Research on Adaptive Comprehensive Learning Artificial Bee Colony Algorithm and Its Application in Constant Pressure Water Supply

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Abstract. The constant pressure water supply control system is nonlinear and hysteretic, which makes the control problem difficult to solve. In order to achieve accurate closed-loop control of water supply pressure, this paper designs ACLABC-PID controller based on improved Artificial Bee Colony algorithm. First of all, in view of the slow convergence speed and easy to fall into the local optimum of the ABC algorithm, an adaptive comprehensive learning strategy of the ABC algorithm (ACLABC) is proposed. The algorithm adopts the learning strategy of learning from other excellent individuals and global optimal individuals, enriches the diversity of the population, adaptively and gradually reduces the search area, and effectively eliminates the defects of easily falling into local extremum and slow convergence in the later stage. ACLABC algorithm takes both local development and global exploration into account, which improves the convergence speed and accuracy of the algorithm. Then, the ACLABC algorithm is applied to the PID control parameter optimization of constant pressure water supply, and compared with the ABC-PID controller and the critical proportion method PID controller, the simulation results show that the ACLABC-PID controller significantly improves the dynamic and steady performance of the system.

Keywords: Artificial Bee Colony Algorithm, PID parameter tuning, Adaptive, Comprehensive Learning, Constant pressure water supply.

1. Introduction
Constant pressure water supply system is a typical nonlinear and hysteretic system, and PID control is often used. Because of its simple principle, good robustness and high reliability, PID control is widely used in process control and motion control, generally, the controller cannot achieve the desired effect of constant pressure difference in the actual operation [1]. Conventional PID parameter tuning usually includes engineering tuning and theoretical calculation analysis [2]. The engineering setting method is mainly based on engineering experience and has great trial and error. The theoretical calculation method relies too much on the mathematical model of the system, which requires a full grasp of the system mechanism. The emergence of bee colony algorithm provides another way for PID parameter optimization [3-6]. In 2005, Turkish scholar karaboga proposed the artificial bee colony algorithm [7]. Because of its simple structure, easy implementation, less control parameters, simple calculation and other advantages, it has been widely concerned by scholars at home and abroad, and has been applied
to solve problems in the real world [8]. Artificial bee colony algorithm has been widely used in
communication field [9-10], signal and graphics processing field [11-14], control field [15-17],
power system field [18-19], etc. Although the basic artificial bee colony algorithm has many advantages, it also
has some defects, such as slow search speed, premature convergence and easy to fall into local optimal
solution. In view of these deficiencies, some scholars have made improvements. Zhu et al. [20] proposed
a GABC algorithm using global optimal information to guide search, which enhanced the development
ability of the algorithm, but this reduced the global optimization ability of the algorithm to a certain
extent. The reinforcement mutual learning bee colony algorithm proposed by Luo Hao et al. [21]
enhances the development ability, but it ignores social experience and fails to converge to the global
optimal faster. Bee colony algorithm has strong coordination ability, but weak learning ability.
Designing new learning strategies is a promising improvement method [22]. In order to further improve
the performance of artificial bee colony algorithm, inspired by particle swarm algorithm [23], this paper
designs an adaptive comprehensive learning strategy artificial bee colony algorithm. Bees further
improve the search ability and development ability of the algorithm by learning the experience of the
better individual and the optimal bee. The improved bee colony algorithm is applied to the parameter
optimization of water supply PID control, which provides a new idea and method for improving the
performance of constant pressure water supply control.

2. Basic artificial bee colony algorithm (ABC)
ABC algorithm is a swarm intelligence algorithm proposed by imitating the honey gathering process of
bee colony. Through role transformation, three kinds of bees, i.e. bee gatherer, observation bee and
reconnaissance bee, work together to complete the search of high-quality honey source [24]. The
honeybees collected nectar in the search space and recorded the abundance of the nectar source. The
observation bees chose to follow the bees according to roulette strategy, and mined nectar near their
neighborhood. When the honey source is exhausted, the honeybee becomes a scout bee, and chooses a
new honey source randomly, so it circulates continuously until the optimal honey source is found. In
practical engineering optimization problems, the location of honey source represents the feasible
solution, and the richness of honey source represents the quality of solution, which is called fitness.
Firstly, ABC algorithm initializes the population containing N bees according to formula.

\[ x_i^j = x_{\text{min}}^j + \text{rand}(0,1)(x_{\text{max}}^j - x_{\text{min}}^j) \]  

In formula (1), \( i = 1, 2, 3, \ldots, N \), \( N \) is the number of bees, which is also the number of honey source
(feasible solution). The value of \( j \) is \{1, 2, \ldots, D\}, and \( D \) is the number of optimization parameters. Then,
according to the memory information, honeybees search in the limited field according to formula (2)
and generate new honey source. By comparing the adaptability of the new and old honey sources, the
honey source with high adaptability is selected as the present honey source.

\[ v_i^j = x_i^j + \text{rand}()(x_i^j - x_k^j), k \neq i \]  

In formula (2), \( x_i \) is the old honey source, \( v_i \) is the new honey source, \( x_k \) is the nearby honey source
randomly selected, and \( \text{rand}() \) is the random number in [-1, 1]. The higher the adaptability of honey
source, the greater the probability of selection by observed bees. After choosing the honey source, the
observation bee will exploit the honey source nearby as the honey bee, and the new honey source will
replace the old honey source according to the greedy criterion.

\[ p_i = \frac{f_i}{\sum_{n=1}^{N} f_n} \]  

In formula (3), \( f_i \) is the fitness function value corresponding to the \( i \)-th honey source, and \( p_i \) is the
probability of the observation bee to select the \( i \)-th honey source. Finally, when the corresponding nectar
source is exhausted, the honeybee is converted into a scout bee, and a new position is generated according to formula (4). If the stop condition is satisfied, the optimal fitness value and the corresponding feasible solution are output, otherwise, the new search is started again.

\[ v_i^j = x_{\text{min}}^j + \text{rand}(0,1)(x_{\text{max}}^j - x_{\text{min}}^j) \]  

(4)

3. ACLABC Algorithm

3.1. Comprehensive Learning Strategy

The search strategy used by bees in the process of searching honey source, that is, the method of generating new solutions in the solution space directly determines the search efficiency and quality. In ABC algorithm, the honeybee produces a new solution according to formula (2), which can be understood as the process that the bee learns from the neighboring bee. However, the selection of the nearby bee is random, which leads to low search efficiency and possible loss of useful information. Moreover, honeybees only learn from a single dimension at a time, which limits the search range to a certain extent, affects the diversity of the population, and easily leads to the algorithm falling into local optimization. Aiming at the defects of the search strategy in the original algorithm, this paper proposes two improvements. On the one hand, aiming at the random learning from the nearest neighbor in ABC algorithm, learning from the relatively optimal individual is replaced. Combined with the social information sharing mechanism of particle swarm optimization (PSO), the social experience of the global optimal individual is introduced, that is, the improved ABC algorithm learns from both the better individual and the optimal individual at the same time. The new individual is generated as formula (5), in which the experience of other better individuals is used to improve the global convergence performance of the algorithm.

\[ v_i^j = x_i^j + c_1 \phi (x_i^j - x_d^j) + c_2 (1 - \phi) (x_g^j - x_i^j) \]  

(5)

In formula (5), \( x_g \) is the optimal individual, \( \phi \) is the random number within \((0, 1)\), \( c_1 \) and \( c_2 \) are learning factors, \( x_d \) is the better neighboring nectar source (i.e. the individual with high fitness is selected from two randomly generated individuals). On the other hand, multiple dimensions are used to learn at the same time. \( j \) is selected from 1 to \( D \) in turn. According to formula (5), all aspects of each dimension are learned, so as to broaden the search range and increase the diversity of the population.

3.2. Adaptive Search

In ABC algorithm, the neighborhood search direction of bees and observation bees is not strong, which cannot guarantee the global search in the initial stage, and the late search is easy to fall into local optimization, which cannot achieve the overall performance of the algorithm. In this paper, the strategy of adaptive adjustment of search space is introduced. The basic idea is that the search area changes from large to small, and the search area is gradually reduced according to the results of each optimization. The larger search area in the early stage can make the poor individuals survive, enhance the diversity of the population, and achieve the purpose of global search. In the later stage, the search space is reduced to facilitate local development and accelerate the convergence of the optimal solution. The adaptive search factor \( \eta_i \) is as follows (6).

\[ \eta_i = \exp(-\text{iter}_i/\text{Maxcycle}) \]  

(6)

In formula (6), \( \text{iter} \) is the number of iteration, and \( \text{Maxcycle} \) is the maximum number of iterations.

3.3. ACLABC Algorithm

Combining the above comprehensive learning strategy and adaptive search strategy to form an improved adaptive comprehensive learning strategy bee colony algorithm (ACLABC). In ACLABC algorithm,
honeybee adopts formula (7) to generate new individuals, which can learn the experience of the better individual and the optimal individual at the same time, and adjust the search step size adaptively, so that the algorithm has strong search ability in the early stage, and guides the algorithm to converge quickly to the excellent solution in the later stage.

\[ v_i^t = x_i^t + \eta_i(c_1\varphi(x_i^t - x_d^t) + c_2(1 - \varphi)(x_g^t - x_i^t)) \]  

(7)

4. Design of ACLABC-PID in water supply control system

Constant pressure water supply system is a complex nonlinear object, it is difficult to obtain an accurate model, which can only be approximately equivalent [25]. It can be considered as a controlled object composed of inertia link, delay link and scale link. In this paper, the transfer function of equation (8) is used as the object of the water supply system.

\[ G(s) = \frac{1}{60s + 1}e^{-4s} \]  

(8)

PID parameter optimization of constant pressure water supply system is to determine the optimal value of Kp, Ki and Kd of PID controller based on a certain objective function. Therefore, by taking a set of PID controller parameters (Kp, Ki, Kd) as a food source of bee colony algorithm, the parameter setting problem of PID controller can be transformed into the optimization process of bee colony algorithm with three-dimensional vector. In order to obtain a satisfactory dynamic transition process, the performance index of absolute error time integral is used as the objective function. At the same time, considering the influence of control input, the objective function T of bee colony algorithm is selected as equation (9).

\[ T = \int_0^\infty \left( w_1 |\varphi(t)| + w_2 u^2(t) \right) dt \]  

(9)

Where \( e(t) \) is the system error; \( u(t) \) is the controller output; \( w_1 \) and \( w_2 \) are the weights.

In order to avoid overshoot, overshoot is taken as one of the optimal performance indicators. When \( e(t) < 0 \), the performance index T is formula (9), \( w_3 \) is the weight.

\[ T = \int_0^\infty \left( w_1 |\varphi(t)| + w_2 u^2(t) + w_3 |\varphi(t)| \right) dt \]  

(10)

Therefore, the PID parameter optimization of the water supply control system based on ACLABC algorithm is to take the water system as the controlled object to make the objective function T get the minimum value.

5. Simulation Experiment and Analysis

Taking the water supply model of equation (8) as the controlled object, the sampling time is \( ts = 1s \), and the controlled object is discretized. ABC and ACLABC are used to adjust PID parameters. The parameters of the two algorithms are the same, \( 0 \leq Kp \leq 50 \), \( 0 \leq Ki \leq 10 \), \( 0 \leq Kd \leq 50 \), the number of population 40, the maximum number of iterations 100, \( w_1 = 1 \), \( w_2 = 0.01 \), \( w_3 = 1 \). After running ABC and ACLABC algorithms for 20 times respectively.

In 20 times experiments, T optimal values, T worst value and T average of ACLABC are 14.2641, 14.2754, and 14.266 respectively. T optimal values, T worst value and T average of ABC are 14.3753, 21.9938, and 16.752 respectively. It can be seen that ACLABC-PID algorithm runs very stable, and it can get better performance index every time it runs. T changes little, almost no overshoot, and steady-state error tends to 0. However, the performance index of ABC-PID algorithm is sometimes good or
bad, and T index has a big difference, sometimes there is a large overshoot, and even a large steady-state error.

In the ABC algorithm, the PID parameters closest to its T-average value are Kp=6.2791, Ki=0.1191, Kd=0. In the ACLABC algorithm, Kp=6.8872, Ki=0.1143, Kd=4.8553. At the same time, the Critical proportionality method (CPM) is used for tuning, and its PID parameter is Kp = 12.63, Ki = 1.4457, Kd = 15. The step responses of the three methods are shown in Figure 1.

![Figure 1. Response of Unit Step.](image)

It can be seen from figure 1 that the setting performance of ACLABC-PID algorithm is significantly improved, there is almost no overshoot and less adjustment time.

6. Conclusions
In this paper, the adaptive all-round learning strategy bee colony algorithm (ACLABC) effectively expands the search area, increases the search path, reduces the probability of falling into the local solution, speeds up the convergence speed and improves the convergence accuracy, and has better robustness. Compared with ABC-PID and CPM-PID controller, ACLABC-PID controller has better response performance, less adjustment time and less overshoot, which verifies the feasibility and effectiveness of the algorithm.

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References
[1] Jinkun Liu. Advanced PID control and MATLAB simulation[M].Beijing:Publishing House of Electronics Industry, 2016: Preface.
[2] Jian Liu, Shuai Yuan, Feng Zhang.MATLAB simulation and application of control system[M]. Beijing: China Machine Press, 2017: 262 - 263.
[3] Mahdi A, Mohammad R H Y, Aghil YK. Optimal running of PID controllers using artificial bee colony algorithm [C]. Proceedings of IEEE/ASME international Conference on Advanced intelligent Mechatronics, Montreal, 2010:379 - 384.
[4] Dongli Zhang, Yinggan Tang, Xinping Guan, Design of optimal fractional order PID controller for AVR system using improved artificial bee colony algorithm, J. Acta automatica Sinica, 2014, 40 (05): pp. 973 - 980.
[5] Jinbao Chai, Xiong Chen, Jingliang Zhao, Kun He, Adaptive fuzzy immune PID control of gas generator pressure based on artificial bee colony optimization. J. Propulsion technology, 2019,
Cai Chao, Zhou Wuneng. Tuning PID controller parameters by artificial bee colony algorithm [J]. Automatic instrument, 2015, 36 (08), pp. 74 - 77.

Karaboga D. An idea based on honey bee swarm for numerical optimization, technical report, Erciyes University, 2005.

Dervis Karaboga, Beyza Gorkemli, Celal Ozturk, Nurhan Karaboga. A comprehensive survey: artificial bee colony (ABC) algorithm and applications [J]. Artificial Intelligence Review, 2014, vol.42 (1), pp.21 - 57.

Okdem S, Karaboga D, Ozturk C. An application of wireless sensor network routing based on artificial bee colony algorithm//Proceedings of IEEE Congress on Evolutionary Computation New Orleans, 2011: 1 – 4.

Goudos S K, Siakavara K, Sahalos J N. Novel spiral antenna design using artificial bee colony optimization for UHF RFID applications. IEEE Antennas and Wireless Propagation Letters, 2014, 13: 528 - 531.

Guolin Pu, Yuhui Qiu, Edge detection of quaternion color remote sensing image based on double search bee colony algorithm [J]. Computer science, 2016, 43 (07), pp. 310 – 313.

Bahriye Akay, Dervis Karaboga. A survey on the applications of artificial bee colony in signal, image, and video processing [J]. Signal, Image and Video Processing, 2015, Vol. 9 (4), pp.967 - 990.

Chidambaram C, Heitor S L. A new approach for template matching in digital images using an artificial bee colony algorithm // Proceedings of World Congress on Nature & Biologically inspired Computing, Coimbatore, 2009, pp.146 - 151.

Akay B, Karaboga D. Wavelet packets optimization using artificial bee colony algorithm // Proceedings of IEEE Congress on Evolutionary Computation, New Orleans, 2011: 89 - 94.

Shao Chen, Weixi Ji, Yongtao Qiu, Guoxiang Zhang. Improved artificial bee colony algorithm for flexible job shop scheduling problem [J]. Modular machine tool and automatic processing technology, 2018 (05), pp. 161 - 164.

B Li, L Gong, C Zhao, Unmanned combat aerial vehicles path planning using a novel probability density model based on Artificial Bee Colony algorithm//Proceedings of 4th International Conference on Intelligent Control and Information Processing, Beijing, 2013, pp.620 - 625.

Seleuk Ozcan, Fuat Simisir. A new model based on Artificial Bee Colony algorithm for maintenance with replacement scheduling in continuous production lines [J]. Engineering Science and Technology, an International Journal, 2019, 22 (6).

Nguyen T L, Nguyen Q A. Application artificial bee colony algorithm (ABC) for reconfiguring distribution network [J]. Proceedings of 2nd International Conference on Computer Modeling and Simulation, Sanya, 2010:102 - 106.

Fahad S, Mouti A, Hawary M E. Optimal distributed generation allocation and sizing in distribution systems via artificial bee colony algorithm [J]. IEEE Transactions on Power Delivery, 2011, 26 (4): 2090 - 2101.

G Zhu, Kwong S, Gbest-guided artificial bee colony algorithm for numerical function optimization. J, Applied Mathematics and Computation. 2010, 217, pp. 3166 - 3173.

Hao Luo, Yu Liu. An artificial bee colony algorithm with enhanced mutual learning [J]. Computer engineering and application, 2016, 52 (16): 23 - 29.

Quande Qin, Shi Cheng, Li Li, Yuhi Shi. A review of artificial bee colony algorithm J, Journal of intelligent systems, 2014, 9 (02), pp.127 - 135.

Huiping Liu, Research on particle swarm optimization algorithm and its multiple learning strategies, Beijing University of Posts and telecommunications, 2017.

Jiang Mingyan, Yuan Dongfeng. Artificial bee colony algorithm and its application [M]. Beijing: Science Press, 2014: 47 - 53.

Daming Liu, Jin Chen, Research on Fuzzy-PID Control of constant pressure water supply. J, Journal of Ningxia University (2nd), 2008, 29 (04), pp.333 - 336.