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Operation Rules Optimization of Cascade Reservoirs Based on Multi-Objective Tangent Algorithm

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ABSTRACT Obtaining optimal operation rules for cascade reservoirs is crucial for making the most of the comprehensive benefits of reservoirs. However, the operation of cascade reservoirs is generally complex, which involves with challenges including various decision variables, multiple conflicting objectives and constraints. In this paper, a new algorithm named multi-objective tangent algorithm (MOTA) is proposed for optimizing operation rules of cascade reservoirs with the objectives of hydropower generation, ecology and navigation. The performance of MOTA is firstly validated through several well-known benchmark problems. Then it is applied to a case study of cascade reservoirs optimization in China's Pearl River. Using observed inflow data (1956–2015) of cascade reservoirs, a uniform Pareto front is obtained eventually via MOTA after 1000 generations. The optimal operation rules fully considers the comprehensive benefits of hydropower generation, ecology and navigation in China's Pearl River. The optimal operation rules can be used as a guidance tool for decision makers, through the objectives' tradeoff without having to embed a priori preferences in the decision process. Finally, this paper use observed inflow data (2016) of cascade reservoirs for examining the operational rule to comprehend the analysis under different optimal operation rules. The obtained results show that MOTA can be a viable alternative for generating optimal operation rules for cascade reservoirs planning and management.

INDEX TERMS Operation rules, tangent algorithm, multi-objective optimization, cascade reservoirs.

I. INTRODUCTION

Dam and reservoir systems often serve multiple purposes, such as flood control, hydropower generation, ecology and navigation [1]. The operation of reservoirs involves a complex decision making process that strives to balance many (often conflicting) objectives of different reservoir benefit [2], aiming mostly at the quantification of uncertainty inflow and the optimization of water allocation [3]. Cascade reservoirs research is a hot issue [4], it must utilize compensation coordination among the reservoirs in regard to the overall comprehensive benefit to maximize water resources use [5]. Operation rule for cascade reservoirs is complex with multiple reservoirs to consider. [6], which increases the difficulty of research [7]. Therefore, the cascade reservoirs operations are crucial for decision making and determining reasonable optimal operation rules to operate scheduling the water volume of reservoirs.

Over the years, numerous optimization models have been employed to generate operation rules for dam and reservoir systems [8]. These models include linear [9], nonlinear [10], stochastic [11] and other concepts, which have been suggested to develop optimal operation rules for dam and reservoir systems to allocate the proper amount of water released according to current reservoir storage and inflow while considering reservoir systems objectives and constraints [12].

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Operating rules are widely used in the reservoir long-term operation because of it provide a more practical and reliable guidance to reservoir system operators in the current period [13]. With in-depth study, cascade reservoirs confronts increasing complexity of the operation context and involves with challenges including various decision variables, multiple conflicting objectives and constraints [14]. The best way to deal with this is the coupling of multi-objective evolutionary algorithms (MOEAs) and simulation models [15], typically produce a set of Pareto optimal solutions. The solutions can then be used as a guidance tool for decision makers, through the objectives' tradeoff without having to embed a priori preferences in the decision process [16].

In past decades, various MOEAs appear, such as non-dominated sorting genetic algorithm II (NSGAII) [17], multi-objective evolutionary algorithm based on decomposition (MOEA/D) [18], an evolutionary many-objective optimization algorithm using reference-point-based non-dominated sorting approach (NSGAIII) [19], a simple but effective θ dominance-based evolutionary algorithm (θ-DEA) [20] and multi-objective artificial sheep algorithm (MOASA) [21]. With the development of MOEAs, more and more researchers have begun to apply it in multi-objective problems of reservoir systems and acquire optimal operation rules [22]. Some MOEAs get good achievements in multi-objective problems of reservoir systems such as multi-objective cultured evolutionary algorithm based on decomposition (MOCEA/D) [23], shark machine learning algorithm (SMLA) [24], strawberry optimization algorithm [25], bounded optimization BY quadratic approximation algorithm (BOBYQA) [26] and honey bee mating optimization (HBMO) [27], which has been employed to provide operational rules to operate scheduling the water volume of reservoirs.

The study of cascade reservoirs in the China's Pearl River is a complex problem, involving multiple benefits such as hydropower generation, ecology and navigation. In order to solve this complex multi-objective problem and obtain optimal operation rules, a tangent algorithm using reference-point-based non-dominated sorting approach (MOTA) is proposed in this paper. The optimal operation rules calculated by MOTA can be used as a guidance tool for decision makers. Major contributions are outlined as follows:

(1) The model established in this paper considers the comprehensive benefits of eleven hydropower stations in the Pearl River System, which mainly focus on the benefits of hydropower generation, ecology and navigation.

(2) A new MOEA named MOTA is proposed for solving the multi-objective model in this paper. The algorithm combines the advantages of NSGAIII and shows its high performance when solve some well-known test functions.

(3) The solutions of optimal operational rules for cascade reservoirs can be used as a guidance tool for decision makers, through the objectives' tradeoff without having to embed a priori preferences in the decision process.

The remaining parts of this paper are arranged as follows: In section 2, the paper build multi-objective model of optimal operation rules based on an overall analysis of the benefit of hydropower generation, ecology and navigation. In section 3, a new MOEA named MOTA is proposed, which is used to solve the model of this paper. In Section 4, the cascade reservoirs in the Pearl River is selected as a case study. The results analysis and discussion are presented in section 5. Finally, section 6 concludes this paper.

II. THE MODEL OF OPTIMAL OPERATION RULES FOR CASCADE RESERVOIRS

Optimal operation rules of cascade reservoirs involves with challenges including various decision variables, multiple conflicting objectives and constraints, which mainly focus on the comprehensive benefits of hydropower generation, ecology and navigation. Therefore, the model considers objectives including: maximizing hydropower generation of the cascade reservoirs, minimizing ecological water deviation of the cascade reservoirs and maximizing guarantee rate of navigation. At the same time, the model considers constraints such as water volume balance, water level, discharge flow, hydropower output and so on.

A. OBJECTIVE FUNCTION

1) Maximizing hydropower generation of the cascade reservoirs.

$$F_1 = \max P = \max \sum_{t=1}^{T} \sum_{i=1}^{R_n} K_i \cdot Q^f_{i,t} \cdot h_{i,t} \cdot \Delta t \tag{1}$$

where: P is the total hydropower generation, K_{i} is the power production coefficient of the i-th hydropower plant, $Q^f_{\mathrm{i,t}}$ is the power generation reference flow of the i-th reservoir during the t-th period, $h_{\mathrm{i,t}}$ is the net head of the i-th reservoir during the t-th period, Δt is the operation interval, T is the number of periods, R_{n} is the number of reservoirs.

2) Minimizing ecological water deviation of the cascade reservoirs.

Reservoir scheduling changes the historical runoff sequence. It may be caused great damage to the living environment of aquatic organisms downstream of the reservoir, and cause a reduction of biodiversity. Therefore, it is very important to pay attention particularly to ecological protection while considering power generation tasks. Wang *et al.* [28]–[30] proposed a new ecological benefit objective — minimizing ecological water deviation of the reservoir system. The objective function can be written as:

$$F_2 = \min W = \min \sum_{t=1}^{T} \sum_{i=1}^{R_n} W_{i,t}$$
$$W_{i,t} = \begin{cases} (Q_{i,t} - EWR^{\max}_{i,t}) \cdot \Delta t & if\ Q_{i,t} > EWR^{\max}_{i,t} \\ 0 & if\ Q_{i,t} \in [EWR^{\min}_{i,t}, EWR^{\max}_{i,t}] \\ (EWR^{\min}_{i,t} - Q_{i,t}) \cdot \Delta t & if\ Q_{i,t} < EWR^{\min}_{i,t} \end{cases} \tag{2}$$

where: $W_{\mathrm{i,t}}$ is the ecological water deviation of the i-th reservoir during the t-th period, $Q_{\mathrm{i,t}}$ is the discharge flow of the

i-th reservoir during the t-th period, $EWR_{\rm i,t}^{\max}$ and $EWR_{\rm i,t}^{\min}$ are the upper and lower limit of the suitable ecological flow of the i-th reservoir during the t-th period.

The method of calculating the suitable upper and lower limits of ecological flow introduces the ideas and recommendations of the RVA framework [31], [32]. The RVA framework recommends taking 25% monthly frequency corresponding flow as the upper limit of suitable ecological flow, and 75% monthly frequency corresponding flow as the lower limit of suitable ecological flow.

$$\begin{aligned} P_{25\%}(Q_{i,t}^{his}) &= EWR_{i,t}^{\max} \\ P_{75\%}(Q_{i,t}^{his}) &= EWR_{i,t}^{\min} \end{aligned} \tag{3}$$

where: $Q_{\rm i,t}^{\rm his}$ is the historical stream flow sequence of the i-th reservoir during the t-th period. $P_{25\%}(Q_{\rm i,t}^{\rm his})$ is the stream flow corresponding to the 25% monthly frequency and $P_{75\%}(Q_{\rm i,t}^{\rm his})$ is the stream flow corresponding to the 75% monthly frequency.

3) Maximizing guarantee rate of navigation.

$$\begin{aligned} F_3 &= \max S = \max \frac{1}{T \cdot R_n} \sum_{t=1}^{T} \sum_{i=1}^{R_n} S_{i,t} \\ S_{i,t} &= \begin{cases} 0 & if\ Q_{i,t} > SR_{i,t}^{\max}\ or\ Q_{i,t} < SR_{i,t}^{\min} \\ 1 & if\ Q_{i,t} \in [SR_{i,t}^{\min}, SR_{i,t}^{\max}] \end{cases} \end{aligned} \tag{4}$$

where: S is the function of navigation guarantee rate, $SR_{\rm i,t}^{\max}$ and $SR_{\rm i,t}^{\min}$ are the upper and lower limit of the navigable discharge of the i-th reservoir during the t-th period.

B. CONSTRAINTS

1) WATER VOLUME BALANCE CONSTRAINTS.

$$V_{i,t+1} = V_{i,t} + (I_{i,t} - Q_{i,t}) \cdot \Delta t \tag{5}$$

$$I_{i+1,t} = Q_{i,t} + q_{i+1,t} \tag{6}$$

where: $V_{\rm i,t}$ is the reservoir storage of the i-th reservoir during the t-th period, $I_{\rm i,t}$ and $Q_{\rm i,t}$ are the reservoir inflow and discharge flow of the i-th reservoir during the t-th period, respectively. $q_{\rm i+1,t}$ is the tributary flow between the i-th reservoir and the $(i+1)$-th reservoir.

2) WATER LEVEL CONSTRAINTS.

$$Z_{i,t}^{\min} \le Z_{i,t} \le Z_{i,t}^{\max} \tag{7}$$

where: $Z_{\rm i,t}^{\max}$ and $Z_{\rm i,t}^{\min}$ are the maximum and minimum limit of upstream water level of the i-th reservoir during the t-th period.

3) RESERVOIR DISCHARGE FLOW CONSTRAINTS.

$$Q_{i,t}^{\min} \le Q_{i,t} \le Q_{i,t}^{\max} \tag{8}$$

where: $Q_{\rm i,t}^{\max}$ and $Q_{\rm i,t}^{\min}$ are the maximum and minimum limit of discharge flow of the i-th reservoir during the t-th period.

4) HYDROPOWER OUTPUT CONSTRAINTS.

$$N_{i,t} \le N_{i,t}^{\max} \tag{9}$$

where: $N_{\rm i,t}^{\max}$ is the maximum limit of hydropower output of the i-th reservoir during the t-th period.

5) GUARANTEE RATE OF HYDROPOWER OUTPUT CONSTRAINTS.

$$\min\{P(N_{i,t} > N_{i,t}^{\min})\} > 90\% \tag{10}$$

where: $N_{\rm i,t}^{\min}$ is the minimum limit of hydropower output of the i-th reservoir during the t-th period. $P(N_{\rm i,t} > N_{\rm i,t}^{\min})$ is the frequency of hydropower output.

III. METHODOLOGY

A. TANGENT ALGORITHM

The Sine Cosine Algorithm (SCA) proposed by Australian scholar Mirjalili [31] in 2016 has a simple structure and few parameter settings, which is inspired by the image of the sine and cosine function. However, SCA has some exists shortcomings in solving complex practical problem, which results in low convergence accuracy and slow convergence [32], [33].

Inspired by the image of tangent function, a tangent algorithm is proposed to solve complex optimization problems, which has high convergence accuracy and fast convergence. In the tangent algorithm, the positions of n individuals are first randomly generated. It is assumed that each solution of the optimization problem corresponds to the position of the individual in the search space and is used to indicate the position of the i-th (i = 1, 2, $\cdots$, n) individual. In the next iteration, the position update formula in the tangent algorithm is as follows:

$$X_i^{t+1} = X_i^t + (r_1 \times \tan(r_2) + r_3)\,(Pb_i^t - X_i^t\ ) \tag{11}$$

$$r_1 = a \cdot e^{-\frac{t}{Ti}} \tag{12}$$

$$r_3 = \begin{cases} 0, & r_4 < 0.5 \\ 1, & r_4 > 0.5 \end{cases} \tag{13}$$

where: X_i^t is the position of the current solution in i-th dimension at t-th iteration. Pb_i^t is the position of the best solution in i-th dimension at t-th iteration. r_2 is a random number in [-$\pi/3$, $\pi/3$], r_4 is a random number in [0, 1]. t is the current iteration, Ti is the maximum number of iterations, a is a constant and the value is 0.025.

There are four parameters r_1, r_2, r_3, r_4 in the formula where r_1 determines the area of the next position (or direction of movement) r_2 determines the distance to move r_3 is a random weight when $r_3 = 0$ means moving around the current individual and $r_3 = 1$ means moving around the best individual r_4 is a random number.

B. THE TANGENT ALGORITHM FOR MULTI-OBJECTIVE PROBLEMS

In order to solve the multi-objective problem, the tangent algorithm uses the framework of NSGAIII [19]. We call

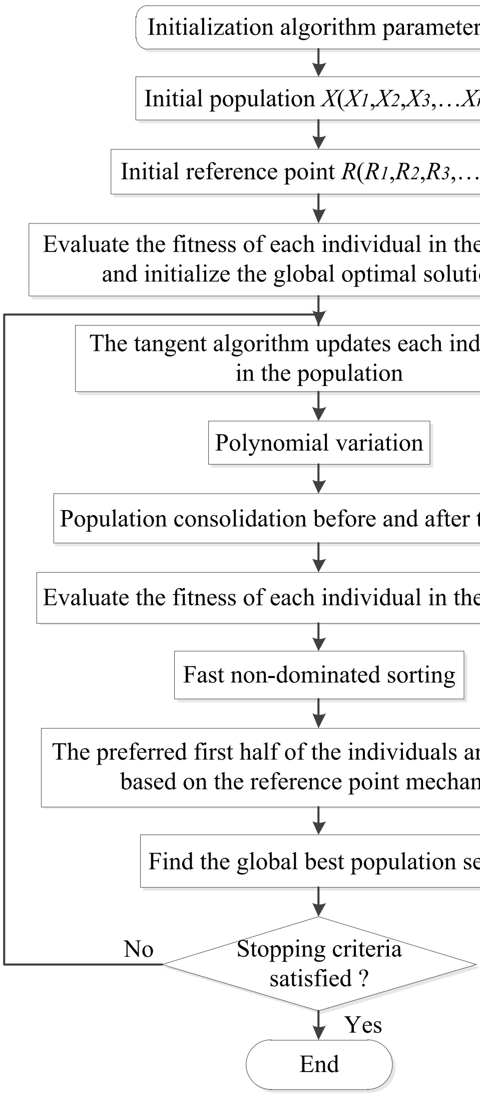


FIGURE 1. MOTA flowchart.

it multi-objective tangent algorithm using reference-point-based non-dominated sorting approach (MOTA). The calculation process of the algorithm is shown in Fig. 1.

The MOTA algorithm first defines a set of reference points then randomly generates the initial population with n members iterates over the next steps until the termination condition is satisfied. In the t-th iteration, the current parent population P_t uses the tangent algorithm and polynomial mutation to produce the offspring population Q_t. The size of the Q_t is the same as that of the P_t. Then two populations of P_t and Q_t are combined to form a new population of $R_t = P_t \cup Q_t$ $(2n)$. In order to select the best n members from the next generation R_t, R_t is classified into different non-dominated levels (F_1, F_2 et al.) using non-dominated sorting based on Pareto dominance. Then starting from F_1 the members of different non-dominant levels are filled one by one to construct a new population S_t filtering until the size of S_t is equal to that of n. In the process of population selection the objectives and reference points are first standardized so that they have the same range. After normalization the ideal point of the set S_t is zero vector and the vertical distance between the members of the St, and each reference line (which is the line between the ideal point and the reference point) is calculated. Each member of S_t is then associated with a reference point with the minimum vertical distance. The next step is to calculate the number of associated members of the j reference point ρ_j (the number of members in the S_t / F_1 associated with the j reference point). To select a member from F_1 we first identify the reference point set J_{min} (J_{min} required to be greater than or equal to 1) with the minimum ρ_j. If $J_{min} = 1$ selects a unique associated member to be added to P_{t+1} if $J_{min} > 1$ randomly selects a member to be added to P_{t+1}. Then increase the count of ρ_j by 1. If the F_1 does not have any member associated with the j reference point the reference point will be excluded from the further consideration of the current generation and the minimum ρ_j will be recalculated. Repeat the above operation until the total number of members filled with P_{t+1} is n. Then Algorithm 1 is used to find the global optimal solution set. The above steps are iterated until the termination condition is satisfied the algorithm converges and the population is uniformly distributed to the Pareto front.

Algorithm 1 Find the Global Best Population Set

Input: P_t (current population), Z^r (reference points)
Output: Pb (best population set)

```
Pb = ∅
for each P_{i,t}(X_{1,t}, X_{2,t}, X_{3,t}, ··· X_{m,t}) ∈ P_t{P_{1,t}, P_{2,t}, P_{3,t}, ··· P_{n,t}}
  if P_{i,t}.getRank == 1
    Pb = Pb ∪ {P_{i,t}}
  end
end
if P_t == Pb
  Normalized Pb ← Normalize all individuals in the best population set.
  for each Pb_i ∈ Pb{Pb_1, Pb_2, Pb_3, ··· Pb_n}
    Find min-distance from Z^r (Z^r_1, Z^r_2, Z^r_3, ···)
    Z^r_min associate Pb_i
  end
  Find minimum association (>0) Z^{r,min} (Z^{r,min}_1, ···) from Z^r (Z^r_1, Z^r_2, Z^r_3, ···)
  for each Pb_i ∈ Pb{Pb_1, Pb_2, Pb_3, ··· Pb_n}
    if Pb_i not associated Z^{r,min} (Z^{r,min}_1, ···)
      Pb remove Pb_i
    end
  end
end
```

C. EXPERIMENTAL DESIGN AND RESULTS

1) TEST PROBLEMS AND QUALITY INDICATORS.

In order to prove the performance of MOTA algorithm DTLZ1-4 [18], WFG6-7 [36], SDTLZ1-2 [37] are used for eight experimental studies. These test problems can be scaled to any number of objectives and decision variables. We consider the number of objectives Mo ∈ {3, 5, 10}. For DTLZ1–4 problems, the number of variables is given by Nv = Mo + k − 1, k is set to 5 for DTLZ1 and set to 10 for DTLZ2-4. For WFG6–7 and SDTLZ1-2 problems, the number of variables is set to the same as in [35].

Inverse generation distance (IGD) [19] and hyper-volume (HV) [37] are two important indexes to measure the convergence and diversity of Pareto optimal set. Let P* be the set of optimal solutions of a group of uniformly distributed (PF) along the Pareto frontier. A is the set of final non-dominated points obtained in objective space. The IGD value of A is calculated as follows:

$$IGD(A, P^*) = \frac{1}{|P^*|}\sum_{i=1}^{|P^*|} \min_{f\in A} d\,(p_i, f) \tag{14}$$

where: $d(p_{\mathrm{i}}, \mathrm{f})$ is the Euclidean distance between the points p_{i} and f. The lower value of IGD (A, P^*) means that the algorithm obtains a better solution set A.

A is the set of final non-dominated points obtained in objective space. $r = (r_1, r_2, \ldots r_{\mathrm{m}})$ are the reference point in the objective space which is dominated by any point in the set A. The hyper-volume index value of A can be expressed as:

$$HV\,(A, r) = volume\left(\bigcup_{f\in A}[f_1, r_1] \times \cdots [f_m, r_m]\right) \tag{15}$$

For a given reference, the larger HV (A, r) value, the better the quality of the optimal solution set obtained.

2) EXPERIMENTAL RESULTS.

In order to verify the MOTA algorithm, this paper uses the NSGAIII [35], MOEA/D [20], dMOPSO [38] algorithm to compare. For each algorithm, each test problem is run independently 20 times. The parameter settings for the test problem are shown in Table 1, other experimental settings are consistent with those in the original NSGA-III, MOEA/D and dMOPSO study. The test results for MOTA on the DTLZ1-4 problem are shown in Figure 2. In the comparison of IGD and HV, the statistical results of the eight questions are shown in Table 2 and Table 3.

TABLE 1. Problem setting for algorithms.

Problem	No.of Objectives (M_o)	Reference points	Population size
DTLZ1	3,5,10	91,210,275	92,212,276
DTLZ2	3,5,10	91,210,275	92,212,276
DTLZ3	3,5,10	91,210,275	92,212,276
DTLZ4	3,5,10	91,210,275	92,212,276
SDTLZ1	3,5,10	91,210,275	92,212,276
SDTLZ2	3,5,10	91,210,275	92,212,276
WFG6	3,5,10	91,210,275	92,212,276
WFG7	3,5,10	91,210,275	92,212,276

From the IGD test index in Table 3, it can be seen that MOTA algorithm outperforms other algorithms on DTLZ1,

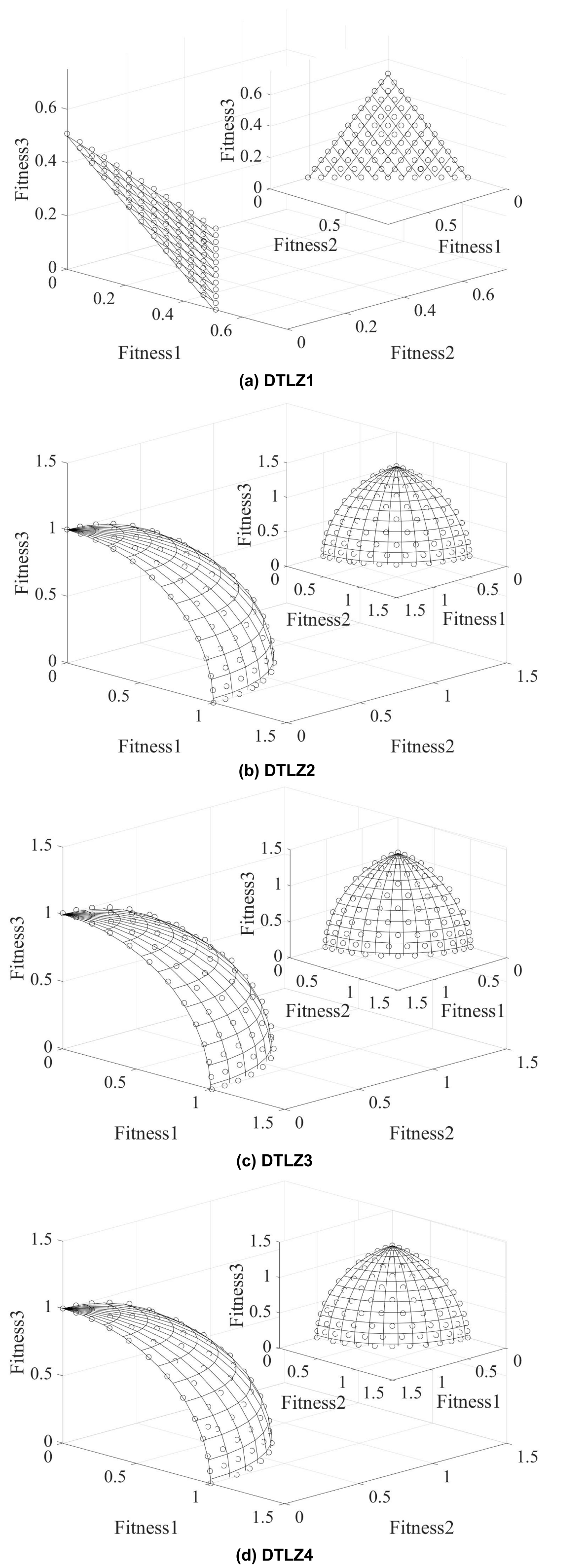


FIGURE 2. Obtained solutions by MOTA for DTLZ1-4. (Dots are the solutions, the grid is the true PF of each problem).

DTLZ2, DTLZ4, WFG6, SDTLZ1, SDTLZ2 problems, whereas NSGAIII wins on WFG7 problem. In the DTLZ3 test function, the MOTA algorithm is better than other algorithms

TABLE 2. Best, median and worst IGD values obtained by MOTA to different algorithms on multi-objective DTLZ1–4, WFG6-7 and SDTLZ1–2 problems. Best performance is shown in bold.

Problem	Obj/ Max Gen	MOTA	NSGAIII	MOEA/D -PBI	dMOPSO
DTLZ1	3/ 400	**4.07E-04**	4.88E-04	4.21E-04	5.21E-04
		1.03E-03	1.31E-03	1.58E-03	1.73E-03
		1.87E-03	4.88E-03	4.68E-03	5.68E-03
	5/ 600	**5.08E-04**	5.12E-04	5.19E-04	5.41E-04
		6.46E-04	9.80E-04	7.59E-04	8.53E-04
		1.83E-03	1.98E-03	1.93E-03	2.06E-03
	10/ 1000	2.46E-03	**2.22E-03**	3.86E-03	4.36E-03
		3.29E-03	3.46E-03	5.02E-03	5.89E-03
		5.51E-03	6.87E-03	6.42E-03	7.02E-03
DTLZ2	3/ 250	**1.20E-03**	1.26E-03	1.43E-03	1.36E-03
		1.29E-03	1.36E-03	1.59E-03	1.41E-03
		1.82E-03	2.11E-03	2.01E-03	1.91E-03
	5/ 350	4.46E-03	4.25E-03	**4.22E-03**	5.11E-03
		5.09E-03	**4.98E-03**	5.01E-03	5.74E-03
		5.28E-03	5.86E-03	**5.26E-03**	6.13E-03
	10/ 750	**8.45E-03**	1.35E-02	9.42E-03	1.43E-02
		1.07E-02	1.53E-02	1.21E-02	1.64E-02
		1.36E-02	1.70E-02	**1.33E-02**	1.83E-02
DTLZ3	3/ 1000	1.12E-03	**9.75E-04**	9.82E-04	9.91E-04
		2.84E-03	4.01E-03	4.12E-03	3.98E-03
		6.15E-03	6.67E-03	8.76E-03	6.75E-03
	5/ 1000	3.55E-03	**3.09E-03**	3.43E-03	3.28E-03
		6.87E-03	**5.96E-03**	6.21E-03	6.69E-03
		9.85E-03	1.20E-02	1.15E-02	1.18E-02
	10/ 1500	1.10E-02	**8.85E-03**	9.79E-03	9.21E-03
		1.35E-02	**1.19E-02**	2.32E-02	1.84E-02
		1.98E-02	2.08E-02	3.01E-02	2.67E-02
DTLZ4	3/ 600	**2.75E-04**	2.92E-04	9.92E-02	3.67E-03
		5.68E-04	5.97E-04	3.81E-01	5.89E-02
		2.35E-03	4.29E-01	5.66E-01	3.62E-01
	5/ 1000	**5.86E-04**	9.85E-04	9.28E-02	3.65E-02
		1.33E-03	**1.26E-03**	4.96E-01	2.17E-01
		4.06E-03	**1.72E-03**	7.55E-01	5.24E-01
	10/ 2000	3.54E-02	**5.69E-03**	3.56E-01	9.62E-02
		3.87E-02	**6.34E-03**	8.22E-01	2.52E-01
		4.25E-02	1.08E-01	9.28E-01	5.23E-01
WFG6	3/ 400	6.83E-03	**4.83E-03**	1.23E-02	8.42E-03
		1.11E-02	1.22E-02	4.13E-02	2.08E-02
		4.93E-02	5.49E-02	9.88E-02	6.21E-02
	5/ 750	**3.99E-03**	5.07E-03	8.57E-03	7.54E-03
		1.65E-02	1.97E-02	4.62E-02	2.13E-02
		2.88E-02	4.47E-02	9.01E-02	8.77E-02
	10/ 2000	2.05E-02	1.06E-02	**9.98E-03**	1.86E-02
		2.24E-02	2.49E-02	4.33E-02	5.13E-02
		4.12E-02	6.13E-02	9.23E-02	1.24E-01
WFG7	3/ 400	3.99E-03	**2.79E-03**	1.13E-02	9.84E-03
		4.77E-03	**3.69E-03**	1.56E-02	1.31E-02
		6.74E-03	**4.79E-03**	1.97E-02	1.84E-02
	5/ 750	1.26E-02	**8.25E-03**	8.88E-03	9.99E-03
		1.74E-02	**9.11E-03**	1.07E-02	1.81E-02
		3.25E-02	**1.05E-02**	1.25E-02	4.51E-02
	10/ 2000	**2.56E-02**	3.23E-02	3.04E-02	3.62E-02
		3.68E-02	4.29E-02	4.22E-02	5.34E-02
		9.98E-02	9.07E-02	**6.49E-02**	8.68E-02
	3/ 400	**3.82E-04**	4.81E-04	7.87E-04	9.41E-04
		1.13E-03	1.29E-03	2.48E-03	3.51E-03
		8.92E-03	9.81E-03	1.21E-02	1.87E-02

TABLE 2. *(Continued.)* Best, median and worst IGD values obtained by MOTA to different algorithms on multi-objective DTLZ1–4, WFG6-7 and SDTLZ1–2 problems. Best performance is shown in bold.

SDTLZ1	5/ 600	**9.42E-04**	1.05E-03	1.45E-03	1.93E-03
		2.18E-03	2.44E-03	2.95E-03	3.37E-03
		3.87E-02	4.12E-02	5.11E-02	6.28E-02
	10/ 1000	4.51E-03	**3.56E-03**	4.56E-03	5.54E-03
		5.29E-03	5.82E-03	6.37E-03	8.87E-03
		2.69E-02	2.97E-02	3.82E-02	6.31E-02
SDTLZ2	3/ 250	**1.31E-03**	1.68E-03	1.89E-03	3.61E-03
		2.15E-03	2.37E-03	2.66E-03	6.12E-03
		4.31E-03	4.91E-03	5.42E-03	9.42E-03
	5/ 350	**1.09E-02**	1.21E-02	1.56E-02	2.97E-02
		2.92E-02	**2.81E-02**	3.01E-02	5.96E-02
		7.88E-02	7.69E-02	**6.79E-02**	8.84E-02
	10/ 750	**2.69E-02**	2.92E-02	2.82E-02	2.97E-02
		3.36E-02	3.54E-02	3.69E-02	5.12E-02
		1.64E-01	1.87E-01	**9.21E-02**	1.62E-01

TABLE 3. Performance comparison of MOTA to different algorithms with respect to the average HV values on DTLZ1–4, WFG6-7 and SDTLZ1–2 problems. Best performance is shown in bold.

Problem	Obj/ Max Gen	MOTA	NSGAIII	MOEA/D -PBI	dMOPSO
DTLZ1	400	**1.118113**	1.117735	1.116581	1.075172
	600	**1.577409**	1.577031	1.577342	1.482581
	1000	**2.592969**	2.592803	2.592318	2.317789
DTLZ2	250	**0.744221**	0.744029	0.744095	0.712682
	350	1.303845	1.303688	**1.307148**	1.224821
	750	2.513962	2.508717	**2.515123**	2.429022
DTLZ3	1000	**0.739035**	0.737425	0.736128	0.665783
	1000	**1.307266**	1.301496	1.303256	1.252318
	1500	**2.511209**	2.508879	2.406869	2.107332
DTLZ4	600	0.744357	**0.744674**	0.407024	0.678021
	1000	1.308021	**1.308903**	1.205641	1.203542
	2000	2.514897	**2.515172**	2.423213	2.438538
WFG6	400	**0.689812**	0.686012	0.654254	0.657863
	750	**1.223401**	1.219088	1.041545	1.116614
	2000	**2.332613**	2.326798	0.811654	1.189546
WFG7	400	0.724052	**0.729641**	0.619345	0.589631
	750	1.291994	**1.292018**	1.073123	0.992531
	2000	**2.508763**	2.507693	0.950453	1.154362
SDTLZ1	400	**1.118021**	1.116023	0.332534	0.470223
	600	**1.578823**	1.575525	0.556354	0.233464
	1000	**2.588195**	2.587997	2.068656	1.378456
SDTLZ2	250	**0.746521**	0.743277	0.210463	0.205541
	350	**1.293511**	1.290520	0.251436	0.246845
	750	**2.506039**	2.504209	0.486876	0.584456

under the condition of three objectives and the NSGAIII algorithm is better than algorithm under the condition of five and ten objectives. From the HV test index in Table 4, it can be analyze that in the DTLZ1, DTLZ3, WFG6, SDTLZ1,

TABLE 4. Typical schemes for multi-objective optimal operation rules.

Scheme	Hydropower generation (10^7MW.h)	Ecological water deviation (10^9m^3)	Navigation guarantee rate
1	**4.8602**	**10.048**	**0.920**
2	**4.8601**	**10.176**	**0.930**
3	4.8592	9.886	0.923
4	4.8586	9.873	0.901
5	4.858	9.949	0.925
6	4.8575	9.759	0.884
7	4.8574	9.796	0.906
8	4.8573	9.852	0.920
9	4.857	9.699	0.873
10	4.8564	9.671	0.881
11	4.8559	9.719	0.895
12	4.8551	9.541	0.859
13	4.8548	9.757	0.923
14	4.8545	9.563	0.879
15	4.8539	9.708	0.909
16	4.8537	9.624	0.898
17	4.8536	9.609	0.884
18	4.8531	9.473	0.847
19	4.8522	9.479	0.865
20	4.8516	9.719	0.923
21	4.8507	9.529	0.899
22	4.8503	9.433	0.872
23	4.8501	9.459	0.889
24	4.8498	9.398	0.881
25	4.8497	9.644	0.916
26	4.8494	9.567	0.915
27	4.8483	9.372	0.858
28	4.8482	9.515	0.91
29	4.8479	9.447	0.901
30	4.8476	9.406	0.900
31	4.8472	9.333	0.854
32	4.8471	9.355	0.874
33	4.8468	9.314	0.863
34	4.8466	9.405	0.890
35	4.8451	9.362	0.889
36	4.8435	9.314	0.879
37	4.8410	9.293	0.837
38	4.8406	9.259	0.830
39	4.8401	9.272	0.854
40	**4.8387**	**9.236**	**0.838**

SDTLZ2 test function the MOTA algorithm is better than other algorithms. MOTA algorithm inferior performs other algorithms on DTLZ2, DTLZ4, WFG7 problems. In conclusion, MOTA algorithm is a strong competitive multi-objective algorithm, which can be used to solve the practical problem in this paper.

IV. CASE STUDY

A. TOPOLOGY STRUCTURE OF STUDY AREA

Taking cascade reservoirs in China's Pearl River System as a study case, this paper determines optimal operation rules to operate scheduling the water volume of reservoirs. The study area is shown in Figure 3. Each reservoir in the study area has the function of hydropower generation, and some reservoirs have the function of navigation and ecology. In terms of reservoir regulation capacity, I, II and IX are annual regulating reservoirs, and others are diurnal regulating reservoirs. The topology structure of cascade reservoirs is shown in Figure 4.

B. ENCODING PROCESS OF THE MODEL

Through the simulation scheduling of 60 years observed historical inflow data (1956-2015), the optimal operation rules of cascade reservoirs are obtained. The optimal operation rules provide a reference for the planning and management of the cascade reservoirs. The optimal operation rules of the annual regulation reservoir (I, II, IX) are presented by scheduling diagrams of reservoir, as shown in Figure 5. Taking the month as the X-axis, the water level as the Y-axis, draw six schedule lines. From the top to the bottom, the schedule lines are the normal water level, level of flood control, the line of increase hydropower output, the line of guarantee hydropower output, the line of reduce hydropower output and dead water level. Since the normal water level, the level of flood control and the dead water level of each reservoir have been determined at the time of reservoir design, it is necessary to optimize the position and shape of the other three lines. In the optimization process of each reservoir, each schedule line includes two variables of water level in flood season and non-flood season, and four time variables of starting and ending time of flood season and non-flood season. Its encoding mode includes 4 time variables and 6 water level variables as shown in Figure 5. Therefore, the three reservoirs have a total of 30 variables.

In addition to satisfying the reservoir constraints, the schedule diagram also needs to meet the following constraints:

(1) Time constraints.

$$t_{i,1} < t_{i,2} < t_{i,3} < t_{i,4} \tag{16}$$

(2) Constraints of each schedule line.

$$x_{i,1} > x_{i,2}\ ,\ x_{i,3} > x_{i,4}\ ,\ x_{i,5} > x_{i,6} \tag{17}$$

(3) Constraints between upper and lower schedule lines.

$$x_{i,1} > x_{i,3} > x_{i,5},\ x_{i,2} > x_{i,4} > x_{i,6} \tag{18}$$

V. RESULTS AND DISCUSSION

A. RESULTS

According to the historical inflow data of cascade reservoirs in the Pearl River System from 1956 to 2017, the proposed

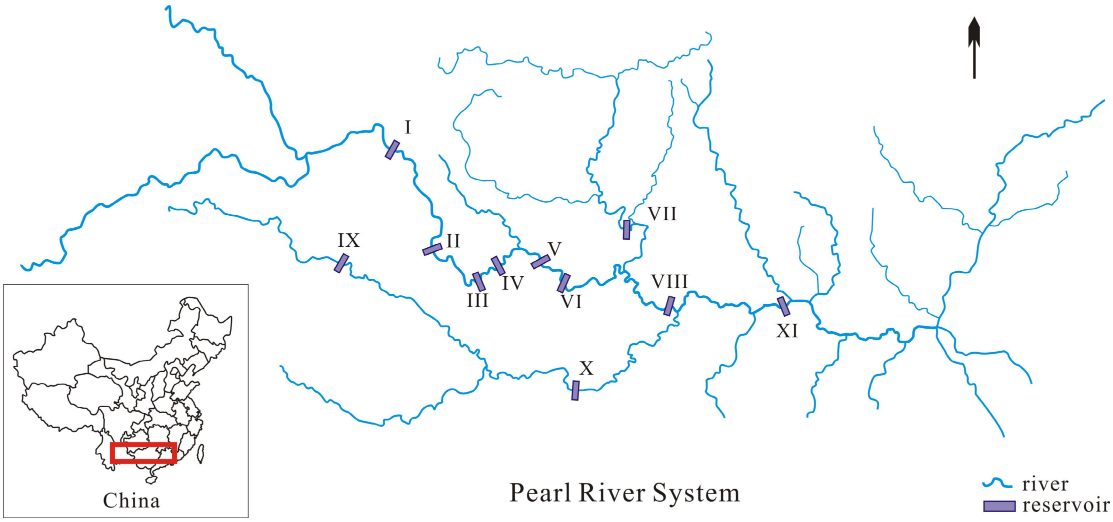


FIGURE 3. Study area.

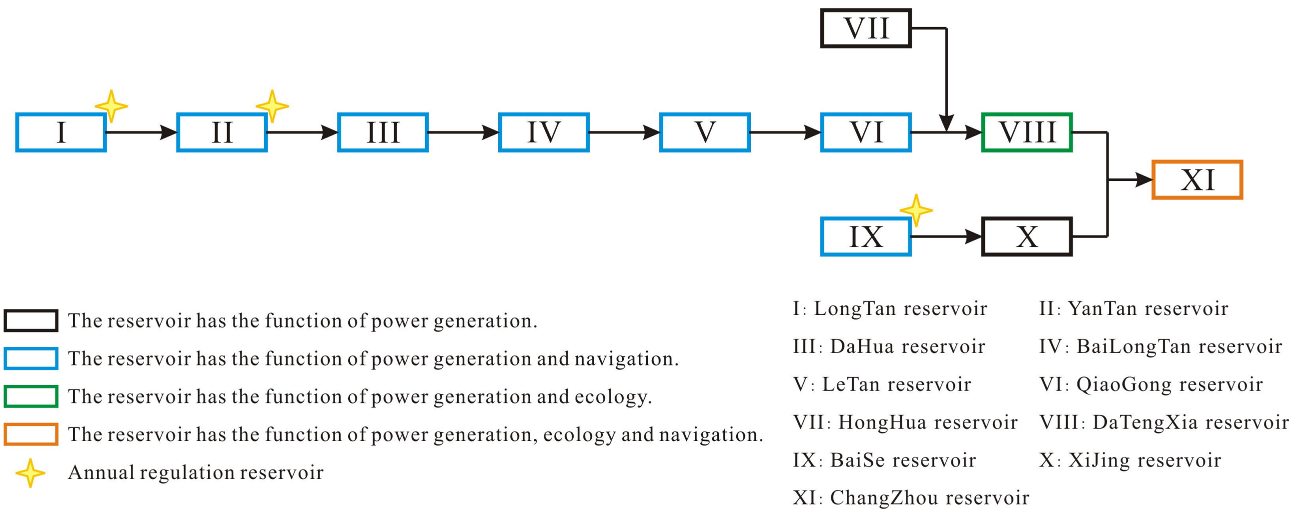
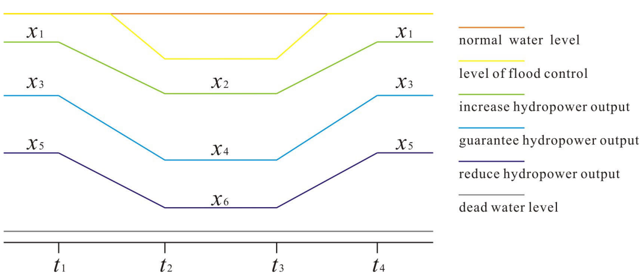


FIGURE 4. Topology structure of cascade reservoirs.



(d) DTLZ4

FIGURE 5. Diagram of optimization encoding.

MOTA algorithm is used to solve the multi-objective optimal operation rules. The algorithm parameters are set as follows: the population size of the algorithm is set to 92, the number of reference points is set to 91, the archive population size of the algorithm is set to 40, the number of iterations is set to 1000 generations, the mutation rate is set to 0.05 and the mutation index is set to 20. The results of the MOTA are shown in Figure 6 and Table 4.

The 3D view of the Pareto frontier of the optimal operation rules solved by the MOTA algorithm is shown in Figure 6(a). It can be seen that the distribution of the entire Pareto front is very uniform, which is reflected by the superiority of the MOTA algorithm. The projection of the Pareto front on any two objectives is represented in Figure 6(b), Figure 6(c) and Figure 6(d), respectively.

As can be seen from the Figure 6(b), the objective of annual average power generation (P) is proportional to the objective of ecological water deviation (W). In the Pareto solution, increasing the annual average power generation (P) of the cascade reservoirs in Pearl River will lead to the increase of ecological water deviation (W). This shows that

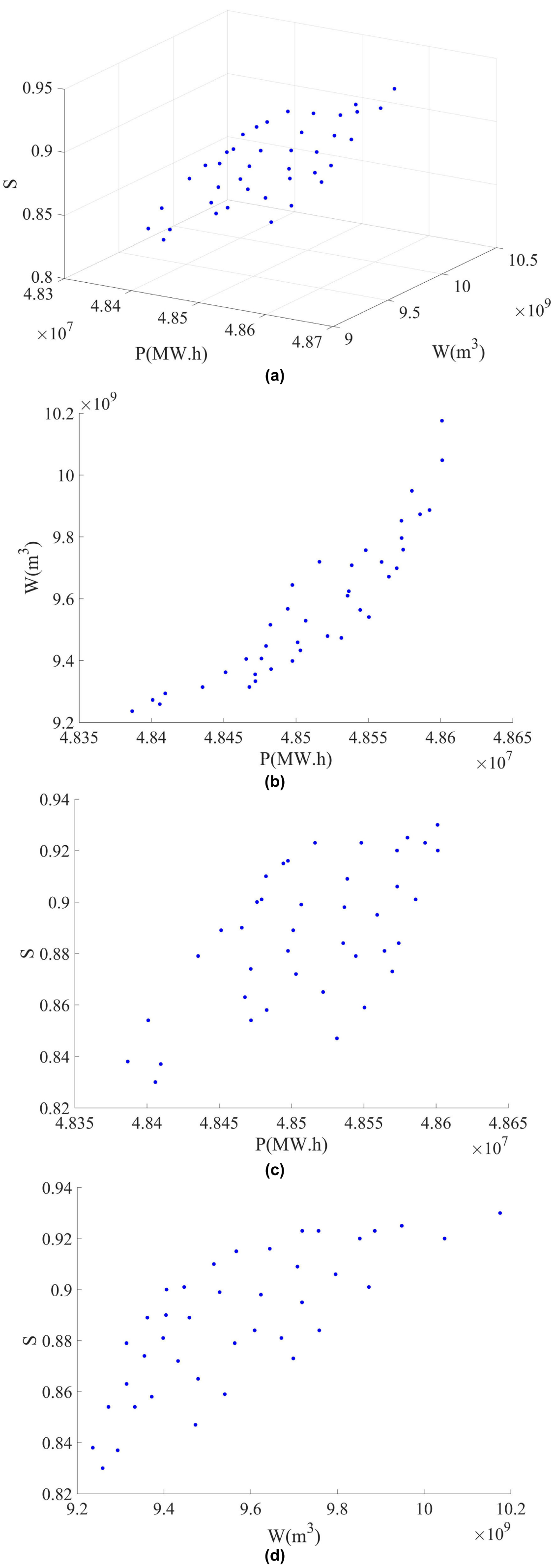


FIGURE 6. Obtained solutions by MOTA for multi-objective optimal operation rules.

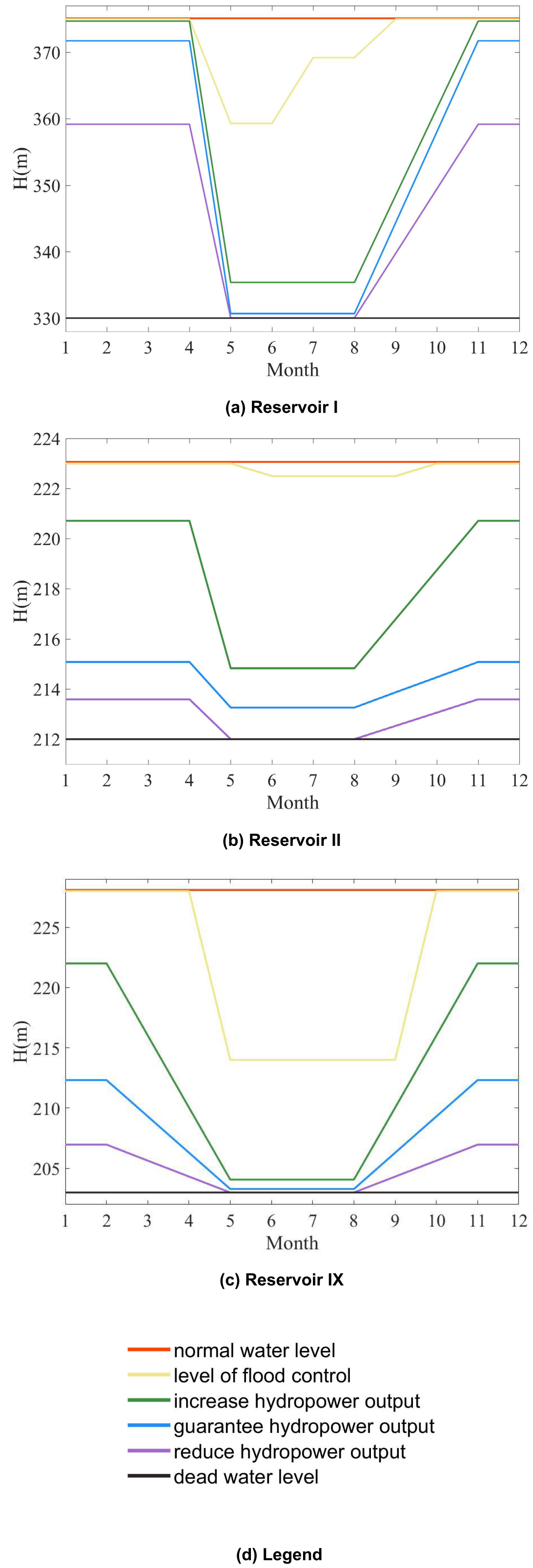


FIGURE 7. Optimal operation rules of Scheme 1.

the conflicting relationship between hydropower generation benefits and ecological benefits of the reservoirs in the Pearl River System. Increasing hydropower generation will destroy the ecological environment of the downstream rivers, it causes the eco-crisis.

As can be seen from the Figure 6(c), the objective of annual average power generation (P) is proportional to the objective

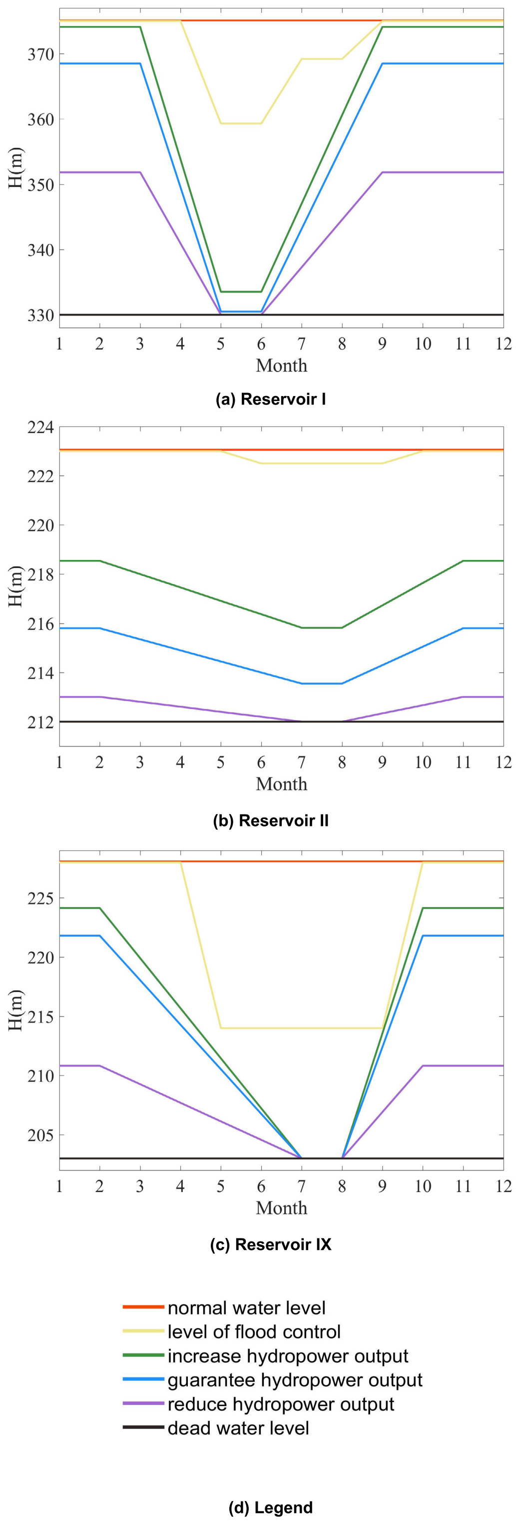


FIGURE 8. Optimal operation rules of Scheme 2.

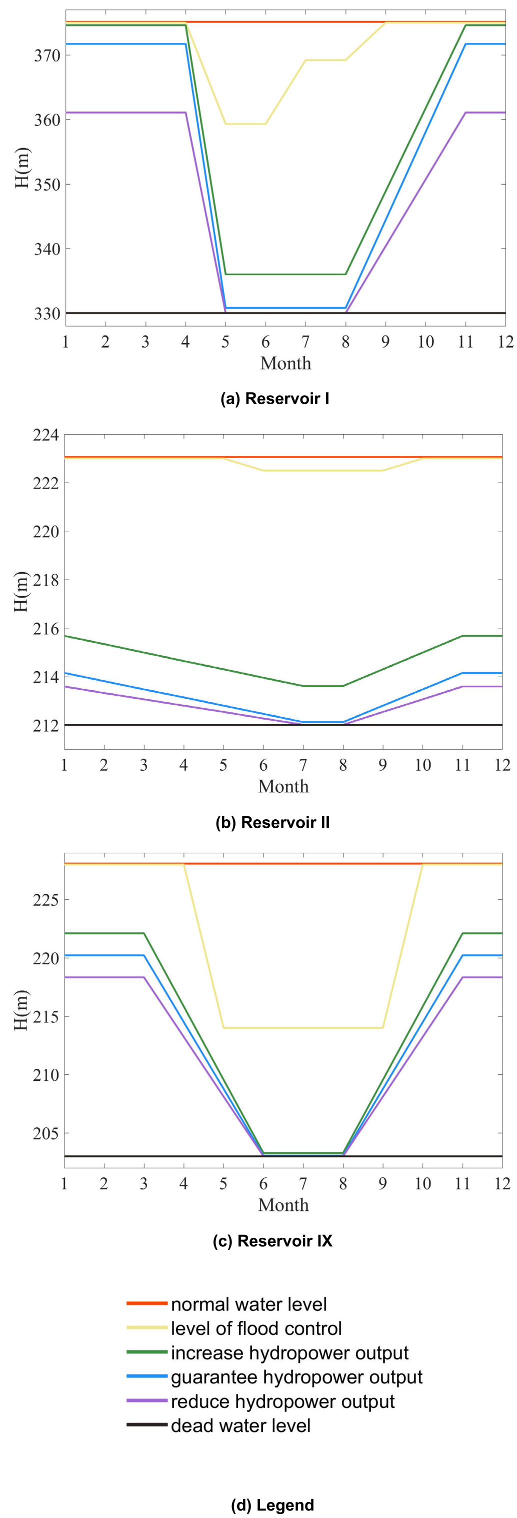


FIGURE 9. Optimal operation rules of Scheme 40.

of navigation guarantee rate (S). This shows that increase the hydropower generation benefits of the cascade reservoirs in Pearl River, the navigation benefits will also increase. In the Pareto solution, there are some schemes in which both the annual average power generation and the navigation guarantee rate are superior.

As can be seen from the Figure 6(d), the objective of ecological water deviation (W) is proportional to the objective of navigation guarantee rate (S). This shows that reduce the

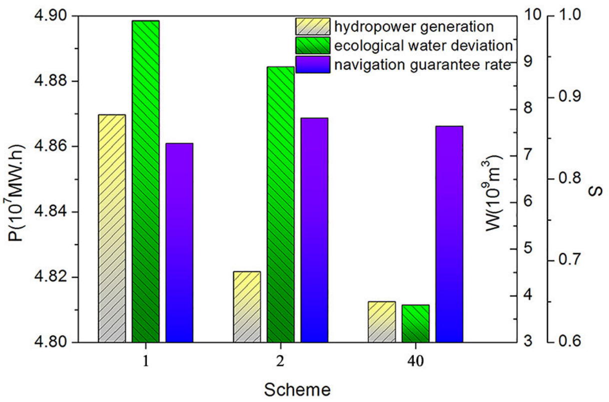


FIGURE 10. Comparison of the results of the three schemes under the three objectives.

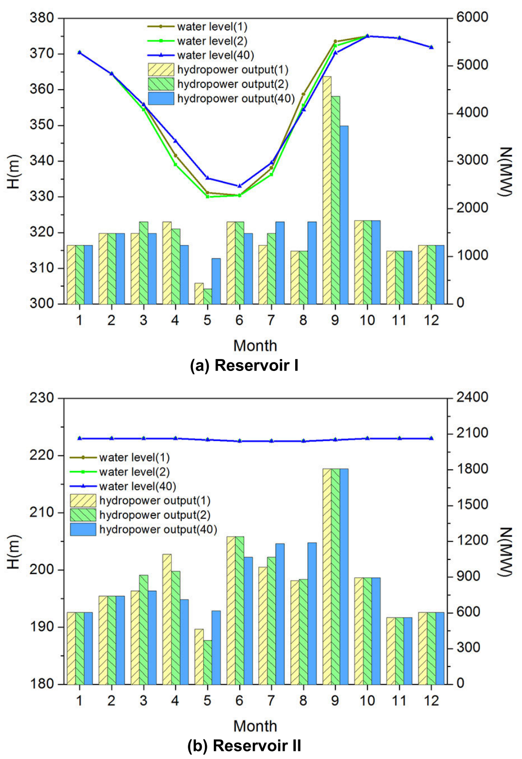


FIGURE 11. The relationship between water level and hydropower output under three schemes.

ecological benefits of the cascade reservoirs in Pearl River, the navigation benefits will also reduce. This is because the upper and lower limits of the navigable discharge are generally different from the upper and lower limits of the ecological flow. It is very difficult to receive the best scheduling scheme with better ecological benefits and navigation benefits.

Table 4 shows a comparison of the 40 different optimal operation rules for the Pareto front on three objectives. In the scheme, the annual average power generation exhibits advantages in scheme 1, the ecological water deviation exhibits advantages in scheme 40 and navigation guarantee rate exhibits advantages in scheme 2. Finally, the paper draws schedule diagrams for the three scheduling schemes, as shown in Figure 7, Figure 8 and Figure 9.

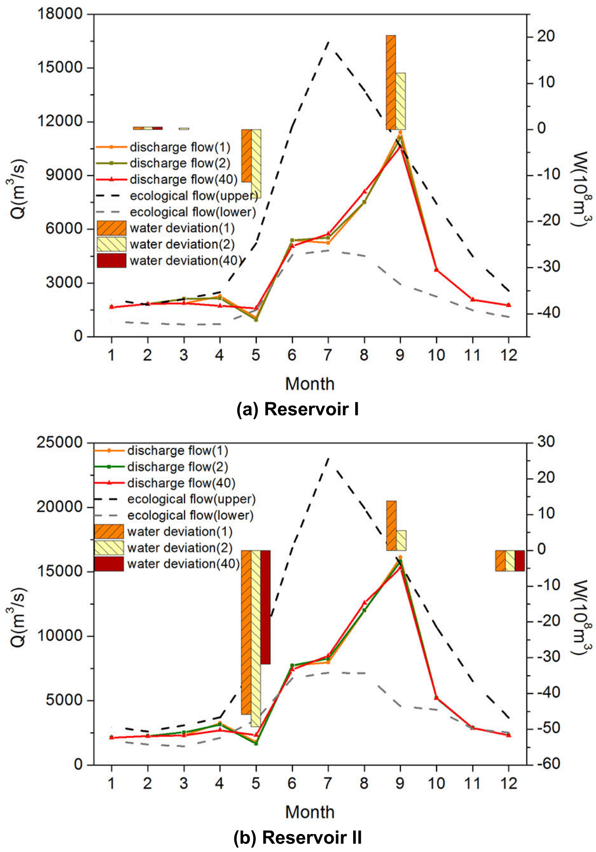


FIGURE 12. The relationship between discharge flow and Ecological water deviation under three schemes.

B. DISCUSSION

In order to deeply analyze the relationship between each objective, the inflow data for each reservoir in 2016 selected to validate schedule diagrams. Scheme 1, scheme 2 and scheme 40 are used for simulation scheduling, and the overall comparison of the three schemes is shown in Figure 10. As can be seen from the Figure 10, it has achieved an advantage in the optimal objective of hydropower generation in scheme 1, and its hydropower generation is $4.8697*10^7$MW.h. It is higher than the other two schemes of $4.8217*10^7$MW.h and $4.8126*10^7$MW.h. It has achieved an advantage in the optimal objective of navigation guarantee rate in scheme 2, and its navigation guarantee rate is 0.875. It is higher than the other two schemes of 0.844 and 0.865. It has achieved an advantage in the optimal objective of ecological water deviation in scheme 40, and its ecological water deviation is $3.8053*10^9m^3$. It is higher than the other two schemes of $9.8983*10^9m^3$ and $8.9113*10^9m^3$.

Under the conditions of scheme 1, scheme 2 and scheme 40, the water level and hydropower output of the annual regulation reservoir (reservoir I and reservoir II) were analyzed and compared in this paper. As can be seen from the Figure 11, the difference in the value of water level and hydropower output mainly occurs in the flood season under three different schemes. Among them, the reservoir I occurred in March-September, and the reservoir II occurred in March-August. In September, hydropower output is at most in reservoir I and reservoir II under three schemes, of which scheme 1 is larger than other schemes. As can be seen from the Figure 11(b), the water level changes very little in the reservoir II under three schemes. The main reason for the change in the hydropower output is that the discharge is different in the reservoir I, resulting in a difference in the inflow from the reservoir II.

In the meanwhile, under the scheme 1, scheme 2 and scheme 40, the discharge and ecological water deviation of the reservoir (reservoir VIII and reservoir XI) which is satisfy the ecological demand of water were analyzed and compared in this paper. As can be seen from the Figure 12, the ecological shortage water mainly occurs in the river in May and the ecological overflow mainly occurs in the river in September. The ecological overflow is not occurred in September in scheme 40. Overall, the annual ecological water deviation is lower in scheme 40 and higher in scheme 1.

VI. CONCLUSION

It is complex to obtain optimal operation rules for cascade reservoirs, which involves with challenges including various decision variables, multiple conflicting objectives and constraints. This paper proposes model of optimal operation rules for cascade reservoirs and strive to make the most of the comprehensive benefits of hydropower generation, ecology and navigation. A new algorithm named multi-objective tangent algorithm (MOTA) is proposed to solve the problem. The performance of MOTA is validated through some well-known benchmark problems. Then, MOTA is applied to a case study of cascade reservoirs optimization in China's Pearl River System. The experimental results show that MOTA obtains a Pareto front composed of forty operation rules, reflecting the comprehensive benefits of hydropower generation, ecology and navigation in China's Pearl River System.

The following points can be concluded from the Pareto front composed of forty operation rules: (a) In the Pareto solution, increasing the hydropower generation benefit will lead to reduce the ecology benefit. (b) In the Pareto solution, there are some schemes in which both the hydropower generation benefit and the navigation benefit are superior. (c) In the Pareto solution, increasing the ecology benefit will lead to reduce the navigation benefit. The optimal operation rules can be used as a guidance tool for decision makers, through the objectives' tradeoff without having to embed a priori preferences in the decision process. Finally, this paper use observed inflow data (2016) of cascade reservoirs for examining the operational rule to comprehend the analysis under different optimal operation rules. It is necessary to use MOTA for generating optimal operation rules to optimize comprehensive benefits of cascade reservoirs, which has profound guidance meaning for cascade reservoirs planning and management.

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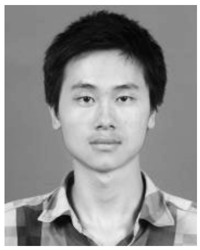

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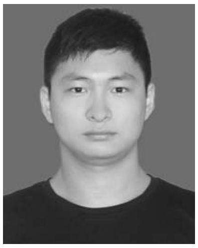

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