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Construction of multi-objective reservoir flood control operation preference model

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ABSTRACT

Reservoirs play an important role in flood control, irrigation, water supply, and environmental protection. The optimal operation of reservoir flood control includes various constraints such as upstream and downstream flood control, dam safety, and irrigation needs. Therefore, it is necessary to build a multi-objective reserve flood control operation preference model. In this experiment, a decomposition based multi-objective evolutionary algorithm was adopted as the basic research method. At the same time, a preference model was combined in the experiment to construct scheduling methods. The results indicate that the multi-objective reserve flood control operation preference model can significantly weaken flood peaks and reduce losses caused by floods. The algorithm has successfully converged to a specific region of the ideal Pareto Front, both of which are extremely close to the ideal Pareto optimal solution set. The inverted generational distance indicators of Multi-objective Evolutionary (MOEA/D-PWA) were tested in test sets 3, 4, and 6 with results of 1.73E-03, 2.04E-03, and 3.61E-03, respectively. The test results of its spacing index in test sets 1 and 3 are 1.56E-03 and 1.73E-03, respectively. The test results of its hypervolume index in test sets 1 and 3 are 7.59E-01 and 6.33E-01, respectively. The results confirmed that MOEA/D-PWA can develop appropriate reservoir flood control scheduling plans and more efficiently utilize flood resources.

Keywords: Preference; Multi-objective optimization algorithm; Electricity generation; MOEA/D-PWA; Reservoir flood control operation

1. Introduction

Flood disasters not only threaten the safety of people's lives and property, but also may cause serious economic losses and have adverse effects on social stability. The particularity of China's terrain and climate conditions can easily lead to frequent floods. In order to prevent floods, the construction of water conservancy projects such as dams and reservoirs for adjusting water discharge and building small flood peaks has been promoted. Reservoir flood control operation (RFCO) is a water conservancy project that considers the inflow of water supply from upstream and downstream of the reservoir, and stores and discharges water in accordance with the regulation regulations. It should not only take into account the flood control work in the upstream and downstream of conflicting reservoirs, but also pay attention to the balance between flood control engineering and revitalization engineering. That is to say, RFCO contains multiple targets [1,2]. Therefore, RFCO can be treated as a multi-objective optimization problem (MOP) and solved through the MOP algorithm [3]. In RFCO, the multi-objective evolutionary algorithm based on decomposition (MOEA/D) has high problem-solving efficiency and accuracy [4]. Therefore, this method was chosen as the fundamental method in this study. And due to the long-term goals of irrigation and water supply for reservoirs after floods, the scheduling plan has preferences. In view of this, this study will develop an appropriate RFCO

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scheme by constructing a multi-objective RFCO preference model. It is hoped to use appropriate RFCO schemes to efficiently utilize flood resources and achieve the goal of weakening flood peaks.

2. Related works

RFCO involves multiple decision variables, and its essence is a MOP. RFCO has many constraints and decision variables. Therefore, researchers use machine learning to solve MOP problems. To improve the problem-solving ability of RFCO, combined cultural algorithm with whale algorithm to solve MOP [5]. The validation experimental results in the test function confirm that this combined method can solve the actual RFCO. In RFCO, genetic algorithms can be used to optimize scheduling method parameters. The researchers conducted a series of optimizations on the penalty coefficient of the model. The results confirm that in flood control scheduling, the optimized model can improve the efficiency of scheduling results. The optimized model can reduce the occupancy of flood control capacity when resources are scarce [6]. However, these methods may experience issues such as reduced efficiency when applied due to parameter settings. For this reason, researchers used MOEA/D as the basic method for scheduling schemes and made improvements. Then they used the improved method to divide RFCO into sub problems corresponding to the scheduling time. In typical flood experiments, it has been confirmed that this method can accurately perform RFCO in hours [7]. MOEA/D can divide MOP into different sub problems. This method can reduce the difficulty of MOP problems. The practical application results in the field of communication have confirmed that this method can improve the efficiency of MOP problem processing. And this method can reduce the difficulty of program coding, thereby reducing the running cost [8]. Due to the accuracy and effectiveness of MOEA/D in solving MOP problems, this method was chosen as the basis for the RFCO model in this experiment.

Water resource management is an important issue that cannot be ignored in RFCO. Reasonable resource scheduling is necessary in water resource management. MOP is the main objective that needs to be addressed in the management and planning of reservoirs. The application of intelligent algorithms can improve the efficiency of solving MOP problems in water resource management. In the study by Yoosefdoost et al. [9], the application of intelligent optimization algorithms, logical operations, and programming techniques can improve the reliability of MOP problem solving. In the optimization of performance indicators, this combined method can also minimize vulnerability to the greatest extent. For the MOP problem of water resources, some scholars use particle swarm optimization to plan the ecological water use of reservoirs. They introduced different patterns to improve the method. In the actual comparison of reservoir scheduling results, the best scheduling plan can effectively solve the problem of water consumption for residents in the region [10]. Kumar and Yadav [11] utilized the Jaya algorithm as the fundamental method for reservoir scheduling strategies. They combined this method with intelligent optimization algorithms to establish a multi group method. In the comparison results of convergence, this method has higher performance than other intelligent algorithms. At the same time, this method can improve power generation while ensuring irrigation efficiency. Mansouri et al. [12] proposed a fuzzy optimization method for water resource management in reservoirs. They use swarm intelligence algorithm to solve MOP problem in water resource management. Compared with Non-Dominated Sorting Genetic Algorithm II (NSGA-II), the fuzzy particle swarm optimization algorithm can meet the water demand of users at the same time. At the same time, this method can ensure the sustainability of reservoir water resources. When studying the water resources management of the reservoir, Mohanavelu et al. [13] used the dynamic programming method to establish the optimal reservoir operation scheme. They use new planning methods to find the optimal solution. The Pareto optimal solution is a key indicator for verifying MOP methods. The validation experiment results confirm that the new planning method can obtain the optimal reservoir operation decision. Therefore, in this experiment, Pareto was used as one of the performance verification test indicators.

From the above research results, RFCO is essentially a MOP problem. To improve the MOP problem in RFCO, MOEA/D with good application results was selected as the basic method for the scheduling model in this study. And to improve the water resource utilization efficiency, the model was optimized by combining the preference information of reservoir irrigation demand. It is hoped to improve the rationality and efficiency of water resource utilization in RFCO through the improvement of methods.

3. RFCO model with decision preference

When an optimization problem has multiple objectives that need to be met simultaneously, and there are often conflicts between the objectives, it can be called MOP. The solution to this problem requires considering multiple decision variables. Models with decision preferences can adjust the time and reduce constraint conflicts [14]. Therefore, in this study, a preference model was introduced for optimization in MOP.

3.1. Two-objective RFCO model with decision preference

MOP model contains multiple objectives and decision variables. Eq. (1) is the mathematical expression of MOP.

$$\begin{aligned} &\text{minimize} F(x) = \left(f_1(x), f_2(x), \ldots, f_m(x)\right) \\ &\text{subject to } \ x \in \Omega \end{aligned} \tag{1}$$

where the feasible region of the decision space is Ω, $\Omega \in R^n$, and $x = \{x_1, x_2, \ldots, x_n\} \in \Omega$ are the decision variables. n, m refers to the decision space dimension and objective functions number, respectively. The objective vector function composed of m objective functions that need to be optimized simultaneously is the objective function $F(x)$: $\Omega \rightarrow R^m$. When m is 1, the above model is a single objective optimization problem. When $m = 2, 3$, the model is a MOP problem. When $m > 3$, the model is a high-dimensional MOP problem.

RFCO should pay attention to the flood control safety of dams and reservoirs themselves, as well as the safety of downstream residents. That is to say, the upstream water level should not be too high, and the downstream flood discharge should not be too large. Taking the two safety tasks of the reservoir as optimization objectives and the discharge flow as decision variables, Eq. (2) shows the two-objective RFCO model.

$$\begin{aligned}&\text{Minimize} \quad F(Q)=\{f_1(Q),f_2(Q)\}\\&\begin{cases}f_1(Q)=\max(Z_t)\\f_2(Q)=\max(Q_t)\end{cases}, \quad t=1,2,\dots,T\\&\text{Subject to:}\\&\quad Z_{\min}\le Z_t\le Z_{\max};\\&\quad 0\le Q_t\le Q_{\max};\\&\quad V_t=V_{t-1}+I_t-Q_t\end{aligned} \tag{2}$$

where Z_t refers to the upstream water level of the dam in dispatch stage t, T and Q_t, respectively refer to the duration of the flood and the discharge flow of the reservoir in dispatch stage t. The objective function $f_1(Q)$ is used to minimize the highest upstream water level. The objective function $f_2(Q)$ means the maximum discharge capacity of the minimized reservoir. The upstream water level constrains $Z_{\min} \le Z_t \le Z_{\max}$ to ensure that the reservoir water level is between the lowest water level $Z_{\min}$ and the highest water level $Z_{\max}$. The discharge flow is constrained by $0 \le Q_t \le Q_{\max}$, and the maximum discharge flow through the reservoir $Q_{\max}$ is used to constrain the discharge flow. In the water balance formula $V_t = V_{t-1} + I_t - Q_t$, I_t refers to the reservoir in scheduling stage t, such as the reservoir flow rate. The reservoir capacity of t and $t + 1$ scheduling stages is represented as V_t and V_{t-1} in sequence.

Due to the long-term irrigation and water supply goals of reservoirs, RFCO schemes have preferences within a certain range and are more likely to be favored by decision-makers.

The center point $M = (M_1, M_2, \ldots, M_m)$ and decision threshold vector $V = (V_1, V_2, \ldots, V_m)$ in Fig. 1a define the preference region. According to MOP, the definition of Pareto optimal solution P^R in the preference region can be obtained in Eq. (3).

$$P^R=\left\{x\,\middle|\,\left|f_i(x)-M_i\right|\le V_i,x\in\Omega,i=1,2,\dots m\right\} \tag{3}$$

Fig. 1b shows the principles of a new preference model that meets RFCO irrigation needs. The center point M and decision threshold vector V in Eq. (3) are the keys to establishing a preference model. When there is a preference Pareto optimal solution S^P with a series of upstream water levels located between CC $Z_{FL} - Z_{PT}$ and $Z_{FL} - Z_{PT}$ at the end, Eq. (4) is used to calculate the optimal solution S^P.

$$S^P=\left\{x\,\middle|\,\left|\mathrm{FL}(x)-Z_{\mathrm{FL}}\right|\le Z_{\mathrm{PT}},x\in\Omega\right\} \tag{4}$$

where Z_{FL}, Z_T, Z_{PT} represent the upper flood controllable water limit, the upstream water at the end, and the positive preference threshold. FL(x) is the final upstream water level for solving x.

$$\begin{aligned}&M=\left\{x\,\middle|\,\min\left\{\left|\mathrm{FL}(x)-Z_{\mathrm{FL}}\right|\right\},x\in S^P\right\}\\&V=\left\{\begin{aligned}&(V_1,V_2,\dots,V_m)\,\middle|\,V_i=1.2\times\hat{V}_i,\hat{V}_i\\&=\max\left\{\left|f_i(x)-M_i\right|\right\},x\in S^P,\\&i=1,2,\dots,m\end{aligned}\right\}\end{aligned} \tag{5}$$

where M and V are the expressions for the center point and the decision threshold vector, respectively. Due to the fact that S^P does not cover the entire preference area, the decision threshold vector V increases the calculation result $\hat{V}=(\hat{V}_1,\hat{V}_2,\dots,\hat{V}_m)$ to 1.2 times the original basis. The improved decision threshold vector has better preference regions coverage. The preference domain in Fig. 1b has been slightly expanded compared to Fig. 1a. By defining each solution obtained through the center point and decision threshold vector, the ranking of preference for Pareto optimal solutions is achieved.

$$\mathrm{PND}(x)=\sqrt{\sum_{i=1}^{m}\left(\frac{f_i(x)-M_i}{V_i}\right)^2} \tag{6}$$

where PND(x) represents the preferred neighbor distance corresponding to the Pareto optimal solution. Mahalanobis

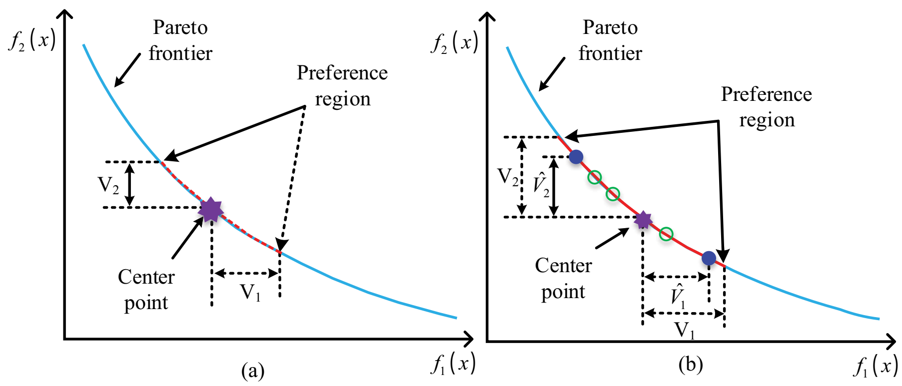

Fig. 1. Two-objective optimization preference model based on irrigation demand.

distance between the center point M and the corresponding solution determines the preferred neighbor distance of the solution x. When PND(x) < 1, it can be inferred from Eq. (3) that the solution x is located within the preferred region.

$$\mathrm{VD}_i^m = \mathrm{VD}\left(\mathrm{ind}^i, m\right) = \prod_{i=1}^{m} L_2^{\mathrm{NN}_i^j} \tag{7}$$

Eq. (7) introduces the neighbor distance of sparsity, that is, the crowding distance. The Euclidean distance between individual i and the j nearest individual of i in the population is represented by $L_2^{\mathrm{NN}_i^j}$. The product of Euclidean distance between individual i and its previous m neighbors is represented by the neighbor distance VD(ind^i, m). The decrease in neighbor distance leads to an increase in individual crowding and a decrease in sparsity.

The algorithm prototype used in this study is the multi-objective evolutionary algorithm with decomposition and preference Multi-objective Evolutionary (MOEA/D-PWA) based on decomposition and preference. It can guide the search to the preference region by removing non preference region subproblems and adding preference region subproblems. The process of multi-objective MOEA/D-PWA with preferences is shown below. The stopping criterion and parameter set (evolutionary population size N, external population size NE, neighbor list size T) were input. Various parameters were initialized. Simulated binary crossover and polynomial mutation were used to generate offspring populations. The population was evolved, and the solutions and reference points of the subproblems were updated. The external population and preference area were updated. Preference based weight vector adjustment was carried out (removing sub problems from non-preference regions and adding sub problems to preference Pareto Front (PF) regions). When the stopping condition is met, the stopping criterion is met. If not, re-evolution is carried out.

3.2. Three-objective RFCO model with decision preference

The optimization direction of the two-objective RFCO model is minimization. To ensure this optimization direction, this study will introduce the reciprocal of the power generation in RFCO as the third optimization objective.

$$\begin{aligned}
&\text{Minimize} \quad F(Q) = \left\{ f_1(Q), f_2(Q) \right\} \\
&\begin{cases} f_1(Q) = Z_{\max} = \max Z_t \\ f_2(Q) = Q_{\max} = \max Q_t \\ f_3(Q) = 1/E = 1\Big/\sum_{t=1}^{T} (N_t \Delta t) E \end{cases}, \quad t = 1,2,\ldots,T \\
&\text{Subject to:} \\
&\quad Z_{\min} \le Z_t \le Z_{\max}; \\
&\quad 0 \le Q_t \le Q_{\max}; \\
&\quad V_t = V_{t-1} + I_t - Q_t; \\
&\quad N_{t,\min} \le N_t \le N_{t,\max}
\end{aligned} \tag{8}$$

Eq. (8) is a three-objective optimization operation model for reservoir flood control. f_3, E, and Δt, respectively represent the generation target, generation capacity, and scheduling period length. The average output $N_t = K \cdot Q_t \cdot H_t$ and K, Q_t, H_t of the reservoir during time t, respectively indicate the power coefficient, the reservoir discharge flow, and the power generation head. $V_t = V_{t-1} + I_t - Q_t$ represents the water balance constraint. The reservoir capacity in stages t and t–1 is V_t and V_{t-1}. The constraints on the discharge capacity and hub output are $Q_t \le Q_{\max}$ and $N_{t,\min} \le N_t \le N_{t,\min}$, respectively and refer to the minimum and maximum power station output.

The preference information of irrigation demand in reservoirs is more important than the electricity generation optimization objective. But its importance is not as significant as the highest water level $f_1(x)$ and maximum discharge flow $f_2(x)$ in front of reservoir. Therefore, when calculating the center point and threshold vector in the three-objective RFCO preference model, only the first two optimization objectives $f_1(x)$, $f_2(x)$ can be considered.

Fig. 2 shows that when calculating the center point M, congestion distance VD, preference distance PND(x), and threshold vector V, only the values of the first two-dimensional optimization objectives need to be noted. As shown in Fig. 2, the preference distance PND is as follows:

$$\mathrm{PND}(x) = \sqrt{\sum_{i=1}^{2} \left(\frac{f_i(x) - M_i}{V_i} \right)^2} \tag{9}$$

The process of the three-objective MOEA/D-PWA algorithm with decision preferences includes the following steps. Firstly, it is necessary to initialize the weight vector, external population, and reference points of a population containing N individuals, and establish a neighbor list for each individual. Eq. (10) is the reference point for initialization.

$$z^* = \left(z_1^*, z_2^*, \ldots, z_m^* \right) \tag{10}$$

Eq. (11) is calculated for z_i^* in Eq. (10).

$$z_i^* = \min\left\{ f_i\left(x^1\right), \ldots, f_i\left(x^N\right) \right\} - 10^{-7} \tag{11}$$

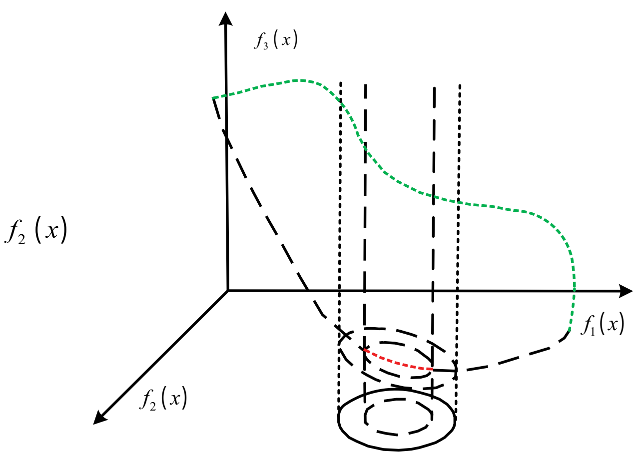

Fig. 2. Three-objective optimization preference model based on irrigation demand.

In the following experiment, simulated binary crossover and polynomial mutation are used to generate offspring populations, and the population is evolved to update the solutions and reference points of subproblems. Then the external population and preference regions were updated. The next step is preference processing based on weight vector adjustment. When performing preference processing, it needs calculate the individual preference distance according to Eq. (9) for deleting and adding sub problems. When adding sub problems, it needs use Eq. (12) to calculate the individual weight vector.

$$w^p = \left(\frac{\frac{1}{f_1^p - z_1}}{\sum_{i=1}^{3} \frac{1}{f_i^p - z_i}}, \frac{\frac{1}{f_2^p - z_3}}{\sum_{i=1}^{3} \frac{1}{f_i^p - z_i}}, \frac{\frac{1}{f_3^p - z_3}}{\sum_{i=1}^{3} \frac{1}{f_i^p - z_i}} \right) \tag{12}$$

Based on the calculation results of the weight vector mentioned above, the sub problem was added to the population. When the stop condition is met, the stop criterion is applied. If not satisfied, then re evolve.

Generally speaking, MOP has two-objectives. One is to make the Pareto front obtained by the algorithm as close as possible to the real Pareto front, that is, convergence. The second is to find as many non-dominated solutions as possible, that is, diversity. This experiment used the inverted generational distance (IGD), spacing (Sp), and hypervolume (HV) metrics to measure the convergence and diversity of Pareto frontiers obtained by various MOP algorithms. IGD can be used to evaluate the convergence of the approximate frontier obtained by the algorithm in Eq. (13).

$$\mathrm{IGD} = \sqrt{\frac{\sum_{i=1}^{n} d_i^2}{n}} \tag{13}$$

where n is the real Pareto front reference points. The Euclidean distance between the real Pareto frontier of d_i and the nearest solution obtained by the optimization algorithm. Sp can be used to evaluate the uniform distribution of approximate frontiers obtained by the algorithm. In Eq. (14), the results diversity obtained by Sp quantitative comparison algorithm can be used.

$$\mathrm{Sp} = \sqrt{\frac{1}{n-1}\left(\sum_{i=1}^{n} \bar{d} - d_i\right)^2} \tag{14}$$

where $\bar{d}$ is the average value of d_i. HV represents the region volume in target space enclosed by the non-dominated solution set and the real Pareto front reference point. HV can be used to evaluate the comprehensive algorithm performance, that is, to simultaneously evaluate convergence and diversity. Eq. (15) is the calculation method for HV.

$$\mathrm{HV} = \delta\left(U_{i=1}^{|S|} v_i\right) \tag{15}$$

where AA δ is Lebesgue measure used for volume measurement. $|S|$ is non dominated solution sets number. v_i is the supervolume formed by reference point and solution i. Among the above three indicators, IGD and SP are smaller, the algorithm performance is better. HV is higher, the algorithm performance is better.

4. Analysis of calculation results

4.1. Two-objective RFCO preference model

This testing experiment was conducted on the same computer. Its specific parameter is Intel Core i7-4900 CPU@3. 60 GHZ12.0 GB RAM. The operating system is 64-bit Windows 10, and the compilation software is MAT-LAB2018b.

To verify the correctness and effectiveness, two representative floods were selected as experimental cases. MOEA/D-PWA was compared with NSGA-II and MOEA/D algorithms [15,16]. The parameters in MOEA/D-PWA are: evolutionary population size N = 20, external population size N^E = 160, neighbor list size T = 4, initial center point M^0 = (32,510,000), decision threshold vector V^0 = (2,100), maximum number of sub problem adjustments N^{WA} = 10, and weight vector adjustment interval algebra I^{WA} = 100.

According to Fig. 3, two algorithms' water level in front of the reservoir are evenly distributed within a range of 1 m above and below as well as a range of 1 m above and below when the control limit is 325 m. The maximum discharge flow rates of these two are both below 8,000 m^3/s, which is lower than half peak flow rate of 17,730 m^3/s. That is to say, the two-objective RFCO preference MOEA/D-PWA algorithm proposed in this experiment can develop a scheduling plan that significantly weakens flood peaks and reduces losses caused by floods.

From Fig. 4, on the ideal Pareto frontier, the MOEA/D algorithm obtains the Pareto optimal solution with the highest coverage. Both two algorithms have converged to their preferred PF. Compared with the solution set obtained by NSGA-II, the solution set obtained by MOEA/D algorithm has slightly stronger convergence, coverage, and uniformity.

The flood in Fig. 5 on 2018.08.28 has two small peaks and a relatively small inflow. Based on Fig. 4, both tow algorithms can provide flood scheduling schemes with stable discharge flow, reducing the likelihood of downstream reservoirs being affected by floods.

4.2. Three-objective RFCO preference model

For three-objective RFCO preference model, its population size N = 100, its external population size N^E = 250, its neighbor list T = 10, its initial point center and threshold vectors are M^0 = (325.0, 10,000.0) and V^0 = (4.0, 2,000.0), respectively. Its evolutionary algebra I^{WA} = 500. Preference information was combined and N^{WA} = 20 was adjusted until the evolutionary algebra reached 10,000. In the two-objective MOEA/D-PWA algorithm, the population size N = 20, external population size N^E = 50, neighbor list T = 6, and other parameters are the same as the three-objective algorithm.

Fig. 6 shows the corresponding Pareto optimal solution set obtained by the MOEA/D-PWA algorithm for the

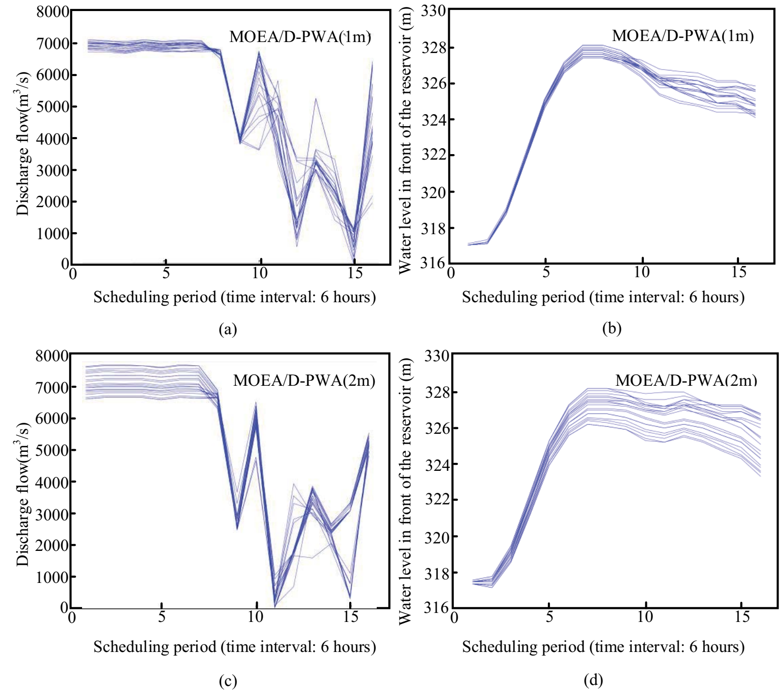

Fig. 3. Discharge and upstream water level: (a,c) discharge flow and (b,d) water level in front of the reservoir.

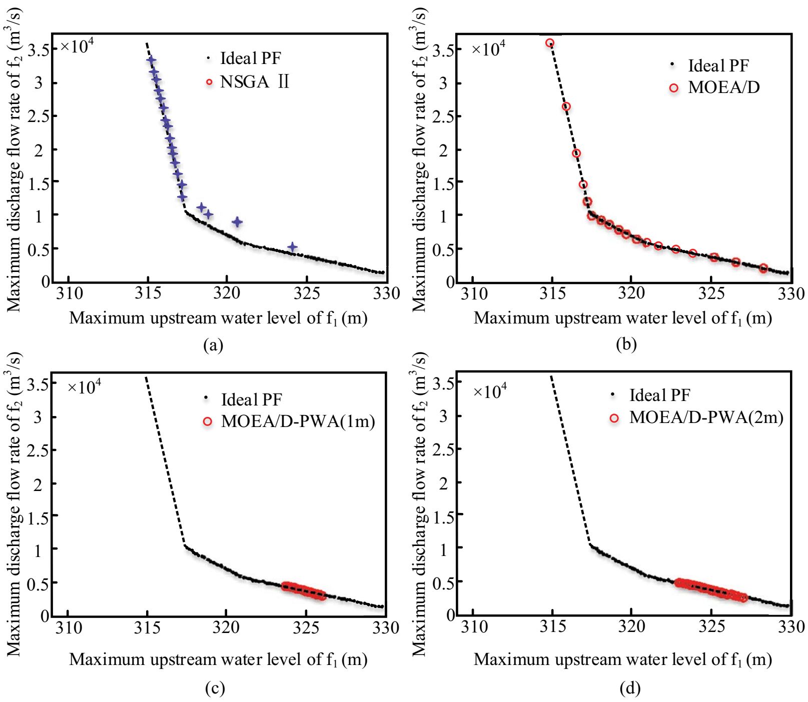

Fig. 4. Comparison of Pareto optimal solution set for flood on 2018.08.28: (a) NSGA II, (b) MOEA/D, (c) MOEA/D-PWA(1 m), and (d) MOEA/D-PWA(2 m).

three-objective RFCO optimization preference model for two typical floods in a certain reservoir, and the relative position of this solution set relative to the ideal Pareto optimal solution set. The ideal Pareto optimal solution set mentioned here is calculated by the three-objective MOEA/D-PWA algorithm through 6 million function evaluations and independent runs of 30 times. That is to say, the three-objective RFCO optimization preference model can efficiently utilize computing resources and successfully converge to a specific region of the ideal PF.

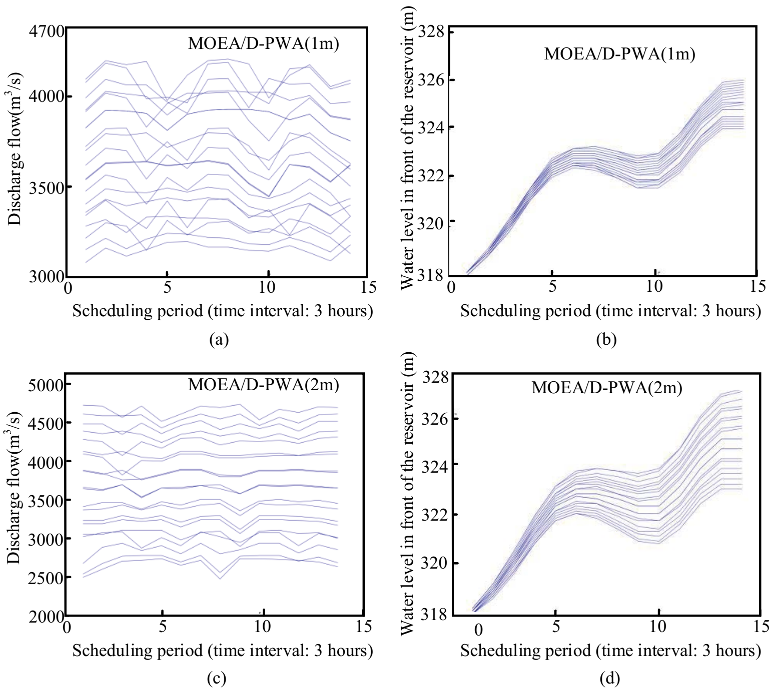

Fig. 5. Discharge and upstream water level: (a,c) discharge flow and (b,d) water level in front of the reservoir.

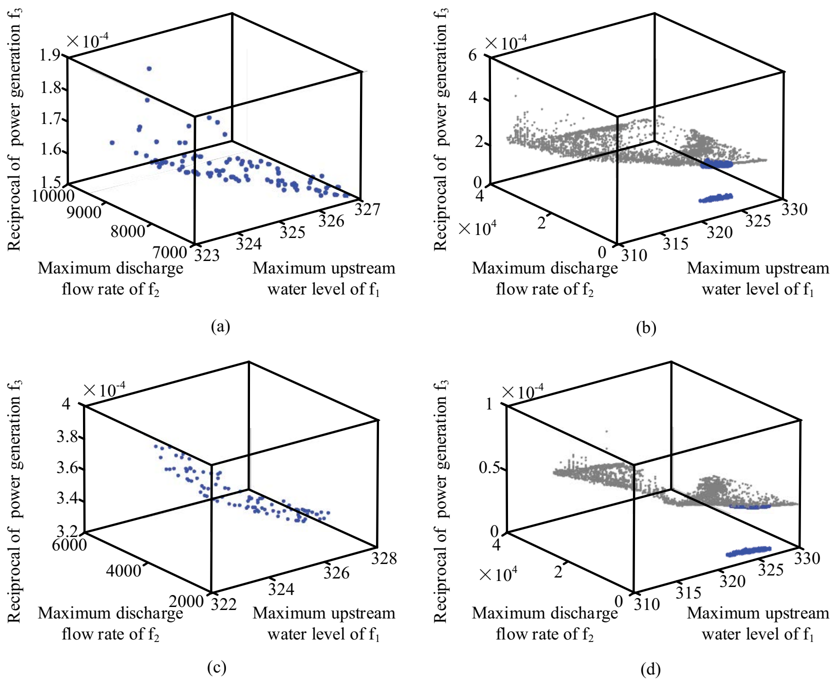

Fig. 6. Pareto optimal solution set and its relative position with the ideal solution set: (a,b) 2020.10.12 and (c,d) 2018.8.28

Fig. 7 shows the projection of the Pareto optimal solution set of ideal PF, two-objective optimization PF, and three-objective optimization on the plane composed of the highest upstream water level f_1 and the maximum discharge flow rate f_2. Comparing the projection results, the target values of the highest upstream water level and maximum discharge flow calculated by both methods are extremely close to the ideal Pareto optimal solution set. Meanwhile, in Fig. 7, the non-dominated solution sets obtained by MOEA/D-PWA are all clustered within the regions of interest for decision-makers on the ideal Pareto optimal solution set.

Fig. 8 shows the corresponding flood scheduling scheme calculated by the MOEA/D-PWA algorithm for the three-objective RFCO optimization preference model in the case

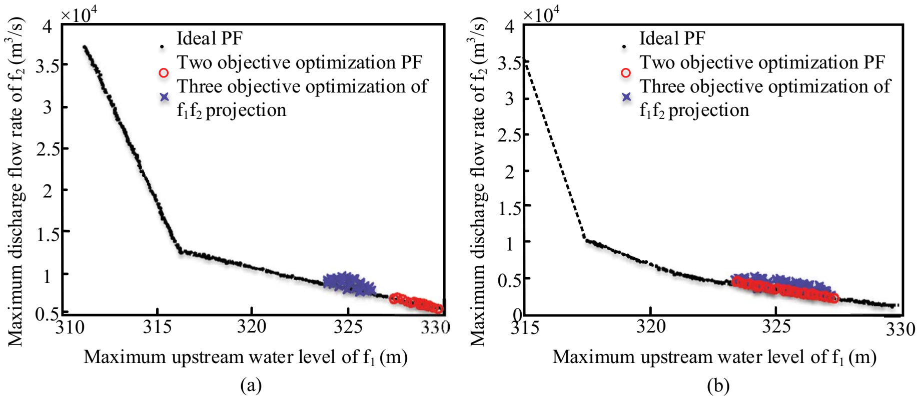

Fig. 7. Comparison of Pareto optimal solution sets for two-objective optimization with preference and three-objective optimization with preference.

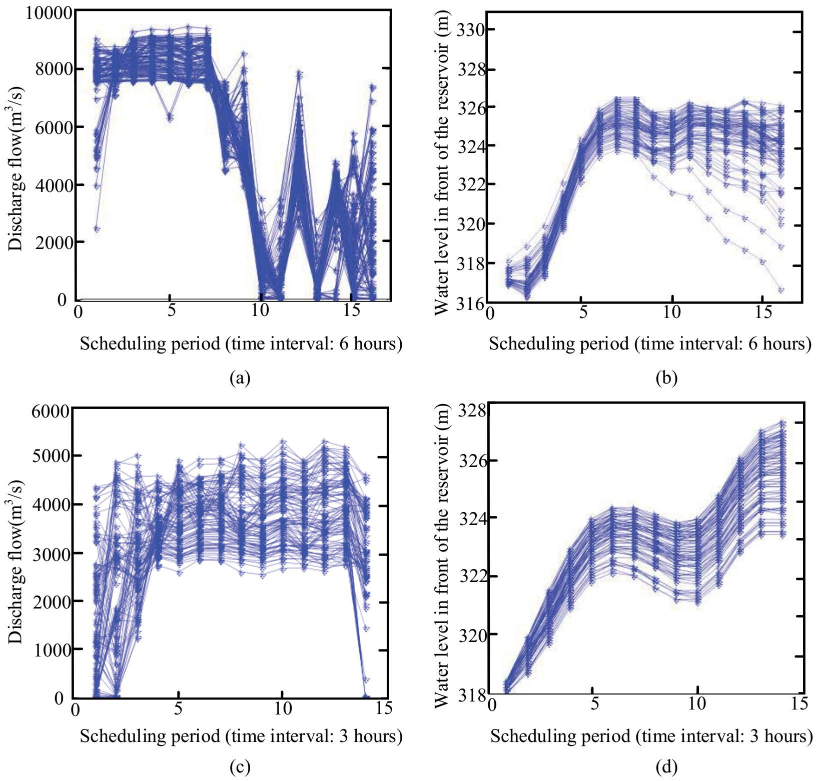

Fig. 8. Three-objective optimization results with preferences for two typical floods on 2020.10.12 and 2018.8.26: (a,b) 2020.10.12 and (c,d) 2018.8.28.

of floods on 2020.10.12 and 2018.8.26. Meanwhile, Fig. 8 also shows the changes in the corresponding reservoir water level under this scheduling scheme. The inability of the scheduling plan to present the true appearance of the flood indicates that the two-objective and three-objective RFCO optimization algorithm has achieved the goal of reducing flood peaks.

In the scheduling scheme provided by two-objective RFCO optimization, the stable period of discharge flow is relatively long. In the scheduling scheme provided three-objective RFCO optimization, the maximum discharge flow is greater than the maximum discharge flow of two-objective RFCO scheme. By adding power generation optimization objectives to increase the discharge flow range in three-objective RFCO scheme, this study validated it through four typical floods as examples. Fig. 9 shows the specific results.

Fig. 9 is a box plot used to reflect the statistical distribution. The short horizontal lines at the top and bottom respectively reflect the maximum and minimum values. The horizontal line in the middle box represents the median sample value, and the box size reflects the data dispersion. On October 12, 2020, the center of the highest reservoir

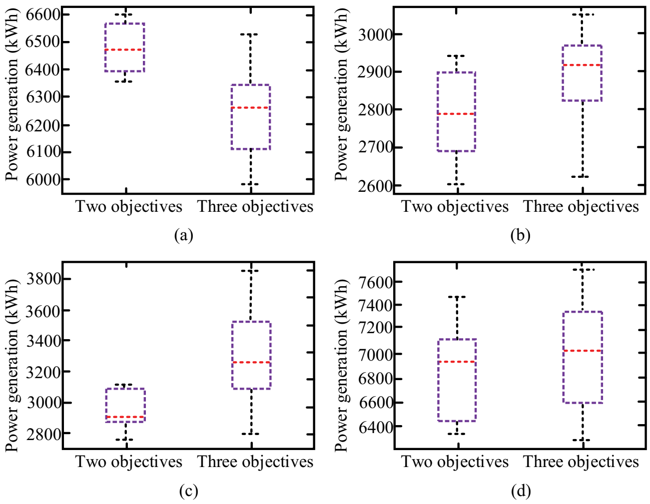

Fig. 9. Box diagram of power generation for two-objective optimizations with preference and three-objective optimizations with preference: (a) 2020.10.12, (b) 2018.8.28, (c) 2017.10.1 and (d) 2015.7.15.

water calculated by three-objective RFCO preference optimization algorithm was lower than the highest reservoir water level calculated by two-objective RFCO preference optimization algorithm. Meanwhile, Fig. 9 shows that the scheduling scheme provided by the latter generates higher electricity generation than the former. The highest reservoir water range for the flood on 2018.08.28 and 2017.10.1 is the same, and three target power generation is higher than two target power generation. On 2015.7.15, the highest reservoir water center calculated by three-objective scheduling plan was lower than that of the two-objectives, and the three-objective power generation was higher than the two-objective power generation. In summary, the flood control scheduling scheme with greater fluctuation can better utilize flood resources and generate more power generation. In terms of the utilization of flood resources and power generation, three-objective RFCO preference optimization algorithm provides a more advantageous solution than two-objective RFCO preference optimization algorithm.

To demonstrate the effectiveness of MOEA/D-PWA, the widely used ZDT standard test function was selected to test the MOP model performance. IGD, Sp, and HV indicators were selected to measure the convergence and diversity of each MOP algorithm. And to verify the performance superiority of MOEA/D-PWA, it was compared with existing more advanced MOP methods in the Zitzler Deb Thiele (ZDT) standard test set in the experiment [5,7,10,15,16].

In Table 1, when solving multi-objective problems, IGD of MOEA/D-PWA showed the best test results in test sets 3, 4, and 6, with values of 1.73E-03, 2.04E-03, and 3.61E-03, respectively. Sp of MOEA/D-PWA showed the best test results in test sets 1 and 3, with values of 1.56E-03 and 1.73E-03, respectively. HV of MOEA/D-PWA showed the best test results in test sets 1 and 3, with values of 7.59E-01 and 6.33E-01, respectively. It should be noted that in the comparison of the same indicator, although MOEA/D-PWA did not perform optimally in other datasets, this method

Table 1
Statistical results of different methods in the ZDT standard test set

Objective function	ZDT1			ZDT2			ZDT3			ZDT4			ZDT6		
Index	IGD	Sp	HV	IGD	Sp	HV	IGD	Sp	HV	IGD	Sp	HV	IGD	Sp	HV
MOEA/D-PWA	2.08E-03	1.56E-03	7.59E-01	2.08E-03	1.61E-03	4.68E-01	2.37E-03	1.73E-03	6.33E-01	2.04E-03	1.51E-03	7.58E-01	3.61E-03	3.43E-02	4.09E-01
Reference 15	2.44E-03	3.63E-03	7.58E-01	7.14E-04	7.32E-04	4.70E-01	6.74E-03	8.45E-03	6.32E-01	4.74E-03	7.84E-03	7.54E-01	3.86E-03	6.41E-03	4.07E-01
Reference 16	1.61E-03	1.44E-02	5.89E-01	4.21E-03	4.67E-03	4.66E-01	1.27E-02	1.86E-02	6.25E-01	5.50E-03	5.26E-03	7.51E-01	3.66E-03	3.21E-03	4.06E-01
Reference 17	9.62E-01	2.14E-02	1.37E-02	6.18E-03	3.87E-03	4.62E-01	6.15E-03	3.93E-03	6.27E-01	6.59E-02	7.38E-02	1.05E-01	3.26E-03	1.54E-01	4.07E-01
Reference 18	4.38E-03	7.96E-03	6.49E-01	4.24E-03	8.30E-04	4.33E-01	2.66E-03	10.40E-03	4.49E-01	5.08E-03	1.11E-03	6.64E-01	6.57E-03	5.55E-03	3.23E-01
Reference 19	4.21E-03	7.46E-03	7.56E-01	8.66E-03	9.60E-03	4.71E-01	1.70E-02	1.14E-02	6.27E-01	2.11E-02	3.00E-02	7.56E-01	4.66E-03	9.75E-03	4.17E-01

did not differ significantly from other methods. From the overall performance test results, MOEA/D-PWA shows certain competitiveness among all methods in solving multi-objective problems.

5. Conclusion

This study analyzed the multi-objective RFCO preference model using two-objectives and three-objective RFCO preference algorithms. The research results indicate that the multi-objective RFCO preference algorithm can develop flood scheduling schemes with stable discharge flow, significantly weakening flood peaks and reducing losses caused by floods. The three-objective RFCO optimization preference model performs better in efficiently utilizing flood resources. The multi-objective RFCO preference algorithm successfully converges to a specific region of the ideal PF. The target values of the highest upstream water level and maximum discharge flow calculated by the multi-objective RFCO optimization preference algorithm are extremely close to the ideal Pareto optimal solution set. The inability of the scheduling plan to present the true appearance of the flood indicates that the multi-objective RFCO optimization algorithm has achieved the goal of reducing flood peaks. In the analysis of flood resource utilization and power generation, the three-objective solution has more advantages than the two-objective solution. IGD of MOEA/D-PWA showed the best test results in test sets 3, 4, and 6, with values of 1.73E-03, 2.04E-03, and 3.61E-03, respectively. Sp of MOEA/D-PWA showed the best test results in test sets 1 and 3, with values of 1.56E-03 and 1.73E-03, respectively. HV of MOEA/D-PWA showed the best test results in test sets 1 and 3, with values of 7.59E-01 and 6.33E-01, respectively. The MOEA/D-PWA model proposed in this study has the ability to weaken flood peaks. However, the impact of parameters such as population size in the experiment has not been thoroughly explored. In the future, the comprehensiveness of research should be further improved.

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