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Nonlinear PID controller parameter optimization using modified hybrid artificial bee colony algorithm for continuous stirred tank reactor

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Abstract. The artificial bee colony (ABC) algorithm is well known and widely used optimization method based on swarm intelligence, and it is inspired by the behavior of honeybees searching for a high amount of nectar from the flower. However, this algorithm has not been exploited sufficiently. This research paper proposes a novel method to analyze the exploration and exploitation of ABC. In ABC, the scout bee searches for a source of random food for exploitation. Along with random search, the scout bee is guided by a modified genetic algorithm approach to locate a food source with a high nectar value. The proposed algorithm is applied for the design of a nonlinear controller for a continuously stirred tank reactor (CSTR). The statistical analysis of the results confirms that the proposed modified hybrid artificial bee colony (HMABC) achieves consistently better performance than the traditional ABC algorithm. The results are compared with conventional ABC and nonlinear PID (NLPID) to show the superiority of the proposed algorithm. The performance of the HMABC algorithm-based controller is competitive with other state-of-the-art meta-heuristic algorithm-based controllers in the literature.

Key words: artificial bee colony; stirred tank reactor; genetic algorithm; nonlinear PID; controller performance measures.

1. Introduction

The proportional-integral-derivative controller is the most commonly employed practical controller since it has simple implementation architecture and robustness [1]. The PID controller has three controller parameters, namely proportional gain (K_p), integral time (T_r), and derivative (T_d). The value of these gains determines the servo and regulatory performance of a controller. These value gains depend upon the process characteristics [2]. In linear systems, determining these parameters using conventional tuning methods such as Ziegler Nichols (ZN) or classical forced oscillation (CFO) may establish better servo and regulatory performance. These conventional methods will not provide better performance for nonlinear systems. Most of the processes found in industries exhibit a nonlinear relationship between input and output [3]. Hence, the controller design for such systems using a conventional tuning method will not provide good servo and regulatory performance [4]. tuning of internal model control (IMC) controller for the nonlinear system is presented in [5]. The other design procedures for the nonlinear controller design available in the literature such as nonlinear model predictive controller design [6], Fuzzy logic controller design [7], and neural network-based model predictive controller are very complex and involve heavy mathematical computations for determining the control action.

To design a nonlinear controller for the CSTR process, linear models at different operating regions are identified and the controller parameters for the identified local linear model are found using conventional tuning methods such as the ZN method, IMC method, and these linear controllers are combined to form a nonlinear controller [8]. The local linear controller designed for the local linear region will not afford satisfactory set-point tracking and disturbance rejection operation for the shifted operating region. Therefore, in these shifted operating regions, the controller has to change its parameters to adapt to the new region or the controller parameters must be optimized to handle the shifted operating point. To design the optimal controller, meta-heuristic approaches are used [9]. Some bio-inspired optimization techniques such as genetic algorithm (GA) and its variants [10] differential evolution (DE), ant colony optimization (ACO), particle swarm optimization (PSO) are also used. Among all other heuristic approaches, the ABC algorithm is widely adapted to find the optimal parameters [11].

Dervis Karaboga proposed a swarm-based meta-heuristic algorithm ABC, which is an optimization that imitates honeybee swarms foraging for food [12]. Currently, this ABC algorithm is gaining popularity among researchers since it yields better optimization performance, is simple and easily implemented. A multi-colony artificial bee colony algorithm was proposed in [13]. The number of algorithm parameters in this technique is smaller than any heuristic optimization technique. The ABC algorithm is also capable of optimizing nonconvex optimization problems. For this reason, ABC is employed in all engineering optimization problems [14]. A high nectar food source is identified by certain bees of ABC collectively. Normally, in a non-

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linear optimization-based problem, ABC may usually get stuck in a local minimum as it is deprived of local searching ability. To overcome these issues, a search scheme–modified GA is designed to improve the local searching ability.

In the proposed HMABC, the suitable choice of nectar source by a scout bee is performed by a modified genetic algorithm. A scout bee is assumed to be present at an arbitrary nectar source from where it is guided to travel to a new food source by using GA reproduction operators. This method results in a high probability of identifying a nectar source of high quality by the scout bee. The proposed novel algorithm is applied to design the nonlinear PID for the CSTR system and a comprehensive study is made with the basic tuning IMC methods, hybrid heuristic tuning techniques GA-ABC. The developed algorithm performance is verified based on the values of integral square error (ISE), integral absolute error (IAE), and integral time absolute error (ITAE). Only the ISE-based results are presented in this paper.

The present research is structured as follows: Section 2 discusses the salient feature of the ABC algorithm; Section 3 presents the HMABC optimization method; Section 4 describes the design of the HMABC-based NLPID controller; and finally, Section 5 discusses the results obtained from the proposed control strategies. The conclusion of the research work is briefed in the last part.

2. Artificial bee colony algorithm

Dervis Karaboga proposed the ABC algorithm based on honey searching behavior for nonlinear optimization problems. The optimization phases of ABC-employed bee, onlooker bee, and scout bee are generally used. The bee starts a food search from a random food source; once it finds the food, the employed bee waves to and fro. On seeing the waggle dance, the on-looker bees would select the nectar source and look for fresh variations of nectar sources. The variation of the existing food source may consist of good nectar or could be worse than the previous food source. This exhausted food source which has a low nectar value is replaced by a random search conducted by the scout bee. This cycle is repeated until a better food source is found. The colony size (C_s) and maximum cycle count ($C_{\max}$) are initialized, and the following stages are conducted to mimic the foraging behavior of the bee.

Step 1. Initialization Phase

The initialization of ABC parameters T_v, F_n, and M_c is done first, where T_v – trail value (max); F_n – food source and M_c – number of the cycle.

The initial food source is randomly selected as shown in Eq. (1)

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

where: i refers to the number of food source and j refers to the dimension of the search (set as 3); $lb_{1,j}$, denotes lower limit of i-th food source; $up_{i,j}$, denotes the upper limit of i-th food source; $rand[0,1]$, represents a random value between 0 and 1.

These food sources are treated as controller parameters.

Step 2. Employed bee phase

These bees explore the neighboring nectar sources, $E_{i,j}$ expressed by (2). The identified nectar replaces the randomly selected initial food source.

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

where
$k = \{1,2\ldots,F_n\}$,
$j = \{1,2,3\}$, (number of parameters to be optimized),
$F_{k,j}$, denotes random food source.

Step 3. Onlooker bee phase

The onlooker bee selects a nectar source from the updated fitness function done during the employed bee phase. Eq. (3) expresses high nectar value selection by onlooker bee.

The onlooker bee searches for a better nectar source near the available selected nectar source as in Eq. (2). For unimproved nectar sources, the trail value of the bees is changed.

$$p_i = \frac{\mathit{fitness}(i)}{\sum\limits_{j=1}^{NF} \mathit{fitness}(j)}. \tag{3}$$

Step 4. Scout bee phase

The employed bee which fails to identify better nectar sources is (trail greater than the limit) transformed into a scout bee and the total search colony is accessed randomly by the scout bee looking for a new food source based on Eq. (1).

One scout bee per cycle is engaged to eliminate the multiple random searches. The proper trail value determines the number of scout bees. Once the scout bee phase ends, the search cycle is incremented by one.

Step 5. Stopping condition

In this algorithm further searching for a new food source is stopped as the maximum cycle is reached and the best food source obtained as far as the optimized value of parameters is concerned, or else Step 2 is repeated.

The ABC search algorithm has been modified by many researchers to enhance its performance. The modification is done by either hybridization of other known search algorithms or by updating the equations. The hybridization of ABC with other algorithms is a well-known approach to enhancement [15].

ABC hybridization is performed with differential evolution (DE) [16], where the number of scout bees is changed by DE. The ABC and the combination of midway disposal trip selection are discussed in [17]. ACO and harmonic search hybridization with ABC are discussed in [18], which outperforms the gradient search, PSO, ACO, and ABC, but takes more time for completing one cycle. ABC with tabu search [19, 20] and ABC with PCO in [21] are used for optimizing the problem in heterogeneous wireless networks. Hill climbing optimizer algorithm [22] and crossover operator [23] are executed for better searching and data clustering. However, the ABC suffers from ineffective exploitation [24].

To improve the exploitation of ABC, the genetic algorithm hybridization is proposed [25], where GA improves the performance of an onlooker bee. This hybridization is achieved by incorporating ABC with an artificial fish swarm (AFS) algorithm [26]. Various hybridization algorithms are discussed in [27] and an improved dolphin swarm optimization algorithm in [28], A nonlinear PID using a neural networks-like approach is discussed in [29]. ABC with ACO for CSTR is applied in [30]. Differential evaluation (H–ABCDE) algorithm [31] and artificial immune system (AIS) [32] are combined with ABC to enhance their performances. The enhancement of the scout bee phase has not been dealt with in any of the earlier approaches.

To improve the scout bee performance, a novel hybrid approach is proposed, which is discussed in a detailed manner in the next section.

3. Modified hybrid artificial bee colony algorithm

The ABC convergence rate is improved by replacing unimproved food sources with a high nectar food source in the scout bee phase. The ABC with a better convergence rate is used in the optimization of controller parameters in many engineering applications. In the proposed HMABC algorithm, genetic operators are used in the scout bee phase to improve its intelligence. In the HMABC, the scout identifies the best nectar source through onlooker bees. If all onlooker bees share the same location with the scout bee, along with this location the scout bee generates other random locations. It starts applying the crossover and mutation operators on the positions of the food source to identify the new improved food source. This search method improves the identification of the quality of the food source identified by scout bees and makes the proposed HMABC converge faster than a conventional ABC.

The proposed HMABC algorithm involves the following steps:

/*Step 1 to Step 3 are similar to the conventional ABC optimization method*/

Step 1. Initialization of ABC parameters.

Step 2. Employed bee phase.

Step 3. Onlooker bee phase.

Step 4. Scout bee phase – the onlooker bee determines the initial population.

Step 5. The food source is selected using a roulette wheel selection based on nectar values.

Step 6. The selected food source is considered as parent chromosomes p1 and p2.

Step 7. The mutation is performed, and new food source locations are identified.

Step 8. The crossover is conducted by a two-point crossover method.

Assign two points x_pt1, x_pt2.

The crossover kids c1 and c2 are derived as per the equations below:

$$\mathrm{c1} = \left[\mathrm{p1}(1:\mathrm{x\_pt1})\mathrm{p2}(\mathrm{x\_pt1}+1:\mathrm{x\_pt2})\mathrm{p1}(\mathrm{x\_pt2}+1:\mathrm{CL})\right],$$

$$\mathrm{c2} = \left[\mathrm{p2}(1:\mathrm{x\_pt1})\mathrm{p1}(\mathrm{x\_pt1}+1:\mathrm{x\_pt2})\mathrm{p2}(\mathrm{x\_pt2}+1:\mathrm{CL})\right],$$

where CL is the chromosome length.

Step 9. The elite food source is identified.

Step 10. Group the mutation, crossover, and elite offspring into the next generation population.

Step 11. The new food source locations are evaluated for the nectar values. And the best nectar value food source is assigned as a fluctuated food source. If the maximum generation is reached, then perform Step 12; otherwise repeat Step 5.

Step 12. Terminating the condition evaluation.

If the upper limit of iteration is reached, then perform Step 13; otherwise, repeat Step 2.

Step 13. Terminate the algorithm and the best nectar source is considered as the optimum result.

The flow chart of the proposed hybrid modified ABC is depicted in Fig. 1.

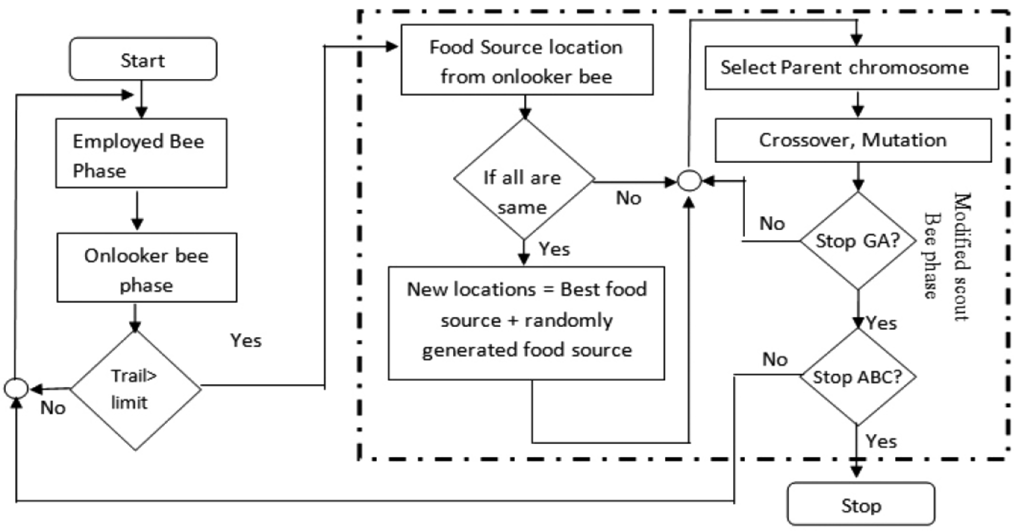

Fig. 1. Flow chart of hybrid modified ABC

Table 1
Benchmark functions and their best values tested on ABC and HMABC

Test function	Range	Result	(ABC)	(HMABC)
Bukin N 6	$x_1 \in [-15,-5]$, $x_2 \in [-3,3]$	Best value	0.1936	0.1037
		Worst value	0.1723	0.1129
Levy	$x_i \in [-10,10]$	Best value	5.380e–19	8.5792e–20
		Worst value	3.98e–18	4.34e–19
Levy N 13	$x_i \in [-10,10]$	Best value	1.8103e–19	1.5282e–19
		Worst value	1.323e–18	1.234e–18
Perm Function 0, d, β	$x_i \in [-10,10]$	Best value	2.074e–07	1.1999e–07
		Worst value	1.923e–06	2.476e–06
Rotated Hyper-Ellipsoid Function	$x_i \in [-65.536,65.536]$	Best value	6.516e–19	4.7396e–19
		Worst value	2.987e–9	8.348e–18
Sphere	$x_i \in [-5.12,5.12]$	Best value	5.916e–19	5.5296e–19
		Worst value	4.345e–17	3.478e–18
Schaffer N 4	$x_i \in [-100,100]$	Best value	0.2925	0.292578
		Worst value	0.9846	0.6473
Ackley	$x_i \in [-32.768,32.768]$	Best value	8.88e–16	8.881 e–16
		Worst value	6.347e–15	7.896e–15

The efficiency of the conventional ABC and proposed HMABC algorithm is tested in a few standard benchmark functions [33–35] and the results are listed in Table 1. The results clearly show that the proposed HMABC algorithm produces better results than the conventional ABC. Different values are chosen and tested and after multiple runs are done, the best values of parameters used in the algorithms for this test are provided in Table 2.

Table 2
The best value used for ABC and HMABC

Parameters	ABC	HMABC
Number of food sources	20	20
Dimension of the population	15	15
Maximum cycle	200	200
Trail limit	20	20
Population size of GA	–	40
Crossover rate	–	0.8
Number of crossover sites	–	2
Mutation rate	–	0.2
Elite Count	–	2
Number of generations	–	20
Chromosome length	–	15

4. HMABC-based optimum controller for CSTR

To evaluate the performance of the proposed HMABC, it is evaluated as shown in Fig. 2 to design an optimum controller for the nonlinear CSTR process. CSTR is one of the benchmark problems considered by researchers in testing the controller performance as is evident in [6, 29, 36].

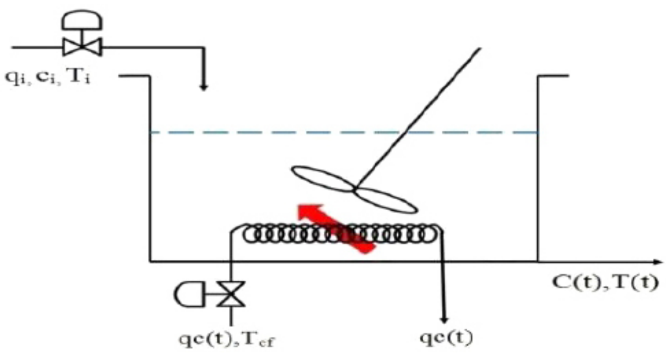

Fig. 2. CSTR process

The CSTR process exhibits a high nonlinear relationship between the inlet coolant flow rate ($q_c(t)$) and the concentration $C(t)$. The objective of the controller is to manipulate the inlet coolant flow rate to maintain the concentration $C(t)$ of the outlet [29].

The process models described in (4) and (5) are nonlinear equations of the state variables $T(t)$ and $C(t)$

$$\frac{\mathrm{d}T}{\mathrm{d}t} = \frac{q_i}{V}(T_i - T(t)) + K_1 C(t)\exp\left(-\frac{E}{RT(t)}\right) + K_2 q_c(t)\left[1 - \exp\left(-\frac{K_3}{q_c(t)}\right)\right](T_{cf} - T(t)), \tag{4}$$

$$\frac{\mathrm{d}C}{\mathrm{d}t} = \frac{q_i}{V}(C_i - C(t)) - K_0 C(t)\exp\left(-\frac{E}{RT(t)}\right). \tag{5}$$

The initial parameters of the CSTR are provided in Table 3 [29].

Table 3
Parameters of CSTR

Input flow, q_i – 100 l/min	Input temperature T_i – 350 K
Input concentration, C_i – 1 mol/l	Inlet coolant, T_{cf} – 350 K
Tank volume, V – 100 l	Energy (E/R), 10^4 K
$K_1 = 1.44 \times 10^{13}$ Kl/min/mol	$K_2 = 0.01$/l
$K_3 = 700$ l/min	$K_0 = 7.2 \times 10^{10}$ min^{-1}

The researchers reported several tuning techniques for the PID controller design. A ZN-based PID controller for the CSTR process is presented in [29]. IMC-based tuning for a PID controller is used in [6]. The IMC tuning technique is considered to be better than other classical methods due to its robust behavior, i.e., it provides fewer oscillations and overshoot. The IMC tuning formulae for the PID settings is given in (6)

$$K_{p,i} = \frac{2\zeta_i}{\omega_{n,i}k_i\lambda}, \qquad T_{r,i} = \frac{2\zeta_i}{\omega_{n,i}}, \qquad T_{d,i} = \frac{1}{2\zeta_i\omega_{n,i}}, \tag{6}$$

where $K_{p,i}$ – proportional gain, $T_{r,i}$ – integral time, $T_{d,i}$ – derivative time, ξ – damping factor, $\omega_{n,i}$ – natural frequency of oscillation and k_i – steady state gain. To determine the ξ, $\omega_{n,I}$ and k_i, the non-linear process is modeled using the Takagi–Sugeno (T–S) fuzzy multiple model design approaches [6].

The possible local linear models are identified over its complete operating regions and the multi-model is derived from the local model through interpolation, using T–S fuzzy [6]. The NLPID is derived for the multi-model with fuzzy fusion through the local model PID settings tuned from the IMC tuning technique. The local model is expressed in (7)

$$\begin{aligned} \dot{x} &= f_i(x, u, v, \theta_i), \\ y &= g_i(y, w, \theta_i), \end{aligned} \tag{7}$$

where x, u, and v represent the state vector, input vector, and disturbance vector, respectively; y and w represent the output and noise vector, respectively; and θ is the parameterized vector used to describe the system dynamics. If the system operates a wider range, then the interpolation of each operating point in the local model structure is needed to give the global model structure, which is expressed in (8)

$$\begin{aligned} \dot{x} &= \sum_{i=1}^{N} f_i(x, u, v, \theta_i)\,\mu_i(\varphi), \\ y &= \sum_{i=1}^{N} g_i(y, w, \theta_i)\mu_i(\varphi), \end{aligned} \tag{8}$$

where μ_i is the interpolation function expressed in (9)

$$\mu_i(\varphi) = \frac{\rho_i(\varphi)}{\sum_{j=1}^{N}\rho_j(\varphi}), \tag{9}$$

where ρ_i is the model validity function and it is designed such that the value closes to 1 for a good model structure otherwise equal to zero. A fuzzy nonlinear PID (F-NLPID) controller is the interpolation of the local PID controllers to form the global model structure.

The grade of the membership function should be $\mu_i : \varphi \to [0,1]$ is a normalization of the model validity function ρ_i and has the property $\sum_{i=1}^{N}\mu_i(\varphi) = 1$ for all $\varphi \in \Phi$.

The NLPID controller output is expressed by (10)

$$u_i(k) = K_{p,i}\left\{e(k) - e(k-1) + \frac{T_s}{T_{r,i}}e(k) + \frac{T_{d,i}}{T_s}(e(k) - 2 \times e(k-1) + e(k-2))\right\} + u_i(k-1), \tag{10}$$

where T_s is the sampling time; $K_{p,i}$, $T_{r,i}$, and $T_{d,i}$ values of NLPID are derived from classical tuning approaches. The local PID of the CSTR process derived through the IMC method for various stable operating regions is listed in Table 4.

Table 4
CSTR operating regions and local PID settings

Operating point	$K_{p,i}$	$T_{r,i}$	$T_{r,i}$
At $qc_1 = 97$; $C_1 = 0.077$; $T_1 = 443.46$	119.43/lamda	0.337	0.192
At $qc_2 = 100$; $C_2 = 0.089$; $T_2 = 441.15$	92.69/lamda	0.298	0.254
At $qc_3 = 103$; $C_3 = 0.098$; $T_3 = 438.77$	67.42/lamda	0.25	0.360
At $qc_4 = 106$; $C_4 = 0.111$; $T_4 = 436.31$	43.28/lamda	0.188	0.580
At $qc_5 = 109$; $C_5 = 0.126$; $T_5 = 433.70$	19.18/lamda	0.103	1.312

The (qc_i, C_i, T_i) represents the linearization point of the ith local model. The stable region of CSTR is expressed by the phase plane analysis shown in Fig. 3. From the response, it is observed that CSTR exhibits nonlinearity behaviour when concentration $c(t)$ rises more than 0.13. Figure 3 shows the phase plane analysis of a stable operating point. If the concentration is raised more than 0.13, the phase plant plot becomes the saddle point.

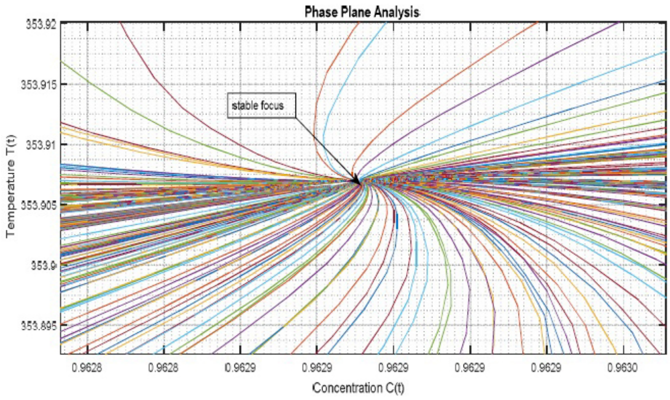

Fig. 3. Phase plane analysis – CSTR stable operating point

In the literature, it is derived that the classical tuning approaches are not sufficient to give satisfactory performance for the complex nonlinear system. The recent optimization technique ABC is applied to calculate the best possible combinations of the NLPID parameters. The various integral performance criteria as shown in (11), (12), (13), and (14) can be taken as cost functions. These Cost functions were minimized by ABC and HMABC.

Integral absolute error

$$IAE = \int_0^\infty |e(t)|\,\mathrm{d}t. \tag{11}$$

Integral time absolute error

$$ITAE = \int_0^\infty t\,|e(t)|\,dt. \tag{12}$$

Integral squared error

$$ISE = \int_0^\infty e^2(t)\,\mathrm{d}t. \tag{13}$$

Integral time squared error

$$ITSE = \int_0^\infty te^2(t)\,\mathrm{d}t. \tag{14}$$

ISE can be considered as an objective function when the error value has large positive and negative values. IAE can be considered when the error value has smaller positive and negative values. Time–weighted ISE and IAE can be considered as objective when we need a lower steady-state error. In this paper, controller performance based on ISE as an objective function is discussed.

5. Simulation results

The algorithm parameters of ABC and HMABC are given in Table 5 and HMABC results are related to ABC.

Table 5
Algorithm parameters

Parameters	ABC	HMABC
Number of food sources (i)	20	20
Dimension of the population (j)	15	15
Maximum cycle	200	200
Trail limit	20	20
Population size of GA	–	40
Crossover rate	–	0.8
Number of crossover sites	–	2
Mutation rate	–	0.2
Elite count	–	2
Number of generations	–	20
Upper limit of Kp,i	200	200
Upper limit of Tr,i	0.3	0.3
Upper limit of Td,i	0.4	0.4
Chromosome length	–	15
Cost function	ISE	ISE

The convergence characteristics of the ABC and HMABC for minimizing the objective function value are shown in Fig. 4. In the HMABC, the objective function value is reduced in every cycle and displays a faster response than the conventional ABC. In the HMABC, 183 cycles to reach the objective function amount to be 2.46, whereas the ABC uses 426 cycles.

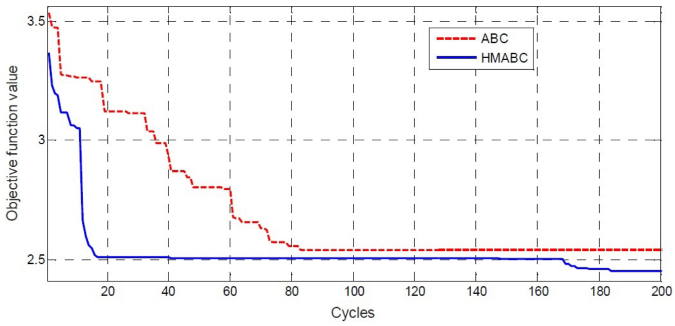

Fig. 4. Convergence comparison of ABC and proposed HMABC

The designed nonlinear controller is applied to CSTR and various performance characteristics are evaluated. The obtained results are explained briefly in the following sections. Table 6 shows the numerical evaluation of the results such as standard deviation, mean of convergence curve, and a detailed comparison of the scout bee fitness value of the HMABC with ABC. From the values, it is found that the HMABC scout bee is better than a conventional scout bee.

Table 6
Statistical evaluation of convergence characteristics curve

Type of optimization technique	Mean	Standard deviation
ABC	2.705	0.2622
HMABC	2.537	0.15

Table 5 shows that the mean of convergence characteristic curves plotted in Fig. 4. From this table, it is clear that, in the ABC-based optimization and with the objective function minimization, the mean is 2.705, whereas, in the HMABC, the mean is only 2.537. This indicates that the HMABC has a better optimization effort than the ABC. From Fig. 5, it is clear that the maximum value of the cost function is lower than the value obtained using a conventional ABC. This reduction in the maximum value shows that the HMABC produces a better solution in each cycle compared to the ABC. Comparing the ABC, the proposed HMABC has a low standard deviation and this indicates that the HMABC reaches a minimum cost function value in fewer cycles. From Fig. 5, it is clear that in all other statistical comparisons, the HMABC is better than the ABC.

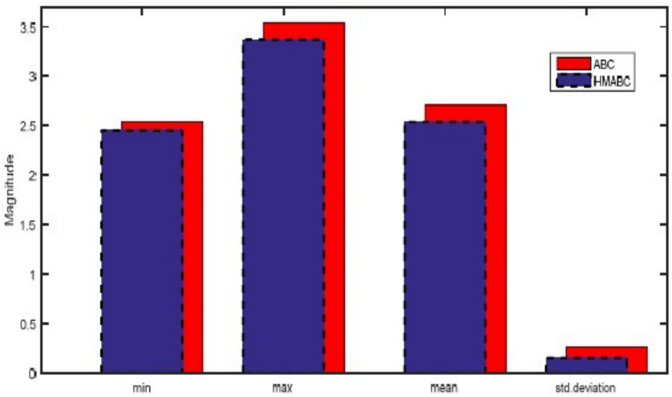

Fig. 5. Statistical evaluation of ABC and HMABC

The food sources identified by the scout bee to replace the unimproved food source are monitored in each cycle of the ABC as well as in the HMABC and depicted in Fig. 6, and the values of the fitness function and the food source are given in Table 7. Based on the results, it is decided that the HMABC performs better as it increases the searching cabbalist of the scout bee by three times.

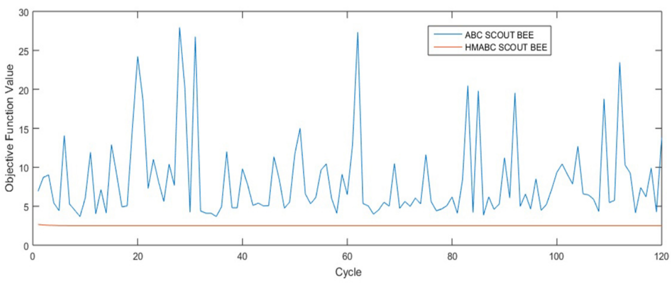

Fig. 6. Scout bee objective values of ABC and HMABC

Table 7
Statistical values of scout bee fitness

Type of optimization technique	Mean	Standard deviation
ABC	8.7549	5.890
HMABC	2.4992	0.026

Figure 7 shows the comparison of results of HMABC-based PID responses for the set-point variations with ABC-based PID. The local PID parameters obtained through the ABC and HMABC optimization methods are given in Tables 8 and 9, respectively.

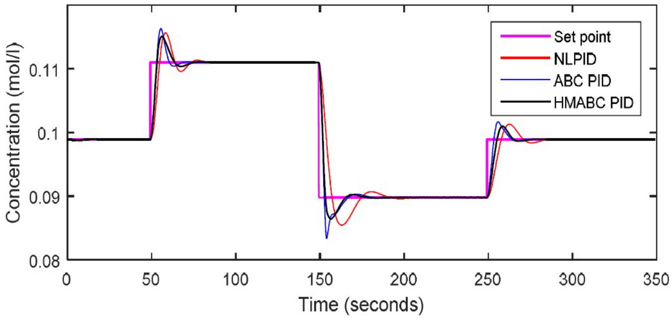

Fig. 7. Servo response of CSTR for HMABC PID

Table 8
ABC – PID settings

Operating point	K_p	$T_{r,i}$	$T_{d,i}$
At $qc_1 = 97$; $C_1 = 0.077$; $T_1 = 443.46$	200/lamda	0.300	0.158
At $qc_2 = 100$; $C_2 = 0.089$; $T_2 = 441.15$	200/lamda	0.300	0.193
At $qc_3 = 103$; $C_3 = 0.098$; $T_3 = 438.77$	200/lamda	0.300	0.163
At $qc_4 = 106$; $C_4 = 0.111$; $T_4 = 436.31$	200/lamda	0.300	0.345
At $qc_5 = 109$; $C_5 = 0.126$; $T_5 = 433.70$	200/lamda	0.291	0.100

Table 9
HMABC – PID settings

Operating point	K_p	$T_{r,i}$	$T_{d,i}$
At $qc_1 = 97$; $C_1 = 0.077$; $T_1 = 443.46$	200/lamda	0.300	0.192
At $qc_2 = 100$; $C_2 = 0.089$; $T_2 = 441.15$	200/lamda	0.300	0.178
At $qc_3 = 103$; $C_3 = 0.098$; $T_3 = 438.77$	66.32/lamda	0.300	0.290
At $qc_4 = 106$; $C_4 = 0.111$; $T_4 = 436.31$	178.44/lamda	0.300	0.370
At $qc_5 = 109$; $C_5 = 0.126$; $T_5 = 433.70$	193.26/lamda	0.263	0.119

A lower value of the lamda provides aggressive control performance. The lamda value and its effectiveness are presented in Fig. 8. The performance of the HMABC is compared with the ABC method to show its effectiveness.

For a smaller value of lamda, the value of K_p will be higher. Thus, setting a smaller value for lamda provides a more aggres-

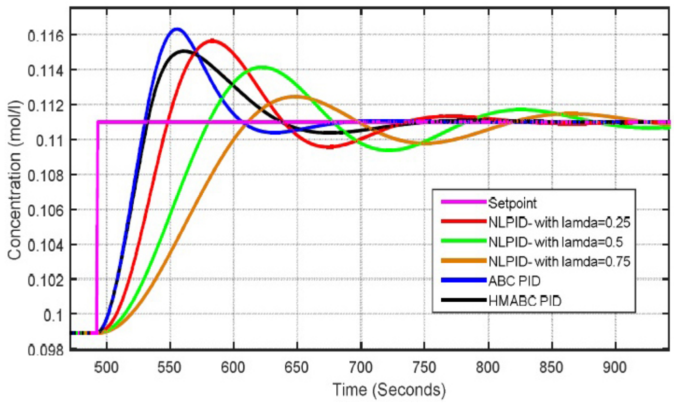

Fig. 8. Servo response of CSTR from 400 sampling instant to 1000 for various controllers

sive control action and more overshoot. The following diagram shows the servo response of the implemented controllers from the sampling instants 400 to 1000.

The cost-function ISE values are shown in Table 10 obtained for various controllers and HMABC-PID at various sampling instants to show the effectiveness of the proposed one.

The results show that the proposed HMABC performs much better than the other conventional methods for nonlinear processes. At sampling instants between 101 and 150, HMABC – PID exhibits ISE value as 1.2344e–7, whereas ISE value of conventional ABC is 5.7433e–7. The regulatory performance of the designed controller is verified by injecting a variation in the feed temperature of the CSTR. At sampling instant 120, the feed temperature "T" is raised to 440 K. This abrupt change introduces a great dynamic in the system. The designed controller can reject that change and brings the system to stability with minimum overshoot. The ISE values obtained during the regulatory operation are presented in Table 11, in which the ISE values during the sampling time 101 to 151 seconds of the ABC-based PID is 1.5732e–3, whereas in the HMABC-based PID controller the ISE value is only about 1.0947e–3. The comparison of regulatory action of the HMABC controller is depicted in Fig. 9. The feed temperature change is regulated by the HMABC-based PID controller with a low ISE value compared to the ABC-based PID controller.

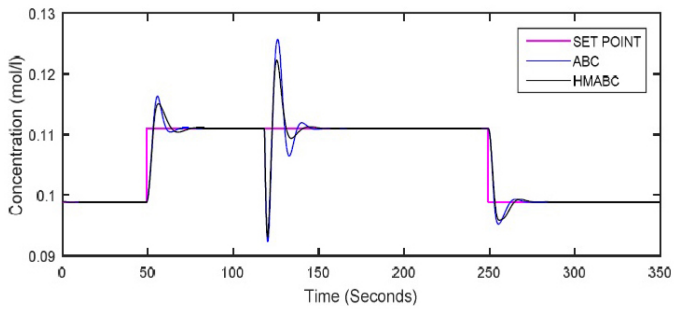

Fig. 9. Regulatory response of CSTR for HMABC PID

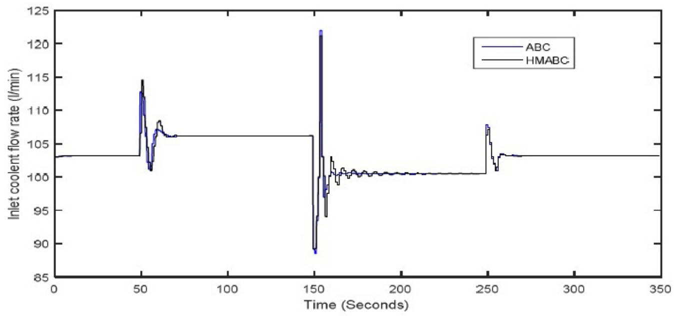

Fig. 10. Control action during the regulatory response of CSTR

Table 10
Sampling time in seconds and ISE values for servo response

PID tuning method	Sampling time in seconds & ISE						
	0 to 50	51 to 100	101 to 150	151 to 200	201 to 250	251 to 300	301 to 350
IMC	7.3086e–6	7.3933e–3	6.5555e–3	4.3560e–3	4.0491e–3	1.9648e–6	1.7321e–6
ABC	5.8054e–7	8.2912e–4	5.7433e–7	1.3918e–3	4.0855e–9	3.2581e–4	8.004e–10
HMABC	1.6517e–7	6.1247e–4	1.2344e–7	1.4140e–3	1.3630e–9	3.0262e–4	1.5593e–9

Table 11
Sampling time in seconds and ISE values for regulatory operation

PID tuning method	Sampling time in seconds & ISE						
	0 to 50	51 to 100	101 to 150	151 to 200	201 to 250	251 to 300	301 to 350
ABC	6.7338e–4	4.2315e–4	1.5732e–3	5.9475e–8	7.8730e–18	3.7585e–4	1.1316e–13
HMABC	6.6400e–4	4.1654e–4	1.0947e–3	6.1824e–8	7.5370e–18	3.8105e–4	1.7453e–13

6. Conclusion

In this manuscript, the authors have presented an effortless and uncomplicated strategy that improvises the searching capability of the ABC, which provides the optimum NLPID control parameters. These NLPID values are tested on a nonlinear reactor process to show the effectiveness of its performance. The simulation responses obtained, clearly prove the superiority of the proposed control algorithm by its good servo and regulatory performance capabilities at various operating points. The proposed algorithm is compared with well-known conventional optimization algorithms for the same process. From the results, it is determined that HMABC – PID helps to reduce the number of cycles that are needed to obtain optimum controller gain values for good servo and regulatory action. The proposed HMABC-based optimization can be considered as a substitute to basic old optimization algorithms.

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