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Optimal Design of PID Controller for a CSTR System Using BF-PSO

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Abstract: Social foraging behavior of a Escherichia–colibacteria has been explored to develop a novel algorithm for distributed optimization and control. Recently hybrid approach developed, involving PSO and BFOA (bacterial foraging optimization algorithm) algorithm for optimizing multi-model and high dimensional function.
This paper presents the optimal design of PID controller based on a Bacterial foraging particle swarm optimization (BF-PSO) approach for continuous stirred tank reactor (CSTR). The mathematical model of experimental system had been approximated near the operating point for the PSO algorithm to adjust PID parameters for the objective function. The results show the adjustment of PID parameters converting into the optimal point. The good control response is obtained based on the optimal values by the BF-PSO technique.
Index Terms: PSO (Particle swarm optimization),BF-PSO, optimal control, simulation.

I. INTRODUCTION

The process control techniques in the industry have made great advances during the past decades. A no of control methods such as adaptive control, neural control, and fuzzy control have been studied. Among them, the best known is the proportional-integral-derivative (PID) controller, which has been widely used in the industry because of its simple structure and robust performance in a wide range of operating conditions. Unfortunately, it has been quite difficult to tune properly the gains of PID controllers because many industrial plants are often burdened with problems such as high order, time delays, and nonlinearities. It is hard to determine optimal or near optimal PID parameters with the classic tuning method (Ziegler-Nichol's method for instance). For these reasons, it is highly desirable to increase the capabilities of PID controllers by adding new features.

Many artificial intelligence (AI) techniques have been employed to improve the controller performances for a wide range of plants while retaining their basic characteristics. AI techniques such as neural network, fuzzy system, and neural-fuzzy logic have been widely applied to proper tuning of PID controller parameters.

Particle swarm optimization (PSO) [1], first introduced by Kennedy and Eberhart, is one of the modern heuristic algorithms. It was developed through simulation of a simplified social system, and has been found to be robust in solving continuous nonlinear optimization problems. The PSO technique can generate a high-quality solution within shorter calculation time and stable convergence characteristic than other stochastic methods. PSO method is an excellent optimization methodology and a promising approach for solving the optimal PID controller parameters. Therefore, this study develops the PSO-PID controller to search optimal PID parameters. This controller is called the PSO-PID controller. In this paper, we propose a particle swarm optimization approach for optimal design of PID controller for continuous stirred tank reactor.

The Bacterial Foraging Optimization Algorithm (BFOA) is currently gaining popularity in the community of researchers, for its effectiveness in solving certain difficult real-world optimization problems. BFOA is based on the foraging strategies of Ecoli bacterium cells and was proposed by Prof. K. M. Passino in 2001 [19]. PSO and DE are excellent heuristics like other evolutionary algorithms

[17]. Practical experiences suggest that they reach stagnation after certain number of generations as the population is not converged locally, so they will stop proceeding towards global optimal solutions. The stochastic search methods are proven in reaching global solutions for certain difficult real world optimization problems [18]. Hence this article comes up with a hybrid approach involving PSO-DE and BFOA algorithm for solving non-convex DED problem considering valve-point loading effects, ramp-rate limits, prohibited operating regions and spinning reserve capacity.

The new method is shown to be statistically significantly better on a test systems consisting of ten generating units. The results obtained through the proposed method are compared with those reported in the literature.

II. FUNDAMENTALS OF PID CONTROLLERS

Widely applied in industry to solve various control problems. PID controllers have been used for decades. During this time, many modifications have been presented in the literatures [2]-[6]. As modeled in this paper, the transfer function of PID controller is described by the following equation in the continuous *s*-domain (Laplace operator).

$$\frac{U(s)}{E(s)} = \left\{ \mathrm{Kc} + \frac{\mathrm{Ki}}{\mathrm{s}} + \mathrm{sKd} \right\} + b \qquad (1)$$

Where $U(s)$ and $E(s)$ are the control (controller output) and tracking error signals in *s*-domain, respectively; k_p is the proportional gain, k_i is the integration gain, and k_d is the derivative gain. *Ti* is the integral action time or reset time and *Td* is referred to as the derivation action time or rate time. In this context, output of the PID controller in time domain is given by

$$\mathrm{u(t)} = \mathrm{K_p e(t)} + \mathrm{K_i} \int_0^t e(\lambda)\, d(\lambda) + \mathrm{K_d} \frac{de(t)}{dx} + \mathrm{b} \qquad (2)$$

Where $u(t)$ and $e(t)$ are the control and tracking error signals in time domain, respectively. The proportional part of the PID controller reduces error responses to disturbances. The integral term of the error eliminates steady state error and the derivative term of error dampens the dynamic response and thereby improves stability of the system. The parameter settings of a PID controller for optimal control of a plant depend on the plant's behavior. To design the PID controller the engineer can appropriately choose the combination of and to simultaneously take care of the transient response as well as the steady-state error. In the design of a PID controller, the three gains of PID must be selected in such a way that the closed loop system has to give the desired response. The desired response should have minimal settling time with a small or no overshoot in the step response of the closed loop system. A performance index is a quantitative measure of the performance of the system. A system is considered an optimal control system when the system parameters are adjusted so that the index reaches an extreme value, commonly a minimum value [7]. A suitable performance index taken for the CSTR system

$$F = e^2 * \beta + sys\_overshoot * \alpha$$

$\alpha = 10$

$\beta = 10$

e = error

III. CSTR PROCESS DESCRIPTION

In this paper, we consider the control problem of an ideal jacketed Continuously Stirred Tank Reactor (CSTR) system (Fig.1), where the following exothermic and irreversible first-order reaction is taking place:

$$\mathrm{A \rightarrow B} \qquad (3)$$

the kinetics rate law

$$-r_A = KT\,(C_A) = K_0 \exp\left(-E^* C_A / RT\right) \qquad (4)$$

Under the assumptions of constant volume, perfect mixing inside the reactor and constant reacting mixture heat capacity, one may write down the following mass balance for species **A**, as well as an overall energy balance for the reactor:

$dC_A/dt = F(C_{A,in})/V - k(T)C_A$ (5)

$dT/dt = F(T_{in}-T)/V - h_r(kT)C_A/\rho c_p - UA_r(T-T_j)/V\rho c_p$ (6)

Under the assumptions of uniform temperature of the jacket fluid inside the circulation tubes and constant water heat capacity, an energy balance for the jacket may also be written down:

$dT_j/dt = F_{cw} * \rho w * (T_{cw}-T_j)/m_o + P/C_w m_o + UA_r\,(T-T_j)/C_w m_o$ (7)

In equations (5) – (7) t is the time, c are concentrations, T represents temperatures, T_j is the jacket temperature, c_p is used for specific heat capacities, F represents Volumetric flow rate, m_0 is overall effective mass of the heating/cooling system, V is reactor volume, ρ represents densities, A_r is the heat exchange surface, c_w is heat capacity of water, P is power input to the heater, T_{cw} is temperature of cooling water and U is the heat transfer coefficient. The numerical values taken from [5] (see, [6] for more details on CSTR). A linear model will be developed around the steady-state operating point. The linearization will be respect to C_A and $T, C_{A,in}$ *.in* and T_{in} . The goal is to control the reactor composition by manipulating the cool rate through the control signal u. Without getting into more details, the transfer function of the system has the form:

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$$H_{yu}=\frac{-1.308*e^{-4.896s}}{(13.515s)(6.241s+1)} \quad (8)$$

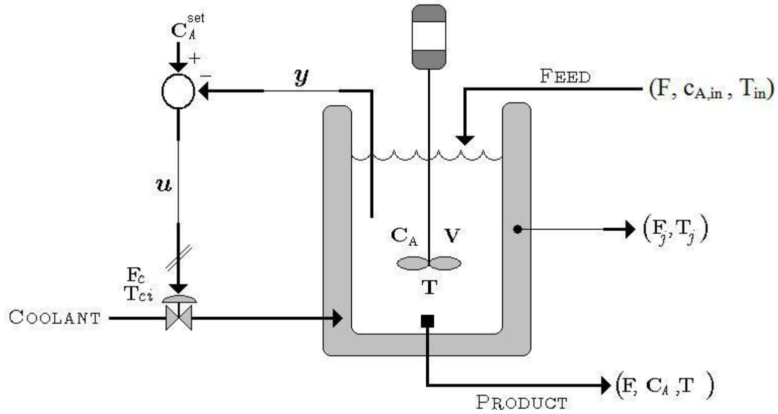


Fig.1. A CSTR Control System

IV. BF-PSO ALGORITHM

Particle swarm optimization (PSO) [1] is a stochastic optimization technique that draws inspiration from the behavior of a flock of birds or the collective intelligence of a group of social insects with limited individual capabilities. In PSO a population of particles is initialized with random positions X_i and velocities V_i , and a fitness function, *f*, is evaluated, using the particle's positional coordinates as input

values. In an n-dimensional search $X_i = (X_{i1}, X_{i2}, X_{i3},\ldots,X_{in})$ and $V_i= (V_{i1}, V_{i2}, V_{i3},\ldots,V_{in})$.

Positions and velocities are adjusted, and the function is evaluated with the new coordinates at each time- step. The velocity and positions and update equation for the d^{th} dimension of the i^{th} particle in the swarm may be given as follows:

$$V_{id}(t+1) = wV_{id}(t) + c_1\Phi_1(P_{1id}-X_{id}(t)) + c_2\Phi_2(P_{gd} - X_{id}(t)) \quad (9)$$

$$X_{id}(t+1) = X_{id}(t) + V_{id}(t+1) \quad (10)$$

The BFOA is on the other hand is based upon search and optimal foraging decision making capabilities of the *E. Coli*bacteria [16]. The coordinates of a bacterium here represent an individual solution of the optimization problem. Such a set of trial solutions converges towards the optimal solution

following the foraging group dynamics of the bacteria population. Chemo-tactic movement is continued until a bacterium goes in the direction of positive nutrient gradient (i.e. increasing fitness). After a certain number of complete swims the best half of the population undergoes reproduction, eliminating the rest of the population. In order to escape local optima, an elimination-dispersion event is carried out where, some bacteria are liquidated at random with a very small probability and the new replacements are initialized at random locations of the search space. A detailed description of the complete algorithm can be traced

in [1].In the proposed approach, after undergoing a chemo-tactic In the proposed approach, after undergoing a chemo-tactic step, each bacterium also gets mutated by a PSO operator. In this phase, the bacterium is stochastically attracted towards the globally best position found so far in the entire population at Synergy of PSO and Bacterial Foraging Optimization 257 current time and also towards its previous heading direction. The PSO operator uses only the 'social' component and eliminates the 'cognitive' component as the local search in different regions of the search space is already taken care of by the chemo tactic steps of the BFO Aalgorithm. In what follows we briefly outline the new BSO algorithm step by step.

[Step 1]Initialize parameter $n,N,N_c,N_s,N_{ed},N_{rc},P_{ef},C(i)$

where,

n = dimension of the search space

N = The no of bacteria in the population

N_c = no of chomo-tactic steps

N_{rc} = The no of reproduction steps

N_{ed} = The no of elimination dispersal events

P_{ef} = elimination dispersal with probability

w = The inertia factor

C(i) = swarm confidence
V_i = velocity vector of ith bacteria
[Step 2] Update the following:
J (i, j, k): Cost or fitness value of the i-th bacterium in the jthchemo-taxis, and k-th reproduction loop.
Θ_{gbest}: Position vector of the best position found by all bacteria.
J_{best} (i, j, k): Fitness of the best position found so far.
[step 3] reproduction loop k=k+1
[step 4] chemotaxix loop j=j+1
[substep a] For i= 1,2,3…..N take a chemotactic bacteria I as follows
[substep b] compute fitness function $J(i, j, k)$
[substep c] let J *least*= $J(i, j, k)$to same this value since weman find a better cost via a run
[substep d] Tumble : generate a random vector
$\Delta(i) \in R$ with each element D$m(i)$,m=(1,2,…p)A random no on[-1,1]
[substep e] Move**:**
Let
$\theta(i, j+1, k) = \theta(j, j, k) + C(i)\,\Delta(i)/\{\Delta T(i)\Delta(i)\}$

[substep f] complete q $(i, j+1, k)$
[substep g] swim: we consider i-th bacteria is swimming while other are not moving then Let $m = m+1$
If $J(i, j+k) < J_{last}$(if doing better)
Let J *last*= J $(i, j+1, k)$and let
$\theta^i(j+1, k, l) = \theta^i(j, k, l) + C(i)\,\Delta(i)/\sqrt{\{\Delta T(i)\Delta(i)\}}$
And use this $J(i, j+1, k)$ to complete the new $J(i, j+1, k)$
as we did in [substep a]
Else let $s\ m = N$ this is the end of the control statement
[step 5] mutation with PSO operator
For i= (1,2,3,4……….S)
Update the q *g _ best*&*J best(i j k)*
Update the position and velocity of the d-th coordinate of thei-th bacterium according the following rule
$V_{id}^{new} = w\,V_{id}^{new} + c_1\Phi_1(q\,g\_best - q_d^{old}(i, j+1, k))$
$q_d^{new}(i, j+1, k)) = q_d^{old}(i, j+1, k) + V_{id}^{new}$
[step 6] LetS_r = S/2
The S_rbacteria with highest cost function (J)values die and the other half of bacteria population with the best values split (and the copies that are made are placed atthe same location as their parent).
[step 7] If $k<N_{re}$, go to step 1. We have not reached the specified number of reproduction steps. So we start the next generation in the chemo-taxis loop.

V. OPTIMAL PID CONTROLLERS With BF-PSO

The control system with a set of optimal PID parameters can obtain an excellent response output show in Fig.2. The value of fitness function defined by optimization algorithm would be the minimum. Performance characteristic of evaluation function includes overshoot, rise time, settling time and static error time. The evaluation function as in (6), to compute the evaluation value of each particle in swarm according to control performance.

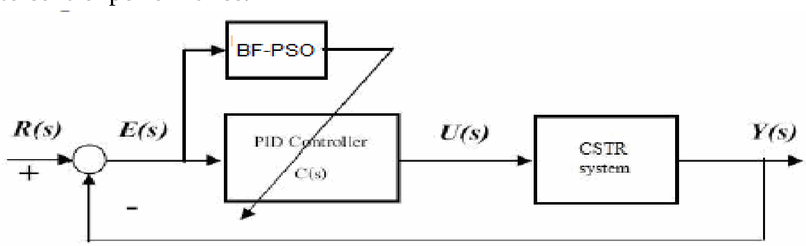


Fig.2 Block dig of optimal PID controller with BF-PSO for CSTR

p =3; Dimension of search space
s=10; The number of bacteria
N_c=15; Number of chemotactic steps
Ns=4; Limits the length of a swim
N_{re}=4The number of reproduction steps
N_{ed} =2The number of elimination- dispersal events
S_r = S/2; The number of bacteria reproductions (splits) per generation
p_{ed}=0.25; The probabilty that each bacteria will be eliminated/dispersed

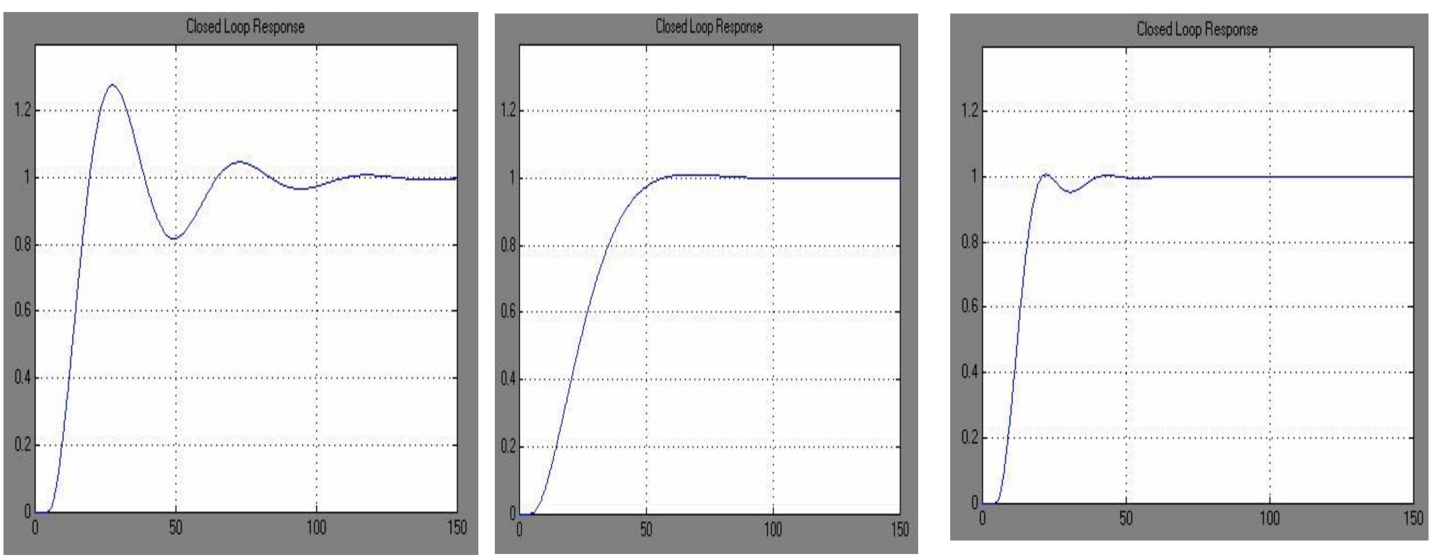
c(:,1)=0.5*ones(s,1); the run length The single loop PID parameter tuning for CSTR system is accomplished by Ziegler Nichols[15] , PSO algorithm and BF-PSO Algorithm,. The desired parameters are obtained according to Table 1

Table 1
Obtained Parameters by Proposed Methods

	K_p	K_i	K_d
Ziegler-Nichols	-1.4702	-0.0601	0
PSO Algorithm	-.43278	-.030605	0.23803
BF-PSO Algorithm	-2.1638	-0.0587	-11.2071

A. Simulation Result

Step response of the proposed method;
(a) Ziegler-Nichols (b) PSO Algorithm (c) BF-PSO Algorithm



Comparision of all three methods used
Comparison of time domain specifications for CSTR System

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	Raise time(in sec)	peak overshoot	Settling time	system
Open loop	25	-	-	unstable
Closed loop(Z-N method)	18.3	27	80	stable
Closed loop(PSO-PID method)	45	1	60	stable
Closed loop(BF-PSO-PID method)	19	.01	45	stable

VI. CONCLUSION

The essence of our work is that we managed to combine two major paradigms PSO and BFA in order to create a robust clustering algorithm. The resulting hybrid method showed improved result. This work explains a design of PID controller by using the BF-PSO algorithm to search for optimal parameters of PID controller (k_p , k_i , k_d) in off linemode. Experiment with CSTR system shows that the parameter obtained from the hybrid-PSO (BF-PSO) method gives better response and tracking to the optimal value. Finally, this experiment is flexible to apply for adaptive control.

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