Application of Adaptive Artificial Bee Colony Algorithm in Reservoir Information Optimal Operation

Lijun Cui[1,2*]
[1]Liaoning Open University, School of Public Administration, Shenyang 110034, China
[2]Liaoning Equipment Manufacturing Vocational and Technical College, School of Public Administration, Shenyang 110161, China
E-mail: lijuncui5@163.com
[*]Corresponding author

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Abstract: The hydrothermal scheduling is complex issue of nonlinear optimization consisting of several constraints that plays a critical role in the operations of power system. In order to meet the safe operation of hydropower stations, how to reasonably dispatch them to achieve the best comprehensive benefits is one of the main problems in the hydropower industry. Artificial bee colony algorithm has the advantages of simple structure and strong robustness. It is widely used in many engineering fields. However, the algorithm itself still has many shortcomings. Based on the current research, an improved artificial colony algorithm based on standard artificial bee colony algorithm is proposed, and the performance of the algorithm is verified in three benchmark functions and three cec213 test functions. Compared with many well-known improved algorithms, it is proved that the improved procedure has greatly enhances the final solution accuracy and convergence outcome. The experimental outcomes observed by improved artificial algorithm are compared with adaptable artificial bee colony procedure and chaotic artificial bee colony procedure and with other existing works in the literature. It is observed from the experimentation that the proposed algorithm performs better in comparison with established optimization algorithms.

Povzetek: Raziskava obravnava optimizacijo razporeditve vodne energije s pomočjo izboljšanega algoritma umetne čebelje kolonije, kar izboljša natančnost in konvergenčne rezultate.

1 Introduction

Power generation, flood control, water storage and irrigation are the goals that many cascade hydropower stations need to coordinate, but there are complex constraints among them. In solving the scheduling scheme of single reservoir hydropower station, the conventional scheduling method is a feasible solution. However, cascade hydropower stations are a high-dimensional, nonlinear and multi constraint problem. When solving this issue by conventional dispatching methods, the calculation efficiency is usually low, and it is easy to drop into problems such as native optimization and "dimension disaster" [1]. Therefore, it is an important issue to combine the process and dispatching issue of cascade reservoirs with emerging calculation methods (swarm intelligence optimization algorithm and constraint processing method). The research on the theory and method suitable for the optimal operation of cascade reservoirs (groups) is conducive to shorten the gap between the application of the theory and method to practical projects. China's hydropower reserves rank first in the world, but the per capita is scarce. However, China is also one of the countries with more flood disasters. On the premise of having a set of better reservoir operation scheme, in the face of flood problem, reservoir is an important protective measure, which can store and discharge water artificially and reduce the loss caused by flood disaster [2]. Therefore, the solution of the operation and operation scheme of cascade reservoirs (groups) is a issue to be solved for a long time at present and in the future. In the past two decades, with the development of computers, many swarm intelligence algorithms have been proposed by the majority of Chinese and foreign scholars. These algorithms are proposed based on the behavioral characteristics of organisms in the biological world, such as foraging, mating and so on. Social animals are more complex work. Just like this feature, many swarm intelligence algorithms can solve complex practical problems [3]. The artificial bee colony (ABC) algorithm is propsoed in 2005 through the observation of bee colony honey collection behavior. The algorithm is to find the optimal solution of the issue by the process of bee colony cyclic iteration. Global search and native development exist in the optimization process at the same time, which is a main feature of the algorithm, as shown in Figure 1.

Much exploration was done to address the downsides of established procedures and enhances the adequacy to determine hydrothermal scheduling in potential frameworks. Wavelet transmission was joined with artificial neural network to work on the capacity of the system in [4, 5]. The genuine coding method was practically implemented to work on looking through capacity of genetic algorithm. Equal computation was embraced to further develop the particle swarm optimization algorithm. The proposed strategy presents a superior scheduling result in comparison with the existing technique. The chaotic searching method has been embraced by researcher and applied in differential evolution to determine the issue of dynamic dispatch issue.

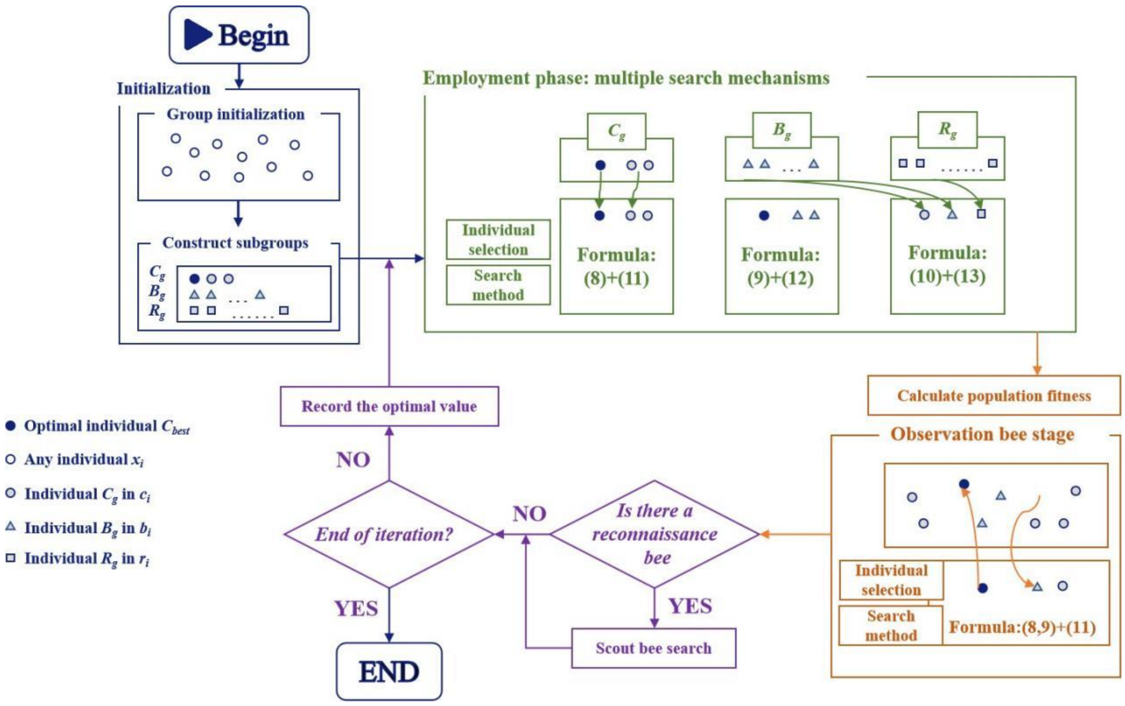


Figure 1: Architecture of artificial bee colony algorithm.

Effectiveness and searching capability of differential evolution was improved in chaotic differential advancement algorithm with an improved outcome. The self-versatile idleness weight instrument was joined with the particle swarm optimization algorithm to decide the age timetable of a flowed hydro framework situated at Narmada stream in India. The outcomes exhibited the adequacy of the planned strategy. These adjustments have worked on different parts of optimization capacity. Though, because of the additional boundaries, the hybrid algorithms might turn out to be more confounded and unsteady.

Recently, another enhancement strategy named artificial bee colony algorithm turns out to be increasingly more adopted due to the fact that it performs strong capacity to deal with different engineering designing issues. The artificial bee colony has a basic design and great union capacity. Though, the coordination of control boundaries is a difficult and uphill errand. Then again, comparable with other current heuristic algorithms, artificial bee colony algorithms additionally have the issue of untimely convergence. Consequently, in this article, we offer a method for an adaptive chaotic artificial bee colony. Control boundary setting technique and chaotic neighborhood search are applied to assist the algorithm with getting away from nearby optimal solution. Additionally, unique adaptation of artificial bee colony did not reflect the obliged optimization issue. Consequently, we propose another limitation taking care of strategy with an adjusted form of artificial bee colony to determine hydropower scheduling with different imperatives. The outcomes show that compared to current methods, the suggested algorithm offers a higher convergence capacity and convergence speed.

This article's remainder is structured as follows: Section 2 displays the recent work done in hydropower scheduling. Section 3 consists the information about the research methods and the algorithmic steps based on chaotic learning. Section 4 deals with the results and examinations. Section 5 describes the concluding remarks.

2 Literature review

The research on optimal operation of reservoir groups in China began in the late 1970s [6]. Ma *et al.* applied stochastic dynamic programming theory to Lancang River reservoir group operation and established an optimization model for dynamic regulation of reservoir information [7]. Jie *et al.* applied the parallel dynamic programming method to the operation of cascade hydropower stations in Lixianjiang River Basin [8]. Mansouri and others established the mathematical model of reservoir group optimal operation for the issue that the convergence of coordination vector and feedback vector is not synchronized in solving the optimal operation of reservoir group by large-scale system objective coordination method, and improved the solution process of real-time optimal operation combined with accelerated convergence technology [9]. With the deepening of artificial intelligence theory, many intelligent optimization algorithms have been applied to cascade reservoir operation. Aiming at the disadvantages of slow convergence speed and easy to fall into local optimization in the later stage of ant colony algorithm, Gavahi *et al.* gradually determined the scope of the optimal solution by increasing the tabu search area, proposed an ant colony algorithm based on tabu search, and applied the improved algorithm to the optimal operation of Zhangze cascade reservoir [10]. Jamshidi and Shourian improved the standard genetic algorithm by using three elite evolution strategies of floating-point coding, adaptive crossover rate and mutation rate, and applied it to the optimal operation of Fengjiashan and Duanjiaxia cascade reservoirs. As a new swarm intelligence algorithm, artificial bee colony algorithm has significant advantages in dealing with the optimization of high-dimensional functions [11]. Bozorg Haddad *et al.* have shown that compared with ant colony optimization (ACO), frog leaping algorithm (FLA), particle swarm optimization (PSO), differential evolution algorithm and other well-known evolutionary algorithms, the performance of artificial bee colony algorithm is better or equivalent [12]. The research on artificial bee colony algorithm is still in its infancy, and the theory and practice are not perfect. Many scholars have always been committed to improving the performance of the algorithm. Barz *et al.* used chaos strategy and reverse learning strategy to make the initialization of individuals in the solution space purposeful and average the distribution of initial solutions as much as possible. However, the chaotic strategy makes the distribution of individuals have direction, which weakens the global examination enactment of the algorithm to a certain extent [13]. Babu and Kumari proposed a RABC procedure. The population alternately adopts two evolutionary policies with Rosenbrock rotation disturbance to dynamically adjust the search balance between the global and local of the algorithm. Shrabbhal401 draws lessons from the concept of native optimal specific in PSO procedure to make the parent data of honey resource participate in the generation of candidate solutions, so as to improve the local development ability of the algorithm [14]. Aiming at the phenomenon of dropping into native optimization due to the reduction of population diversity, Gao *et al.* proposed a MABC algorithm. The fixed parameter p is used instead of observing the selection probability of bee roulette, and the improved algorithm has achieved good outcomes [15]. Gupta *et al.* improved the artificial bee colony algorithm with the idea of chaotic driving, so that the offspring coefficients are generated by the parent coefficients using the chaotic strategy, which greatly improves the local search ability of the algorithm [16].

3 Research methods

This section includes the discussion of proposed flowchart for addressing the issue of hydro scheduling. The algorithm steps are described in this section.

The standard algorithm simulates the honey collection process of bees, and solves the issue through division of labor, cooperation and information sharing among different individuals. Among them, bee colony is composed of employed bees, onlookers and scout bees. The degree of perfection is dependent on the fitness specified by the optimization issue, and honey source symbolizes a workable solution. Hire bees to search in the global scope. Once a high-quality honey source is found, they fly back to the hive to inform other bees. The observation bee selects a honey source and searches nearby according to the information transmitted by the hired bee. Initialization: assume that the total number of bee colony members for the d-dimensional issue is Sn, the amount of honey bases is FN, SN = 2FN, and the number of hired bees and observation bees are FN. FN initial honey sources are generated from the search space through Equation (1), and each honey source position is a D-dimensional vector, which is recorded as x_{ij}.

$$x_{i,j} = x_{\min,j} + rand(0,1)(x_{\max,j} - x_{\min,j}) \tag{1}$$

Population update: employ bees to update the position according to Equation (2). Compared with the original honey source, greedy selection strategy is used to record the location of higher quality honey source.

$$v_{i,j} = x_{i,j} + \phi_{i,j}(x_{i,j} - x_{k,j}) \tag{2}$$

Where, the random number in $k \in \{1,2,\ldots,FN\}$ and $I \neq K, \emptyset_{i,j}$ represents the random quantity between [- 1, 1], x_{ij} represents the original honey source location, $x_{k,j}$ represents the neighborhood honey source location, and $v_{i,j}$ represents the updated honey source location. The flowchart of the proposed algorithm is depicted in Figure 2. The prime focus of the proposed algorithm is to address the issue of hydro scheduling.

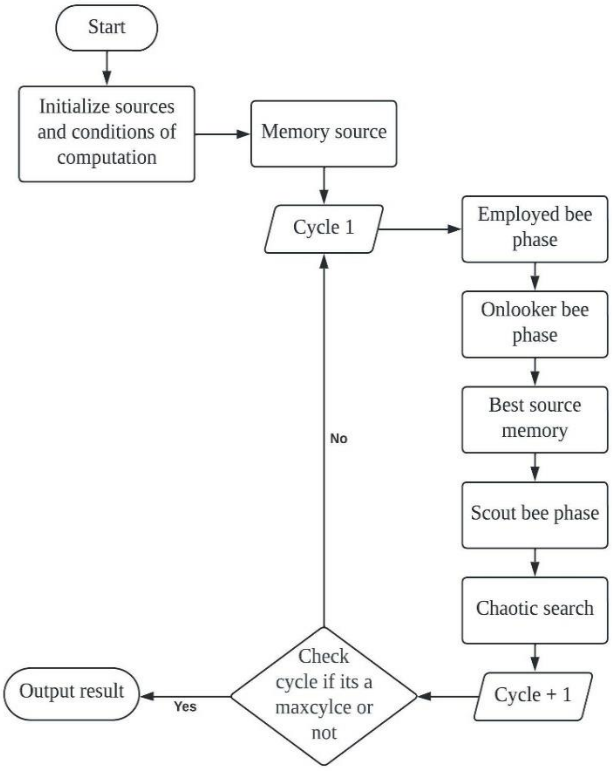


Figure 2: Process flow of proposed algorithm.

Step 1: Determine the swarm size Sn, the variety of sources for honey FN, the size D of the solution to the optimization issue, and set the limit times imit. FN solutions are randomly generated to form the initial honey source position, and the fitness of each honey source is calculated.

Step 2: Employ bees to update according to Equation (2) and evaluate the adaptability of new honey sources. Keep the excellent honey source for the next iteration.

Step3: Select the honey source according to roulette, let the observation bee update according to Equation (2), evaluate the fitness of the new honey source and select the best.

Step 4: If the location of a honey source does not change and is not the current global optimum after the search of limit iterations, the hired bee converts a reconnaissance bee, and in accordance with equation (1), a fresh source of honey is created at random [17].

Step 5: If the specified number of iterations is reached or the global optimal solution meets the needs of the problem, terminate the algorithm. Otherwise, return to Step 2.

Aiming at the shortcomings of slow convergence speed and low convergence accuracy of standard bee colony algorithm, an artificial bee colony algorithm with improved special center (ISC-ABC) is proposed based on the narrow center idea of particle swarm optimization algorithm. First, improve the narrow central thought. By comparing the fitness, the better honey source is selected to form an improved narrow center, and the greedy strategy is compared with the current global optimal position to lead the bee colony to converge. Secondly, change the update strategy of the original bee colony [18]. The employment bee always searches around the current global best, strengthens the ability of the bee colony to develop hidden solutions near the best, and improves the accuracy of the algorithm solution. The special center is formed by the central position of the population and changes in real time with the population movement. The narrow sense center, like other individuals, has the attributes of location update, fitness evaluation and so on. It is found that due to the special position, the narrow center tends to the optimal solution of the issue more than the global optimal position. For every iteration, the narrow center is equated with the current global optimum, and a better position is certain to lead the bee colony movement, so as to speed up the population convergence. The narrow sense center expression is as follows:

$$c = \frac{\sum_{i=1}^{FN} xij}{FN} \tag{3}$$

Where c is the narrow central position in the population, and FN represents the number of honey sources in the population.

In ISC-ABC algorithm, employed bees and observed bees adopt different search strategies [19]. The current global optimal information is added to the update formula to improve the local development ability of the algorithm near the current global optimal; The observation bee update formula remains unchanged to ensure the global search ability of the algorithm. The evolutionary strategy adopted by employing bees and observing bees ensures that the scope of the search of population is mainly around the current global optimum, reduces the search of a large number of random positions, and improves the convergence speed of the algorithm; It also has a certain global development ability, which can maintain the diversity of the population and reduce the possibility of the population falling into local optimization. The employment update formula is as follows:

$$v_{i,j} = gbest_j + \phi_{i,j}\left(gbest_j - x_{k,j}\right) \tag{4}$$

Where, $k \in \{1,2,\dots,FN\}$ is a random number and $i\#k$, $\emptyset_{i,j}$ represents a random number between [0,1], $w_{i,j}$ represents the original honey source location, gbest represents the current global optimal location, x_k represents the neighborhood honey source, and $v_{i,j}$ represents the updated honey source location. At present, the global optimality is a key position. In the iterative process, all bee individuals are guided to approach the optimality, which directly affects the overall convergence speed of the algorithm and the quality of the final solution. With the progress of search, the current global optimum will be closer and closer to the position of the theoretical optimal solution [20]. The update of the current global optimum in the standard bee colony only depends on the improvement of the extreme value after the individual evolution of the population. When the extreme value does not change or changes very little after individual evolution, the current global optimum will not change greatly. ISC-ABC algorithm guides the convergence direction of the population by introducing the current global best, ensures that the employed bees gradually approach the current global best, and increases the convergence capability of the procedure [21].

Step 1: Determine the colony size Sn, the amount of honey sources FN, the dimension D of the optimization problem's solution, and set the limit number. FN solutions are randomly generated to form the initial honey source location, and the fitness of each location is estimated.

Step 2: Determine the improved narrow sense center of the current iteration and make greedy selection with the current global optimal.

Step 3: Update according to Equation (4) to evaluate the fitness of the new location. Keep the excellent honey source for the next iteration.

Step 4: Select the honey source according to the way of roulette, let the observation bee update according to Equation (4), evaluate the fitness of the new location, and select the best.

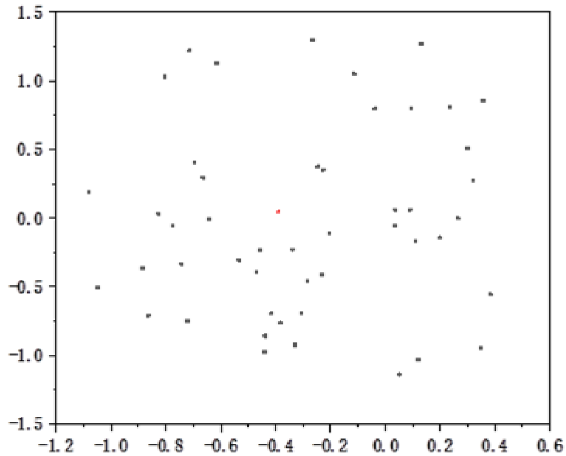
Step 5: If the location of a honey source does not change and is not the current global optimum after the search of limit iterations, the employed bee converts a reconnaissance bee, and according to Equation (3), a fresh source of honey is created at random.

Step 6: If the specified number of iterations is reached or the global optimal solution meets the needs of the problem, terminate the algorithm. Otherwise, return to step 2.

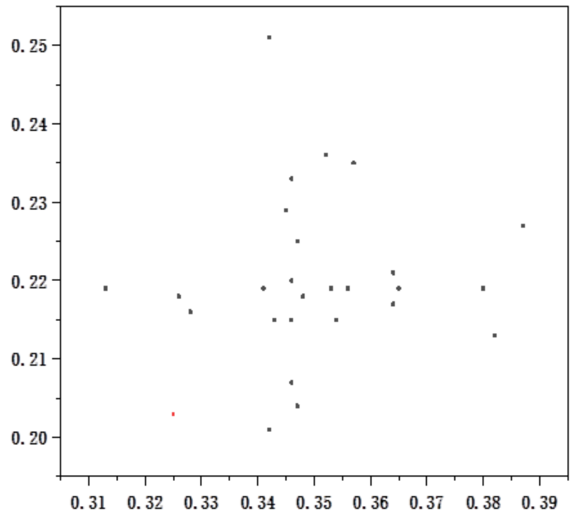
4 Results and analysis

This segment describes the examination of outcomes attained from the proposed algorithm for addressing the issue of hydro scheduling.

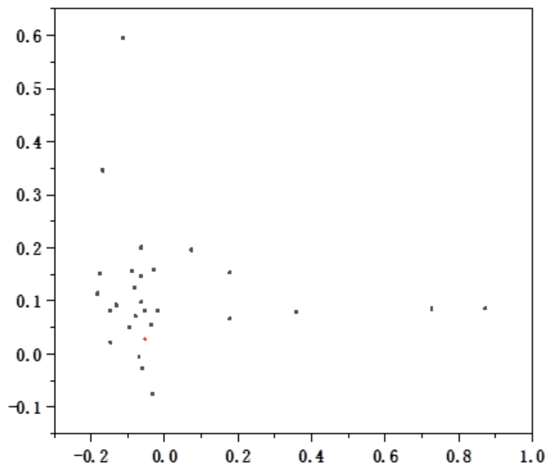
In order to show the population distribution and convergence in different iterative periods, Quatic function is used for testing. Figure 2 and Figure 3 are the population individual motion scatter diagrams of 0ABC algorithm and ISC-ABC algorithm respectively. The dot represents the position of the individual in the population, and the asterisk represents the position of the theoretical optimal solution.



(a): FEs=0

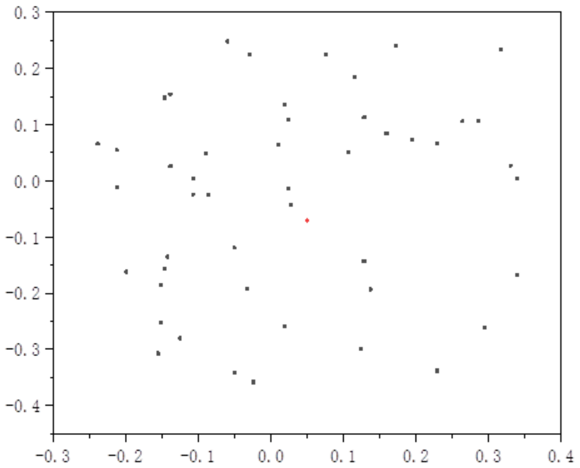


(b): FEs=30000

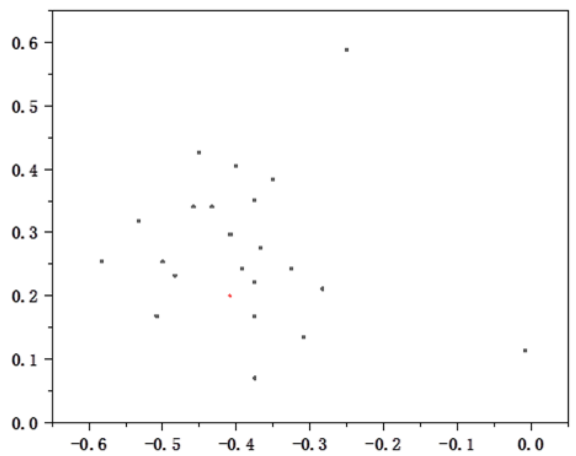


(c): FEs=60000

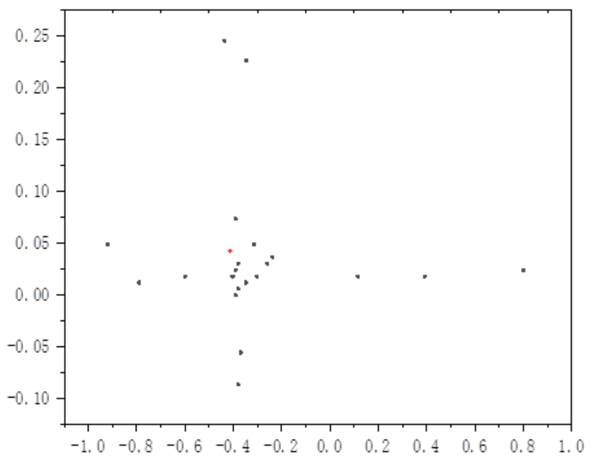
Figure 3: Feature extraction under normal conditions for several iterations.



(a): FEs=0



(b): FEs=30000



(c): FEs=60000

Figure 4: Feature extraction with improved narrow center strategy for several iterations

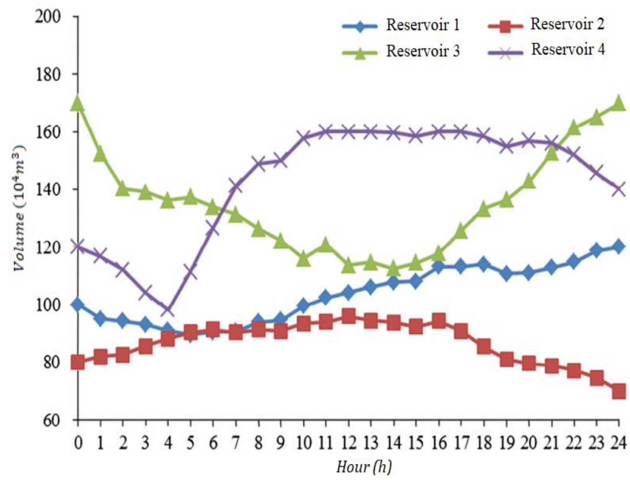


Figure 5: Ideal reservoir storing standards of case 1.

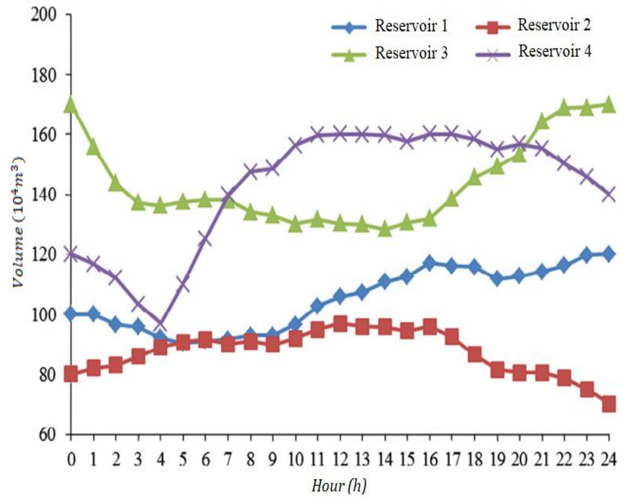


Figure 6: Ideal reservoir storing standards of case 2.

Table 1: Comparison of Friedman test outcomes

Algorithm	Rankings
ISC-ABC	2.12
MABC	2.75
MEABC	2.75
GABC	3.45
ABC	4.37

It can be seen from the comparison between Figure 2 and Figure 3. In the early stage of the algorithm (the number of iterations is before 60000), the improved narrow center strategy can significantly accelerate the convergence speed of the population and quickly find the region where the optimal solution is located; In the middle and later stages of the algorithm (after 60000 iterations), the improved narrow sense center can be used as the advanced part of the global optimum. It can generate a location closer to the optimal solution than the current best advantage, and may also produce a far away from the current optimal location. The swarm moves around the optimal solution in a large range to enhance the individual's ability to explore the solution space. The diversity of individual distribution is maintained under the condition of ensuring the convergence speed, which reduces the possibility of the population falling into local optimization. With the progress of the search and the continuous change of the population activity area, the current global best point and the improvement of the individual are closer and closer to the optimal solution. Finally, the final solution is obtained to complete the search.

The simulation outcomes are observed for two cases. In case 1 the power transmission loss is not considered whereas it is considered in case 2. The optimal capacity volumes of the hydro capacity are depicted in Figure 5. It is observed from Figure 4 that every one of the imperatives were fulfilled, and that implies every one of the solutions acquired by the proposed technique are practical. The loss of power transmission has been considered in second case. The outcomes got by various techniques were recorded and the reservoir supply volume for case 2 is depicted in Figure 5.

Then the Friedman examination is implemented to analyze the outcomes of the test function, which can effectively distinguish the performance gap between procedures. The smaller the Friedman value, improved the algorithm performance. According to Table 1, ISC-ABC algorithm has the smallest Friedman value and the best comprehensive performance compared to the algorithms ABC, GABC, MABC, and MEABC.

5 Conclusion

Aiming at the shortcomings of slow convergence speed and low final solution accuracy of standard bee colony algorithm, an improved narrow center bee colony algorithm is constructed by referring to and improving the narrow center idea of particle swarm optimization algorithm. First, improve the narrow central thought. Select the better honey source to form an improved narrow center to lead the bee colony to converge. Secondly, change the original bee colony update strategy. Make the hired bee search around the current global optimum, and strengthen the ability of the bee colony to develop hidden solutions near the best. Finally, the simulation test outcomes of three classical benchmark functions and three cec213 functions show that compared with a variety of similar algorithms, the artificial bee colony algorithm based on improved narrow center guided convergence has significantly improved in convergence speed and resolution accuracy, indicating the effectiveness of the improved method.

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