

Design of optimal Linear Quadratic Regulator for the stabilization of Continuous Stirred Tank Reactor(CSTR) Process

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Abstract

Continuous Stirred Tank Reactor (CSTR) is widely used in chemical industries. Chemical reactions in a reactor are either exothermic or endothermic and therefore require that energy either to be removed or added to the reactor to maintain constant temperature. This paper deals with the stabilization of CSTR using optimal linear quadratic regulator (LQR) method. Since the performance of the LQR controller mainly depends on the state and control weighting matrices (Q and R), it is necessary to select them optimally and are done based on trial and error method, which makes the controller design cumbersome also time consuming. Hence, to address the selection of weighting matrices problem of LQR, Bacterial Foraging Algorithm (BFA) method is proposed. The matrices Q and R are determined from the optimized algorithm. Performance indices like ISE (integral squared error) and IAE (integral absolute error) are considered to evaluate the optimally tuned values of controller parameters. The performance of the

proposed method is compared with those of LQR method, Particle Swarm Optimization (PSO), Artificial Bee Colony (ABC) based LQR and conventional PID controller (tuned by Ziegler-Nichols method). Simulation results show that the proposed controller has better closed loop response in terms of ISE and IAE values.

Key Words: CSTR, Linear Quadratic Regulator (LQR), Particle Swarm Optimization (PSO), Artificial Bee Colony (ABC) and Bacterial Foraging Algorithm (BFA).

1 INTRODUCTION

CSTR plays a vital role in almost all chemical industries. Due to the nonlinear behaviour, modelling of CSTR becomes difficult. For analysis and understanding the CSTR behaviour, it is essential to develop a mathematical model. Models are used for simulations, analysis of the systems behavior, better understanding of the underlying mechanisms in the system and for controlling purposes. In control engineering, modelling and identification are important steps in the design of control, supervision and fault detection. The study of mathematical stability and input multiplicity of CSTR were considered [1]. The mathematical model is developed from material balance for a CSTR process and the steady-state analysis and dynamic analysis was implemented [2]. The basic PID controllers have difficulty in dealing with problems that appear in complex nonlinear process such as CSTR. Ruiyao Gao et.al., [3] reported a practical nonlinear PID controller that deals with these nonlinear difficulties. Mohammad Ali Nekoui et.al., [4] has considered the optimal design of PID controller based on a particle swarm optimization (PSO) approach for CSTR. Nonlinear PID controller and Nonlinear Model Predictive Controller using the family of local linear state space models has been developed for CSTR [5]. Neha Due to the disadvantages of PID, adaptive and predictive controller necessitates the optimal control strategy such as LQR for CSTR process. A classical method in the optimal feedback controller synthesis is the well-known Linear Quadratic Regulator (LQR). The objective of a LQR controller is to drive a linear system to a desired state by optimizing a quadratic performance index. Solution of the infinite-horizon LQR control problem for infinite dimensional systems in-

volves solving an algebraic matrix Riccati equation. Faruk Bin Poyen [6] reported a basic LQR for CSTR process. Amir Alizadeh Moghadam [7], designed an infinite-dimensional LQR control-based design for a CSTR process. However, selection of Q and R matrix in the design of LQR is not reported. Section 2 presents the mathematical modelling of CSTR and its state space model. Section 3 details the design of PID controller based on Z-N tuning method. Section 4 reviews the basic design of LQR controller. Section 5 presents 3 different optimization algorithms viz. Bacterial Foraging Algorithm (BFA), Particle Swarm Optimization (PSO), Artificial Bee Colony (ABC) based LQR. Comparison of simulated results are presented in section 6 and the performance indices are also evaluated followed by conclusion and some references.

2 PROCESS DESCRIPTION AND MATHEMATICAL MODELLING OF CSTR

- The schematic diagram of the CSTR process is shown in Figure 1. In the CSTR process model, 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 is fed to the reactor from the feed tank through a pump. A catalyst is placed inside the reactor which speeds up the reaction and remains chemically unchanged throughout the reaction. The concentration is measured using a conductivity meter. The temperature of the fluid in the tank and the jacket are measured using a thermocouple.

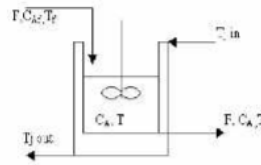


Figure 1: CSTR process with cooling jacket

A mathematical model of the CSTR process is developed from energy and material balance equations and is given by (1) and (2).

$$\frac{dC_A}{dt} = \frac{F}{V}(C_{Af} - C_A) - k_0 e^{-\left(\frac{\Delta E}{RT}\right)} C_A \quad (1)$$

$$\frac{dT}{dt} = \frac{F}{V}(T_f - T) + \frac{\Delta H}{\rho c_p} k_0 e^{-\left(\frac{\Delta E}{RT}\right)} C_A - \frac{UA}{V\rho c_p}(T - T_j) \quad (2)$$

In the above model, A is the heat transfer area, C_A the concentration of reactant A in the reactor, C_{Af} the concentration of A in the feed stream, C_p the heat capacity, F the volumetric flow rate of the feed as well as the product stream, K_0 the pre-exponential factor, R the universal gas constant, t the time, T the reactor temperature, T_f the feed temperature, T_j the jacket temperature, U the overall heat transfer coefficient, V the reactor volume, ΔE the activation energy, (ΔH) the heat of reaction, and ρ is the density.

A. State space model

The state space model of the system is represented in equation (3).

$$\begin{aligned} \dot{x} &= Ax + Bu \\ y &= Cx + Du \end{aligned} \quad (3)$$

The system is assumed to have two state variables, the reactor temperature (T) and the reactor concentration (C_A) and these are also the output variables to be controlled. The input variables are

the feed flow rate (F) and the jacket temperature (T_j). The system is modeled using the parameters specified in Tables 1.

$$A = \begin{bmatrix} -\frac{F}{V} - k_0 \exp\left(-\frac{E}{RT_s}\right) & -k_0 \exp\left(-\frac{E}{RT_s}\right) \left(\frac{E}{RT_s^2}\right) * C_{AS} \\ \left(-\frac{\Delta H}{\rho C_p}\right) * k_0 \exp\left(-\frac{E}{RT_s}\right) & -\frac{F}{V} - \frac{UA}{V\rho C_p} \left(-\frac{\Delta H}{\rho C_p}\right) * k_0 \exp\left(-\frac{E}{RT_s}\right) \left(\frac{E}{RT_s^2}\right) * C_{AS} \end{bmatrix} \quad (4)$$

$$(5)$$

A and B matrices are obtained by substituting the CSTR parameters [10] in equation (4) and (5)

$$A = \begin{bmatrix} -1.567 & -0.0829 \\ 1.868 & -0.3115 \end{bmatrix} \quad (6)$$

$$B = \begin{bmatrix} 1.4364 & 0 \\ -13.171 & 0.3 \end{bmatrix} \quad (7)$$

$$C = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} \quad (8)$$

$$D = \begin{bmatrix} 0 & 0 \\ 0 & 0 \end{bmatrix} \quad (9)$$

Table 1: CSTR parameter values

Reactor parameters	values
F/V	1
K_0	9703 x 3600
(-ΔH), kcal/kmol	5960
E, kcal/kmol	11843
ρC_p , kcal/m ³ c	500
T_f , °c	25
C_{A0} , kmol/m ³	10
UA/V, kcal/m ³ .hr	150
T_j , °c	25

3 PID CONTROLLER DESIGN FOR CSTR

The PID controller is simple and easy to implement. It is widely applied in industry to solve various control problems. the transfer

function of PID controller is given by the following equation in the continuous s-domain

$$G_{PID}(s) = K_p + \frac{K_i}{S} + K_d.S \tag{10}$$

or

$$G_{PID}(s) = K_p + (1 + \frac{1}{T_i S} + T_d.S) \tag{11}$$

K_p is the proportional gain, K_i is the integral gain, and K_d is the derivative gain. T_i is the integral action time and T_d is referred to as the derivation time.

The transfer function of CSTR for concentration is given by the equation (12a)

$$G_p(s) = \frac{1.346s + 1.539}{s^2 + 1.878s + 0.643} \tag{12a}$$

The transfer function of CSTR for temperature is given by the equation (12b)

$$G_p(s) = \frac{0.3s + 0.4701}{s^2 + 1.878s + 0.643} \tag{12b}$$

Figure 2 shows the open loop response of CSTR for temperature and concentration.

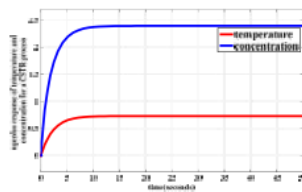


Figure 2: Open loop response of CSTR for temperature and concentration

The PID controller parameters are determined using Zeigler Nichols (Z-N) tuning method.

4 LQR OPTIMAL CONTROLLER DESIGN AND ITS IMPLEMENTATION

The design of optimal control systems is an important function of control engineering. The purpose of design is to realize a system with practical components that will provide the desired operating performance. The performance of a control system can be represented by integral performance measures, the design of a system is based on minimizing a performances index. Systems that are adjusted to provide minimum performance index are often called optimal control system. Linear-quadratic-regulator (LQR) is a part of optimal control strategy which has been widely developed and used in various applications. LQR design is based on the selection of feedback gains K such that the cost function J is minimized. This ensures that the gain selection is optimal for the cost function specified

A system can be expressed in state variable form as

$$\dot{x}(t) = Ax(t) + Bu(t) \quad (13)$$

We assume here that all the states are measurable and to find a state variable feedback (SVFB) control

$$u(t) = -Kx(t) \quad (14)$$

that gives desirable closed-loop properties. To design a SVFB that is optimal, the performance index is defined as

$$J = \int_0^{\alpha} (x^T Q X + u^T R u) dt \quad (15)$$

where, Q is positive definite (or positive semi-definite) or real symmetric matrix is required to be positive definite symmetry matrix. The feedback control function limits to a linear function so that:

$$K = R^{-1} B^T P \quad (16)$$

and it will result in

$$A^T P + PA + PBR^{-1}B^T P + Q = 0 \quad (17)$$

Equation (17) is known as the algebraic Riccati equation (ARE) and can be solved for the auxiliary matrix P , given (A , B , Q , and R).

5 OPTIMIZATION TECHNIQUES BASED LQR

In LQR method. Q and R matrices are chosen by trial and error method. To optimize these values, Bacterial Foraging Algorithm, Artificial Bee colony algorithms and Particle Swarm Optimization techniques are proposed in this work.

A. Performance indices for the system

A system is called as an optimal control system when the system parameters are adjusted so that the index reaches a minimum value. Integral Square Error is emphasized to minimize initial large amount of errors. Another index is IAE (Integral absolute error), which is particularly useful for computer simulation studies.

B. Bacterial Foraging Algorithm

Bacterial Foraging Algorithm (BFA) introduced by Kevin Passino et.al., (2002), is a new comer to the family of nature inspired optimization algorithms. Application of group foraging strategy of a swarm of Escherichia Coli (E. coli) bacteria in multi-fittest function optimization is the main idea of this new algorithm. To maximize energy obtained per unit time, bacteria search for nutrients. Each bacterium communicates with others by sending signals. Chemotaxis is the process in which the bacterium moves in small steps to search for nutrients. The main idea of BFA is mimicking chemotaxis movement of virtual bacteria in the problem search space.

In the optimization algorithm development, the parameters are defined as follows:

P is dimension of the search space (number of parameters to optimize)

S is the number of bacteria in the population (for simplicity, S as chosen for even number)

N_c is the number of chemotactic steps per bacterium lifetime between reproduction steps

N_s is the maximum number of swim of bacteria in the same direction

N_{re} is the number of reproduction steps

N_{ed} is the number of elimination and dispersal events

p_{ed} is the probability that each bacterium will be eliminated/dispersed.

$i=1, 2, \dots, S$ as the index for the bacterium

$j=1, 2, \dots, N_c$ as the index for chemotactic step

$k=1, 2 \dots N_{re}$ as the index for reproduction step
 $l=1, 2 \dots N_{ed}$ as the index of elimination and dispersal event
 $m_s = 1, 2 \dots N_s$ as the index for number of swim.

The BFA algorithm is implemented with the following steps:

Step 1: Elimination and dispersal loop $l = l+1$

Step 2: Reproduction loop $l = l+1$

Step 3: Chemotaxis loop $j = j+1$

a. For $i= 1, 2, 3 \dots S$, a chemotaxis step for i th bacterium will be as follows:

b. Calculate fitness function $J(i, j, k, l)$.

Let $J(i,j,k,l)=J(i,j,k,l)+J_{cc}(\theta^i(j,k,l),P(j,k,l))$ is cell to cell attractant effect to the nutrient concentration).

c. Let $J_{last} = J(i,j,k,l)$

d. Tumble: generate a random vector $(i)R_p$ with each element $m(i)$, $m = 1, 2 \dots P$ a random number on $[-1,1]$

e. Move: Compute: ,

f. Compute $J(i,j+1,k,l)$

g. Swim:

Let $m=0$

While $m < N_s$

Let $m=m+1$

If $J(i,j+1,k,l) < J_{last}$

Compute $J_{last} = J(i, j, k, l)$ & calculate and use this $\theta^i(j+1, k, l)$ to compute the new $J(i,j+1,k,l)$ as same in step (f) Else, let $m= N_s$. This is the end of the while statement.

h. Go to next bacterium $(i+1)$, if $i=S$ go to step (b)

Step 4: If $j < N_c$, go to step 3 for next chemotaxis step as the chemotaxis process not complete.

Step 5: Reproduction. With current values of k, l , compute overall fitness (cost function)

$J_i, =1$ for each i th bacterium and sort the fitness in descending order. Higher value of cost function means less fitness.

Step 6: Half of the bacteria with less fitness will die and the other half will reproduce. They will split into two and placed at the same locations of their parents. So, population remains constant.

Step 7: If $k < N_{re}$, go to step 2. Increment the reproduction counter and start new chemotaxis process.

Step 8: Elimination-dispersion. Eliminate the bacterium with probability P_{ed} and disperse one at a random location in the optimization space.

S

tep 9: If $l < N_{ed}$, go to step1. Otherwise end.

C.Parameters used for BFA algorithm

Dimension of search space, $n = 2$;

Number of bacteria in the colony, $S = 60$;

Number of chemotactic steps, $N_c = 25$;

Number of swim steps, $N_s = 4$;

Number of reproductive steps, $N_{re} = 4$;

Number of elimination and dispersal steps, $N_{ed} = 2$;

The number of bacteria reproductions (splits) per generation,

$S_r = S/2$;

The probability that each bacterium will be eliminated/dispersed,

$P_{ed} = 0.5$;

6 PARTICLE SWARM OPTIMIZATION ALGORITHM

Particle swarm optimization (PSO) is a population based stochastic optimization technique developed by Dr. Eberhart and Dr. Kennedy in 1995, inspired by social behaviour of bird flocking or fish schooling. Every particle monitors its directions in the issue space which are related with the best arrangement (fitness) it has accomplished up until now. (The fitness value is also stored.) This value is called p_{best} . Another "best" value that is followed by the particle swarm enhancer is the best esteem, acquired so far by any particle in the neighbours of the particle. This area is called

lbest. At the point when a particle takes all the populations as its topological neighbours, the best value is a global best and is called gbest.

The particle swarm optimization concept consists of each time step, changing the velocity of (accelerating) each particle toward its pbest and lbest locations (local version of PSO). Acceleration is weighted by a random term, with separate random numbers being generated for acceleration toward pbest and lbest locations. The basic idea of particles searching individually while communicating with each other concerning the global best in order to produce a more capable collective search applies to all forms of PSO from the originally conceived algorithm through the more capable models available today. Particle swarm, as originally published by Kennedy, J. (2011), consisted of a swarm of particles each moving or flying through the search space according to velocity update equation

$$\bar{V}_i = (k+1) = \bar{V}_i(k) + C_1 r_{11}(k)(\bar{P}_i(k) - \bar{x}_i(k)) + C_2 r_{21}(k)(\bar{g}(k) - \bar{x}_i(k)) \quad (18)$$

where, $v_i k$ is the velocity vector of particle i at iteration k ,

$x_i k$ is the position vector of particle i at iteration k ,

$P_i k$ is then-dimensional personal best of particle i found from initialization through iteration k ,

$g k$ is then-dimensional global best of the swarm found from initialization through iteration k ,

C_1 is the cognitive acceleration coefficients on a med for its terms use of the personal best, which can be thought of as a cognitive process whereby a particle remembers the best location and tends to return to that state, C_2 is the social acceleration coefficients on a med for its terms use of the global best which attracts all particles simulating social communication, $r_1(k)$ and $r_2(k)$ are vectors of pseudo-random numbers with components selected from uniform distribution $U(0,1)$ at iteration k , and r is the Hadamard operator representing element-wise multiplication.

PSO uses particles which represent potential solutions of the problem. Each particle flies in search space at a certain velocity which can be adjusted in light of preceding flight experiences. The projected position of i th particle of the swarm x_i , and the velocity

of this particle v_i at $(t+1)$ th iteration are defined and updated as the following two equations,

$$V_i^{t+1} = V_i^t + C_1 r_1 (P_i^t + x_i^t) + C_2 r_2 (g_i^t + x_i^t) \quad (19)$$

$$X_i^{t+1} = X_i^t + V_i^{t+1} \quad (20)$$

where $i=1, \dots, n$ and n is the size of the swarm, c_1 and c_2 are positive constants, r_1 and r_2 are random numbers which are uniformly distributed, determines the iteration number, p_i represents the best previous position (the position giving the best fitness value) of the i th particle, and g represents the best particle among all the particles in the swarm. At the end of the iterations, the best position of the swarm will be the solution of the problem. It cannot be always possible to get an optimum result of the problem, but the obtained solution will be an optimal one.

A. Parameters used for PSO algorithm

The observation time $T_{ob}=20$ Sec

The step size of the simulation $H_s=0.001$ Sec,

The average generations =150

The number of particles = 10

The range of c_1 and c_2 = 0 to 2. The PSO setting parameters are $C_1 = C_2=1.5$.

7 ARTIFICIAL BEE COLONY ALGORITHM

In a genuine honey bee province, a few obligations are performed by devoted individuals. These particular honey bees attempt to expand the nectar sum put away in the hive utilizing productive division of work and self-association. The artificial bee colony (ABC) algorithm for real parameter optimization proposed by Karaboga (2005) is an optimized algorithm that simulates the forging behaviour of bee colony. The insignificant model of swarm wise scrounge determination in a honey bee state which the ABC calculation reenacts comprises of three sorts of honey bees: employed bees, onlooker bees and scout bees. The colony consist employed bees, onlooker bees on nearby equal quantity.

The parameters of the fundamental ABC calculation are the quantity of food sources (SN) that is equivalent to the quantity of

the utilized honey bees or spectator honey bees, the colony size is $2 \cdot SN = (NP)$, The number of trials after which a food source is assumed to be abandoned (limit), and a termination criterion (MCN). In the fundamental ABC algorithm, the quantity of utilized honey bees or the spectators is set equivalent to the quantity of food sources in the populace. At the end of the day for each sustenance source, there is just a single employed honey bee. Delivering beginning food source sites if the inquiry spaces considered being the earth of the hive that contains the nourishment source destinations, the algorithm begins with arbitrarily creating food sources sites that correspond to the solutions in the search space. Beginning food sources are created arbitrarily inside the range of the parameters characterized by equation (19).

$$X_{ij} = X_j^{min} + rand(0, 1)(X_j^{max} - X_j^{min}) \quad (21)$$

Where $i = 1 \dots SN$, $j = 1 \dots D$, SN is the number of food sources and D is the number of optimization parameters. Also, counters which store the number of trials of arrangements are reset to zero in this stage. After introduction, the population in the food sources (solutions) is subjected to rehash cycles of the pursuit procedure of the utilized honey bees, the onlooker honey bees and the scout honey bees. Sending utilized honey bees to the nourishment sources locales as said before, each utilized honey bee is related with just a single food source site. Henceforth the quantity of food source site is equivalent to the quantity of utilized honey bees. An employed bee creates the changes on the position of the food source (solution) in her memory depending upon local information (visual information) and finds neighbouring food source, and then evaluates its quality. In ABC, finding a neighbouring food source is defined by equation (22).

$$V_{ij} = X_{ij} + \phi_{ij}(X_{ij} - X_{kj}) \quad (22)$$

Within the neighbouring of every food source site represented by X_i , a food source V_i is determined by changing one parameter of X_i . In equation (20), j is a random in the range $[1, D]$ and $k \in \{1, 2 \dots SN\}$ is a randomly chosen index that has to be different from i . ϕ_{ij} is a uniformly distributed real random number in the range $[-1, 1]$. From equation (20) it is to be noted that the difference between the parameters of the X_{ij} and X_{kj} decreases, the

perturbation on the position X_{ij} also decreases. In such a way, as the search approaches to the optimal solution in the search space, the step length is adaptively reduced. On the off chance that a parameter value created by this operation surpasses its foreordained limits the parameter can be set to an acceptable value. If the value of the parameter exceeds its boundary is set to its corresponding boundaries. If $X_i > X_i^{max}$ then $X_i = X_i^{max}$; If $X_i < X_i^{min}$ then $X_i = X_i^{min}$; $X_i = X_{max}$ after producing V_i within the boundaries a fitness value for a minimization problem can be calculated to the solution V_i by (23).

$$Fitness_i = \begin{cases} \frac{1}{(1 + F_i)}, & \text{if } f_i \geq 0 \\ 1 + abs(F_i) & f_i < 0 \end{cases} \quad (23)$$

Where f_i is cost value of the solution V_i . For maximization problems, the cost function can be directly used as a fitness function. A covetous determination is connected amongst X_i and V_i , the better one is chosen relying upon wellness values speaking to the nectar measure of the food sources at X_i and V_i . On the off chance that the source at V_i is better than that of X_i regarding wellness values, the utilized honey bees retain the new position and overlook the old one. Generally, the past position is kept in memory. On the off chance that X_i can't be enhanced its counter holding the quantity of trials is increased by one, generally the counter is reset to zero.

In basic ABC, roulette wheel selection scheme in which each slice proportional to size to the fitness value is employed in Equation (24).

$$P_i = \frac{Fitness_i}{\sum_{i=1}^N Fitness_i} \quad (24)$$

A. Parameters used for ABC algorithm Number of ants=15

Number of scout bees =5

Number of iterations =100

Number of best selected patches =7

8 SIMULATION RESULTS AND DISCUSSION

LQR controller parameters are evaluated from the optimization techniques. The performance of the optimization techniques has been compared for different set-points and load disturbances of reactor temperature(T) and concentration(CA). Servo responses of CSTR concentration for the control strategies like PID, LQR, PSO-LQR, BFA-LQR and ABC-LQR controllers are recorded in the Figure 3. LQR without optimization algorithms has large overshoot but other methods have less overshoot. By comparing the ISE and IAE values the proposed method has very less value. Figure 4 shows the regulatory response of CSTR in which the disturbance is given at 20th instant. PID controller took a long time to restore its original position, whereas proposed BFA-LQR controller has quickly come to the set point. Figure 5 indicates the servo regulatory response for temperature control of CSTR, in which PID controller has overshoot but the proposed BFA-LQR controller strategy has no overshoot. With respect to performance indices comparison, proposed controller has very less ISE and IAE values than the other optimized techniques and the LQR without optimization. However, by considering the performance indices, the proposed BFA-LQR controller has relatively less value while considering other controller strategies.

From the responses and Table 2, it is inferred that the control strategy with BFA-LQR has less ISE and IAE values than LQR, PSO-LQR, ABC-LQR and conventional PID controller. This means that the system with proposed strategy has fast convergence and relatively more stable than the other Control strategies. The comparative study of different algorithms in terms of ISE and IAE is shown in Figure 6 and 7 respectively. From the figures it is observed that, BFA-LQR outperformed the other optimization techniques for set-point tracking as well as regulatory responses.

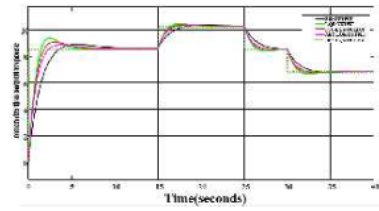


Figure 3. Servo response of CSTR (concentration) with setpoint changes.

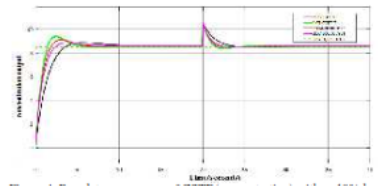


Figure 4. Regulatory response of CSTR(concentration) with 10% load disturbance

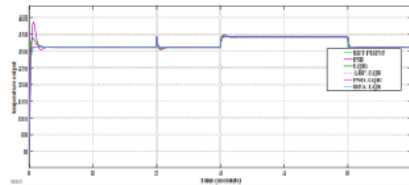


Figure 5. Servo Regulatory response of CSTR (Temperature control) with PID, PSO, ABC and BFA based LQR method

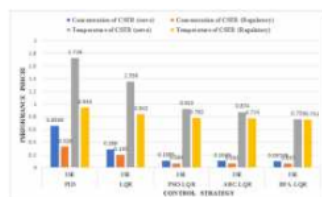


Figure 6: Comparison of performance index(ISE) for set-point tracking and regulatory response of CSTR

Table 2: Performance measures of CSTR with PID, LQR, PSO-LQR, ABC-LQR and BFA-LQR techniques

Control Strategy Type of response	PID		LQR METHOD		PSO-LQR		ABC-LQR		BFA-LQR	
	ISE	IAE	ISE	IAE	ISE	IAE	ISE	IAE	ISE	IAE
Concentration of CSTR (servo)	0.6558	2.02	0.28	1.85	0.10	1.2	0.104	1.07	0.0974	0.852
Concentration of CSTR (Regulatory)	0.32	1.25	0.195	1.1	0.06	1.02	0.061	0.09	0.057	0.09
Temperature of CSTR (servo)	1.726	3.53	1.306	3.02	0.923	2.17	0.874	2.08	0.759	1.95
Temperature of CSTR (Regulatory)	0.943	2.17	0.842	1.11	0.782	1.96	0.774	1.87	0.751	1.78

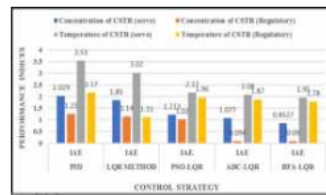


Figure 7: Comparison of performance index(IAE) for set-point tracking and and regulatory responses

9 CONCLUSIONS

BFA based LQR controller using state space methodology has been designed for a CSTR process (both concentration and temperature) and simulated using MATLAB. Servo and regulatory responses of the CSTR process using BFA based LQR has been analysed and compared with those of LQR, PSO based LQR, ABC based LQR and conventional PID controller. The effectiveness of the proposed method is also compared with the performance measures with other control strategies. From the results, it is observed that BFA based LQR controller produces better results in terms of ISE and IAE. All the algorithms implemented in this work have used computational intelligence technique and are less sensitive to the nonlinearities present in the system. Optimal solution can be reached with good convergence and it has less computational complexity and the time required is also less when compared to other design technologies.

References

- [1] Penlidis, A., MacGregor, J. F., & Hamielec, A. E, Continuous emulsion polymerization: design and control of CSTR trains, Chemical engineering science, 44(2), 273-281.

- [2] Seborg, Dale E., et al. Process dynamics and control. John Wiley & Sons, 2010.
- [3] Gao, Ruiyao, Aidan Odywer, and Eugene Coyle, A nonlinear PID controller for CSTR using local model networks, Intelligent Control and Automation, 2002. Proceedings of the 4th World Congress on. Vol. 4. IEEE, 2002.
- [4] Nekoui, Mohammad Ali, Mohammad Ali Khameneh, and Mohammad Hosein Kazemi., Optimal design of PID controller for a CSTR system using particle swarm optimization, Power Electronics and Motion Control Conference (EPE/PEMC), 2010, 14th International. IEEE, 2010.
- [5] Prakash, J., and K. Srinivasan, Design of nonlinear PID controller and nonlinear model predictive controller for a continuous stirred tank reactor, ISA transactions 48.3 (2009): 273-282.
- [6] Poyen, Faruk Bin, Implementation of linear quadratic regulator for CSTR tank., Proceedings of Advances in Electronics and Electrical Engineering (2013): 11-15.
- [7] Moghadam, Amir Alizadeh, LQ control of coupled hyperbolic PDEs and ODEs: Application to a CSTR-PFR system., IFAC Proceedings Volumes 43.5 (2010): 721-726.
- [8] B.WayneBequette, Process Dynamics Modeling, Analysis, and Simulation, Prentice Hall International Series in the Physical and Chemical Engineering Sciences.