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Control of Continuous Stirred Tank Reactor System using Hybrid Bacteria Foraging Optimization Algorithm

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Abstract:

Bacterial Foraging Optimization (BFO) algorithm is one of the newly developed biologically inspired stochastic search technique based on mimicking the foraging behaviour of Escherichia coli (E. coli) bacteria. This paper focuses on the design and global tuning of Proportional Integral Controller (PID) controller parameters for Continuous Stirred Tank Reactor (CSTR) system to improve the steady state performance and robustness of the system using BFO algorithm. Due to its promising features such as high computational efficiency, easy implementation and stable convergence, it is widely applied to solve complex engineering optimization problems. A shortcoming of the BFO algorithm is, it depends on random search directions which may delay the search process in achieving global solution. But Particle Swarm Optimization Algorithm (PSO) has the ability to exchange social information and faster convergence for finding corresponding positions of bacteria in the search space, thereby the computational time is reduced. Therefore a hybrid approach involving PSO and BFO algorithm named as Hybrid Bacteria Foraging Optimization Algorithm (HBFO) is proposed in this paper, which combines advantages of both algorithms in order to get better optimization results. Performance indices like ISE, ITSE, IAE and ITAE are considered to guide HBFO algorithm for evaluating the optimally tuned values of controller parameters. It is obvious from the simulation results that the HBFO algorithm is efficient in achieving good set point tracking in the entire range of the CSTR process with the brilliancy of rejecting individual and combined loads.

Keywords: PID controller, global tuning, CSTR process, performance indices, hybrid approach, metaheuristic algorithms.

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1. Introduction

In Recent years, research on optimization has attracted many researchers. There are different optimization methods and algorithms which are classified as deterministic and stochastic [1], [2]. Deterministic techniques depend on the mathematical nature of the problem, which in turn depends on gradient, local optimums and inefficiency to handle large-scale search space, whereas stochastic techniques do not depend on the mathematical properties of a given function and are hence more appropriate for finding the global optimal solutions for many real-world optimization problems that are complex, multimodal and non-differentiable. Especially swarm intelligence is an innovative optimization technique which is inevitable that mimic the specific structures or behaviours of certain animal swarms in nature. The individuals have simple behaviours, no centralized control and exhibit complex collective intelligence by their interaction and cooperation. Several swarm intelligence algorithms have been proposed, such as Ant Colony Optimization (ACO) [3], Particle Swarm Optimization (PSO) [4], Artificial Bee Colony [ABC] [5] and Bacterial Foraging Algorithm (BFO) [6]. BFO is a powerful optimization tool first proposed by Passino in 2002, inspired by the foraging and chemotactic behaviours of bacteria, especially the E. coli present in human intestine. The chemotactic is the most attractive behaviour of bacteria. It has been studied by many researchers [7], [8].

BFO has been applied successfully to many engineering problems, such as optimal control [9], harmonic estimation [10], transmission loss reduction, [11] and control of time delayed unstable systems [12]. However, experiments for complex and multimodal functions reveal that the standard BFO algorithm has poor convergence behaviour, and its search performance decreases with increase in search space and the complexity of the problem. Therefore there is a need for the hybrid algorithm that combines the positive features of both the algorithm. Many hybrid approaches using Genetic algorithm and PSO with BFO have produced appreciable results in several applications [13]-[16].

In this study, a hybrid approach of using combined features of both PSO and BFO algorithms has been tried for optimal concentration control of CSTR system. The

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performances of PSO and standard BFO algorithm have been compared to prove the efficiency of the HBFO algorithm. Various performance indices are attempted to evaluate the better PID parameter values to achieve global optimization. Simulation results convey that HBFO algorithm provides better set point tracking and disturbance rejection both for individual and combined loads such as feed temperature (T_f) and feed concentration (C_{Af}) of CSTR process.

This article is organized as follows: Section 2 describes the CSTR system considered in this work, Section 3 presents the design of PID controller based on HBFO algorithm and Section 4 discusses PSO algorithm and the biological motivation behind the BFO algorithm, outlining the algorithm in a comprehensive manner. Section 5 furnishes the description of HBFO algorithm. Simulation results are reported in Section 6 and finally concluding remarks are discussed in Section 7.

2. Materials and Methods

CSTR process:

Continuous Stirred Tank Reactor (CSTR) is one of the common reactors in chemical process, which is a complex nonlinear system. Due to its strong non-linearity, the problem of identification and control of CSTR is always a challenging task for control systems engineer [17]. The schematic diagram of CSTR process is shown in Figure. 1.

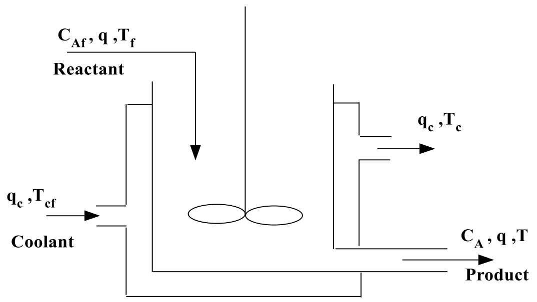


Figure 1: CSTR with cooling jacket

In this process an irreversible, exothermic reaction A → B (Reactant A of concentration C_{Af} is converted to Product B of Concentration C_A) occurs in a constant volume reactor that is cooled by a single coolant stream. The goal of the PID controller is to maintain the desired reactor concentration as close as possible to its steady state value by adjusting the manipulated variable coolant flow rate. The feed concentration and feed temperature are considered as disturbances. The first principles model of the CSTR system and the operating point data as specified by Pottmann and Seborg [18] has been used in the simulation studies (Refer Table. 1).

Table 1: Steady state operating data of CSTR process

Process variable	Normal operating condition
Measured product concentration(C_A)	0.0989 mol/lit
Reactor temperature (T)	438.7763 K
Coolant flow rate (q_c)	103 lit/min
Process flow rate (q)	100.0 lit/min
Feed concentration (C_{Af})	1 mol/lit
Feed temperature (T_f)	350.0 K
Inlet coolant temperature (T_{cf})	350.0 K
CSTR volume (V)	100 lit
Heat transfer term (hA)	$7*10^5$ cal/(min.k)
Reaction rate constant (k_0)	$7.2*10^{10}$min^{-1}
Activation energy term (E/R)	$1*10^4$ K
Heat of reaction (-ΔH)	$2*10^5$ cal/mol
Liquid density (ρ, ρ_c)	$1*10^3$ g/lit
Specific heats (C_p, C_{pc})	1 cal/(g.k)
Fouling coefficient $\varphi_h(t)$	1
Deactivation coefficient $\varphi_c(t)$	1

The process model equations are given in (1) and (2).

$$\frac{dC_A}{dt} = \frac{q}{V}\left(C_{Af} - C_A\right) - k_0 C_A \exp\left(-\frac{E}{RT}\right)\varphi_c(t) \quad (1)$$

$$\frac{dT}{dt} = \frac{q}{V}\left(T_f - T\right) + \frac{(-\Delta H)k_0 C_A}{\rho C_p}\exp\left(-\frac{E}{RT}\right)\varphi_c(t) + \frac{\rho_c C_{pc}}{\rho C_p}\frac{q_c}{V}\left(1 - \exp\left(-\frac{hA}{q_c \rho C_p}\varphi_h(t)\right)\right)\left(T_{cf} - T\right) \quad (2)$$

3. Design of PID controller based on HBFO Algorithm:

Even though many control methods such as adaptive control, neural network, fuzzy control etc. have been studied, PID controller is the most common controller in process industries still because of its simplicity and has less number of parameters to tune. A PID controller is defined by its three parameter values K_p, K_i and K_d. Tuning of a PID controller refers to the process of determining the PID gain values for the given system. But, unfortunately it is quite difficult to tune PID parameters because industrial plants are subjected to problems such as higher order of the system, time delay and nonlinearities associated with the system. Although the structure of PID controllers is simple, the method of tuning them controller is of great importance because it depends on the plant or process model subjected to various disturbances, operators lack practical knowledge about process control, and plant response may be transient requiring fine tuning of controller parameters [19]. Therefore, it is difficult to obtain optimal PID parameters using conventional techniques. Many soft computing techniques like fuzzy control, neural network and heuristic algorithms are used nowadays for proper tuning of PID controllers [20]-[24].

PID controllers have the feature of automatic gain adjustment and hence capable of high initial gain to obtain a fast response, followed by a low gain to prevent an oscillatory behaviour. The PID controller equation is given by

$$G(s) = K_P + \frac{K_i}{s} + K_D \cdot s \tag{3}$$

$$K_P = K_c$$

$$K_i = \frac{K_c}{T_i}$$

$$K_D = K_c \cdot T_D$$

where

K_p -Proportional controller gain
K_i -Integral controller gain
K_D- Derivative controller gain
K_c- Controller gain
e - Error Signal
y (t) -output signal
u (t) - controller output
T_D - Derivative time constant
T_i - Integral time constant

The output of the PID controller in time domain is given by

$$u(t) = K_p e(t) + K_i \int_0^t e(t) + K_D \frac{d}{dt} e(t) \tag{4}$$

where, u (t) and e (t) are the control and tracking error signals in time domain respectively. In the case of optimization of the PID controller discussed throughout this work, the cost functions chosen are the integral square error (ISE), Integral Absolute Error (IAE), Integral Time Absolute Error (ITAE) and Integral Time Squared Error (ITSE) and these error criteria are defined in (5), (6), (7) and (8) respectively. These cost functions are used to evaluate better PID parameters. The block diagram of the proposed BFO/HBFO based PID controller has been presented in figure.1

$$ISE = \int_0^\infty [e(t)]^2 \, dt \tag{5}$$

$$IAE = \int_0^\infty |e(t)| dt \tag{6}$$

$$ITAE = \int_0^\infty t|e(t)| dt \tag{7}$$

$$ITSE = \int_0^\infty t[e(t)]^2 \, dt \tag{8}$$

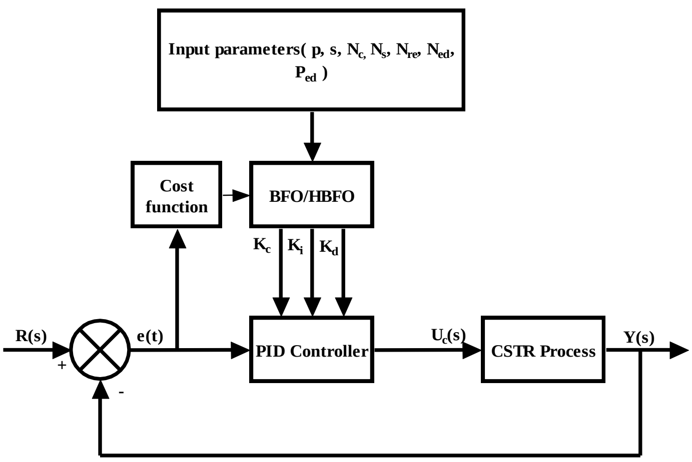


Figure 2: Block diagram of BFO/HBFO based PID controller tuning.

4. An overview of Swarm based algorithms, PSO and Standard Bacteria Foraging Algorithm:

4.1 Particle swarm optimization algorithm:

PSO, one of the popular swarm based algorithm was introduced by Eberhart and Kennedy [4] in 1995. Each individual of the population, called particle, has an adaptable velocity, according to which it moves over the search space. In a search space of *p*-dimensions, the i^{th} particle can be represented by a vector $X_i = X_1, X_2, \ldots, X_p$. Similarly, the relevant velocity is represented by $V_i = V_1, V_2, \ldots, V_p$. Each particle keeps track of its coordinates in search space to find a fitness solution. This value is called personal best and is denoted by $p_{best.}$ The best among p_{best} is called the global best and is denoted by g_{best}. Fitness evaluation is done by subjecting the candidate solution to the objective functions considered. Individual and global best fitness values and positions are updated by comparing the newly evaluated fitnesses with the previous individual and global best fitness values and replacing the best fitnesses and positions as required.

The velocity and position update step is responsible for the optimization ability of the PSO algorithm. The velocity of each particle in the swarm is updated using the following equation:

$$V_i(t+1) = wV_i(t) + c_1 r_1 [p_{best} - X_i(t)] + c_2 r_2 [g_{best} - X_i(t)] \tag{9}$$

Let i be the index of the particle. Thus, V_i (t) is the velocity of particle i at time t and X_i (t) is the position of particle i at time t. The parameters w is the inertia weight (0, 1), cognitive coefficient c_1 and social coefficient c_2 ($c_1 = c_2 = 2$) are used in this algorithm. The values r_1 and r_2 are random values, generated for each velocity update between zero to one. The value p_{best} is the individual particle's best solution and g_{best} is the swarm's global best solution at time t. Each of the three terms of the velocity update equation has different roles in the PSO algorithm.

- The first term wV_i (t) is the inertia component, responsible for keeping the particle moving in the same direction. Inertial coefficient w accelerates the particle in its original direction. Generally, lower values of the inertial coefficient speed up the convergence of the swarm to optima, and higher values of the inertial coefficient encourage exploration of the entire search space [25].
- The second term $c_1r_1[p_{best}-X_i$ (t)], called the cognitive component, acts as the particle's memory and c_1 affects the size of the particle's step which is stepping towards p_{best}.
- The third term $c_2r_2[g_{best}-$ Xi (t)], called the social component, causes the particle to move to the best region the swarm has found so far. c_2 represents the size of the step the particle takes toward the g_{best}. The random values r_1 in the cognitive component and r_2 in the social component cause these components to have a stochastic influence on the

velocity update which causes each particle to move in a semi-random manner influencing the particles to move towards p_{best} and g_{best}.

Once the velocity for each particle is calculated, each particle's position is updated by applying the new velocity to the particle's previous position:

$$X_i(t+1) = X_i(t) + V_i(t+1) \quad (10)$$

The PSO algorithm consists of three steps, which are repeated until desired stopping condition is met [26]:

1. Evaluate the fitness of each particle.
2. Update individual and global best fitness values and positions.
3. Update velocity and position of each particle.

This process is repeated until desired stopping condition is met. It may be either the number of iterations considered or the predefined target fitness value.

4.2 Standard Bacteria Foraging Algorithm:

BFO mimics the foraging strategy of *E. coli* bacteria, which has emerged as a powerful technique for solving optimization problems. The bacterial foraging system consists of three principal mechanisms, namely chemotaxis, reproduction and elimination-dispersal. A brief description of each of these processes and the step by step algorithm has been described below.

4.2.1 Chemotaxis:

The process, in which a bacterium moves by taking small steps while searching for nutrients, is called chemotaxis. This process simulates the movement of an *E. coli* cell through a set of consequent swim steps followed by tumble via flagella. Running speed is 10–20 μm/s, but they cannot swim straight. A maximum of swim steps with a chemotactic step is defined by N_s. The actual number of swim steps is determined by the environment. If the environment shows good nutrients concentration, bacteria swim more steps in a specified direction and are stopped by a tumble action (bacteria modifies its direction of search), when there is poor nutrient concentration. These two modes of operations are performed continuously to move in random directions in search of sufficient positive nutrient gradient for the entire lifetime.

Suppose θ^i (j, k, l) represents the bacterium at j^{th} chemotactic, k^{th} reproductive, and l^{th} elimination-dispersal step. C (i), namely, the run-length unit parameter, is the chemotactic step size during each run or tumble.

Then, in each computational chemotactic step, the movement of the i^{th} bacterium can be represented as

$$\theta^i(j+1,k,l) = \theta^i(j,k,l) + C(i)\frac{\Delta(i)}{\sqrt{\Delta^T(i)\Delta(i)}} \quad (11)$$

where Δ(i) is the direction vector of the j^{th} chemotactic step. When the bacterial movement is run, Δ(i) is the same with the last chemotactic step; otherwise, Δ(i) is a random vector whose elements lie in [−1, 1]. While performing run or tumble at each step of the chemotaxis process, a step fitness denoted as J (i, j, k,), will be evaluated.

4.2.2 Reproduction:

When they get sufficient food, they are increased in length and in the presence of suitable temperature they break in the middle to form an exact replica of itself. After reproduction, the bacteria based on its health values are sorted in ascending order. The bacteria which have low health value will die (higher cost function value means lower health) and the bacteria with the high health value will split into two and reproduce to retain the constant population.

4.2.3 Elimination and Dispersal:

The chemotaxis provides a basis for local search, and the reproduction process speeds up the convergence. Chemotaxis and reproduction are not enough for global optima searching since bacteria may get trapped into local optima. The changes of environment like the sudden change of temperature or nutrient concentration, the flow of water may affect the bacteria in the population to die or move to another place [27]. To simulate this phenomenon, elimination-dispersal is added in the BFO algorithm. After every N_{re} times of reproduction steps, an eliminate-dispersal event happens. For each bacterium, a random number is generated between 0 and 1. If the random number is less than a predetermined parameter, known as P_{ed}, the bacterium will be eliminated and a new bacterium is generated in the environment. After dispersal, sometimes the bacteria may be placed near the good nutrient source in order to support the chemotaxis to find the food sources. The above procedure is repeated until the optimized solutions are achieved. This operator enhances the diversity of the algorithm.

Let j be the index for the chemotactic step. Let k be the index for the reproduction step. Let l be the index of the elimination-dispersal event. Also let

p: Dimension of the search space,
s: Total number of bacteria in the population,
N_c : The number of chemotactic steps,
N_s : The swimming length.
N_{re} : The number of reproduction steps,
N_{ed} : The number of elimination-dispersal events,
P_{ed}: Elimination-dispersal probability,
C (i): The size of the step taken in the random direction specified by the tumble.

4.2.4 Step-by-Step Algorithm

Outline of the original BFO algorithm step by step is given as follows as in [28].

Step 1. Initialize parameters p, s, N_c, N_s, N_{re}, N_{ed}, P_{ed}, C (i) (i = 1, 2, . . . , s).
Step 2. Elimination-dispersal loop: l = l+1.
Step 3. Reproduction loop: k = k+1.
Step 4. Chemotaxis loop: j = j+1.

1. For i = 1, 2, . . , s, take a chemotactic step for bacteria i as follows.
2. Compute fitness function, J (i, j, k).
3. Let J_{last} = J (i, j, k, l) to save this value since we may find better value via a run.
4. Tumble: generate a random vector Δ(i) ∈ R_n with each element Δ_m (i), m=1, 2, . . . , s, a random number on [−1, 1].
5. Move: This results in a step size C (i) in the direction of the tumble for bacteria i.
6. Compute J (i, j+1, k, l) with θ^i (j+1, k, l).
7. Swim:
   i. let m = 0(counter for swim length)
   ii. while m <Ns (if not climbed down too long)
      (a) Let m = m+1
      (b) If J (i, j+1, k, l) < J_{last}, let J_{last} = J (i, j+1, k, l), Then, another step of size C (i) in this same direction will

be taken and use the new generated $\theta^i(j+1, k, l)$ to compute the new J (i, j+1,k, l).

(c) Else let m = Ns.

8. Go to next bacterium (i+1): if i≠ s go to (b) to process the next bacteria.

Step 5. If $j < N_c$, go to Step 3. Continue chemotaxis for the whole life time of the bacteria.

Step 6. Reproduction.

- For the given k and l, and for each i = 1, 2, . . ., s, let

$$J^i_{health} = \sum_{i=1}^{N_c+1} J(i,j,k,l) \qquad (12)$$

be the health of the bacteria. Sort bacterium in order of ascending values (J_{health}).

- The S_r bacteria with the highest J_{health} values die, and the other S_r bacteria with the best values split, and the copies that are made are placed at the same location as their parent.

Step 7. If $k < N_{re}$ go to Step 2. In this case, if the number of specified reproduction steps is not reached; start the next generation in the chemotactic loop.

Step 8. Elimination-dispersal: for i =1, 2, . . ., s, with probability P_{ed}, eliminate and disperse each bacterium, which results in keeping the number of bacteria in the population constant. To do this, if a bacterium is eliminated, simply disperse one to a random location on the optimization domain. If $l < N_{ed}$, then go to Step 2, otherwise, end.

5. Implementation of Hybrid Bacteria Foraging Optimization Algorithm:

In this hybrid method HBFO makes use of PSO's ability to exchange social information to speed up the process and BFO algorithm's ability to find a new solution utilising elimination and dispersal event for providing the optimal PID parameter values [15]. The flowchart for HBFO algorithm is shown in figure. 3 and parameters value assigned for PSO, BFO and HBFO are presented in Table. 2.

Table 2: Assigned parameter values for PSO, BFO and HBFO algorithms

Algorithms used	**Assigned parameters value**
BFO	p = 3, s = 10, $N_c = 2$, $N_s = 2$, $N_{re} = 2$, $N_{ed} = 1$, $S_r = s/2$, $P_{ed} = 0.25$.
HBFO	p = 3, s = 10, $N_c = 2$, $N_s = 2$,$N_{re} = 2$, $N_{ed} = 1$, $S_r = s/2$, $P_{ed} = 0.25$, $c_1 = 1.2$, $c_2 = 0.5$
PSO	Dimension = 3, Swarm size = 20, $c_1 = c_2 = 2$, r_1, r_2: Random numbers obtained from a uniform random distribution function in the interval [0, 1].

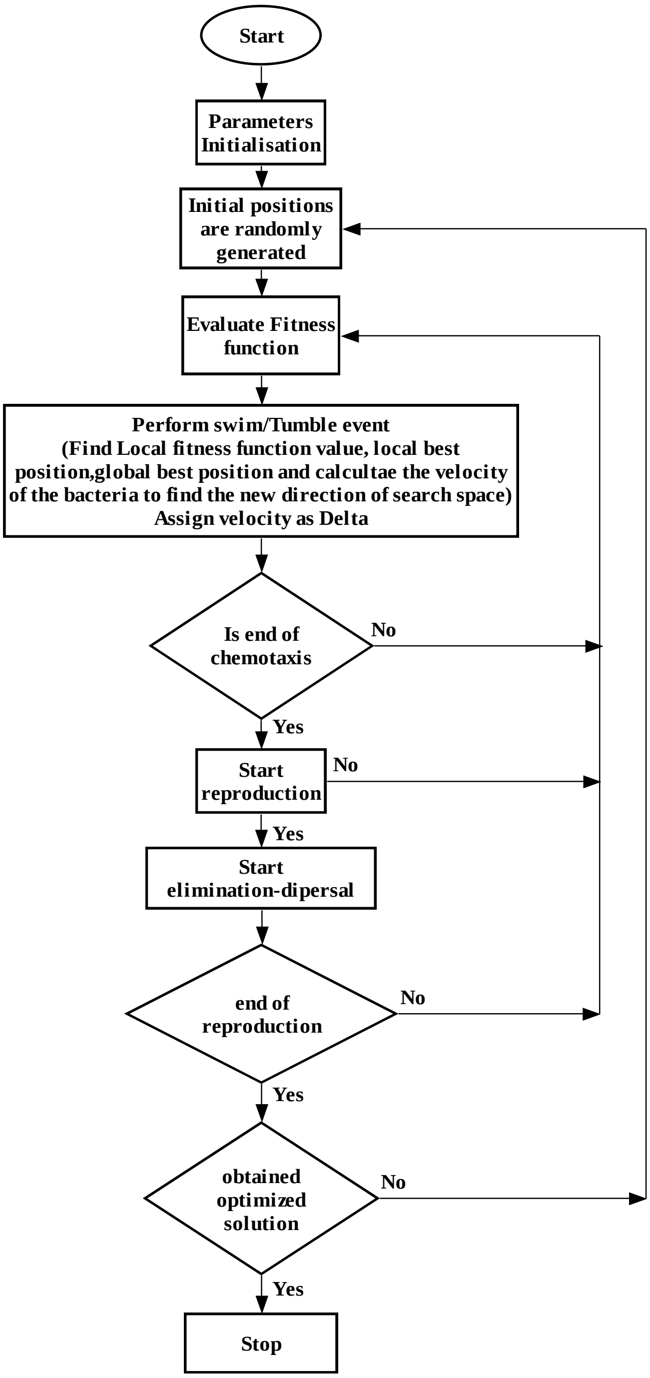


Figure 3: Flowchart of the proposed algorithm.

6. Results and Discussions:

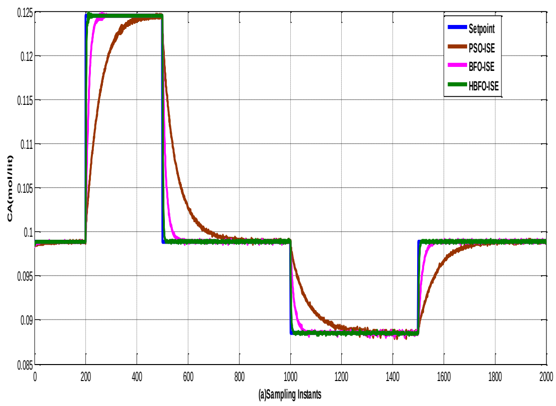
The significance of HBFO algorithm has been validated by comparing the performance of algorithms PSO and BFO individually, both for servo and servo regulatory cases under various performance indices like ISE, ITSE, IAE and ITAE. The CSTR process has been simulated using the nonlinear first principles model given by (7) and (8) and the process output concentration has been computed by solving the nonlinear differential equation using Matlab 7.0. The controller saturation limit between 97 and 109 lit/min is considered with initial conditions given by q_c = 103 lit/min, C_A = 0.0989 mol/lit and T = 438.77 K and the sampling time of about 0.083s is selected for all the simulation studies.

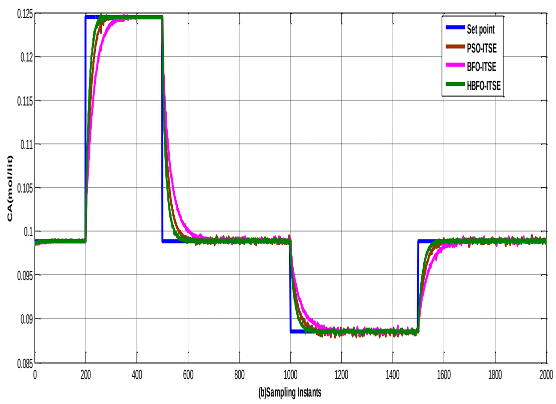
6.1 Servo performance of CSTR process:

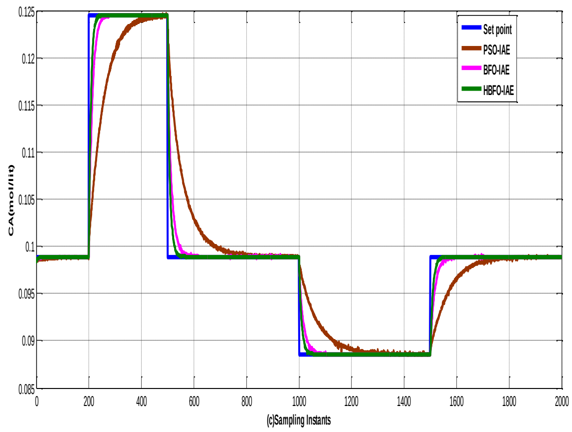
With nominal and shifted operating points, simulation studies have been carried out to demonstrate the set point tracking capability of the CSTR process. The variation in the concentration outputs of PSO, BFO and HBFO based PID controllers have been depicted in Figure 4(a), Figure 4(b), Figure 4(c) and Figure 4(d). Globally optimized PID parameter values for various error criteria such as ISE, IAE, ITSE and ITAE and the corresponding calculated error have been presented for all the algorithms considered for study in Table 3

Table.3 Performance comparison of algorithms in terms of error criteria with its corresponding controller gains (Servo response)

Algorithm used	Error Criteria	Error Criteria values	Optimally tuned PID parameters		
			K_p	K_i	K_d
PSO	ISE	0.0374	16.6751	3.6637	1.1515
	ITSE	6.958	23.1348	1.8789	4.7422
	IAE	4.030	17.8812	4.0203	0.8529
	ITAE	1290	23.954	2.5231	1.8540
BFO	ISE	0.0085	17.8698	0.8869	0.3939
	ITSE	10.12	35.1456	4.3205	1.3414
	IAE	0.9646	39.2451	2.0858	1.8310
	ITAE	1792	32.8315	4.7275	1.9277
HBFO	ISE	**0.0015**	34.1229	0.2798	0.0158
	ITSE	**4.558**	31.8913	1.8003	0.6549
	IAE	**0.5873**	19.9791	0.6465	0.0393
	ITAE	**142.7**	59.8080	0.7085	0.4282







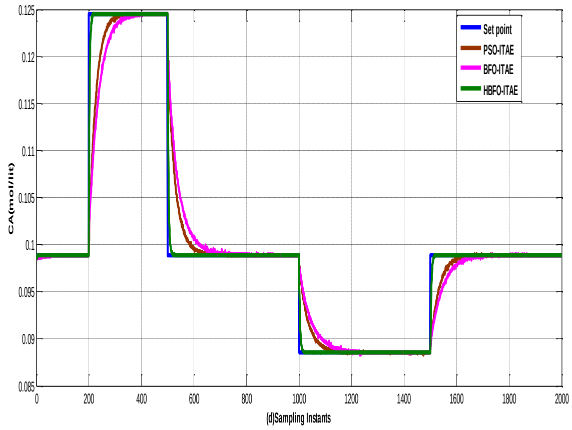
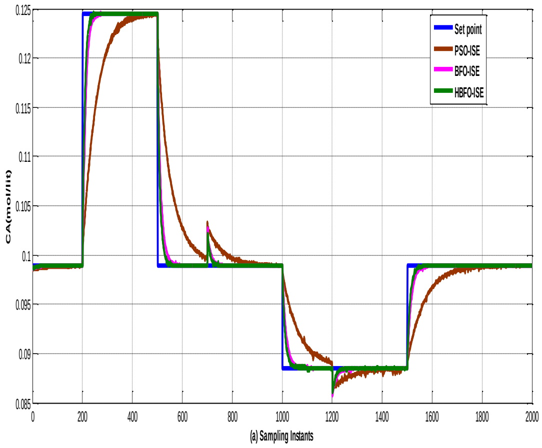


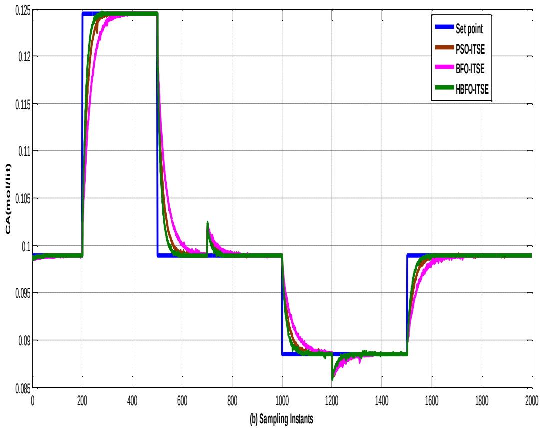
Figure. 4: Servo response of CSTR process. (a) Process output of PSO, BFO, & HBFO algorithm using ISE (b) Process output of PSO, BFO, & HBFO algorithm using ITSE (c) Process output of PSO, BFO, & HBFO algorithm using IAE (d) Process output of PSO, BFO, & HBFO algorithm using ITAE

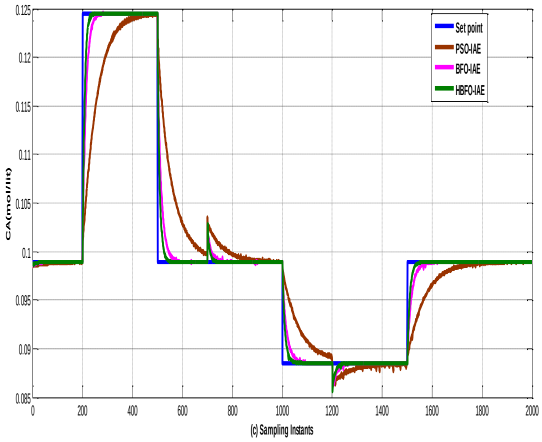
In all set point variations, tracking capability of PSO, BFO and HBFO based PID controllers' exhibit satisfactory performance. Also, it has been inferred that HBFO based PID controllers perform with better set point tracking and faster settling time in all set point transitions. From Table. 3, it has been observed that HBFO based PID controller provides reduced error compared to other algorithms. In addition, cost function ISE is capable of producing minimized error compared to other cost functions in the allowed set point variations.

6.2 Servo Regulatory response of CSTR process: (C_{Af} as disturbance)

Simulation studies have been carried out to demonstrate the load rejection capability of the CSTR process at nominal and shifted operating point in the presence of change in the feed concentration. A step change in the feed concentration of magnitude 0.005 mol/l (from 1 to 0.995 mol/l) has been introduced at the 700th sampling instant and maintained up to 1200th sampling instant.







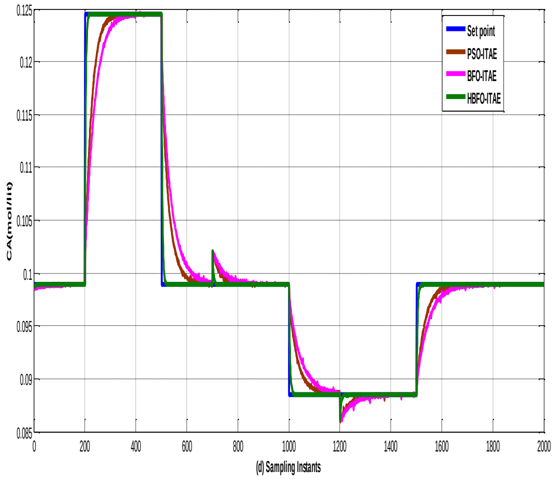
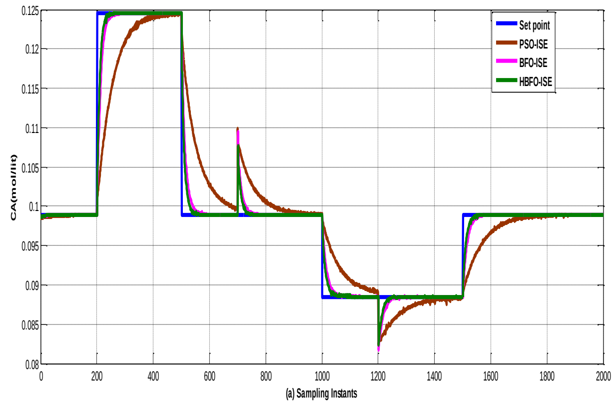


Figure 5: Servo regulatory response of CSTR process. (a) Process output of PSO, BFO, & HBFO algorithm using ISE (b) Process output of PSO, BFO, & HBFO algorithm using ITSE (c) Process output of PSO, BFO, & HBFO algorithm using IAE (d) Process output of PSO, BFO, & HBFO algorithm using ITAE.

PSO, BFO and HBFO based PID controllers using ISE, IAE, ISE and ITAE as objective functions are able to reject the disturbance provided at 700th sampling instant and bring the reactor concentration back to the nominal value of the set point as shown in Figure 5(a), Figure 5(b), Figure 5(c) and Figure 5(d). Also at shifted operating point the controllers are capable of rejecting the disturbance without much delay (refer 700th sampling instant). HBFO based PID controllers provide better performance in terms of set point tracking and disturbance rejection in comparison with other algorithms based PID controllers.

6.3 Servo regulatory response of CSTR process (T_f as disturbance)

The controllers using different performance indices as objective functions are able to reject the sudden change in the disturbance quickly and bring the reactor concentration back to the set point at nominal and shifted operating point as shown in Figure 6(a), Figure 6(b), Figure 6(c) and Figure 6(d).



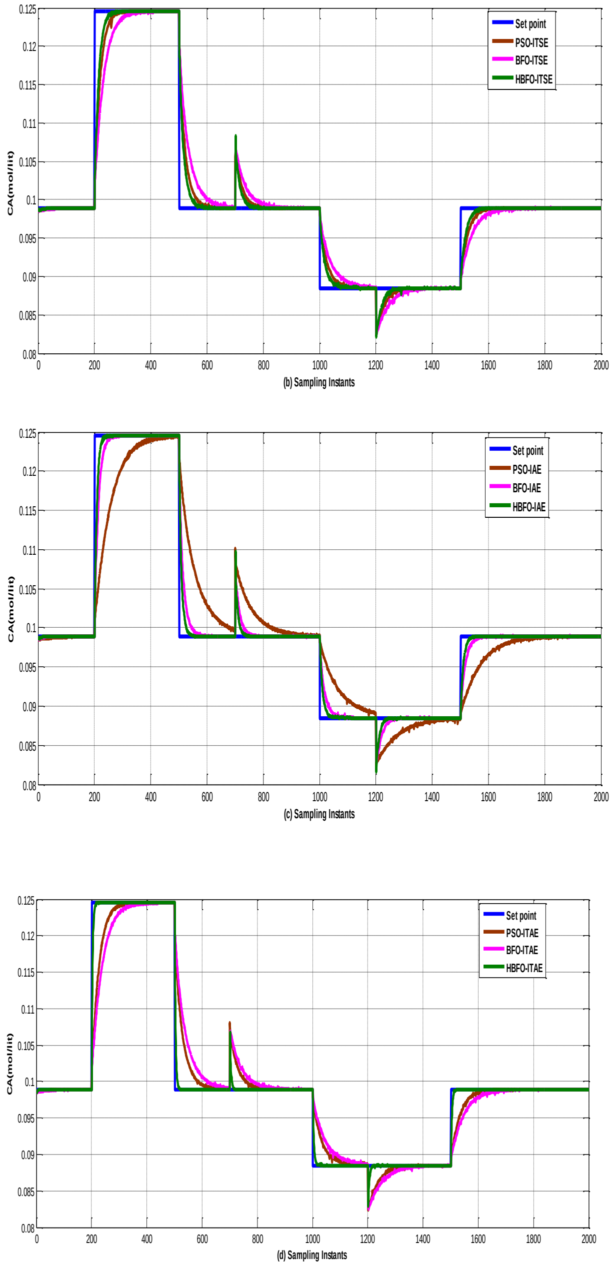


Figure 6: Servo regulatory response of CSTR process. (a) Process output of PSO, BFO, & HBFO algorithm using ISE (b) Process output of PSO, BFO, & HBFO algorithm using ITSE (c) Process output of PSO, BFO, & HBFO algorithm using IAE (d) Process output of PSO, BFO, & HBFO algorithm using ITAE.

6.4 Servo regulatory response of CSTR process (Feeding C_{Af} and T_f simultaneously)

Simulation study has been carried out by providing the disturbances feed temperature and feed concentration simultaneously. For combined disturbance also, PSO, BFO and HBFO based PID controllers with various error criteria have given satisfactory performance at nominal and shifted operating points as shown in Figure 7(a), Figure 7(b), Figure 7(c), Figure 7(d). Performance indices such as ISE, IAE, ITSE and ITAE, the calculated error for individual disturbances namely feed concentration (C_{Af}) and feed temperature (T_f) and for combined disturbances (C_{Af} & T_f) have been presented for all the algorithms in Table 4.

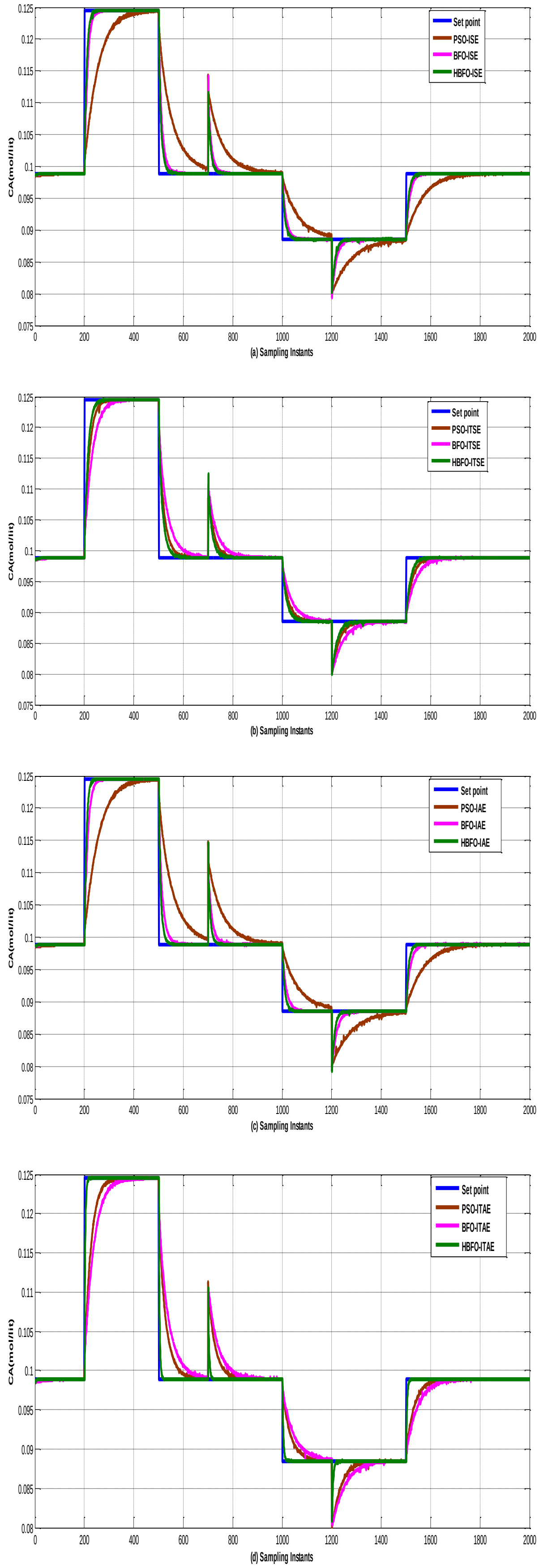


Figure 7: Servo regulatory response of CSTR process. (a) Process output of PSO, BFO, & HBFO algorithm using ISE (b) Process output of PSO, BFO, & HBFO algorithm using ITSE (c) Process output of PSO, BFO, & HBFO algorithm using IAE (d) Process output of PSO, BFO, & HBFO algorithm using ITAE.

Table 4: Performance comparison of algorithms in terms of disturbance rejection. (Servo regulatory)

Algorithm used	Error Criteria	Disturbances		
		C_{Af}(mol/lit)	T_f (K)	Combined load
PSO	ISE	0.0381	0.0413	0.0449
	ITSE	7.261	8.276	9.455
	IAE	4.338	4.943	5.337
	ITAE	1467	1743	1922
BFO	ISE	0.0087	0.0094	1.0102
	ITSE	10.45	11.94	13.69
	IAE	1.053	1.199	1.291
	ITAE	2022	2404	2654
HBFO	ISE	**0.0058**	**0.0062**	**0.0067**
	ITSE	**4.803**	**5.506**	**6.31**
	IAE	**0.6437**	**0.7305**	**0.7868**
	ITAE	**162.3**	**192.9**	**212.3**

From the results obtained from Table. 4 it has been concluded that for individual and combined loads, in all the error goals like ITAE, ITSE, ISE and IAE, HBFO technique provides satisfactory disturbance rejection.

Conclusions:

Study and simulation of swarm based algorithms like BFO, PSO individually and hybrid algorithm HBFO have been done using various performance indices as cost functions for optimal control of reactor concentration in a CSTR process. It has been inferred that hybrid approach of combining positive features of both the algorithms provide better convergence property, less computation time and capable of achieving global solution. Simulation results convey that HBFO algorithm provides satisfactory servo and servo regulatory control for a CSTR system than individual performance of the algorithms considered in this research work.

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