OPEN ACCESS

International
Journal
Of Modern Engineering Research (IJMER)

An Hybrid Learning Approach using Particle Intelligence Dynamics and Bacterial Foraging Behavior for Optimized PID Parameters Evolutionary Computation of Control System Transfer Functions

Astha Singh[1], Saifur Rahman[2]

[1](ECE, Integral University, India)

[2](Department of ECE, Integral University, India

Abstract: *The foraging behavior of E. Coli is used for optimization problems. This paper is based on a hybrid method that combines particle swarm optimization and bacterial foraging (BF) algorithm for solution of optimization results. We applied this proposed algorithm on different closed loop transfer functions and the performance of the system using time response for the optimum value of PID parameters is studied with incorporating PSO method on mutation, crossover, step sizes, and chemotactic of the bacteria during the foraging. The bacterial foraging particle swarm optimization (BFPSO) algorithm is applied to tune the PID controller of type 2, 3 and 4 systems with consideration of minimum peak overshoot and steady state error objective function. The performance of the time response is evaluated for the designed PID controller as the integral of time weighted squared error. The results illustrate that the proposed approach is more efficient and provides better results as compared to the conventional PSO algorithm.*

Keywords: *PSO, Bacterial foraging, PID tuning, Evolutionary Algorithm, Optimum Control.*

I. INTRODUCTION

In the recent time optimization methods using on PSO have received great interest from the researchers and design engineers for dealing with problems objectives that have been shown to be unaccomplished by using conventional solving techniques. Some researchers have used hybrid optimization algorithm approaches [1] are also proposed for many design problems. In this method combined reasoning takes place by use of fuzzy aggregation functions, capable of combining information by compensatory connectives that replicates the human reasoning process, employed in traditional set theories. The optimum value of parameters of the connectives is evaluated by genetic algorithms.

Similarly the use of different methods from the fuzzy logic for classification was proposed [3] with the potential of their application in providing better classification results. This method considered the integration of techniques with an initial rule generation step and a following rule tuning approach using different evolutionary algorithms. Lee and Lee [4] introduced a hybrid search algorithm combining the genetic algorithms and ant colony optimization (ACO) that can help in exploring the search space and exploit the best solutions.

The methodology related to natural selection works with the eliminations of animals with poor foraging strategies through methods of locating, handling, and ingesting food, and supports the propagation of genes in animals that have successful foraging strategies, because they have more likely to obtain reproductive success [7, 8]. In this way after many generations, poor foraging strategies are either eliminated or converted into better strategies. Since a foraging organism/animal takes actions to maximize the energy utilized per unit time spent foraging, considering all the constraints presented by its own physiology, such as sensing and cognitive capabilities and environmental parameters (e.g., density of prey, risks from predators, physical characteristics of the search area), natural evolution could lead to optimization. This is the main theory idea that are applied in the complex optimization problems. The optimization problem search space could be modeled as a social foraging environment where groups of parameters communicate cooperatively for finding solutions to difficult engineering problems [9].

II. RELATED WORK

As a result of extensive investigation to devise methods of choosing optimum controller setting for the PID controller, Ziegler and Niclhols showed how they could be estimated using open and closed loop tests on the plants. The method is referred to as ZN rules. The ZN setting usually experiences excessive overshoot of the plant response. With the ease of computation, numerical optimization methods become significant in devising formula for PI and PID controller parameter tuning. The squared error integral criteria are the most common for such optimization.

Several optimization techniques using the swarming principle have been adopted to solve a variety of engineering problems in the past decade. Ant Colony Optimization (ACO) was introduced around 1991-1992 by M. Dorigo and colleagues as a novel nature-inspired metaheuristic for the solution of hard combinatorial optimization problems. Farooq et al developed a bee inspired algorithm for routing in telecommunication network. The work is inspired by the way these insects communicate. Swarming strategies in bird flocking and fish schooling are used in the Particle Swarm Optimization (PSO) introduced by Eberhart and Kennedy [5]. A relatively newer evolutionary computation algorithm, called Bacterial Foraging scheme has been proposed and introduced recently by K.M.Passino [2]. In this paper, the use of both PSO and (E coli) based optimization for PID parameter tuning is investigated. A new algorithm bacterial foraging oriented by particle swarm optimization (BF-PSO) is proposed that combine the above mentioned optimization algorithms.

III. METHODOLOGY

3.1Bacterial foraging algorithm:

Recently, search and optimal foraging of bacteria have been used for solving optimization problems [6].To perform social foraging, an animal needs communication capabilities and over a period of time it gains advantages that can exploit the sensing capabilities of the group. This helps the group to predate on a larger prey, or alternatively, individuals could obtain better protection from predators while in a group.

Overview of chemo tactic behavior of Escherichia coli: In our research, we considered the foraging behavior of E. coli, which is a common type of bacteria.

Its behavior and movement comes from a set of six rigid spinning (100–200 r.p.s) flagella, each driven as a biological motor. An E. coli bacterium alternates through running and tumbling. Running speed is 10–20 lm/s, but they cannot swim straight. The chemo tactic actions of the bacteria are modeled as follows:

- In a neutral medium, if the bacterium alternatively tumbles and runs, its action could be similar to search.
- If swimming up a nutrient gradient (or out of noxious substances) or if the bacterium swims longer (climb
- up nutrient gradient or down noxious gradient), its behavior seeks increasingly favorable environments.
- If swimming down a nutrient gradient (or up noxious substance gradient), then search action is like avoiding unfavorable environments.

Therefore, it follows that the bacterium can climb up nutrient hills and at the same time avoids noxious substances. The sensors it needs for optimal resolution are receptor proteins which are very sensitive and possess high gain. That is, a small change in the concentration of nutrients can cause a significant change in behavior. This is probably the best-understood sensory and decision-making system in biology [6].

Mutations in E. coli affect the reproductive efficiency at different temperatures, and occur at a rate of about 10_7 per gene per generation. E. coli occasionally engages in a conjugation that affects the characteristics of the population. There are many types of taxis that are used in bacteria such as, aerotaxis (attracted to oxygen), phototaxis (light), thermotaxis (temperature), magnetotaxis (magnetic lines of flux) and some bacteria can change their shape and number of flagella (based on the medium) to reconfigure in order to ensure efficient foraging in a variety of media. Bacteria could form intricate stable spatio-temporal patterns in certain semisolid nutrient substances and they can survive through a medium if placed together initially at its center.

Moreover, under certain conditions, they will secrete cell-to-cell attractant signals so that they will group and protect each other.

3.2Particle swarm optimization (PSO):

The Particle Swarm Optimization (PSO) model [5] consists of a swarm of particles, which are initialized with a population of random candidate solutions. They move iteratively through the d-dimension problem space to search the new solutions. Each particle has a position represented by a position-vector Xik where (i is the index of the particle), and a velocity represented by a velocity-vector V Ik . Each particle remembers its own best position PiLbest. The best position vector among the swarm then stored in a vector PiGlobal. During the iteration time k, the update of the velocity from the previous velocity to the new velocity is determined by.

$$V\,ik{+}1 = V\,ik + C1R1(PiLbest - Xik) + C2R2(PiGlobal - Xik) \quad (1)$$

The new position is then determined by the sum of the previous position and the new velocity.

$$Xik{+}1 = Xik + V\,ik{+}1 \quad (2)$$

Where R1 and R2 are random numbers. A particle decides where to move next, considering its own experience, which is the memory of its best past position, and the experience of the most successful particle in the swarm .

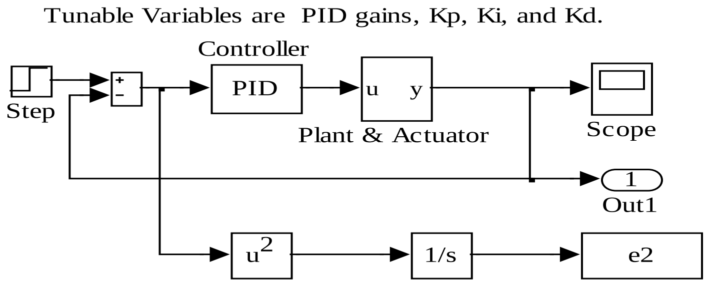


Fig 1: Block Diagram of Tunable closed loop PID controller system.

IV. Results And Discussion

In this section we will discuss the results of our developed hybrid Bacterial Foraging and PSO optimization algorithm for determining optimize solution of tuned values of the PID controller parameters. The results consist of time response of the system having tuned PID values at which we get minimum steady state error and peak over shoot in the step response for a plant. We have drive the values of PID parameters using PSO and Bacterial Swarm Optimization hybrid method (BSO) on a systems of different types and order system as a plant transfer function. The cost function is considered as the sum of peak over shoot and squared of the integral error. Each iteration algorithm selected the parameter which gives minimum cost. The Block diagram of our control system is designed by simulink model as shown in fig 1 for different transfer functions of plant. Results are calculated using PSO and Hybrid BFO-PSO algorithm implemented in MATLAB 10. The optimization alogorithm is written that runs the close loop control system (fig 1) design iteratively under the formulation of respective optimization technique.

The transfer functions considered for the plants are given are:

Table 1: List of Transfer Function Considered for PID Tunning

S.No.	Transfer Function Name	**Equation**
(a)	TF1	$\left(\frac{S+5}{S^4+17S^3+60S^2+10S}\right)$
(b)	TF2	$\frac{5}{S^4+3S^3+7S^2+5S}$
(c)	TF3	$\left(\frac{S+5}{S^4+17S^3+60S^2+10S}\right)$
(d)	TF4	$\left(\frac{300(S+100)}{S(S+10)(S+40)}\right)$

Fig 2 shows the best response out of responses obtained by the BSO algorithm(dashed line) with the step response having minimum steady state error and error in the peak overshoot for all the transfer functions TF1 to TF4. In same figures in fig 2 we demonstrate the step response obtained by running PSO algorithm(solid line) for best optimum values of PID gain with minimum steady state error and peak over shoot out of these five responses from both PSO and BSO. Below the figures we have also given the peak over shoot (MPBSO and MPPSO)of all the four cases of both algorithms for TF1 to TF4 in the table .It is giving a clear idea about the variation in peak values from steady state response that cannot be easily observed from the fig 2 plots. From the tabulated values we can conclude that BSO is giving minimum peak over shoot.

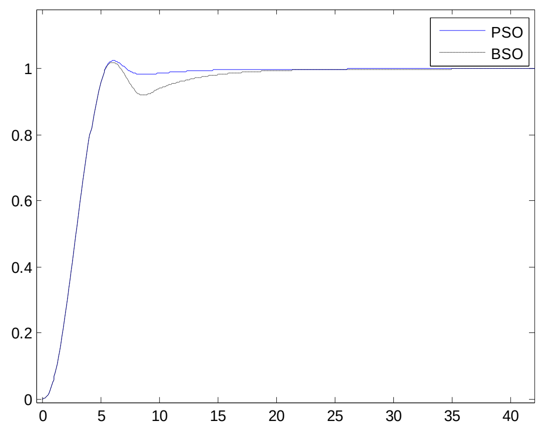
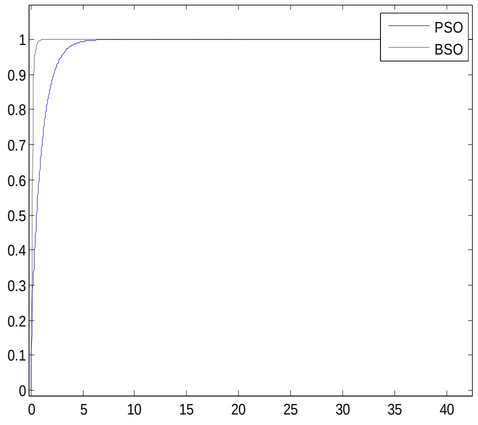
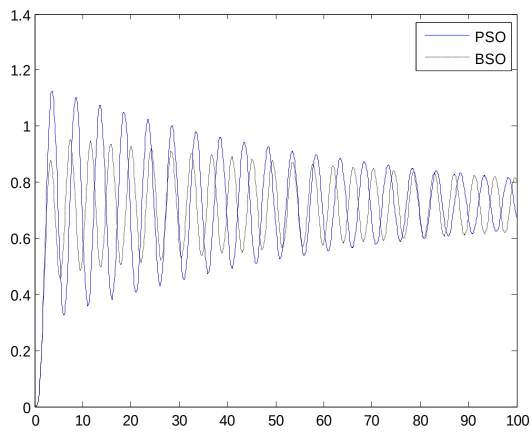
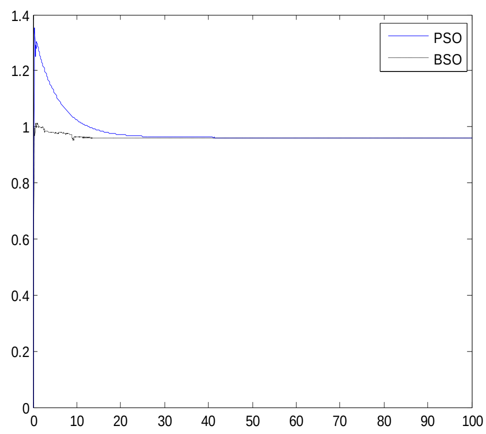
		
MP_{BSO} MP_{PSO}	0.024897113162271 0.020736526713352	$0.823320191 \times 10^{-4}$ $0.210999901082420 \times 10^{-4}$
	(a)TF1 step response for BSO and PSO.	(b) TF2 step response for BSO and PSO.
		
MP_{BSO} MP_{PSO}	0.1256 -0.0494	0.351458065311533 0.014747796747556
	(c) TF3 step response for BSO and PSO.	(d) TF4 step response for BSO and PSO.

Fig 2 : Time Response of Different Transfer functions.

V. CONCLUSION

In this article a new hybdrib optimization approach is proposed by combining benefits of Particle swarm and Bacterial Foraging technique in order to get better optimization valueswith higher accuracy and in less time. The proposed hybrid optimization BSO method is utilized to the problem of tuning of PID controller at the minimum cost of peak over shoot and steady state error and is compared with conveniently Particle swarm optimization.

The cost function here is the square of integral error. The closed loop PID controller cascaded with the process is tuned for values Kp, Ki and Kd. Results obtained by using (BSO) algorithm are presented in terms of step response and peak overshoot values. Figure 2 presents the tuning results using PSO and BSO. The parametric value of Kp,Ki and Kd are randomly initialized in the same range for all methods.The result founded by the both algorithms nearly gives the the same conclusion i.e in each algorithm peak overshoot in case of BSO is less than PSO.

REFERENCES

[1] A. Abraham, EvoNF: A framework for optimization of fuzzy inference systems using neural network learning and evolutionary computation, in: The 17th IEEE International Symposium on Intelligent Control, ISIC'02, IEEE Press, ISBN 0780376218, 2002, pp. 327–332.

[2] K.M.Passino, "Biomimicry of Bacterial Foraging for Distributed Optimization and Control," IEEE Control Systems Magazine, vol. 22, no. 3, pp. 52–67, June 2002.

[3] P. Angelov, A fuzzy controller with evolving structure, Information Sciences 161 (1–2) (2004) 21–35.

[4] J. Arabas, Z. Michalewicz, J. Mulawka, GAVaPS – A genetic algorithm with varying population size, in: Proceedings IEEE International Conference on Evolutionary Computation, Orlando, 1994, pp. 73–78.

[5] J. Kennedy and R. C. Eberhart, "Particle Swarm Optimization," in Proc. of the IEEE Int. Conf. on Neural Networks. Piscataway, NJ: IEEE Service Center, 1995, pp. 1942–1948.

[6]. Xu JX, Liu C, and Hang CC (1996), Tuning of Fuzzy PI Controllers Based on Gain/Phase Margin Specifications and ITAE Index, ISA Transactions, Volume 35, pp. 79–91.

[7] A.L. Buczak, R.E. Uhrig, Hybrid fuzzy – genetic technique for multisensor fusion, Information Sciences 93 (3–4) (1996) 265–281.

[8] D.R. Carvalho, A.A. Freitas, A hybrid decision tree/genetic algorithm method for data mining, Information Sciences 163 (1–3) (2004) 13–35.

[9] P. Chootinan, A. Chen, Constraint handling in genetic algorithms using a gradient-based repair method, Computers and Operations Research 33 (8) (2006) 2263–2281.