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Enhanced ABC based PID Controller for Nonlinear Control Systems

Vijayakumar Kaliappan[1] and Manigandan Thathan[2*]

[1]Dr. Mahalingam College of Engineering and Technology, Pollachi, 642003, Tamilnadu, India; vijay.aswath2008@gmail.com

[2]P. A. College of Engineering and Technology, Pollachi, 642002, Tamilnadu, India; manigandan_t@yahoo.com

Abstract

A Nonlinear PID (NPID) controller tuning based on the Enhanced Artificial Bee Colony (E-ABC) algorithm is presented. The ABC algorithm uses the foraging behavior of honey bee swarm to find the optimal PID parameters k_p, k_i and k_d. In this proposed E-ABC, the Particle Swarm Optimization (PSO) swarm intelligence behavior is inherited to ABC scout bee to get proper selection of food source. The convergence characteristics of the E-ABC based optimization shows that the proposed method provides better controller settings with minimum iteration. To show the effectiveness of the proposed method, it is presented to the nonlinear Continuous Stirred Tank Reactor (CSTR) process and the results are compared with the conventional Internal Model Control (IMC) tuning method, and heuristic approaches viz., Genetic Algorithm (GA), Simulated Annealing (SA), PSO and other hybrid methods based PID performances. From the results of integral performance criterions viz., ISE, IAE and ITAE, it is evident that the proposed E-ABC provides better tracking and improves closed loop accuracy.

Keywords: Artificial Bee Colony, CSTR, Genetic Algorithm, Integral Performances, Particle Swarm Optimization

1. Introduction

In process industries, the PID controllers are widely preferred because of its simple architecture and robustness[1]. For linear systems, PID provides better servo and regulatory tracking performance, but for the complex nonlinear system doesn't provide satisfactory performances[1]. Most of the processes such as CSTR, distillation column, pH process, etc., in industries are nonlinear in nature and has high dynamic process characteristics[2]. The controller design for such systems is very complex due to the process behavior.

The local linear model of the nonlinear process is derived around the steady state operating point and local PID controller is tuned by conventional tuning techniques such as Ziegler-Nichols method, Internal Model Control method, etc[2,3]. The controller tuned for particular region will not provide satisfactory response for the other region. Therefore local PID is not suitable for shifted operating regions of nonlinear process and time varying process. The nonlinear PID controller designed through the multiple linear models overcomes this issue. The Takagi-Sugeno (T-S) fuzzy model[2] network is used to formulate the multi model from the linear models. The interpolation of the local model using T-S fuzzy weight is termed as multiple model of the process. In T-S model, local model and its corresponding PID values are used to formulate the nonlinear PID which works in the varying operating region of the process[2].

From the literatures[3-5], it is observed that the conventional PID tuning methods involves complex numerical computations to obtain controller gain values. The complex computation leads to improper PID settings and provides poor closed loop performance for nonlinear process. The meta-heuristic approaches reported by Zwe-Lee Gaing[6] are used for the proper tuning of PID

**Author for correspondence*

controllers in the complex process control. The GA, SA, ABC, PSO and Ant Colony Optimization (ACO) are some of the heuristic optimization techniques widely preferred to find the optimum settings of PID[4-5,7-9].

The ABC swarm based heuristic algorithm proposed by Karaboga[10], emulates the foraging behavior of honey bee swarms to get optimal N-PID settings. In recent years, ABC receives much attention among researchers due to its performance and simplicity[11]. In the bee colony optimization, the specialized bees are used to identify the food source of high nectar content in a self organized manner. From the responses of ABC, it is observed that it performs better than other heuristic techniques viz., GA, SA and PSO. However, it has poor local searching capability i.e., trapped in local minimum for the complex nonlinear optimization problems[12]. To overcome these issues, the ABC algorithm is modified with new search methods and many researchers reported the hybridization of some Evolutionary Algorithm's to get collective benefits of each[12,13].

In this paper, PSO is inherited with ABC and in this hybrid approach the proper selection of food source by scout bee is examined through knowledge of PSO bird flocking for food[6]. The scout bee's initial food source position is assumed randomly and made to move new position without colliding each other from PSO bird flocking algorithm which improves scout bee searching capability. The fitness function of the new food source is calculated and the steps were repeated until the bee finds food source with high nectar value.

In this enhanced approach (E-ABC) the initial random PID parameters (k_p, k_i and k_d) are chosen as food source for scout bees and to find new improved food source, scout bees move into next food source position without colliding. The scout is moved until it gets the optimal PID settings with better nectar amount i.e., better integral performance parameters ISE, IAE and ITAE[2]. To show the effectiveness of the proposed scheme, it is presented to CSTR system and an exhaustive comparative study is carried out with the conventional method, heuristic tuning techniques and hybrid ACO-GA. The performance criterions viz., ISE, IAE and ITAE values of the proposed system shows that the E-ABC based N-PID provides better servo and regulatory performance than other methods.

The rest of the paper is organized as follows: Section.2 explains about the Artificial Bee Colony algorithms. Section.3 discusses about the E-ABC optimization technique. Section.4 elaborates the nonlinear PID controller design based on E-ABC for the nonlinear process. Section.5 discusses about the simulation results of the proposed scheme. The detailed conclusion of the work done is given in section.6.

2. Artificial Bee Colony Algorithm

Intelligent behavior of honey bees for searching food sources is the inspiration of ABC optimization algorithm developed by Dervis Karaboga to provide solution for complex nonlinear optimization problem[3]. ABC uses minimum number of algorithm parameters (colony size (C_s), maximum iteration count (M_i) and limit of trail (T)) than GA, PSO, and ACO[14-19]. Based on foraging behavior of honey bee colonies searching for food source, the artificial optimization procedure consists of employed bees, onlooker and scout bees searching for food source (optimized values) with high nectar amount (fitness). The onlooker bees select the quality food source based on the employed bees information and searches for new variations of food sources. The scout bee replaces the unimproved food source or exhausted food source by random search and the whole search process for the food source is carried out until the maximum number of iteration is reached.

The steps involved in design of N-PID using ABC algorithm[20-21] are expressed as;

Step.1: Initialization Phase

The maximum trail value (limit), number of food sources (NF), maximum iteration and initial PID gain values are taken as initial colony of artificial food sources. The initial food sources are calculated through the Equation (1)

$$F_{i,j} = lb_{i,j} + rand[0,1] \times (up_{i,j} - lb_{i,j}) \quad (1)$$

Where

$F_{i,j}$, denotes the i^{th} food source and j refers dimension of the problem to be optimized.

$lb_{i,j}$, denotes the lower bound of i^{th} food source

$up_{i,j}$, denotes the upper bound of i^{th} food source

$rand[0,1]$, indicates the random number between 0 and 1

Step.2: Employed Bees Phase

The employed bees are used to search neighbor food sources $E_{i,j}$ (New PID gain values) which is having high nectar value (fitness value) by the Equation (2). The parent food source is replaced by the identified better food source, otherwise increase the trail value of the bee corresponding to unimproved food source.

$$E_{i,j} = F_{i,j} + rand[-1,1] \times (F_{i,j} - F_{k,j}) \quad (2)$$

$i \neq k$

Where,

k = {1, 2, . . . , NF},

j = {1, 2, . . . , D} (D denotes the problem dimension),

$rand[-1,1]$, uniform random number between [-1, 1],

$F_{i,j}$, reference i^{th} food source

$F_{k,j}$, randomly selected food source

Step.3: Onlooker Bees Phase

The onlooker bee selects the food source based on the fitness function which is derived from the employed bee's information. The food source which is having high nectar value has high probability for the selection by onlooker bees and it is explained in Equation (3). Onlooker bees search for neighbor food source around the selected food source using Equation (2). The fitness of new food source is determined and then greedy technique is employed between food sources. The trail value is increased for bees that correspond to unimproved food source.

$$p_i = \frac{fitness(i)}{\sum_{j=1}^{NF} fitness(j)} \quad (3)$$

Step.4: Scout Bees Phase

In scout bee phase, the employee bee which is not able to find improved food (Trail value is greater than T) source is considered as scout bee and then search is carried out as shown in Equation (1).

Step.5: Stopping Condition

If maximum iteration is reached then stop search process and return the best food source obtained so far, otherwise go to step 2;

3. Enhanced ABC Algorithm

From the numerous literatures collected, it is found that the ABC is trapped at local minimum[12] i.e., within 200 iteration. The fitness of all food sources is similar and there is no exploration of new food source having more nectar amount. If the scout bee replaces discarded food source with more quality food source by accessing search space then the convergence rate, quality of search will be improved. But the scout bee searches food source randomly which leads the slower convergence rate of ABC and provides poor global search capabilities. To overcome these issues, the ABC algorithm is modified with new search methods. In this paper, PSO[6] based ABC viz., Enhanced ABC (E-ABC) is presented to get improved convergence and search. In E-ABC, the key idea is to inherit bird flocking behavior to the scout bee. The scout bee in scout phase is assumed to be at random food source and then move the positions of scout bee based on simple mathematical relations without colliding with neighbor bee. The fitness function of the new food source is calculated and the following steps are repeated until the bee finds food source with high nectar value.

The E-ABC has the following steps:

/*step 1 to step 3 are similar to the existing ABC optimization algorithm*/

Step.1 Initialization phase

Step.2 Employed Bees Phase

Step.3 Onlooker Bees Phase

Step.4 Scout Bees Phase

If the food source fitness decrease below a level called 'limit', the employed bee of respective food source is made as scout bee and then Scout bee is assigned at random food source, random velocities. The social attraction (c_1), cognitive attraction (c_2), p_{bests} and g_{best} are assigned as given in Table 1.

step.5 /*PSO phase of scout bee*/

The nectar value of food source that is identified by scout bees are determined and then compared with its p_{bests}. The p_{bests} is replaced by current nectar value if current food has more nectar value than the p_{bests} value. Best nectar value among p_{bests} is considered as g_{best}. [Zwe-Lee Gaing[6]]

Adjust the velocity of each scout bee "S" based on the Equation (4)

Table 1. PSO Initial parameters

PSO parameters	Initial values
social attraction (c_1)	0.5
cognitive attraction (c_2)	1.25
Initial inertia Weight	0.9
Population size	20
No.of roam	50

$$v_{j,g}^{r+1} = q.v_j^{(r)} + c_1 * rand(g_{best,j} - s_{j,g}^{(r)}) + c_2 * rand * (p_{best,j} - s_{j,g}^{(r)}) \quad (4)$$

Where,
j - Number of scout bees assigned to search for new food source.
g - {1, 2, . . . , D} (D denotes the problem dimension),
q - inertia weight. to increase convergence, it is decreased in each iteration by Equation (5)

$$q = q_{\max} - \frac{q_{\max} - q_{\min}}{roam_{\max}} \times roam \quad (5)$$

Where,
$roam_{max}$ - Maximum number of generations carried out in modified scout bee phase
roam - denotes current generation in modified scout bee phase
q_{max}=maximum inertial weight
q_{min}=minimum inertial weight
the selection of c_1 and c_2 also has significance if c_1 is more, the acceleration towards g_{best} increases and if c_2 is chosen to larger value then the acceleration towards p_{bests} increases.

Step.6 /*check to avoid collision*/
The velocity adjustment is made to obey following constraints to avoid collision.

$$\text{if } v_{j,g}^{r+1} > v_g^{\max} \text{ then } v_{j,g}^{r+1} = v_g^{\max} \quad (6)$$

$$\text{if } v_{j,g}^{r+1} < v_g^{\min} \text{ then } v_{j,g}^{r+1} = v_g^{\min} \quad (7)$$

Step.7 /*position update*/
The calculated velocity is added with each scout bee to update its position based on Equation (8) and Equation (9)

$$s_{j,g}^{(r+1)} = s_{j,g}^{(r)} + v_{j,g}^{r+1} \quad (8)$$

$$s_{j,g}^{(\min)} \le s_{j,g}^{(r+1)} \le s_{j,g}^{(\max)} \quad (9)$$

Step.8 : increment the roam.
Step.9 : If maximum roam (M_r) is reached, then latest food source belonging to latest g_{best} is treated as best fluctuated food source and go to step 10 else go to step 5
Step.9 : Stopping condition

If maximum iteration is reached then stop the algorithm for searching new food source and return the best food source obtained so far as global best parameter else go to step 2.

4. E-ABC Based NPID for CSTR Process

The Schematic diagram of the CSTR process used in this work is shown in Figure 1[1]. Inlet coolant stream with a volumetric flow rate q_c, and inlet temperature T_{cf} continuously takes out the heat to maintain the desired reaction temperature and concentration. The proposed E-ABC is presented to design proper controller for the process to get improved tracking and closed loop performance.

The nonlinear CSTR process is characterized by the nonlinear differential Equation (10) and Equation (11)[8] and its initial parameters are given in Table 2.

$$\frac{dT}{dt} = \frac{q_f}{V}(T_f - T(t)) + K_1 C(t)\exp(-\frac{E}{RT(t)}) + K_2 q_c(t)\left[1 - \exp\left(-\frac{K_3}{q_c(t)}\right)\right](T_{cf} - T(t)) \quad (10)$$

$$\frac{dC}{dt} = \frac{q_f}{V}(C_f - C(t)) - K_0 C(t)\exp\left(-\frac{E}{RT(t)}\right) \quad (11)$$

The linear model of the CSTR is derived around the steady state operating point and PID controller is tuned for each identified operating point by IMC tuning method[2]. The locally tuned PID controllers are not suitable for the nonlinear process, due to the process condition variations. The

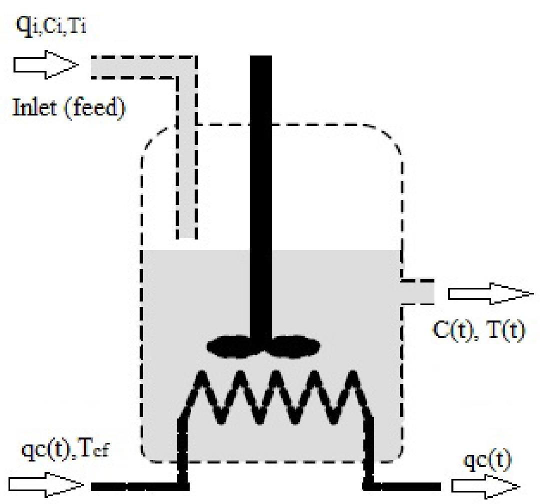


Figure 1. CSTR process.

Table 2. CSTR initial parameters

Inlet flow rate (q_i),100 l/m	Inlet temperature (T_i), 350K
Inlet concentration (C_i), 1mol/l	Coolant temperature (T_{cf}), 350K
Volume of the tank (V),100 L	Activation energy (E/R),104K
K_1= 1.44xe^{13} Kl/min/mol	K_2= 0.01/l
K_3= 700 l/m	K_0= 7.2e^{10}

Nonlinear PID (NPID) controller tuned through multi model technique can eradicate these issues. The overall behavior of the nonlinear system can be described by combining the individual linear system behavior derived from the T-S model[2]. There are two methods used to obtain the linear model from the fuzzy model around the steady state operating point. The first one is based on the interpolation of T-S between linear models and second one is based on the Taylor series expansion of the linear model. In first method, the rule associated with particular local model of the system can be defined as,

$$Rule: i - IF\ Z_1(t)\ is\ M_{i1} .....and\ Z_1(t)\ is\ M_{i1}$$

$$THEN \begin{cases} \dot{x}(t) = A_i x(t) + B_i u(t) \\ y(t) = C_i x(t) \end{cases} \tag{12}$$

i= 1,2,…..,r

where, $x(t) \in R^n$is the state vector, $u(t) \in R^m$is the input vector, $A_i \in R^{n\times n}$, $B_i \in R^{n\times m}$, $C_i \in R^{q\times n}$ and {z_1(t), z_2(t),…,z_p(t)} are nonlinear functions derived from the nonlinear systems and $M_{ij}(z_i)$s are the degree of membership of z_i(t) in a fuzzy set M_{ij}. The output of the fuzzy model can be expressed as,

$$\begin{aligned} \dot{x} &= \sum_{i=1}^{r} h_1(z)[A_i x(t) + B_i u(t)] \\ y(t) &= \sum_{i-1}^{r} h_1(z) C_i x(t) \end{aligned} \tag{13}$$

Where,

$$h_1(z) = \frac{w_1(z)}{\sum_{i=1}^{r} w_1(z)}$$

$$w_1(z) = \prod_{j=1}^{i} M_{ij}(Z_j)$$

The grade of membership function is expressed as

$$h_i(z) \in [0,1]; and \sum_{i=1}^{N} h_i(z) = 1$$

The identified local operating regions and its corresponding PID settings used in local PID and NPID are given in the Table 3.

The classical IMC tuning approach has limitations that the filter time constant (λ) value is chosen through trial and error method. It leads the poor tracking performance and closed loop performance. Recently, the modern optimization technique ABC[18-19] is used to find the optimal settings of the N-PID. The E-ABC is presented to the nonlinear CSTR process as shown in Figure 2.

The steps involved in E-ABC based NPID are,

Step.1: Algorithm parameters initialization phase, randomly generated PID gain values are taken as initial artificial food sources.

Table 3. CSTR operating regions and Local PID settings

Operating point	$K_{p,i}$	$T_{r,i}$	$T_{d,i}$
At qc=97;C_{a0}= 0.0795;T_0= 443.4566	119.4321/λ	0.3367	0.1926
At qc=100; C_{a0}=0.0885; T_0= 441.1475	92.6928/ λ	0.2973	0.2546
At qc=103; C_{a0}=0.0989; T_0= 38.7763	67.4294/ λ	0.2491	0.3601
At qc=106; C_{a0}=0.1110; T_0= 436.3091	43.2812/ λ	0.1876	0.5792
At qc=109; C_{a0}=0.1254; T_0= 433.6921	19.1813/ λ	0.1037	1.3124

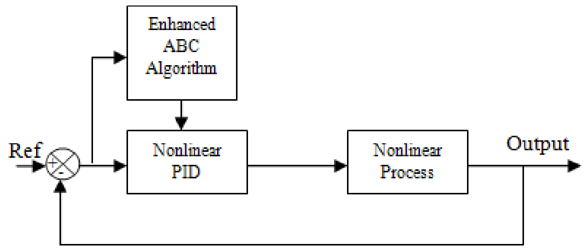


Figure 2. Optimum NPID for nonlinear process.

Step.2: Employed bee phase-Search new PID gain values and replace the parent if it is better. Increase the trail value of the bee corresponding to the unimproved food source.
Step.3: Scout bee phase-compute g_{best} and P_{best}
Step.4: Find new PID values (food source) from new velocity and avoid collision.
Step.5: go to step.3 if maximum roam is not reached else go to step.6.
Step.6: Keep the best solution achieved and Increment the cycle.
Step.7: If maximum iteration is not reached then go to step.2 otherwise stop the algorithm.

The cost function to be minimized by ABC and E-ABC is taken as ISE and IAE. The performance of the controller is verified by evaluating the integral performance functions described in Equation (14).
Integral Absolute Error

$$\left.\begin{aligned} IAE &= \int_0^\infty |e(t)|\,dt \\ &\text{Integral Squared Error} \\ ISE &= \int_0^\infty e^2(t)\,dt \end{aligned}\right\} \quad (14)$$

5. Simulation Results

The proposed E-ABC based NPID is presented to the CSTR process and the performance is compared with its counter parts viz., GA, SA, PSO, ABC and hybrid GA - ACO. From the convergence characteristics shown in Figure (3), it is found that E-ABC converges quickly within 100th iteration compared to ABC which demonstrates optimization capabilities of E-ABC. The comparison results of mean, median and standard deviation of convergence characteristics of E-ABC and ABC are given in Table 4.

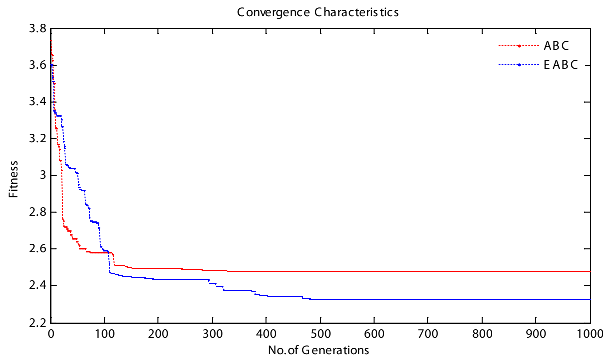


Figure 3. Convergence comparison of ABC & E-ABC.

Table 4. Mean, Median and Standard deviation of convergence characteristics

Optimization technique	Mean	Median	Standard deviation
ABC	2.514	2.48	2.514
E-ABC	2.423	2.327	2.423

From table 4 it is clear that the proposed E-ABC has quick convergence as the meadian value is less than the mean value of ABC based optimisation. Lower standard deviation of E ABC convergence characteristics indicates that the search has more acceleration towards the global minimum.

The E-ABC based tuned PID parameters for the selected operating regions are further combined through fuzzy model to form the NPID. After obtaining the optimal controller value, the servo and regulatory tracking perfromances of the EABC are obtained. From the curves shown in Figure 4-6, it is observed that the E-ABC has better tracking and closed loop perfromance for the compex nonlinear system.

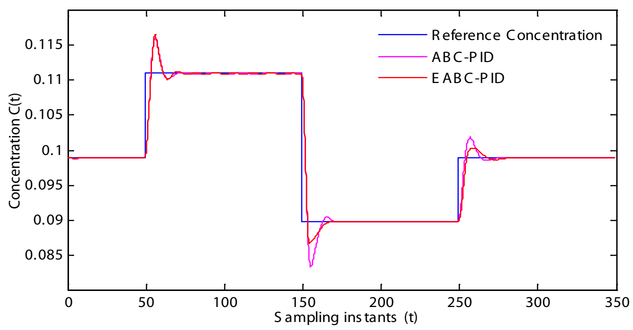


Figure 4. Servo tracking perfromance of EABC.

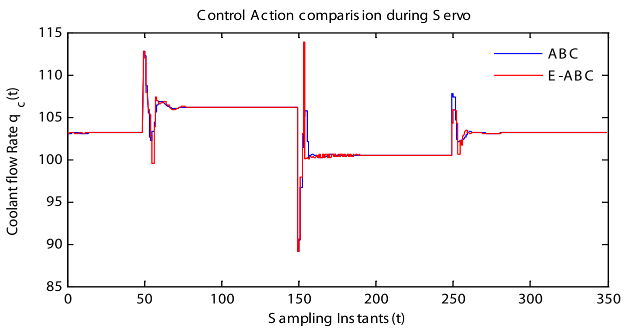


Figure 5. Control action comparison during servo operation.

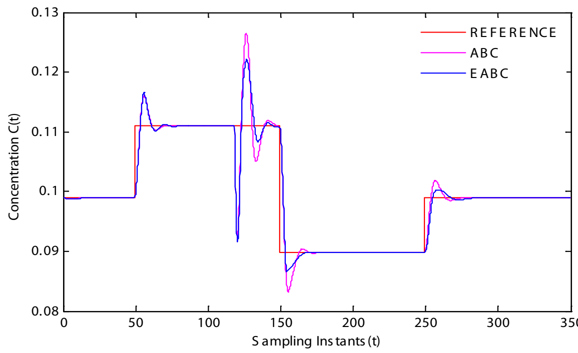
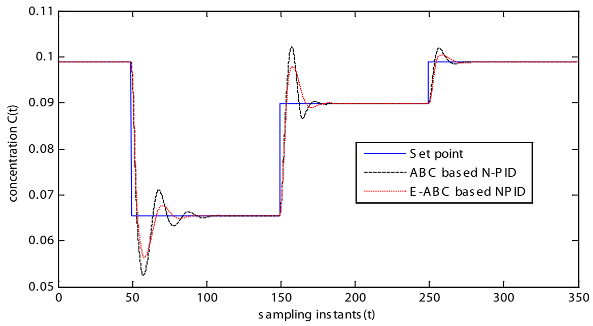


Figure 6. Regulatory tracking perfromance of EABC.

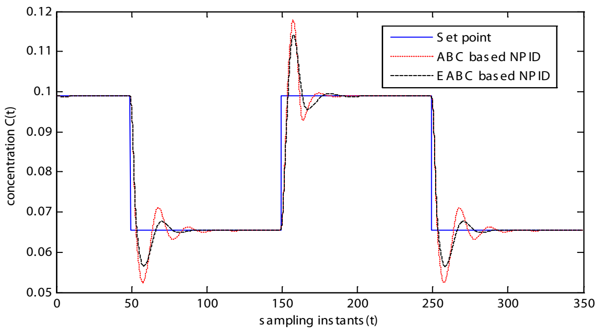
The integral performance criterions such as ISE, IAE and ITAE values for chosen PID parameters against sampling instants points are obtained to show the performance of the propose scheme. The observed values listed in Table 5 used to evaluate the error during the validation. For proper PID settings, ISE, IAE and ITAE should be made lesser. The performance of designed non linear PID controller for different set point profile is shown in Figure 7 (a) to (d).

The obtained IAE values of E-ABC against different sampling instants are compared with its counterparts. From the comparison results given in Table 6, it is observed that the EABC provides better IAE = 1.8639e^{-6} and ISE = 1.7576e^{-3} for 100 to 150 sampling instants. The graphical representation of the IAE values is given in Figure 8.

The white noise is injected to the system to show the effectiveness of the E-ABC. The noise rejection perfor-



(a)



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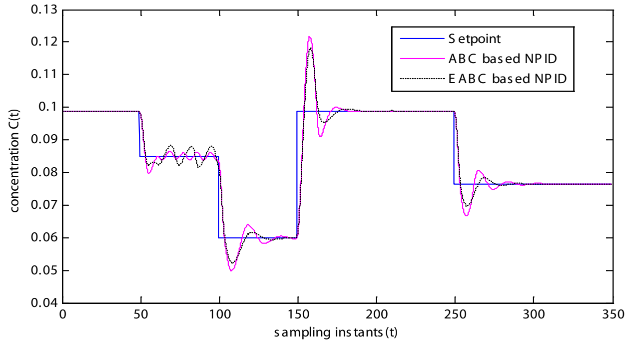

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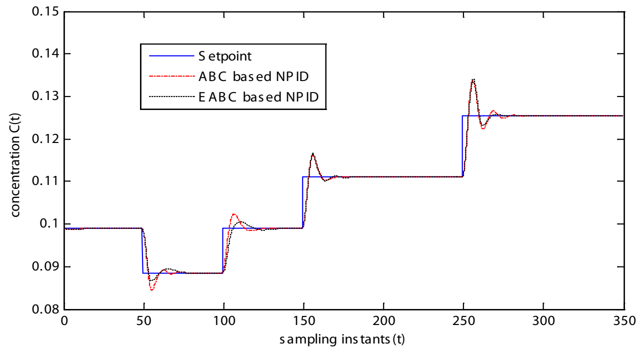

(d)

Figure 7. Servo responses of EABC based NPID.

Table 5. ISE, IAE and ITAE values of the E-ABC

Sampling Instants	Type of Tuning	Integral Performances	
0 - 50	ABC	ISE	7.2817e-4
		IAE	7.2817e-4
	E-ABC	ISE	6.6905e-4
		IAE	6.6905e-4
100 - 150	ABC	ISE	1.7576e-3
		IAE	1.5702e-1
	E-ABC	ISE	1.3952e-3
		IAE	1.3132e-1
300 – 350	ABC	ISE	5.0102e-10
		IAE	8.7933e-5
	E-ABC	ISE	4.5727e-12
		IAE	7.1746e-6

Table 6. IAE values comparison

Sampling Instants	Type of Tuning	IAE
300 - 350	IMC	3.0727e-4
	GA	5.3003e-5
	SA	2.9237e-4
	PSO	1.9416e-5
	EGA	3.1879e-5
	ABC	8.7933e-5
	E-ABC	7.1745e-6

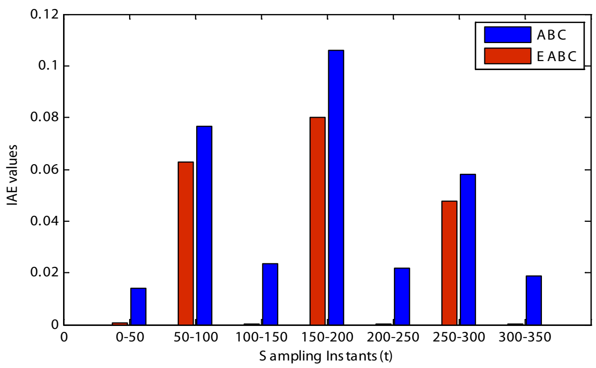

Figure 8. IAE comparison of E-ABC and ABC.

mance of proposed E-ABC based N-PID is compared with conventional ABC based N-PID is shown in Figure 9 and the corresponding ISE, IAE and ITAE values given in Table 7 demonstrates the better noise rejection capabilities of E-ABC based N-PID compared to its counterpart.

The values of ISE and IAE for different sampling instants show that the effectiveness of the proposed scheme. Thus the proposed E-ABC provides much better performances for the complex nonlinear systems than any other methods.

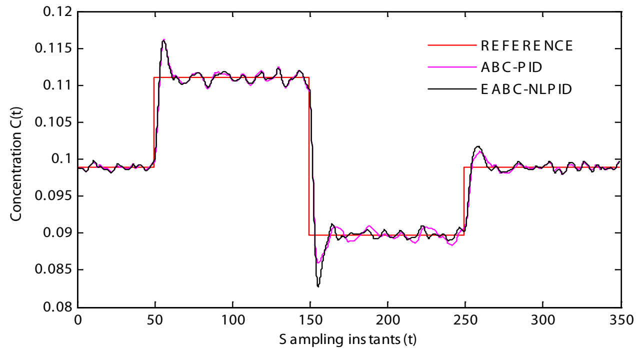

Figure 9. Performance comparison of E-ABC and ABC based N-PID in the presence of measurement noise.

Table 7. IAE Values of E-ABC based NPID corresponds to noise rejection

Sampling Instants	Type of Tuning	Integral Performances	
100 - 150	ABC	ISE	2.1778e-5
		IAE	2.7449e-2
	E-ABC	ISE	1.6968e-5
		IAE	2.3393e-2
200 – 250	ABC	ISE	2.5169e-5
		IAE	3.0045e-2
	E-ABC	ISE	1.3698e-5
		IAE	2.1777e-2

6. Conclusion

In this paper, we have proposed a novel scheme for improving the searching ability of Artificial Bee Colony algorithm in designing a Nonlinear PID control (N-PID) scheme for the nonlinear CSTR plant. The proposed controller has good set point tracking, disturbance rejection capabilities at nominal and shifted operated points and robustness properties. Further, the performance of the E-ABC based NPID is compared with other heuristic approaches. The proposed NPID helps to reduce the number of computations needed good servo and regulatory action. Hence the proposed ABC-PSO based optimization can be considered as an alternative to conventional optimization algorithms.

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