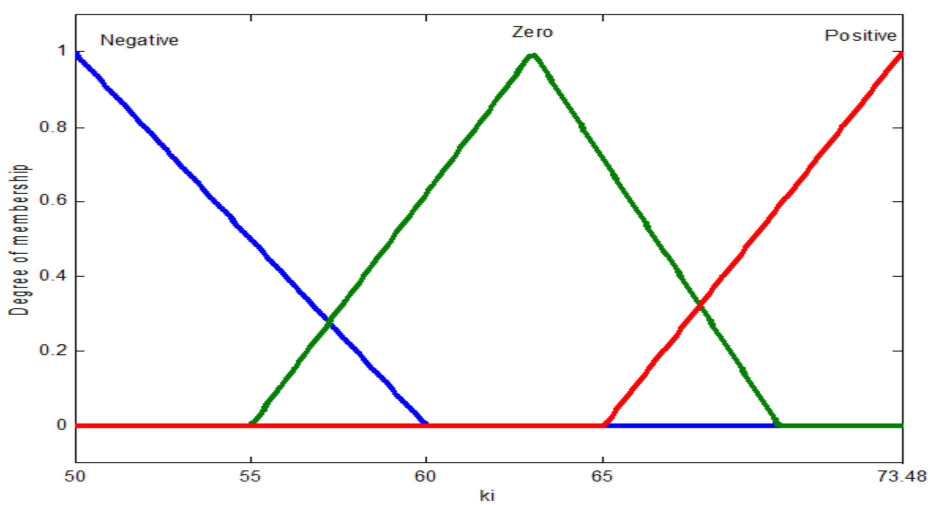

Figure 21. Modified membership function of output variable k_i by ICA

Table 5. Comparing the result of three different controllers

MODEL	SSE
Fuzzy gain scheduling controller	21.7
Optimized fixed gain PI controller	31.03
Fixed gain PI controller	43.11

Consequently, simulation results corresponding to fuzzy gain scheduling controller based on the ICA in presence of the set point variations, is depicted in Figure 22.

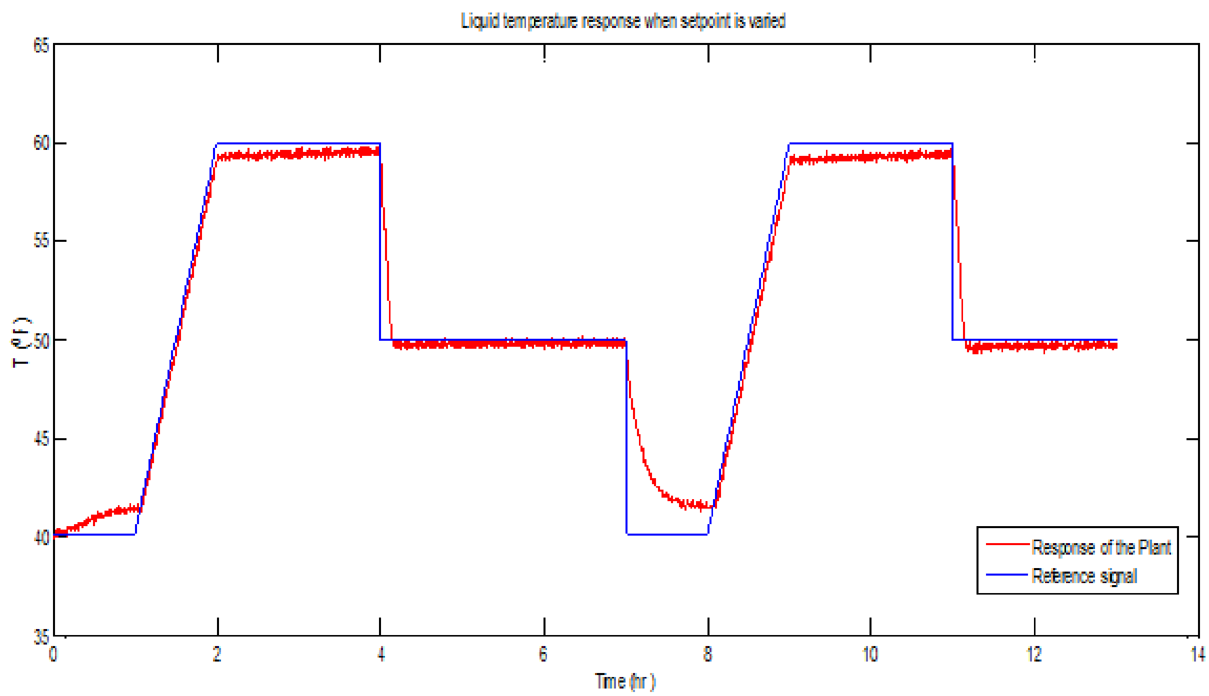

Figure 22. Response of the system based on the fuzzy gain scheduling controller

c. Performance comparing of PI, fuzzy gain scheduling based controllers

In this part, a fair comparison is done to precise evaluating of the performance of the suggested control strategies. In addition to the SSE criterion, offered in pervious part, IAE index, which represents how close the response is to the reference signal, is considered as well. In Table 6 this evaluation is indicated.

Table 6. Evaluation of the performance of the proposed controller

Criterion \ Controller	Fixed-gain PI	Optimized PI	Self-adaptive PI	Fuzzy-PI
IAE	10.595	10.171	9.987	9.935
SSE	43.11	31.03	28.86	21.7

VI. CONCLUSIONS

In this research two novel strategies of control have been applied on the model of continuous stirred tank reactor, which has the intrinsic nonlinear characteristics. Gain scheduling technique has been devoted to design the adaptive and intelligent controller based on the least square and fuzzy reasoning structure. Furthermore a novel heuristic search ICA applied to both controllers to offer the optimum performance. At first, PI based gain scheduling played a role of controller in the CSTR process model. The proportional an integral parameters of the proposed PI was formed based on the quadratic form where the unknown coefficients were found by combination of the ICA and least square approach. In the second place, gain scheduling was presented by means of fuzzy logic to form an intelligent controller to overcome the nonlinearity and set point variation problems. ICA was employed to determine the optimum fuzzy membership function which results in high performance of the control action. The simulated results indicated that both strategies offering the accurate performance and are robust in presence of the functional changes in the plant. Fair comparisons, due to the SSE and IAE criteria, have been done to evaluate the performance of the suggested controllers. The results indicated that both offered controllers are more accurate and having the high performance in compare with fixed-gain PI and optimized PI. In addition, fuzzy based structure presented the least SSE and IAE which pointed to the robustness and accuracy of controller especially in tracking problem and dealing with uncertainties.

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