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Multi-objective hydropower station operation using an improved cuckoo search algorithm

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ABSTRACT

Efficient utilization of water resources in hydropower station operation is an important part of mitigating water and energy scarcity. Exploring efficient multi-objective optimization algorithms and studying the trade-off between water and energy have become the primary goal of multi-objective hydropower station optimal operation (MOHSOO). In this paper, a new improved multi-objective cuckoo search (IMOCS) algorithm is proposed to overcome the shortcomings of MOCS. Specifically, a population initialization strategy based on constraint transformation and the individual constraints and group constraints technique (ICGC) and a dynamic adaptive probability (DAP) are used to improve the search efficiency and the quality of solutions, respectively. A flock search strategy (FSS) is proposed to greatly speed up the convergence and improve the quality of the non-dominated solutions. In addition, the MOCS and NSGA-II are presented as a comparison to test the performance of IMOCS as well as three hybrids of MOCS combined with these strategies. An MOHSOO model of Xiaolangdi and Xixiayuan cascade hydropower stations in the lower Yellow River is built to verify the effectiveness of these algorithms together with five benchmark problems. The results show that IMOCS performs better than other algorithms in convergence speed, convergence property, and diversity of solutions. For the Xiaolangdi hydropower station, there is a strong competitive relationship between power generation and water supply from September to next February, which severely restricts the power generation of the hydropower station.

1. Introduction

The relationship between water and energy is a matter of great international concern [1]. It is predicted that global water consumption for energy sectors will increase by 85% in 2030 relative to that in 2012 [2]. The current study suggested that not only renewable energy potential but also water resources available for energy use should be considered in the energy development [3]. On the one hand, rapid economic development has pushed the continuing growth of energy demands and led to severe pollutant emissions derived from fossil energy [4]. Exploration of clean and renewable alternative energy sources has attracted increased attention [5]. Hydropower is one of the most effective and mature forms of clean and renewable energy [6]. In power systems, hydropower is usually applied to insure the safe operation of electric network by means of peak and frequency modulation due to its convenient start and stop of power generation [7]. However, hydropower plants usually undertake multiple tasks besides power generation, such as flood control, irrigation, water supply, and recreation, among others, which generally prevail over the power generation and prevent the physical flexibility of hydropower [8]. Therefore, the hydropower generation is seriously restrained by the integrated tasks of hydropower stations [9]. On the other hand, with the continuous increase in water demand, the contradiction of supply and demand is made more severe. The scarcity of high-quality water even impedes social improvements [10]. UN-Water (United Nations - Water) [11] calls attention to the fact that water stress is already high and that improved management is critical to ensuring sustainable development. Hydropower station operation plays a great role in positive contribution to the development of socio-economic sectors and the reduction of the vulnerabilities of water systems [12].

Therefore, efficient utilization of water resources in hydropower station operation has become an important part of mitigating water

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and energy scarcity. It is necessary and significant to explore the relationship between water and energy, which can help managers make reasonable hydropower station operation plans in power and water systems. These issues motivate the research on multi-objective hydropower station optimal operation (MOHSOO). Zhou et al. [13] proposed a multi-objective model solved by non-dominated sorting genetic algorithm-II (NSGA-II) to improve water utilization and hydropower generation without increasing flood risk. However, one of the difficulties is that the optimal hydropower station operation is a high-dimensional, non-linear, multi-stage and stringent constraint optimization problem [14]. Another difficulty is that it is time-consuming or even impossible to find all of the Pareto optimal solutions on the Pareto front [15]. Therefore, exploring efficient multi-objective optimization algorithms and obtaining a set of representative solutions with good coverage and uniformity have become the primary goals for MOHSOO.

With the development of computing technology, numerous optimization algorithms have been used to solve optimal operation problems, and such algorithms can be classified as classic or evolutionary methods. The classic optimization methods may have poor performance in many complex problems, while evolutionary algorithms (EAs) can handle any type of objective function [16]. For hydropower station operation, EAs are recognized as good decision-making tools due to their flexibility and superiority [17]. Therefore, EAs, such as the genetic algorithm (GA) [18], differential evolution algorithm (DE) [19], and progressive optimality algorithm (POA) [20], are being applied more often in optimal hydropower station operation. However, it is not possible to find a single scheme that can optimize all objectives simultaneously for MOHSOO. The decision makers would rather obtain a set of candidate solutions that can provide more information for decision making. Therefore, multi-objective evolutionary algorithms (MOEAs) that can obtain a set of non-dominated solutions from the Pareto optimal front are more applicable to decision making and recommended for the solution of many difficult water resources problems [21,22]. In recent years, a variety of newly developed MOEAs have been applied to solve MOHSOO, including the non-dominated sorting genetic algorithm-II (NSGA-II) [13,23], differential evolution algorithm (DE) [24], artificial bee colony algorithm (ABC) [25], gravity search algorithm (GSA) [16], and so on. Note that NSGA-II is one of the most popular multi-objective evolutionary algorithms and is often employed as a comparison method to test the performance of other multi-objective optimization algorithms due to its fast speed and good convergence. Furthermore, many MOEAs are improved by combining them with other algorithms to overcome their shortcomings. Fang et al. [26] presented a hybrid algorithm by combining the real-coded genetic algorithm and artificial fish swarm algorithm (RCGA–AFSA), which takes advantage of their complementary abilities of global and local search to find an optimal solution.

Recently, a relatively new meta-heuristic search algorithm named cuckoo search (CS) was proposed by Yang and Deb [27]. They found that CS is potentially far more efficient than PSO and GA. Therefore, this algorithm has been used in many fields due to its advantages of fewer parameters and good global searching ability [28–30]. Some studies have even demonstrated that CS can perform significantly better than other algorithms [31]. Nevertheless, there are still some challenging issues that must be resolved. One is that the parameters will largely influence the performance of an algorithm. Another issue is that we must improve the algorithm with a good understanding of the working mechanism [32]. The challenging issues motivate more research to improve CS. These improvements can be divided into four types. First, self-adaptive parameter setting is one of the most widely used approaches and is designed to enhance the diversity of the solutions with the dynamic change of parameters [33,34]. Second, some studies have attempted to improve the properties of exploration and exploitation by inducing a Cauchy operator to generate the step size instead of Lévy flights or using better search strategies, i.e., the random long-distance search strategy, stochastic moderate-distance search strategy and stochastic short-distance search strategy [34,35]. The third common method is the hybridization of other algorithms. Recently, numerous new CS variants have been proposed that may also become a hot topic for further development. For example, Kanagaraj et al. [36] proposed a new cuckoo search algorithm hybridized with the genetic algorithm, called CS–GA, to solve the reliability and redundancy allocation problem by embedding the genetic operators in CS. Conversely, another hybrid algorithm was developed by incorporating the egg-laying and immigration mechanisms of the cuckoo optimization algorithm (COA) into the harmony search (HS) algorithm (HSCOA) [37]. Finally, there is improving the initial solutions, which also greatly influences the optimization of EAs. Therefore, an improved cuckoo search (ICS) algorithm is proposed to rapidly obtain the optimal solutions by incorporating a constructive heuristic called NEH with the initial solutions [38].

Moreover, to solve the multi-objective optimization problem, Yang and Deb [39] proposed multi-objective cuckoo search (MOCS), which also has been used in myriads of engineering applications. More importantly, various researchers have made improvements to the algorithm to overcome its shortcomings (e.g., slow convergence speed). Balasubbareddy et al. [40] proposed the non-dominated sorting-based hybrid cuckoo search algorithm, which introduces arithmetic crossover operations to the conventional cuckoo search algorithm to update the newly generated population and thereby speed up the convergence. In addition, the non-uniform mutation operator and differential evolution operator are used to improve the accuracy and rate [41]. However, the research on CS and MOCS improvement usually uses one or two measures to improve the algorithm. The quantifiable effect of each improvement measure is not analyzed separately when more than one measure is included in the new algorithm. In particular, there is insufficient research on MOCS improvements.

This paper aims to explore efficient multi-objective optimization algorithm for MOHSOO and study the relationship of the multiple objectives of hydropower stations. For this purpose, we propose a new improved multi-objective cuckoo search (IMOCS) algorithm by coupling three improvement strategies to solve MOHSOO in this paper. Specifically, the population initialization strategy based on constraint transformation and the individual constraints and group constraints technique (ICGC) is used to improve the search efficiency. A flock search strategy (FSS) including a flock search mechanism and fast non-dominated sorting approach is proposed to greatly speed up the convergence and improve the quality of the solutions. The dynamic adaptive probability (DAP) is adopted to converge to the global optimal solution. In addition, to verify the superiority of the IMOCS, two other algorithms, MOCS and NSGA-II, are presented as comparisons in this paper. More importantly, the hybrids of MOCS combined with group constraints and individual constraints (ICGC-MOCS), the flock search strategy (FSS-MOCS), and dynamic adaptive probability (DAP-MOCS) are proposed in this paper to verify the effectiveness of the improvement strategies. Finally, the Xiaolangdi and Xixiayuan cascade hydropower stations in the lower Yellow Rive are taken as a case study to verify the effectiveness of IMOCS for MOHSOO and study the relationship of power generation and water supply. This study provides an efficient multi-objective optimization algorithm for MOHSOO and acts as a reference for long-term operation of hydropower stations in the lower Yellow

River.

2. Hydropower station operation model for power generation and water supply

As we know, there are multiple demands among different water-using sectors, including flood control, power generation, irrigation, river ecosystem health, etc., which interact or compete with each other. This fact causes difficulties for the decision maker for hydropower station operation and gives rise to the idea that the traditional single-objective operation cannot provide acceptable solutions to the various water using sectors. In this paper, a multi-objective optimal model considering power generation and water supply is built for the water resources management of hydropower stations.

2.1. Objective functions

There are two objectives in the model: one is the minimization of comprehensive water shortage, and the other is the maximization of cascade power generation, which can be formulated as follows,

$$MinW = \sum_{t=1}^{T}\sum_{m=1}^{M}[D_{(m,t)} - Q_{(m,t)}\times \Delta t] \tag{1}$$

$$MaxE = \sum_{t=1}^{T}\sum_{m=1}^{M}N_{(m,t)} \times \Delta t \tag{2}$$

where W is the comprehensive water shortage. T is the total number of periods. Δt is the time interval. m is the serial number of a hydropower station, and the number of reach between hydropower station m and hydropower station $m+1$. $M$is the total number of hydropower stations and reach. $D_{(m,t)}$ is the integrated water requirement of reach m at period t. $Q_{(m,t)}$ and $N_{(m,t)}$ are the outflow and average output of hydropower station m at period t, respectively. E is the total cascade power generation.

2.2. Constraints

(1) flow balance constraint

$$Q_I(m+1,t) = Q_O(m,t) + q(m,t) \tag{3}$$

(2) water balance constraint

$$V(m,t+1) = V(m,t) + [Q_I(m,t) - Q_O(m,t)] \times \Delta t \tag{4}$$

(3) water level constraint

$$Z_{min}(m,t) \le Z(m,t) \le Z_{max}(m,t) \tag{5}$$

(4) outflow constraint

$$Q_{Omin}(m,t) \le Q_O(m,t) \le Q_{Omax}(m,t) \tag{6}$$

(5) output constraint

$$N_{min}(m,t) \le N(m,t) \le N_{max}(m,t) \tag{7}$$

where $Q_O(m,t)$, $Q_{Omax}(m,t)$ and $Q_{Omin}(m,t)$ represent the outflow and the maximum and minimum outflow of hydropower station m at period t, respectively. Note that $Q_{Omin}(m,t)$ and $Q_{Omax}(m,t)$ are determined by the water requirement and flood control task of downstream, respectively. $Q_I(m,t)$ and $V(m,t)$ are the inflow and storage capacity of hydropower station m at period t, respectively. $q(m,t)$ is the local inflow of reach m at period t. $Z(m,t)$, $Z_{min}(m,t)$ and $Z_{max}(m,t)$ represent the water level and the minimum and maximum water level of hydropower station m at period t, respectively. $N(m,t)$, $N_{min}(m,t)$ and $N_{max}(m,t)$ are the output and the minimum and maximum output of hydropower station m at period t, respectively.

(6) Non-negativity conditions.

All the variables mentioned above are greater than or equal to zero.

3. Improved multi-objective cuckoo search

3.1. Multi-objective cuckoo search

3.1.1. Cuckoo search

The cuckoo search is a relatively new meta-heuristic search algorithm, proposed recently by Yang and Deb [27], and has shown good results compared to other algorithms for optimization problems. Cuckoo search is inspired by obligate brood parasitism and Lévy flights behavior. First, brood parasitism is the most special habit of cuckoos. Some species of cuckoos (e.g., Guira) lay their eggs in the nests of other host birds. Once the local host bird finds the alien eggs, it may either remove the eggs or abandon its nest. To increase the hatching probability of the alien eggs, a cuckoo often searches for a nest that has similar eggs and replaces the local host's eggs with their own eggs to keep the total number of eggs in the host nest unchanged. In this process, the cuckoo looks for new candidates for its nest with a certain probability. This aggressive breeding strategy has resulted in the evolution of cuckoos. Second, the flight behavior of a cuckoo looking for the nest of another host bird is characterized by Lévy flight. Lévy flight is an optimum random search pattern and is frequently found in nature. Moreover, the random step length is dynamic, which obeys the Lévy distribution.

It is clearly observed from Fig. 1 that short explorations and the occasional long walk appear alternately. Therefore, Lévy flight is very efficient for exploring unknown large-scale search space [42].

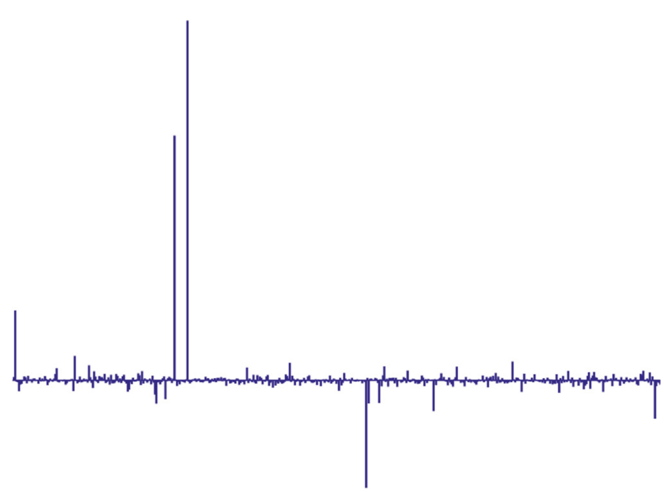


Fig. 1. Distribution of Lévy flights with 1000 consecutive steps.

Lévy flight can help intelligent optimization algorithms expand the search scope and increase the population diversity. In this manner, the algorithms gain the ability to easily escape from local optima solutions, thereby achieving a balance between global search and local search.

The behaviors of cuckoos mentioned above have given researchers the idea to propose CS for optimization. The basic principles are as follows: (1) each cuckoo lays one egg at each time and puts it in a nest randomly; (2) the nest with the best eggs or solutions is reserved for the next generation; and (3) the number of host nets is fixed, and a host bird discovers the egg with a given probability. If the host bird finds the alien egg, it will discard the egg or the nest and find a new nest in a new location.

3.1.2. Multi-objective cuckoo search

Cuckoo search is originally designed to cope with single objective optimization. In order to solve multiple objective optimization problems, Yang and Deb [39] proposed multi-objective cuckoo search in 2013. The first and last rules are modified to solve the multi-objective optimization problems. In particular, for an optimization problem with K objectives, each cuckoo lays K eggs at a time and puts them in a host nest randomly. Each nest will be abandoned with a given probability and a new nest with K eggs will be built. Note that all of the objectives must be fully considered when evaluating the quality of nests, and the non-dominated Pareto optimal solutions should be sought. Based on the three rules, the path and position iterative formula of the cuckoo random search nest is as follows:

$$x_i^{iter+1} = x_i^{iter} + \alpha \oplus \text{Lévy}(\lambda) \tag{8}$$

$$\alpha = \alpha_0 \left(x_i^{iter} - x_{best}^{iter} \right) \tag{9}$$

$$\text{Lévy}(\lambda) \sim \mu = t^{-\lambda}, 1 < \lambda \leq 3 \tag{10}$$

where $\boldsymbol{x}_i^{iter}$ is the candidate position of generation *iter*. α is the step size, which is related to the scales of the problem to be solved. α_0 is a constant. $\oplus$ means entry-wise multiplications. Lévy(λ) is a Lévy distribution function describing randomly walked steps.

Mathematically speaking, the three rules can be considered as forms of crossover, elitism, and mutation, respectively. These features work in combination, which can ensure the efficiency of the algorithm [39]. However, there are several shortcomings of MOCS for multi-objective optimization. The slow convergence speed, and the poor diversity and stability of the Pareto front limit the application of this algorithm. Moreover, the elite selection strategy affects the global search ability of MOCS, which easily leads to local optima. Therefore, we attempt to propose several improvement measures in this paper to solve the problems and improve the quality of the optimization solutions within the acceptable time.

3.2. Population initialization strategy

Optimal hydropower station operation is an optimization problem with complicated constraints, including equality (i.e., the water level constraint and outflow and output constraint) and inequality constraints (i.e., the water balance constraint). Specifically, the penalty function method is an effective approach for the inequality constraints but not for the equality constraints. However, the search ability becomes poor with the increase of the number of penalty functions. A constraint transformation method based on the water balance equation is one possible way to change some constraints (the outflow and output constraint) into a water level constraint. In this manner, the number of penalty functions can be reduced, and the computing efficiency can be improved by controlling the search space of decision variables. This method has been employed in hydropower station optimal operation and has been proven to effectively alleviate the influence of the infeasible solution space on the population quality [4,43–45]. Therefore, the constraint transformation method is coupled with MOCS to improve the search efficiency.

Moreover, the quality of the initial population has a major impact on the optimization of an intelligent evolutionary algorithm. If the feasible region accounts for a smaller proportion of the optimization space, the randomly generated initial solution tends to be of poor quality. The constraint-based population generation strategy has proved to be an effective method to solve this problem [4,46]. This method constraints the initial solution within a certain range, thereby reducing the search space and improving the quality of the initial feasible solution. In this paper, we adopt the individual constraints and group constraints technique (ICGC) to improve the population initialization [46].

3.2.1. Constraint transformation

In optimal hydropower station operation, the water levels at each period are usually chosen as decision variables, and the hydropower station outflow at all stages should meet the given constraints (e.g., the outflow constraint). Given that the current outflow is restrained by the current inflow and the next water level, we attempt to change the outflow constraint into a water level constraint according to the following water balance equation:

$$V(m, t+1) = V(m, t) + [Q_I(m, t) - Q_O(m, t)] \times \Delta t \tag{11}$$

The variation range of the hydropower station storage capacity can be determined according to inflow and the outflow constraint, which is defined as follows:

$$V_{max}(m, t+1) = V(m, t) + [Q_I(m, t) - Q_{Omin}(m, t)] \times \Delta t \tag{12}$$

$$V_{min}(m, t+1) = V(m, t) + [Q_I(m, t) - Q_{Omax}(m, t)] \times \Delta t \tag{13}$$

where $V(m, t)$ is the storage capacity of hydropower station m at period t; $V_{max}(m, t)$ and $V_{min}(m, t)$ are the maximum and minimum storage capacity of hydropower station m at period t, respectively. $Q_I(m, t)$ represents the average inflow of hydropower station m at period t; $Q_{Omax}(m, t)$ and $Q_{Omin}(m, t)$ signify the maximum and minimum outflow of hydropower station m at period t, respectively.

Next, according to the range of the hydropower station storage capacity (formulas 18 and 19), the corresponding water level is determined based on the relationship of the hydropower station water level and the storage capacity, which is the range of the water level with constraint satisfaction.

3.2.2. Initial population generation with ICGC

For multi-stage decision making problems, the decision variables at adjacent stages are often highly correlated, which means that the values of decision variables at previous stage usually affect the feasible space of decision variables at the current stage. Therefore, researching the inner restriction relationship of decision variables between different stages and reducing the search space can improve the efficiency of optimization. The individual constraints technique (IC) is an effective approach for determining the next feasible space of decision variables based on their inner restriction relationship between adjacent stages and the current values of decision variables. More importantly, the feasible space of IC is calculated from the first stage to the final stage. The principle can be seen in Fig. 2.

However, the search space tends to have a large amount of infeasible space for multi-constraint optimization problems. Furthermore, a larger problem is that the sequential decision making of IC (shown in Fig. 2) may lead to constraint violation in the final stage. For hydropower station operation, this means that the final water level is not back to the initial water level, which is considered unreasonable. To solve these problems, we propose a method called the group constraints technique (GC) to remove the infeasible space based on the constraints from the final stage to the first stage (shown in Fig. 2). Note that the feasible space of GC is determined by the boundary of the decision space in previous stage. This method can not only reduce the search space but also satisfy the constraints. In addition, the largest difference between IC and GC is that the feasible space of decision variables obtained by IC only works in one stage, while that obtained by GC is effective in all stages.

In this paper, the hydropower station water levels are selected as the decision variables. We can determine the feasible search space of the water level with the initial water level constraints and the new water level constraints transformed from the outflow constraints. First, GC is used to determine the feasible space of the water level from stage $T-1$ to stage 1 based on the water balance equation. Second, IC is applied to determine the feasible space of each individual from stage 1 to stage $T-1$ based on the water balance equation. It is important to note that the upper boundary of the water level is related to the minimum outflow and that the lower boundary of the water level is related to the maximum outflow. Finally, the new feasible search space is the intersection set of the ranges of water level obtained by GC and IC, and the original water level constraint. After obtaining the new feasible search space, the algorithm can generate the initial population in the new feasible search space, which removes the infeasible space and reduces the search space. In this manner, the quality of the initial population is improved, thereby improving the search efficiency.

In addition, it is known that the values of decision variables in the feasible region boundary can improve the quality of the optimal solution. Therefore, we increase the feasible space of IC by multiplying a value greater than 1 (1.1 in this paper) to improve the diversity of the decision variable values of the initial population. In this manner, it can help the initial population reach a balance between the diversity and feasibility of decision variable values, even though the proportion of feasible individuals to the initial population is reduced to some extent.

3.3. Flock search strategy

3.3.1. Flock search mechanism

According to the rules of the MOCS, this algorithm chooses a cuckoo to find one candidate nest every time via Lévy flight. This model of evolution may result in a low probability of the new candidate nest being better than the host nest, which indicates poor efficiency of population regeneration. Furthermore, the algorithm often suffers premature convergence and is easily trapped in local optima. In order to improve the efficiency of the algorithm, we propose a new strategy, named the flock search mechanism, and apply it to the nest search. Specifically, many cuckoos look for the same number of candidate nests at the same time, and it is still guaranteed that there is one cuckoo in each host nest that can find one candidate nest via Lévy flight. In this manner, multiple candidate nests can be generated each iteration. Therefore, the flock search strategy can improve the efficiency of population regeneration and accelerate the convergence of the algorithm. The new position iterative formula of the cuckoo random search nest is as follows:

$$X_{new}^{iter+1} = X^{iter} + A_1 \oplus \text{Lévy}(\beta) \quad (14)$$

where X^{iter} is the location of old nests, $X_{new}^{iter+1} = \begin{bmatrix} x_{new}^{iter+1}(1) \\ \vdots \\ x_{new}^{iter+1}(POP) \end{bmatrix}$ is the location of new nests generated by Lévy flight. A_1 is the step size

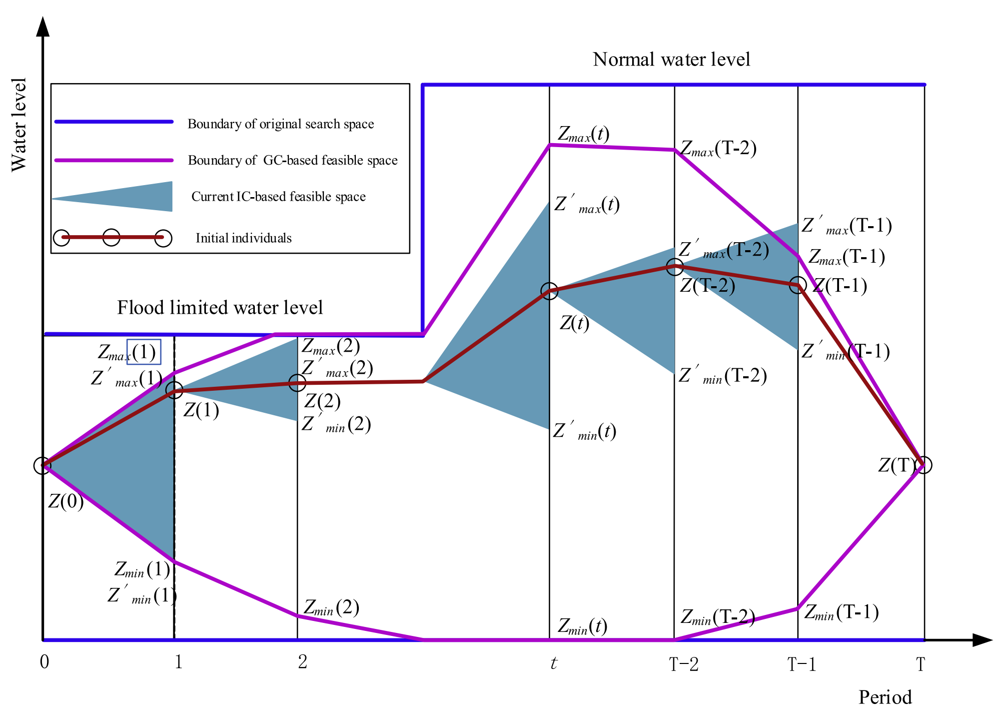


Fig. 2. A sketch of ICGC.

set, and $A_1 = \begin{bmatrix} \alpha_1 \\ \vdots \\ \alpha_{POP} \end{bmatrix}$.

$$\alpha_i = \alpha_0 \left[x^{iter}(i) - x^{iter}_{best}(j) \right] \tag{15}$$

Next, the new position iterative formula of each nest is

$$x^{iter+1}_{new}(i) = x^{iter}(i) + \alpha_0 \left[x^{iter}(i) - x^{iter}_{best}(j) \right] \oplus \text{Lévy}(\beta) \tag{16}$$

where $x^{iter}_{best}(j)$ is randomly selected from the non-dominated set X^{iter}_{best}.

Similarly, the flock search strategy is also applied when replacing the worst nests (e nests). The new locations of the replenished nests (e nests) are

$$X^{iter+1}_{replenish} = X^{iter+1}_{selecting} + A_2 \oplus \text{Lévy}(\beta) \tag{17}$$

where $X^{iter+1}_{replenish} = \begin{bmatrix} x^{iter+1}_{replenish}(1) \\ \vdots \\ x^{iter+1}_{replenish}(e) \end{bmatrix}$ is the set of new replenished nests. $X^{iter+1}_{selecting}$ is randomly selected from the remaining nests ($X^{iter+1}_{remaining}$) after eliminating the worst nests, which includes e nests. $A_2 = \begin{bmatrix} \alpha'_1 \\ \vdots \\ \alpha'_e \end{bmatrix}$.

$$\alpha'_i = \alpha'_0 \left[x^{iter+1}_{selecting}(i) - x^{iter+1}_{remaining}(j) \right] \tag{18}$$

The new location of each replenished nest is

$$x^{iter+1}_{replenish}(i) = x^{iter+1}_{selecting}(i) + \alpha'_0 \left[x^{iter+1}_{selecting}(i) - x^{iter+1}_{remaining}(j) \right] \oplus \text{Lévy}(\beta) \tag{19}$$

where $x^{iter+1}_{remaining}(j)$ is randomly selected from the remaining nests $X^{iter+1}_{remaining}$, and $j \neq i$.

3.3.2. Fast non-dominated sorting approach

In addition, the flock search mechanism is a form of mathematical population variation. It is inspired by the non-dominated sorting genetic algorithm (NSGA), which is a multi-objective optimization algorithm first proposed by Srinivas and Deb [47]. This algorithm works well in finding a Pareto optimal front and maintaining the diversity of the population. However, this algorithm has been criticized for limitations including the high time complexity of sorting, non-elitism strategy, and influence of the sharing parameter on the diversity of the population. To overcome these difficulties, Deb et al. [48,49] later proposed the NSGA-II. Specifically, a fast non-dominated sorting approach is adopted to reduce the computational complexity. A selection operator based on the crowding degree and crowding distance is presented to ensure the diversity. Moreover, the elite strategy is introduced to improve the population quality and convergence efficiency. At present, NSGA-II has been widely applied to MOHSOO [50]. In addition, it has become the benchmark for testing other multi-objective optimization algorithms.

In this paper, after improving the search mechanism, we also introduce the improvement ideas of NSGA-II into MOCS. First, a fast non-dominated sorting approach based on the elite strategy is used to select the new nests of host birds after merging the host nests with the newly created candidate nests instead of randomly selecting new individuals in the MOCS. In this manner, IMOCS can make full use of the previous excellent host bird's nests. Second, a selection operator based on the crowding degree is employed to maintain the diversity of the population. In general, a flock search strategy that contains the flock search mechanism and fast non-dominated sorting approach is introduced to IMOCS to accelerate the convergence.

3.4. Dynamic adaptive probability

In the MOCS, the probability P_a is a fixed value. If P_a is too small, the algorithm is easy to trap in local optima. Therefore, a probability that gradually decreases with the evolution generations can help the algorithm quickly converge to the global optimal solution. In this paper, the cosine decreasing strategy [30] is applied to implement the dynamic adaptive change of the probability, which is shown below:

$$P_a = P_{a,max} \cos\left(\frac{\pi}{2} * \frac{T_{iter} - 1}{T_{max} - 1} \right) + P_{a,min} \tag{21}$$

3.5. Procedure of IMOCS

In this paper, we propose some improvement strategies in the generation of the initial population and the search process of the population. First, combining the constraint transformation, ICGC is used to improve the quality of the initial population. Second, the flock search strategy is proposed to improve the efficiency of population regeneration. Finally, a dynamic adaptive probability is applied to help the algorithm converge to the global optimal solution. These methods work together to enable IMOCS to achieve faster convergence and better solutions than the traditional MOCS in hydropower station optimal operation. In summary, the main flowchart of the proposed IMOCS for solving the optimal problem is shown in Fig. 3. The detailed steps of IMOCS are as follows:

(1) Set the population size POP, the maximum iterations $Iter_{max}$, the value range of the probability $P_{a,max}$ and $P_{a,min}$, the constant α_0 and α'_0.
(2) Transform the constraints with formulas (11)–(13), and randomly generate the initial nests with ICGC.
(3) Calculate the fitness of the initial nests, perform the non-dominated sorting and choose the non-dominated nests.
(4) Get the new candidate nests by Lévy flights according to formula (16).
(5) Calculate the fitness values of all nests.
(6) Combine the new nests and old nests.
(7) Perform the non-dominated sorting and choose the non-dominated nests.
(8) If the algorithm reaches the maximum number of iterations, stop and output the results. Otherwise, find and eliminate part of the worst nests with a certain probability, generate new replenished nests based on formula (19), and return to step (4).

4. Numerical experiments

4.1. Benchmark functions and parameter setting

In order to verify the feasibility and effectiveness of IMOCS method compared with MOCS and NSGA-II, we tested the

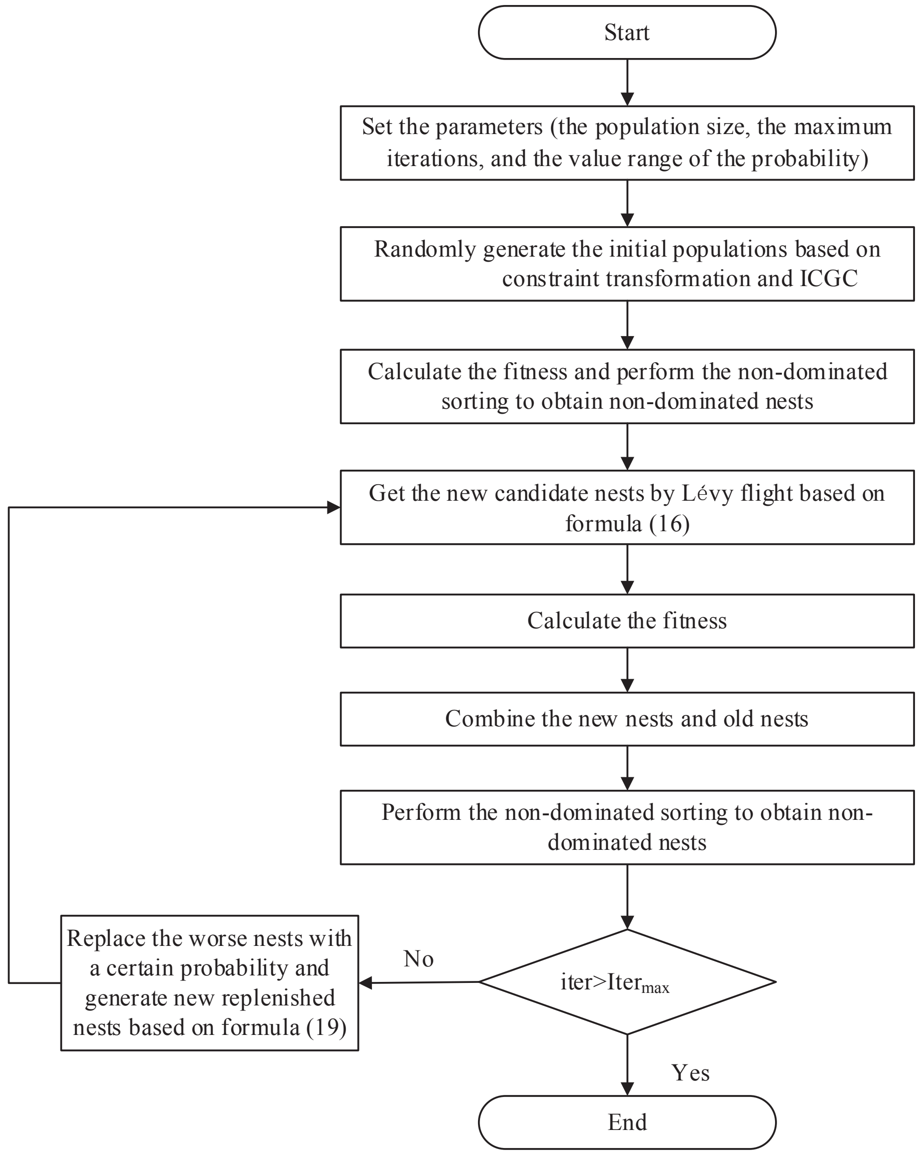


Fig. 3. The flowchart of IMOCS.

performance with five typical benchmark functions (ZDT1, ZDT2, ZDT3, ZDT4, and ZDT6) developed by Zitzler [51] in experiments. These functions represent the benchmark problems with convex, non-convex and discontinuous Pareto fronts. Besides, all of them have two objective functions but no constraint.

It is known that parameter setting usually affects the performance of optimization algorithms. To obtain fair results, all the implementations were conducted under the same conditions. The population size is 100 in all functions. The maximum number of iterations is 500 in all functions except ZDT4, where the maximum number of iterations is 5000 due to its solving complexity. In NSGA-II, the crossover and mutation operators are 20 and 20, respectively. The probability in MOCS is 0.25. The value range of the probability in IMOCS is $0.1 \leq P_a \leq 0.4$. In addition, in order to decrease the influence of the randomness, we have run 20 times for every method on each function. Note that the population initialization strategy is not included in the experiments because this strategy is suitable for practical problems with multiple constraints that have correlation. Furthermore, this strategy is verified in the following case study.

4.2. Performance comparisons

Moreover, two performance metrics are used to evaluate the quality of non-dominated solution sets found by IMOCS and the comparing algorithms. Specially, a convergence metric is applied to estimate the distance or error between the estimated Pareto front to its corresponding true front [39]. It should be clear that a value of zero indicates that all the elements generated are in the Pareto optimal set. A diversity metric is used to measure the extent of spread achieved among the obtained solutions [49]. For the most widely and uniformly spread-out set of non-dominated solutions, the metric would be zero. For any other distribution, the value of the metric would be greater than zero. The mean and variance of the distance metric and diversity metric are respectively presented in Table 1 and Table 2, where the best and worst values are marked in bold and italics, respectively.

From Table 1, it can be seen that the mean and variance of convergence metric of IMOCS are the smallest, while those of NSGA-II are the biggest in all problems. This illustrates that the Pareto front obtained by IMOCS is closest to the true front

Table 1
Mean (first rows) and variance (second rows) of convergence metric for different algorithms.

Method	ZDT1	ZDT2	ZDT3	ZDT4	ZDT6
NSGA-II	*8.66E-03*	*1.26E-02*	*2.04E-03*	*7.19E + 02*	*2.46E-01*
	3.32E-03	5.09E-03	1.82E-03	3.56E+02	2.18E-01
MOCS	8.53E-05	1.02E-04	1.47E-05	5.74E-03	3.29E-11
	6.22E-05	9.22E-05	1.11E-05	4.62E-03	3.69E-12
IMOCS	**4.25E-08**	**3.64E-08**	**5.22E-09**	**4.78E-09**	**2.41E-11**
	1.15E-07	1.21E-07	9.09E-09	9.00E-09	1.99E-12

Table 2
Mean (first rows) and variance (second rows) of diversity metric for different algorithms.

Method	ZDT1	ZDT2	ZDT3	ZDT4	ZDT6
NSGA-II	0.47	0.58	0.69	0.95	**0.34**
	0.04	0.15	0.03	0.01	0.03
MOCS	*0.87*	*0.81*	*1.02*	*0.64*	*1.27*
	0.08	0.07	0.06	0.07	0.08
IMOCS	**0.40**	**0.39**	**0.68**	**0.39**	0.39
	0.04	0.04	0.02	0.05	0.03

compared with other two algorithms. Therefore, IMOCS performs best compared with MOCS and NSGA-II methods in terms of convergence. It can be seen from Table 2 that IMOCS performs best compared with MOCS and NSGA-II methods in terms of diversity in all problems except ZDT6, where NSGA-II performs best compared with other two algorithms. In addition, the worst performance is observed with MOCS compared with IMOCS and NSGA-II methods in terms of diversity in all problems. The results show that IMOCS and NSGA-II methods can obtain more uniform non-dominated front due to the non-dominated sorting approach based on crowding degree. Further, the diversity metric is related to the average distance of all solutions and the distances between the extreme solutions and the boundary solutions of the obtained non-dominated set. Because NSGA-II has worse convergence compared with IMOCS, the distances between the extreme solutions and the boundary solutions of the obtained non-dominated set by NSGA-II are greater than those of IMOCS. Thus, NSGA-II performs worse than IMOCS in terms of diversity.

The convergence trends of curves of the different algorithms for ZDT4 are shown in Fig. 4. It can be detected from the figure that the proposed IMOCS has best convergence compared with other algorithms. NSGA-II converges to local optima after 500 iterations. MOCS and IMOCS can obtain better solutions due to Lévy flight compared with NSGA-II. Fig. 5 presents the non-dominated fronts of different algorithms for ZDT4. It is observed from the figure that

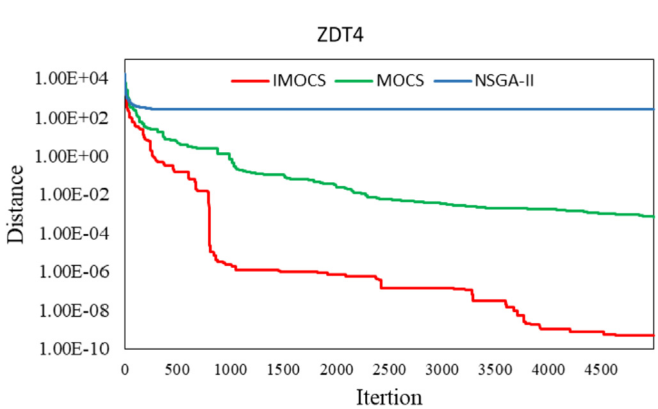


Fig. 4. Convergence curves of the different algorithms for ZDT4.

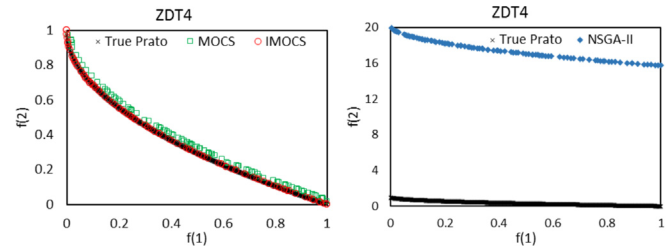


Fig. 5. Non-dominated fronts of different algorithms for ZDT4.

the proposed IMOCS performs better than MOCS in terms of convergence to the true Prato curve. Conversely, the non-dominated front of NSGA-II is far from the true Prato front, which means bad quality of solutions.

In conclusion, IMOCS and MOCS perform better compared with NSGA-II method in terms of convergence, IMOCS and NSGA-II perform better compared with MOCS in terms of diversity. This result is consistent with other research found in the literature. For example, Yang and Deb [39] founded that the generalized distance of MOCS is less than that of NSGA-II, which means that MOCS performs better compared with NSGA-II method in terms of convergence. In Ref. [40], a non-dominated sorting-based hybrid cuckoo search algorithm was proposed and proven to reach the final best value in less iteration than MOCS and POA. There are several reasons for this result. First, Lévy flight can balance the global optima and local optima to some extent in searching. Thus, IMOCS and MOCS can find the solutions that are closer to true Pareto front compared with NSGA-II. Second, MOCS only finds a new nest every time, while IMOCS can generate multiple candidate nests each iteration and conduct sorting, which can speed up the convergence. Third, crowding degree is employed in IMOCS to maintain the diversity of the solutions. However, MOCS lacks this strategy, thus leading to poor diversity of solutions. Finally, the dynamic adaptive probability can keep more exploration ability in later searching. Therefore, IMOCS can obtain better solutions that are closer to the true Prato front compared with MOCS.

5. Case study

5.1. Introduction of hydropower stations

The Xiaolangdi and Xixiayuan cascade hydropower stations in the lower Yellow River are taken as a case study to verify the effectiveness of IMOCS in multi-objective hydropower station operation. The Yellow River, with a length of more than 5400 km and a drainage area of 752,443 km^2, is the second longest river in China. It is also of great importance to the water supply in northwestern and northern China. The Xiaolangdi hydropower station, located in the lower Yellow River, with a height of 281 m, has a total storage capacity of 1.265* $10^{10} m^3$. It controls a drainage area of 694 thousand km^2, which accounts for 92.3% of the total drainage area of the Yellow River. It has incomplete yearly regulation capacity and undertakes the task of flood control, ice flood control and sedimentation reduction along with water supply, irrigation, and power generation. Thus, it is the crucial project for the water resources management of the lower Yellow River. The Xixiayuan hydropower station, located downstream of the Xiaolangdi hydropower station, has a total storage capacity of 1.62*10^8 m^3. It is of daily regulation capacity and is an auxiliary project of the Xiaolangdi hydropower station. The task of the hydropower station is readjusting the outflow of the Xiaolangdi hydropower station along with power generation, irrigation, water supply. Fig. 6 shows the

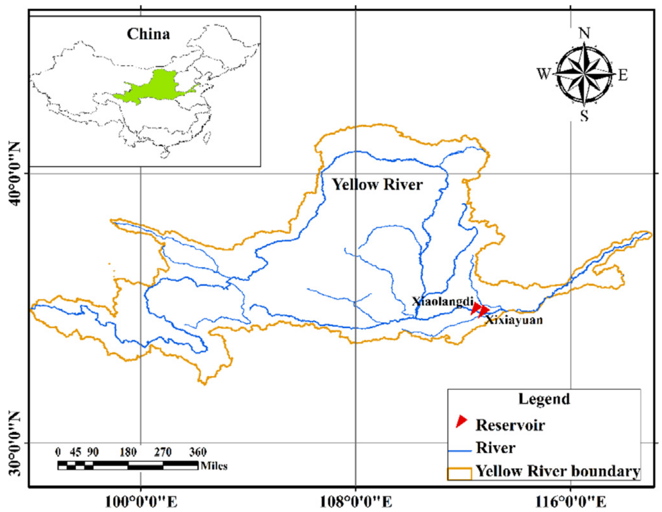


Fig. 6. Location of the cascade hydropower stations in the Yellow River.

location of the cascade hydropower stations in the Yellow River.

The tasks of this multiple-purpose project vary over different periods (i.e., the main flood season, later flood season and water supply period), thereby leading to various water level limitations of the hydropower stations. Furthermore, with the continuous increase in water demand, the contradiction of supply and demand is made more severe, and the requirement of efficient utilization of water resources becomes higher than ever before. These issues bring difficulties to the hydropower station operation. In this paper, the monthly inflow of the Xiaolangdi hydropower station (1956–2000) and the water demand downstream are employed to research the multi-objective hydropower station operation. In addition, a typical dry year (1990) is selected to analyze the results in this paper due to the space limitation. Note that the water demand of the lower Yellow River includes life, industry, agriculture and ecological water utilization. All of the data are provided by the Yellow River Conservancy Commission (YRCC).

Table 3
The proportion of feasible solutions.

Average proportion	random generation	ICGC-based generation
initial population to the search space	0.6336	0.5208
initial population to the feasible space	0.5820	0.5539
feasible solutions to the initial population	0.0015	0.1835

5.2. *Effect of improvement strategies*

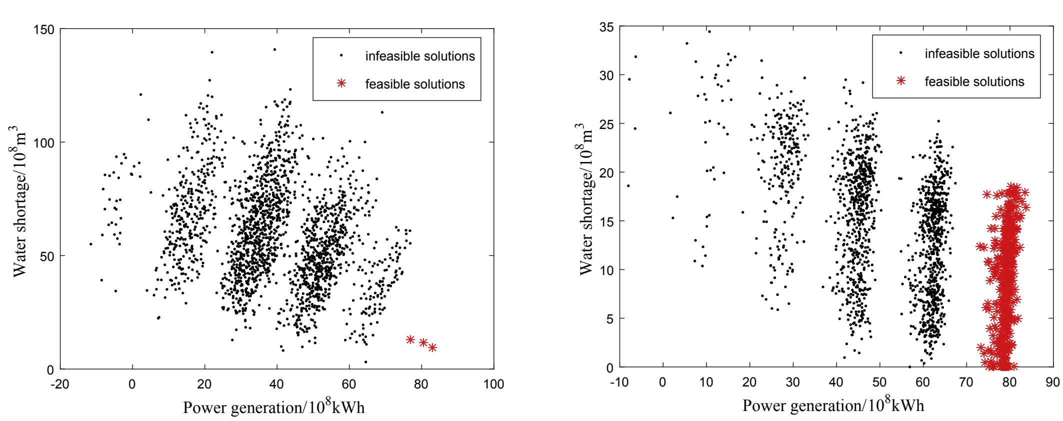
In this paper, the hydropower station water levels at the end of each stage are selected as decision variables, and real coding is adopted due to the clear physical meaning of decision variables. The algorithm generates and updates the population in the form of a two-dimensional matrix. In addition, the MOCS and NSGA-II methods are presented for comparison in the case study. Moreover, to verify the effectiveness of the improvement strategies, hybrids featuring the MOCS combined with group constraints and individual constraints (ICGC-MOCS), the flock search strategy (FSS-MOCS), and dynamic adaptive probability (DAP-MOCS) are proposed in the case study.

In the case study, IMOCS can obtain the convergent Pareto front rapidly when the population size $POP = 100$, the maximum number of iterations $Iter_{max} = 1000$, and the value range of the probability $0.1 \leq P_a \leq 0.4$. With the same population size, MOCS and NSGA-II obtained the convergent Pareto front when $Iter_{max} = 50000$ and $Iter_{max} = 5000$, respectively.

5.2.1. *Diversity of the initial population and proportion of feasible solutions*

If the feasible space represents a small share of the search space, the initial population is usually of poor quality. The constraint-based initial population generation strategy can effectively solve this problem, but it may reduce the diversity of the initial population at the same time. In this paper, the diversity of the initial population is described by the distribution of decision variables in the feasible space. First, divide the values of decision variables at each stage into 100 intervals. Second, calculate the number of intervals where the values of the decision variables are contained. Finally, calculate the proportion of the number obtained in the second step to the number of total intervals and regard it as the evaluation index of the initial population diversity. In addition, the index may be different in various experiments due to the randomness of initial population generation. Therefore, the average (over 20 experiments) of various indexes (shown in Table 3) is used to evaluate the diversity, and $POP = 100$.

Table 3 and Fig. 7 show that the initial randomly generated population is uniformly distributed but that the proportion of that



(a) random generation of the initial population (b) ICGC-based generation of the initial population

Fig. 7. The proportion of feasible solutions.

to the feasible space is relatively small (58.2%). Moreover, after several generations of evolution, most of the initial population is eliminated through the penalty function. Hence, the later population is produced by a few initial feasible individuals, thereby decreasing their diversity. As a result, the proportion of feasible solutions to the initial population with random generation is only 0.15%.

The initial population generated based on ICGC is mainly distributed in the feasible space, even though the proportion of that to the search space decreases by 11.3% compared to that generated randomly. However, importantly, the proportion of the initial population to the feasible space with ICGC decreases by just 2.8% compared to that generated randomly. Note that, with the ICGC-based generation strategy, this feasible space is obtained by GC, and the initial population is also constrained by IC, thereby decreasing the proportion of the initial population to the feasible space. Finally, the proportion of feasible solutions to the initial population based on ICGC is 18.35%.

The proportion of feasible solutions to the initial population has influence on the search efficiency. The greater the proportion is, the higher the search efficiency is. From Table 3 and Fig. 7, it can be observed that the proportion of feasible individuals to the initial population based on ICGC is much larger than that with random generation, which lays a good foundation for finding the Pareto optimal front. Therefore, the later population is of high diversity because the values of the decision variables have a large proportion and a uniform distribution in the feasible space.

5.2.2. *Diversity and convergence of the optimal solution*

The hypervolume (HV) is usually employed to describe the convergence and diversity of the Pareto front of a multi-objective algorithm [52]. The greater the HV is, the better the convergence of the algorithm is, and the higher the diversity of the individuals is. In addition, the convergence speed may be different in various tests due to the randomness of evolutionary algorithm. In this paper, the average values of HV (over 10 experiments) are used to plot the HV convergence curves of different algorithms.

The HV convergence curves and Pareto fronts of different algorithms are shown in Fig. 8 and Fig. 9, respectively. It is clearly observed that IMOCS is the first to converge to a steady hyper volume, which is the largest HV compared to that of the other algorithms. Conversely, MOCS requires more iterations to converge to a steady HV, and the final HV is the smallest compared to that of the other algorithms. The convergence and diversity of Pareto front of NSGA-II are close to those of IMOCS and vastly superior to those of MOCS. However, in earlier generations (before 3000 iterations), the convergence of NSGA-II is worse than that of IMOCS. Therefore, NSGA-II requires more iterations to reach the steady HV e compared to IMOCS. In summary, IMOCS is superior to MOCS and NSGA-II in terms of convergence and diversity.

Moreover, it can be seen that ICGC-MOCS, DAP-MOCS, and FSS-MOCS are superior to MOCS in both convergence and the diversity of solutions. Specifically, FSS-MOCS is very close to IMOCS in both convergence property and convergence speed. ICGC-MOCS and DAP-MOCS are superior to MOCS in convergence and the diversity

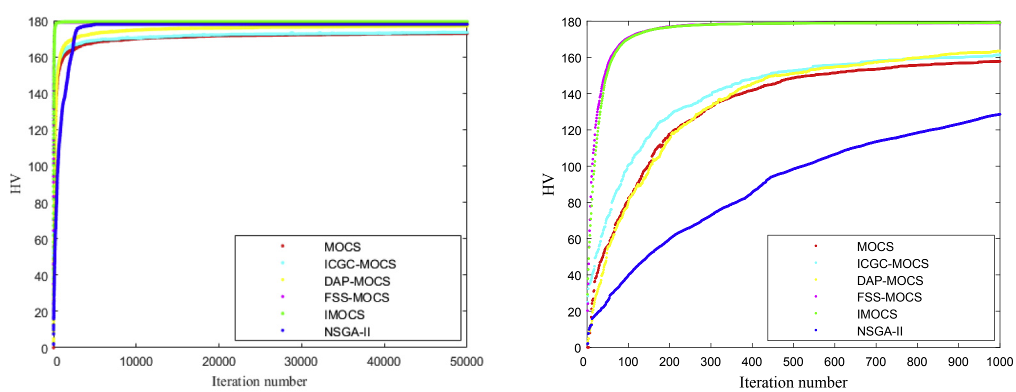


Fig. 8. HV convergence curves of different algorithms.

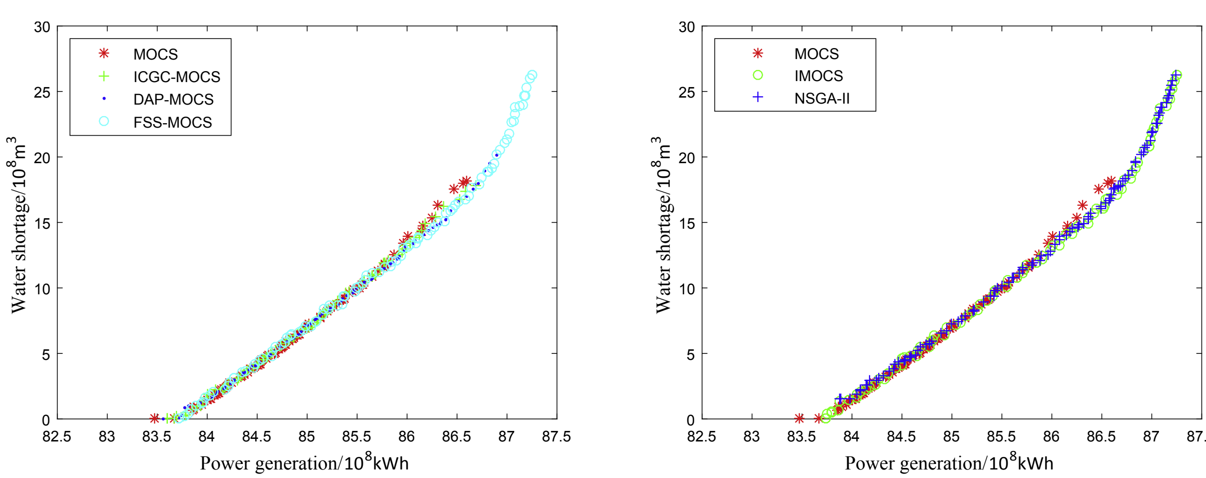


Fig. 9. The final Pareto fronts of different algorithms.

of solutions. In addition, ICGC-MOCS performs better than DAP-MOCS and MOCS in earlier generations in terms of HV. To be sure, IMOCS that combines the three improvement strategies together, is superior to either of them. The results illustrate that IMOCS performs best in convergence speed, convergence property, and the diversity of solutions compared to the other five algorithms mentioned in this paper.

5.2.3. Iterations and time of convergence

Fig. 10 shows the Pareto fronts at different iterations for different algorithms. It can be seen that the diversity of solutions and the value of objectives become better and better with the increase of iterations and finally reach a steady state. Moreover, the iterations when the values of the objectives and HV achieve stability are consistent. With the same population size, MOCS, ICGC-MOCS, and DAP-MOCS require 50,000 iterations to converge to the optimal front. FSS-MOCS and IMOCS only require 1000 iterations to converge to the optimal front, while NSGA-II requires 5000 iterations. In summary, IMOCS can converge to a better global optimal solution faster than other algorithms.

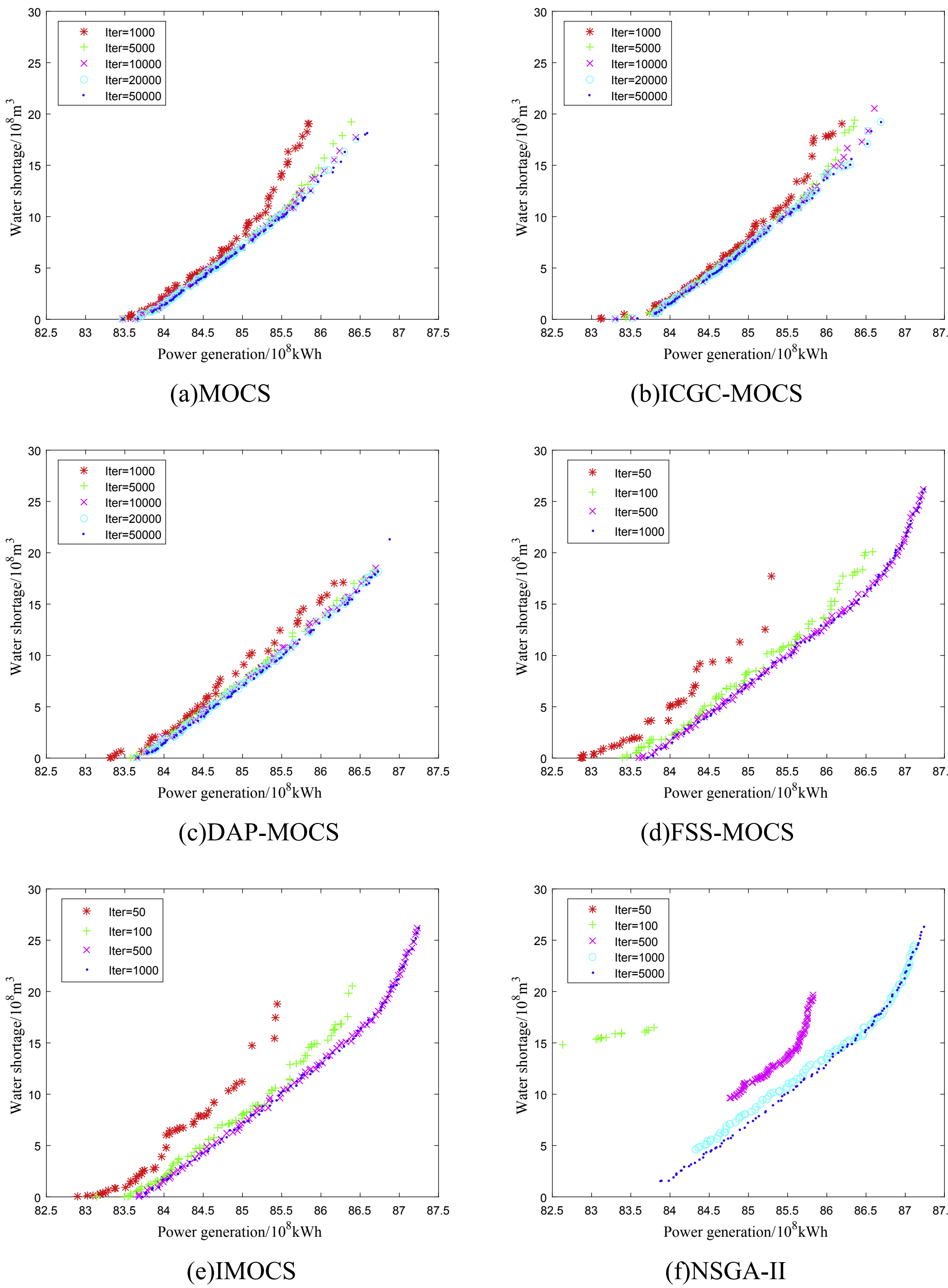


Fig. 10. The Pareto fronts at different iterations for different algorithms.

The number of iterations for convergence cannot fully reflect the computation rate of various algorithms because the time complexities of various algorithms are different. It must be applied to estimate the computation rate together with the computation time. The numbers of iterations for convergence and computation times of various algorithms are shown in Table 4. It is clearly found from Table 4 that DAP-MOCS is the most time-consuming algorithm, closely followed by MOCS and ICGC-MOCS with the same population size and iterations. The three algorithms are time-consuming because they are not suitable for parallel computing. Conversely, with parallel computing, IMOCS is the most time-saving algorithm, closely followed by FSS-MOCS with the same population size and iterations. NSGA-II is the third time-saving algorithm because it requires more iterations than IMOCS does.

To be sure, the population initialization strategy can improve the search efficiency because it can reduce the search space and improve the quality of the initial feasible solution. The flock search strategy can help the algorithm quickly converge to the optimal solutions and greatly reduce the number of iterations, which can overcome the time-consuming shortcoming of MOCS. This is because the flock search mechanism can generate multiple candidate nests through one iteration to significantly speed up the convergence. Furthermore, the flock search strategy can also improve the quality of the non-dominated solutions. The main reason is that the crowding degree can maintain the diversity of the solutions. The dynamic adaptive probability can help the algorithm avoid falling into local optima prematurely, thus improving the quality of solutions with the same population size and iterations, and similar computing time. Therefore, with these three improvement measures, IMOCS can obtain better solutions quickly compared with the existing methods mentioned above.

5.2.4. Robustness of algorithms

The degree of dispersion of the non-dominated fronts obtained through multiple computations is used to analyze the robustness of the algorithms. Fig. 11 shows the union of the non-dominated fronts of different algorithms through multiple computations. It is seen that the distribution of the non-dominated front of MOCS is relatively dispersed, indicating that the robustness of MOCS is obviously poorer than that of IMOCS and NSGA-II. In contrast, the non-dominated front of IMOCS is concentrated on the line. Therefore, the robustness of the IMOCS is better than that of other algorithms. In other words, the deviation of solutions obtained by IMOCS through multiple computations is relatively small.

5.3. Results of hydropower station operation

Fig. 11 shows that there is a clear competitive relationship between the power generation and water supply, which means that the water shortage downstream increases with the increase of power generation. In this paper, we selected nine solutions from the final non-dominated front of IMOCS, which are featured with the maximum power generation (solution 1), the minimum water shortage (solution 9), and a compromise between power

Table 4
Computing times of different algorithms.

Algorithms	Population size	Iterations for convergence	Computing time (s)
MOCS	100	50000	932.8
ICGC-MOCS	100	50000	930.2
DAP-MOCS	100	50000	938.2
FSS-MOCS	100	1000	122.3
IMOCS	100	1000	121.8
NSGA-II	100	5000	144.3

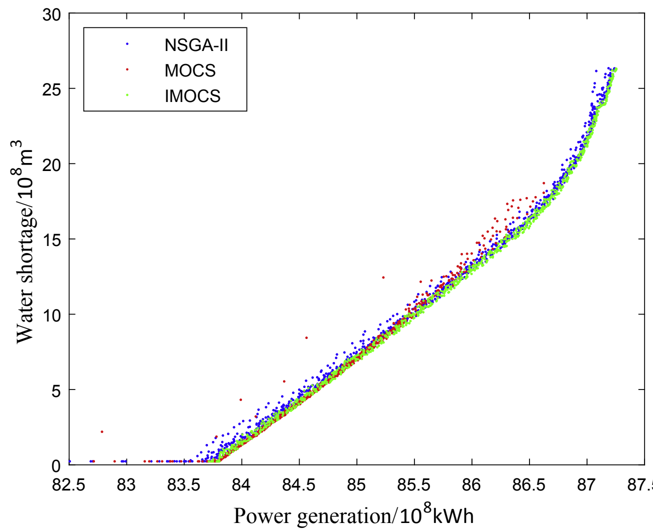


Fig. 11. Union of the non-dominated fronts of different algorithms.

generation and water shortage (solutions 2–8). The power generation and water shortage of different schemes are shown in Table 5, and the water level and outflow of the Xiaolangdi hydropower station are shown in Fig. 12 and Fig. 13, respectively.

It is seen from Figs. 12 and 13 that, in solution 1, the water level continuously increases from September to next February and finally reaches the normal water level (i.e., 265 m). More importantly, the water level of solution 1 is the highest compared to other solutions in this period. Next, the water level lowers to the flood limited water level (i.e., 230 m) in June and remains at this value until August, which is aimed at providing flood control capacity. In addition, the outflow decreases sharply in September and remains at a relatively small value until next February. Note that the outflow of solution 1 is the smallest compared to other solutions in this period. Next, the outflow increases rapidly until May. It is worth emphasizing that the outflow of solution 1 is the largest compared to other solutions in this period. From June to August, the outflows of different solutions are almost the same. This is because the outflow is equal to the inflow, which is designed to keep the water level at the flood limited water level.

In solution 9, the changing trends of water level and outflow are similar to those of solution 1. In other words, the water level increases from September to next March, then lowers to the flood limited water level in June, and remains at this value until August. The outflow decreases from September to next March, then increases until May, and remains it equal to the inflow from May to August. Nonetheless, the differences are very conspicuous. Specifically, the water level of solution 9 is the lowest compared to other solutions from September to next March, and the highest water level (in March) is lower than the normal water level. The outflow

Table 5
The power generation and water shortage of different solutions.

Solution	power generation (10^8 kWh)	water shortage (10^8m^3)
1	87.25	26.26
2	87.02	22.21
3	86.52	16.06
4	86.00	13.21
5	85.55	10.11
6	85.05	7.19
7	84.50	4.61
8	83.97	1.45
9	83.74	0.00

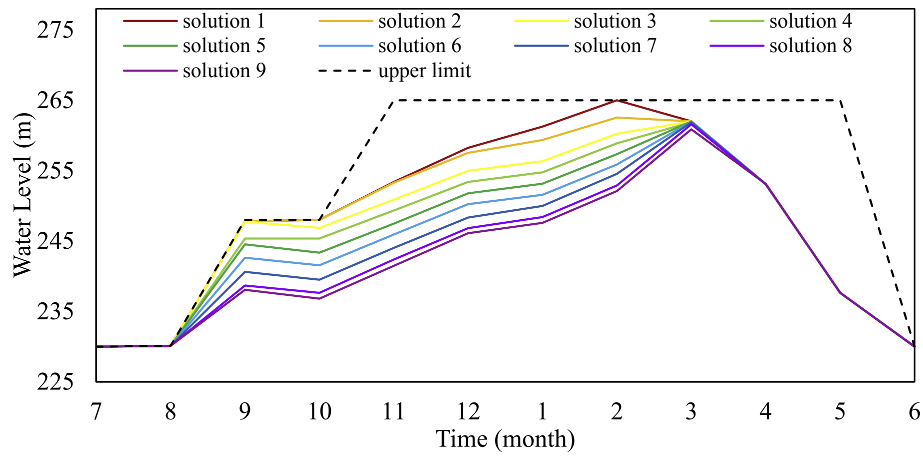


Fig. 12. The water level of the Xiaolangdi hydropower station.

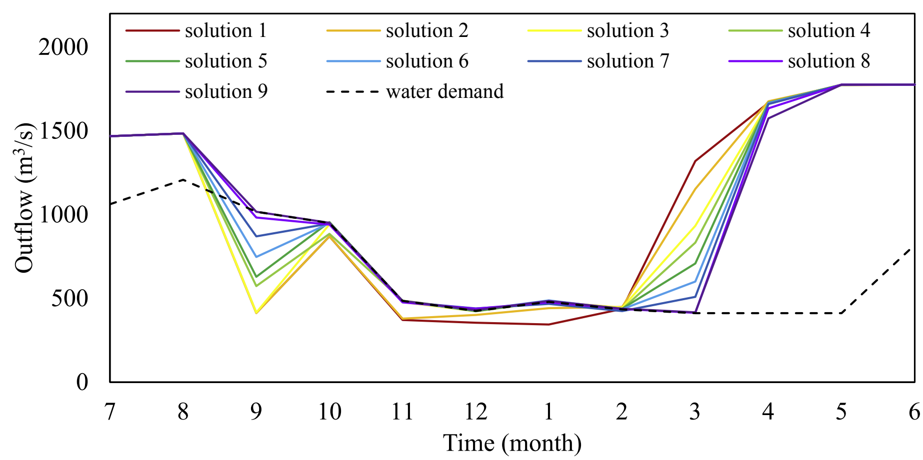


Fig. 13. The outflow of the Xiaolangdi hydropower station.

of solution 9 is the largest from September to next February, while it is the smallest from March to May compared to other solutions. These phenomena in solution 9 are just the opposite of those in solution 1. For other solutions, the changing trends of water level and outflow are also similar to those of solution 1 and solution 9. The difference is that both the water level and the outflow of these solutions are between those of solution 1 and solution 9.

In addition, the interrelationship of power generation and water shortage can be revealed by the differences between the water demand and the outflow processes of various solutions. It can be seen from Fig. 13 that the outflow process of solution 9 is consistent with the water demand change from September to next March, and exceeds the water demand in other months. Therefore, there is no water shortage in solution 9, indicating that the hydropower station gives priority to the downstream water requirement by reducing the power generation. In contrast, the outflow processes of some solutions with more power generation are less than the water demand from September to next February. In other words, the hydropower station gives priority to the power generation rather than the downstream water requirement in these solutions, especially solution 1, which has the smallest outflow in this period.

It can be seen from Figs. 12 and 13 that the competitive relationship of power generation and water shortage mainly exists from September to next February when the hydropower station has to refill water but has relatively small inflow in latter months. Hence, the water level cannot rise rapidly if the water requirement is well satisfied. In other words, more power generation will inevitably lead to more serious water shortage, while less water shortage will cause less power generation. There are several reasons for this conclusion. First, in flood season, the outflow of Xiaolangdi reservoir is generally larger than the maximum flow for power generation. Similar situation occurs in ice flood control and sediment regulation and does not last long. On the contrary, the outflow of Xiaolangdi reservoir is generally less than 800 m^3/s in the water supply period. Hence, the reservoir can optimize the power generation process by taking of its good regulating ability in this period. Moreover, one effective way is to store more water in the early scheduling period to make full use of the water head and water volume in the later scheduling period for more power generation. However, the current scheduling mode is that hydropower generation plan is affected by the comprehensive utilization of water resources. In other words, the power generation has to give priority to the water supply, which dramatically affects the efficiency of power generation. Therefore, the trade-off between the two objectives must be weighed carefully in decision making. Similar results were found in previous studies with a similar scope. For example, Liu [53] pointed out that the economic dispatch of power generation of Xiaolangdi reservoir and Xixiayuan reservoir is feasible in the period of water supply. Further, it is worth exploring new and more reasonable scheduling mode for water system and power system. This advice was also found in previous studies with a similar scope. Ref. [54] pointed out that China must amend its existing operational mode for reservoirs to enhance the economic benefits of cascade hydropower stations.

6. Conclusions

The large and growing demand for water and energy emphasize the role of hydropower operation. Efficient utilization of water resources in hydropower station operation has been an important part of mitigating water and energy scarcity. However, the complexity of multi-objective hydropower station optimal operation (MOHSOO) gives rise to more difficulties in solving the model. We propose a new algorithm named IMOCS to solve the issue. In the new algorithm, three improvement strategies, including a population initialization strategy, flock search strategy and dynamic adaptive probability, are employed to improve the convergence speed, convergence property, and diversity of solutions. Moreover, ICGC-MOCS, FSS-MOCS, DAP-MOCS, together with MOCS and NSGA-II, are used to verify the effectiveness of each improvement strategy and test the performance of IMOCS. The results show that the population initialization strategy can improve the search efficiency by limiting the initial solution within a certain range, which is designed to reduce the search space and improve the quality of the initial feasible solution. The dynamic adaptive probability can improve the quality of solutions because it can help the algorithm avoid falling into local optima prematurely, as well as converge to the global optimal solution quickly. Most importantly, the flock search strategy can greatly speed up the convergence and improve the quality of solutions simultaneously. This is because the flock search mechanism can generate multiple candidate nests through one iteration to significantly speed up the convergence. Moreover, the fast non-dominated sorting approach inspired by NSGA-II can improve the population quality and the convergence efficiency. Finally, for the Xiaolangdi hydropower station, the competitive relationship of power generation and water shortage mainly exists from September to next February when the hydropower station has to refill water but has relatively small inflow in latter months. The water supply demand seriously impacts the power generation of the hydropower station.

However, there are still some problems that require further study to resolve. Specifically, the population initialization strategy based on ICGC may perform better in short-term hydropower station operation because the water level has a large variation range in a monthly scale, which cannot embody the role of ICGC completely. Therefore, further study of more effective improvement measures and their application to more complex models is necessary. Moreover, more objectives can be expanded to the model, thereby helping managers realize and handle the competition or cooperation relationship between different objectives, which is their top concern. In addition, long series of runoff can be used to calculate the reliability of water supply instead of water shortage.

Acknowledgements

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