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The multi-objective operation for cascade reservoirs using MMOSFLA with emphasis on power generation and ecological benefit

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ABSTRACT

To efficiently develop power generation and solve downstream ecological health protection in Qingjiang basin, multi-objective ecological operation for cascade reservoirs (MOEOCR) model is established in contrast to conventional models that set ecological water requirement as constraint. The basic, suitable and ideal ecological water requirements in Geheyan and Gaobazhou sections are calculated using a requirement level index. Instead of the traditional evolution mode based on population, we introduce a shuffled frog leaping algorithm (SFLA) which evolves independently in sub-populations. Moreover, the SFLA is converted into a modified multi-objective algorithm (MMOSFLA) with strategies including chaotic population initialization, renewed frog grouping method and local search method, and elite frog set evolution based on cloud model. The water level corridor is used to help effectively handle complex constraints. The IGD and GD indexes are used to evaluate quality of solutions acquired by each method. In terms of normal year, the mean IGD and GD of MMOSFLA are 1.2×10^{-1} and 2.75×10^{-2}, respectively. The scheduling results verify efficient search ability and convergence performance in solution diversity and distribution in comparison with other methods. Therefore, MMOSFLA is verified to provide an effective way to fulfill hydropower and ecological benefits facing the MOEOCR problem.

Key words | chaotic population initialization, cloud model, ecological water requirement, elite frog set evolution, modified multi-objective algorithm (MMOSFLA), multi-objective ecological operation

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INTRODUCTION

Reservoir operation and management have played very considerable roles in flood control, electricity generation, water supply and navigation (Wu *et al.* 2012). Conventional reservoir operation predominantly focuses on maximizing social-economic benefits and addresses ecosystem values only as the constraints on reservoir release and elevations (Jager & Smith 2010; Labadie 2014). With the increasing ecological protection awareness and substantial deterioration in the ecological environment, there is now widespread recognition that water resources management must take account of the vulnerability of ecosystems. Accordingly, the multi-objective reservoir scheduling considering ecological factors has attracted much attention (Mao *et al.* 2016). Vogel *et al.* (2007) designed an ecological flow regime to capture the natural flow variability for maintaining the functional integrity of aquatic ecosystems. In China, increasing attention has also been focused on economical benefit and ecosystem health (Cai *et al.* 2013; Hu *et al.* 2014). In traditional reservoir operation, ecological requirements are typically addressed by meeting certain constraints of minimum instream flow

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(Castelletti et al. 2008). Later, a multi-objective ecological operation for reservoirs with the objective of ecological water requirements has been developed to coordinate conflicting objectives. Currently, the multi-objective ecological operation for cascade reservoirs (MOEOCR) is still challenging as the competitive objectives are difficult to reconcile and the problem is often non-convex, non-linear, multi-dimensional and discontinuous, making it harder to optimize.

Historically, multi-objective problems were solved with conventional methods such as linear programming (LP), nonlinear programming (NLP), dynamic programming (DP) and progress optimality algorithm (POA), through converting the multi-objective problem into a single objective (Feng et al. 2017). For ecological operation problems, the ecological factors and objective could be converted into constraints of ecological water demand for aquatic species or arranged weight to describe their importance. Li (2016) gives corresponding weights to target of power generation, flood control and ecology, and adopts a genetic algorithm to optimize the multi-objective Longyangxia Reservoir operation. Kang et al. (2010) established an ecological scheduling model of Danjiangkou Reservoir and used the POA method to solve it. Yin et al. (2013) and Long & Mei (2017) took cascade reservoirs located in downstream Jinsha River as a case study, and analyzed the reservoir scheduling scheme under different ecological flow constraints. Yang et al. (2015) built the cascade reservoirs scheduling model that is coupled with modified DP. Optimization is achieved based on analyzing the relationship between power generation and ecological flow. Although massive computation can be avoided in most cases, there are such issues as sensitivity to transformation coefficients, and difficulty to obtain trade-off solutions (Zhang et al. 2013).

Due to the presence of the multiple objectives, it is difficult to find a single optimal solution that optimizes all goals with a conventional single-objective method. Instead, multiple solutions exist in the form of trade-offs, also referred to as Pareto optimal solutions. After identifying the trade-offs, the Pareto optimal solutions are ranked to enable decision makers to select the best scheduling solution (Zhu et al. 2017). In recent years, intelligent algorithms and multi-objective optimization techniques have been applied to the hydrology area, including reservoir operation (He et al. 2014; Luo et al. 2015a, 2015b; Jia et al. 2016; Moazenzadeh et al. 2018). Both Lu et al. (2011) and Wang et al. (2013) optimized the target with the minimum ecological water shortage and maximum power generation, and the multi-objective differential evolution method was adopted to solve the problem. Zhang et al. (2016) proposed the ecological scheduling model based on the ecological flow interval, and optimized multiple objectives including power generation, corresponding guarantee and ecological guarantee rate by NSGAII. Reddy & Kumar (2006, 2007) employed the multi-objective genetic algorithm (MOGA) and particle swarm to generate a pareto optimal set for a multi-objective reservoir system that serves multiple purposes including irrigation, power generation, and downstream water quality requirements in India. Li & Qiu (2016) put forward a multi-objective reservoir optimization model incorporating ecological adaption and applied this model (using NSGAII) to the Three Gorges Reservoir, the operation of which has damaged the downstream ecosystem. However, to our knowledge, few papers are concerned with the multi-objective reservoir ecological operation problem using the meta-heuristic method. Moreover, the studies mainly focus on the single reservoir ecological operation. In view of complex constraints and targets for large cascade reservoirs compared with a single reservoir, it is more difficult to find an optimal trade-off ecological scheduling solution. The algorithms above, including the NSGA, MOGA, MOEA and MODE, accomplish the evolution and update process based on advantages of the entire population (this means that individuals are updated together in the population community). The evolution information obtained by each individual is from the best individual in the population. The Shuffled Frog Leaping Algorithm (SFLA), by contrast, divides the population into several communities. Individuals in each community are permitted to develop independently. The new population will form through the shuffling strategy after a defined number of iterations. This evolution pattern helps improve the solution by sharing information independently obtained by each community rather than the single information from the entire community.

The SFLA was first proposed by Eusuff & Lansey (2003). It is a memetic meta-heuristic method that is developed to seek global optimal solution by performing an informed heuristic search with a heuristic function (Eusuff & Lansey 2003). The SFLA is a combination of deterministic and stochastic methods which was initially applied into the optimization of a water network distribution design. The deterministic method allows algorithms to effectively use response information to guide a heuristic search, while the stochastic element in SFLA ensures flexibility and robustness of the search patterns. It is found that SFLA can perform the search towards a global optimum using global information exchange and internal communication mechanisms (Sun *et al.* 2016). The SFLA, which is easy and convenient to code with less control parameters, is testified compatible with handling comprehensive optimization problems including the non-linear and high dimensional discrete systems (Cao 2014; Li & Yin 2014).

Qingjiang River is the largest tributary of the middle Yangtze River. Following increasing concerns for ecology health in the downstream watershed dramatically influenced by reservoirs, the ecology protection objective should be considered in reservoir operation. For this purpose, the basic, suitable and ideal ecological water requirements downstream of Geheyan and Gaobazhou reservoirs are analyzed based on the requirement level index. Moreover, to coordinate the hydropower and ecological protection benefits, the power generation in the hydropower station and ecological water spill and shortage are selected as competing objectives in the MOEOCR model. Then, the modified multi-objective shuffled frog leaping algorithm (MMOSFLA) is proposed to achieve multiple trade-off solutions (Pareto optimal solutions) for the model. MMOSFLA is a modified version of conventional SFLA which is initially designed to solve the single-objective optimization problem. We accomplish the conversion and performance improvement with strategies such as population initialization update, renewed frog sub-population partition, dynamic maintenance and evolution mechanism for external elite frog set, and local search capability enhancement. Furthermore, the water level corridor combined with a penalty function is used to handle constraints efficiently. Finally, by using the MMOSFLA, we study the optimal trade-off between power generation and ecological water spill and shortage. Scheduling solutions under scenarios of different ecological flow requirements obtained by MMOSFLA is analyzed to demonstrate the practicability and effectiveness of the proposed model and method.

THE MULTI-OBJECTIVE ECOLOGICAL OPERATION MODEL FOR CASCADE RESERVOIRS (MOEOCR)

The multiple objectives contain the maximum power generation for the hydropower station located in the reservoir and the minimum ecological water deficit and spill. Both ecological water spill and shortage can lead to adverse effects on the health and stability of ecology. The two objectives dominate each other and we may find it difficult to acquire the conventional optimal solution. Instead, we can obtain a relative optimal solution set. The objectives are expressed by Equations (1) and (2), respectively.

Objective function

1. Maximum power generation:

$$\begin{aligned} &Max\ f_1 = Max\ E_{LEC} = \sum_{i=1}^{G}\sum_{t=1}^{T} N_{i,t}\Delta t \\ &N_{i,t} = K_i Q_{i,t}^{ELC} H_{i,t} \end{aligned} \tag{1}$$

2. Minimum ecological water spill and shortage:

$$Min\ f_2 = Min\ W_{YS} = \sum_{j=1}^{C}\sum_{t=1}^{T} |Q_{j,out}^{t} - Q_{j,eco}^{t}|\Delta t \tag{2}$$

where E and W_{YS} denote power generation and ecological water spill and shortage; Δt is the scheduling interval; G and T are the total amount of reservoir and scheduling intervals, respectively; C represents the quantity of control cross-section which is matched with the reservoirs; $N_{i,t}$ is the power output of the ith hydropower station at the tth interval; K_i denotes the efficiency coefficient of unit in the ith hydropower station; $Q_{i,t}^{ELC}$ is the power generation flow for the ith reservoir at the tth interval; $Q_{j,out}^{t}$ represents the reservoir water release corresponding to the jth control cross-section; $Q_{j,eco}^{t}$ shows the different levels of ecological water requirements downstream from the reservoir corresponding to the jth control cross-section.

Constraints

1. Water connection of cascade reservoirs:

$$I_{i,t} = Q_{i-1,t-\tau_{i-1}} + L_{i-1,t-\tau_{i-1}} + I_{inflow,i,t} \tag{3}$$

where $I_{i,t}$ and $I_{inflow,i,t}$ are the inflow and local inflow of the ith reservoir at the tth interval, respectively; $Q_{i-1,t-\tau_{i-1}}$ and $L_{i-1,t-\tau_{i-1}}$ denote the water release and surplus water released from the ith reservoir at the $t-\tau_{i-1}$ th interval.

2. Water balance constraint:

$$V_{i,t+1} = V_{i,t} + (I_{i,t} - Q^{out}_{i,t} - L_{i,t}) \cdot \Delta t \tag{4}$$

where $V_{i,t+1}$ and $V_{i,t}$ signify the ith reservoir storage at $t+1$ and the tth interval; $I_{i,t}$, $Q^{out}_{i,t}$ and $L_{i,t}$ are the inflow, water release and surplus water from the ith reservoir at the tth interval, respectively.

3. Hydro-unit output constraint:

$$N^{\min}_{i,t} \le N_{i,t} \le N^{\max}_{i,t} \tag{5}$$

where $N^{\min}_{i,t}$ and $N^{\max}_{i,t}$ are the minimum and maximum hydro-unit output of the ith reservoir at the tth interval.

4. Reservoir water level constraint:

$$Z^{\min}_{i,t} \le Z_{i,t} \le Z^{\max}_{i,t} \tag{6}$$

where $Z^{\max}_{i,t}$ and $Z^{\min}_{i,t}$ denote the upper and lower bounds for the ith reservoir water level.

5. Reservoir storage and water discharge constraints:

$$\begin{cases} V^{\min}_{i,t} \le V_{i,t} \le V^{\max}_{i,t} \\ Q^{\min}_{i,t} \le Q_{i,t} + L_{i,t} \le Q^{\max}_{i,t} \end{cases} \tag{7}$$

where $V^{\min}_{i,t}$ and $V^{\max}_{i,t}$ are the minimum and maximum reservoir storage volume of the ith reservoir. $Q^{\min}_{t}$ and $Q^{\max}_{t}$ denote the minimum and maximum water discharge. $Q_{i,t}$ and $L_{i,t}$ are water release and surplus water at the tth interval.

THE MODIFIED MULTI-OBJECTIVE SHUFFLED FROG LEAPING ALGORITHM (MMOSFLA)

The traditional single-objective SFLA

Inspired by foraging behavior of frogs in the swamp, the SFLA is a metaheuristic optimization which adopts particle swarm intelligence (PSO) as a local search tool and the idea of competitiveness and mixing information from parallel local searches to gradually approach global optima from the shuffled complex evolution (SCE) (Duan *et al.* 1992).

The frog population is partitioned into a number of parallel sub-populations called memeplexes, of which frogs move toward the prey and exchange ideas independently, i.e. memetic evolution. Frogs in each sub-population or memeplex can be seen as potential feasible solutions and are impacted by ideas of other frogs (Eusuff & Lansey 2003; Zou *et al.* 2012). Information is exchanged between memeplexes in a shuffling process after a number of memetic evolutions, and the best ideas are passed down. The details of SFLA are shown below:

Step 1. The frog population initialization and objective function fitness of each frog calculation.

Step 2. Frogs are ranked in descending order according to the fitness quality.

Step 3. The frogs are grouped into P sub-populations which contain $\underline{n}$ frogs. In the first round, the frogs are divided into sub-populations one by one until the mth frog is grouped in the mth sub-population. Then, the $(m+1)$th frog is grouped in the first sub-population and so on (Sun *et al.* 2016). The rest of the frogs adopt the same measure to accomplish the grouping.

Step 4. The local search is activated to update the worst frogs in all sub-populations in line with frog leap step and position equations:

$$d_i = rand\ () * (\mathrm{u_b} - \mathrm{u_w}) \tag{8}$$

$$u'_w = u_w + d_i, \quad d_{\min} \le d_i \le d_{\max} \tag{9}$$

where the *rand*() generates random number in the interval [0,1] which presents uniform distribution; d_i is frog leap step, $i = 1,2,3 \ldots m$; $d_{\min}$ and $d_{\max}$ are the lower and upper bounds of the frog leap step, respectively; u_b and u_w

correspond to the best and worst frog position in each sub-population, respectively; u'_w is the updated worst frog position.

Step 5. If the new position of the worst frog is better than before, the new position will eliminate the worst one. Otherwise, the u_b in Equation (8) is replaced by the overall best frog position u_g to produce a new frog position. If the new position is still incapable of improving the position quality, a random frog position is generated for the worst frog. After predefined iterations are finished in all sub-populations, the whole population is mixed in the shuffling process to realize the information exchange and transmission in all sub-populations or memeplexes (Luo *et al.* 2015a, 2015b; Yang *et al.* 2018).

The multi-objective SFLA realization and modification

Conventional SFLA is incapable of handling multiple competing targets. Moreover, conventional multi-objective methods such as MOEAs, MOEAD and MOPSO may have deficiencies in optimization strategies. For example, the performance of most MOEAs is alleviated as the number of conflicting objectives increases. MOEAD guides the evolution based on the uniformly distributed weight vectors. However, a uniform weight vector on the unit hyper plane cannot guarantee the uniform distribution of solutions. For the MOPSO, the best local guide for each particle of the population from Pareto-optimal solutions is selected inefficiently. Thus, the concepts such as non-dominant relation, external elite frog set, and crowding distance are introduced to convert SFLA into MMOSFLA. In addition, improvements are proposed to further strengthen the capability of multi-objective problem optimization.

The population initialization based on chaos theory

The initialization process has significant effects on population diversity and quality. The population initialization in evolutionary multi-objective methods including the MOEA, MOPSO, MOGA and SFLA is accomplished through the random guided search strategy. However, random initialization makes algorithms difficult to quickly locate a feasible solution zone and consume a large amount of computer resources to eliminate worst solutions later.

A chaos theory possesses properties of inherent stochasticity and ergodicity, which is highly sensitive to a given initial value and is easy to escape from local optimum (Zou *et al.* 2016). It is confirmed by Cheng *et al.* (2008) that the distribution diversity and homogeneity of the initial population can be improved by chaos initialization. To promptly locate a feasible search zone and improve computation efficiency, the modified chaotic logistic mapping developed in Equation (10) is applied to strengthen the overall population quality during the initialization process:

$$X^j_{t+1} = 1 - 2(X^j_t)^2 \ \mathrm{t} \ = \ 1,\ 2\ldots \mathrm{t}_{\max} \tag{10}$$

where t is the current tth iteration; $t_{\max}$ is the maximum iterations predefined; j represents the chaotic variable dimension, i.e. the dimension of the optimization problem; variable X^j_t is described as the jth chaos variable after the tth iteration, sliding in the interval [–1,1]. It distributes more uniformly in comparison to the conventional method.

The details of chaotic initialization are as follows:

1. Ensure the frog population scale; set $t = 0$ and generate initial chaos variable $X_0 = (X^1_0, X^2_0, X^3_0, \ldots .X^j_0)$.
2. Produce chaos variable X^j_t (the number of variables is $O{*}\mathrm{M}$ and O represents the optimization target amount).
3. When the chaotic sequence X^j_t is created according to Equation (10), we need to map X^j_t to the feasible zone of optimization variable $[H_{\min,j}, H_{\max,j}]$. The specific mapping method is shown in Equation (11):

$$H^j_t = \frac{(X^j_t + 1)}{2} {*} (H_{\max,j} - H_{\min,j}) + H_{\min,j} \tag{11}$$

   where $H_{\min,j}$ and $H_{\max,j}$ are the lower and upper bounds of the optimization variable.
4. Calculate the objective function value of H^j_t and make a judgment on the non-dominant relation to select the best Mth non-dominant solutions (chaos variable) for the initial frog population.
5. Terminate the chaos search until the predefined iterations are accomplished and obtain the final initial population.

Elite frog set maintenance and update

As the Pareto optimal solution set, the main function of the elite frog set is to save the non-dominated solutions in each iteration. The frogs in the elite frog set are not involved in population evolution. However, these frogs are devoted to guiding and correcting the evolution direction of the entire population. In the process of frog iteration, if the original frog and new elite frog display the non-dominant relationship, both frogs are included in the elite frog set for an alternative optimal solution. The details of update mechanism are as follows:

1. The alternative frog will be added directly to the elite frog set in the case where that frog set is empty.
2. The new alternative frog will be listed into the elite set if it dominates the current frogs in the set. The frogs which are dominated by the new frog will be deleted.
3. The elite frog set grows in size based on iterations. It is adverse to the search efficiency if the set scale is out of control. Therefore, we develop a crowding distance strategy to take control of the elite frog quantity. First, the frog set scale is defined as S_{ca}, and we calculate the crowding distance of frogs and rank them in descending order according to the crowding distance. Then, the redundant low-ranking frogs $ENU - S_{ca}$ are eliminated from the set. Finally, the frogs with large crowding distance are retained to maintain diversity and distribution uniformity in the elite frog set. The crowding distance is determined by Equation (12):

$$Crowd_{m,dis} = \begin{cases} \sum_{obj=1}^{K} \left(\frac{(Fit_{m-1,obj} - Fit_{m+1,obj})}{(Fit_{\max,obj} - Fit_{\min,obj})} \right)^2, m \in [2, S_{ca} - 1] \\ \sum_{obj=1}^{K} \left(\frac{(Fit_{1,obj} - Fit_{2,obj})}{(Fit_{\max,obj} - Fit_{\min,obj})} \right)^2 *2, \mathrm{m} = 1 \\ \sum_{obj=1}^{K} \left(\frac{(Fit_{S_{ca}-1,obj} - Fit_{S_{ca},obj})}{(Fit_{\max,obj} - Fit_{\min,obj})} \right)^2 *2, \mathrm{m} = \mathrm{S_{ca}} \end{cases} \quad (12)$$

where $Crowd_{m,dis}$ denotes the crowding distance of the mth elite frog. $Fit_{m-1,obj}$, $Fit_{m,obj}$ and $Fit_{m+1,obj}$ are fitness of m–1, m, $m+1$th frog corresponding to the objth optimization objective, respectively. Analogously, the meanings of $Fit_{\max,obj}$ and $Fit_{\min,obj}$ are the best and worst fitness in the elite frog set.

To eliminate the frogs with lower crowding distance, all the alternative elite frogs are selected into the elite frog set and ranked by the crowding distance in the conventional method. Nevertheless, this method can effectively reduce counts of dominant comparisons, it may lead to the dense distribution of optimal solutions in the narrow space. Eventually, all frogs in this narrow space may be excluded during the elite frog set maintenance. As a result, we propose an improved maintenance strategy whereby alternative elite frogs are added into the set successively and the distribution density of frogs is evaluated. The frogs distributed intensively are eliminated after each addition. The new method proposed contributes to make optimal solutions uniformly distributed on the Pareto front.

The renewed grouping strategy

For the multi-objective optimization problem, it is critical to confirm a reasonable fitness evaluation index to determine the dominance relationship between frogs owing to the distinct fitness value of each objective function. The dominance relationship can be expressed as follows:

$$Y_i = \{u_j | u_i \succ u_j, u_j \in F\} \quad (13)$$

where u_i is the frog. The frogs dominated by it form a set defined as Y_i.

Assuming that $|Y_i|$ represents the dominance relation of frogs in set Y_i, frogs are ranked in descending order by $|Y_i|$ and random permutation is adopted if frogs have the same dominance relationship. Finally, all frogs will be assigned to corresponding sub-populations using conventional grouping strategy as mentioned. The method above shows defects on handling the Pareto dominance relationship between frogs which are not dominated by each other. The random permutation may cause extreme cases in the grouping process whereby most frogs assigned into sub-populations are the best or worst frogs. Accordingly, the population diversity significantly decreases and stagnation will be brought to the evolution process. For this purpose, the frog grouping method is modified as follows:

Step 1. Evaluate the fitness of each frog to determine the non-dominant frogs for the whole population. Rank these frogs in descending order according to the distribution density.

Step 2. For the rest of the dominant frogs, calculate its Euclidean distance from the nearest non-dominant frog and rank these frogs behind the excellent frogs in descending order.

Step 3. The method shown in Equation (14) is to further distinguish between frogs whose dominance relationship is difficult to confirm. This method determines the relationship by means of calculating the fitness offset of the frog. The frog with a smaller fitness offset will be selected for the non-dominant one.

$$PY = \sum_{i=1}^{M} \sum_{obj=1}^{O} (Fit_{i,obj} - \max(Fit_{k,obj}))k \in M \tag{14}$$

where $Fit_{i,j}$ is fitness of the objth optimization objective corresponding to the ith frog. M represents the population scale. O is the total number of objectives.

Step 4. Frogs are arranged into a respective sub-population (the number of sub-populations is P) successively with the method described above under 'The traditional single-objective SFLA'. Apparently each sub-population contains $n = \frac{M}{P}$ frogs.

The modified local search strategy

The conventional single-objective SFLA merely enables the best individual in the sub-population to provide guidance information for the evolution of the worst frog. It is incapable of making full use of the evolution information delivered by both local (within sub-population) and global optimal frogs simultaneously. In this paper, we fully take into account the two optimal frogs and preeminent frog from the elite frog set to direct the iteration of the worst frog. The leap step and predation location renewal are accomplished by the Equations (15) and (16):

$$d_{new} = \beta_1^*(u_b - u_w) + \beta_2^*(u_g - u_w) + \beta_3^*(u_{elite} - u_w) \tag{15}$$

$$u_{w,new} = u_w + d_{new}, d_{\min} \le d_{new} \le d_{\max} \tag{16}$$

where u_b and u_w denote the best and worst frog location, respectively. u_g is the global optimal individual currently. u_{elite} is the frog location selected from elite frog set. The functions of β_1, β_2, β_3 are producing uniform distribution random number ranging from [0,1].

The crowding distance $Crowd_{m,dis}$ and distance from the optimal Pareto front D_{tPF} are introduced concerning the elite frog u_{elite} selection strategy. The elite frog is obtained from the two selection decisions to effectively conduct the evolution and improve the diversity of the frog population. Details are shown in the following steps:

Step 1. Define the fitness of D_{tPF} as $f(D_{tPF})$ whose value is reciprocal of D_{tPF}. The roulette wheel is introduced to choose the lower D_{tPF} frog which is the elite frog with high probability. The fitness of D_{tPF} is calculated by Equation (17):

$$f(D_{tPF}) = \frac{1}{D_{tPF}} \tag{17}$$

Step 2. To avoid the excessively dense distribution of frogs selected in the former step, we continue to screen out the individuals with large crowding distance $Crowd_{m,dis}$. Similarly, the roulette wheel method is used to locate the targeted frog with large probability.

The new frog $u_{w,new}$ obtained from Equations (15) and (16) is evaluated to determine the dominance relationship with the original worst one u_w. The dominant frogs will be eliminated. Here are three cases for the elimination decision:

Case 1: If $u_{w,new}$ dominates u_w, the former will replace the latter.

Case 2: If $u_{w,new}$ is dominated by u_w, it indicates that the algorithm may be trapped into search stagnation because of a marked decrease in the population diversity. Therefore, to reactivate the search performance we need to seek more energetic and potential frogs to replace the current one. The new frog creation is achieved by Equation (18):

$$new\ u_w = u_w(1 + \theta \cdot \beta) \tag{18}$$

where β is the random number in [0,1]. θ denotes the adjustment coefficient which is changeable dynamically using the arc tangent function shown in Equation (19). The larger θ makes the algorithm escape from the local area and search within a larger space the initial iteration stage, while in the later iteration stage, a relatively lesser θ is used for maintaining the fast convergence characteristic of MMOSFLA:

$$\theta = \theta_e + \arctan\left(1.56\left(1 - \left(\frac{t^* L_t}{L_s^* L_g}\right)^{\varphi}\right)\right)^{*} (\theta_s - \theta_e) \tag{19}$$

where θ_s and θ_e are the initial and terminal values of θ (0.9 and 0.4, respectively); φ represents the controlling factor which is in the range of [0.4,0.7]. t and L_t are the current iterations for the local search in the sub-population and global shuffling. T, L show the maximum iterations for local search and global shuffling, respectively.

Case 3: If $u_{w,new}$ and u_w do not dominate each other, it is equal (50% of the time) to make $u_{w,new}$ replace u_w or keep u_w unchanged.

After each local search iteration, frogs are reordered according to the dominant relationship. Repeat the above steps until the local iterations in the sub-population are accomplished.

Elite frog evolution strategy

The elite frog set plays an important role in guiding the evolution direction of the frog population by using the elite set maintenance strategy based on crowding distance. However, especially in the later iteration, the evolution will gradually slow down and trap into stagnation because of a decrease in the population diversity, even in the elite frog set. To this end, we explore the potential dominated frog to reactivate the search performance using the evolution strategy based on the normal cloud model theory. The normal cloud model first proposed by Li et al. (1995) has characteristics of randomness and stability orientation. Recently, the cloud model has been introduced and combined with a number of algorithms such as GA, PSO and an evolution algorithm (Dai et al. 2007; Zhang et al. 2008, 2012). The cloud model helps the algorithm to profoundly search in the local space and effectively improve overall performance.

The normal cloud model (NCM) is brought forth to describe the uncertain conversion relation of qualitative concept or qualitative knowledge with its quantitative expressions. The expectation E_x, entropy E_n and hyper-entropy H_e are parameters for characterizing the digital features of the cloud (Ma et al. 2013). The details on E_x, E_n and H_e are elaborated as follows and are depicted in Figure 1.

The E_x is central to all droplets and the most representative cloud droplet for qualitative concept.

The entropy E_n denotes the uncertainty measurement of the qualitative concept. It reflects emergence randomness of the cloud droplet and correlation of fuzziness and randomness. The scope of the cloud droplet generated and its randomness highly depends on the value of E_n. Specifically,

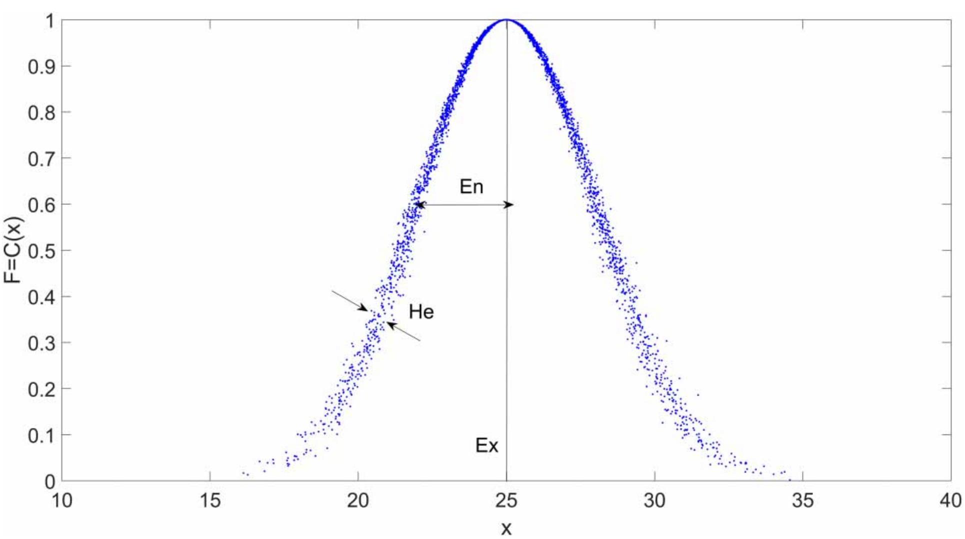

Figure 1 | The cloud and digital characteristic of parameters.

the larger E_n is, the more obvious the randomness and broader the scope is.

The hyper-entropy H_e, determined by randomness and fuzziness, represents the measurement of entropy, i.e. the entropy of entropy. To boost search randomness in the initial iteration stage and maintain search stability later, the value of H_e is defined as $E_n/5$.

The cloud droplet is created by the normal cloud generator. Usually, the processes can be described as follows (Sun *et al.* 2016):

Step 1. Generate a normal random number E_{nn} with expectation E_n and standard deviation H_e.

Step 2. Thereafter, generate a normal random number x as a cloud droplet, which is taken as E_x, $|E_{nn}|$ as expectation and standard deviation, respectively.

Step 3. The calculation E_{nn} and x are plugged into formula $F = e^{\frac{-(x-E_x)^2}{2(E_{nn})^2}}$ to determine certainty pertaining to the qualitative concept C.

Step 4. Repeat the above-mentioned processes until the total cloud droplets meet the terminal condition.

For the MMOSFLA, we select the excellent dominated frog of the elite set to execute evolution strategy in the later iteration stage. The location of the elite frog is defined as E_x, and the variance of frogs in the elite set is E_n which can dynamically change the search space. Furthermore, to enhance the search randomness in the early iteration stage and guarantee search stability in the later stage, we set the value of H_e as $E_n/5$. The specified number of cloud droplets is generated by the cloud generator, which represents potential solutions. Through the fitness evaluation, we establish a dominance relationship between new and original elite frogs. The original one will be replaced if the new cloud droplet (the frog) dominates it.

The flow chart of MMOSFLA

The specific processes of MMOSFLA for solving MOEOCR problem are shown in Figure 2.

Numerical simulations

Numerical simulations are conducted to demonstrate the performance of the proposed MMOSFLA approach. Simulation test functions are from the ZDT and DTLZ package, of which the optimum is '0' theoretically. The NSGAII (fast elitist non-dominated sorting genetic algorithm), MOEAD (multi-objective evolutionary algorithm based on decomposition), MOEADDE (MOEAD based on differential evolution operators), dMOPSO (multi-objective particle based on decomposition) and MOPSO (multi-objective particle swarm optimization) are selected to compare with MMOSFLA. The frog population and sub-population size are set to 100 and 10, respectively. The number of local iterations in the sub-population and global shuffling iterations are defined as 100 and 10,000. The 30 independent simulations are conducted to offset randomness of the simulation results.

The iteration curves of the optimal Pareto front are partially shown in Figure 3. Furthermore, the IGD and GD indicators are analyzed to evaluate the performance of MMOSFLA quantitatively. The IGD is an indicator for assessing convergence and solution diversity. The GD represents the distance between the true Pareto front and the Pareto front searched by MMOSFLA. The smaller the IGD and GD are, the better the convergence and distribution of the solution. The comparative results of IGD and GD are demonstrated in Tables 1 and 2.

From inspection of Figure 3 and Tables 1 and 2, it is evident that the mean and STD of the IGD indicator for ZDT1-ZDT3 calculated by MMOSFLA are the best. Similarly, MMOSFLA also outperforms in DTLZ4 and DTLZ6 optimization. The results indicate the convergence performance and solution diversity by MMOSFLA is at a higher level than other approaches. For DTLZ2 and DTLZ5, the margin of optimization result is insignificant even if MMOSFLA is not the best. In terms of the GD indicator, MMOSFLA dominates other approaches in optimizing ZDT1-ZDT3, ZDT6 and DTLZ4-DTLZ6. It is clear that solutions gained by MMOSFLA are multiple and of higher precision (closer to true Pareto-front) in comparison to other methods.

In summary, MMOSFLA shows more excellent optimization performance than other algorithms. Even though IGD and GD indicators do not perform well in terms of several test functions, the final solutions on the Pareto front present good distribution uniformity and diversity. Therefore, we verify significant adaptability and effectiveness of MMOSFLA in complex nonlinear multi-objective problems.

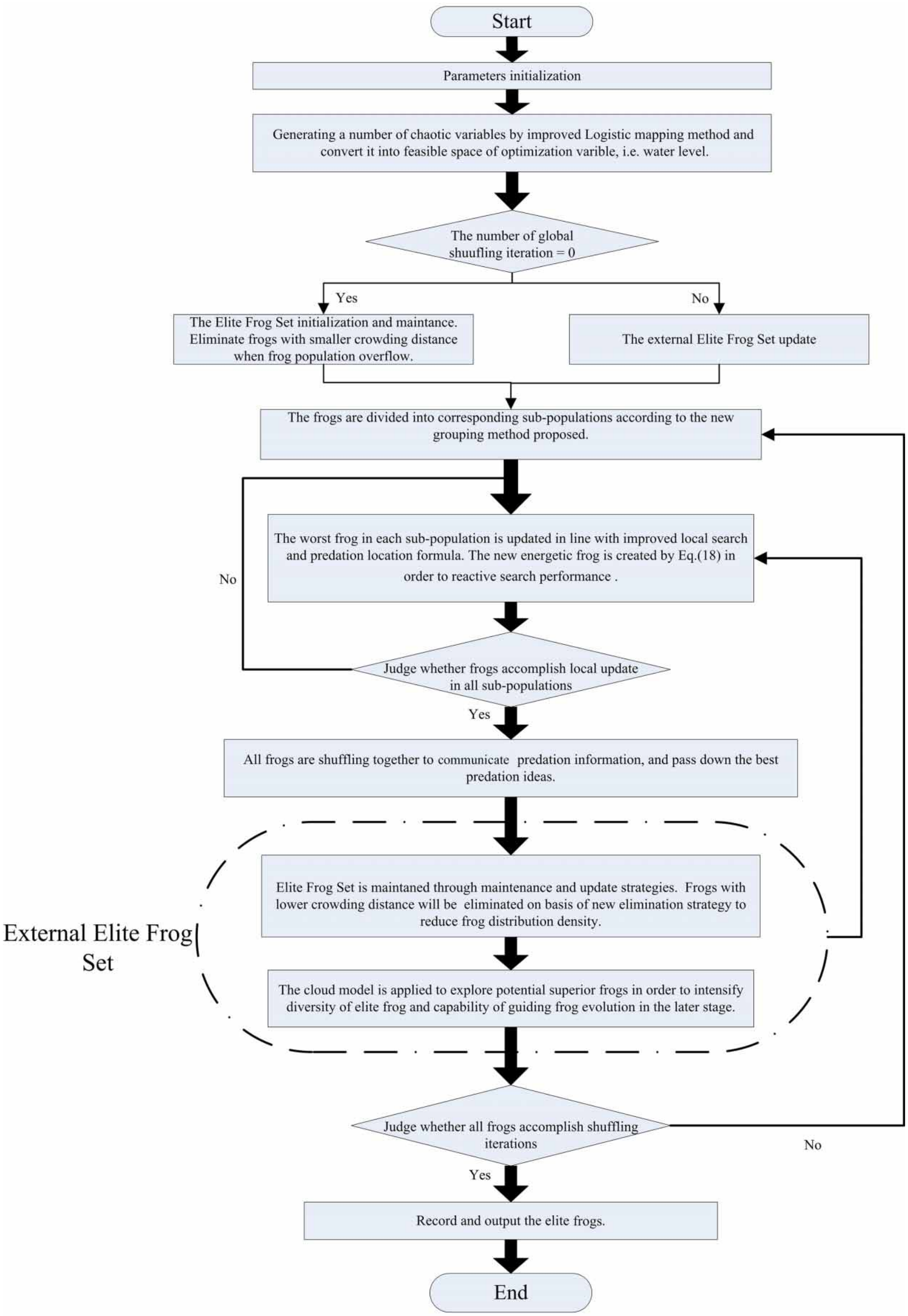

Figure 2 | The flow chart of MMOSFLA approach for MOEOCR problem.

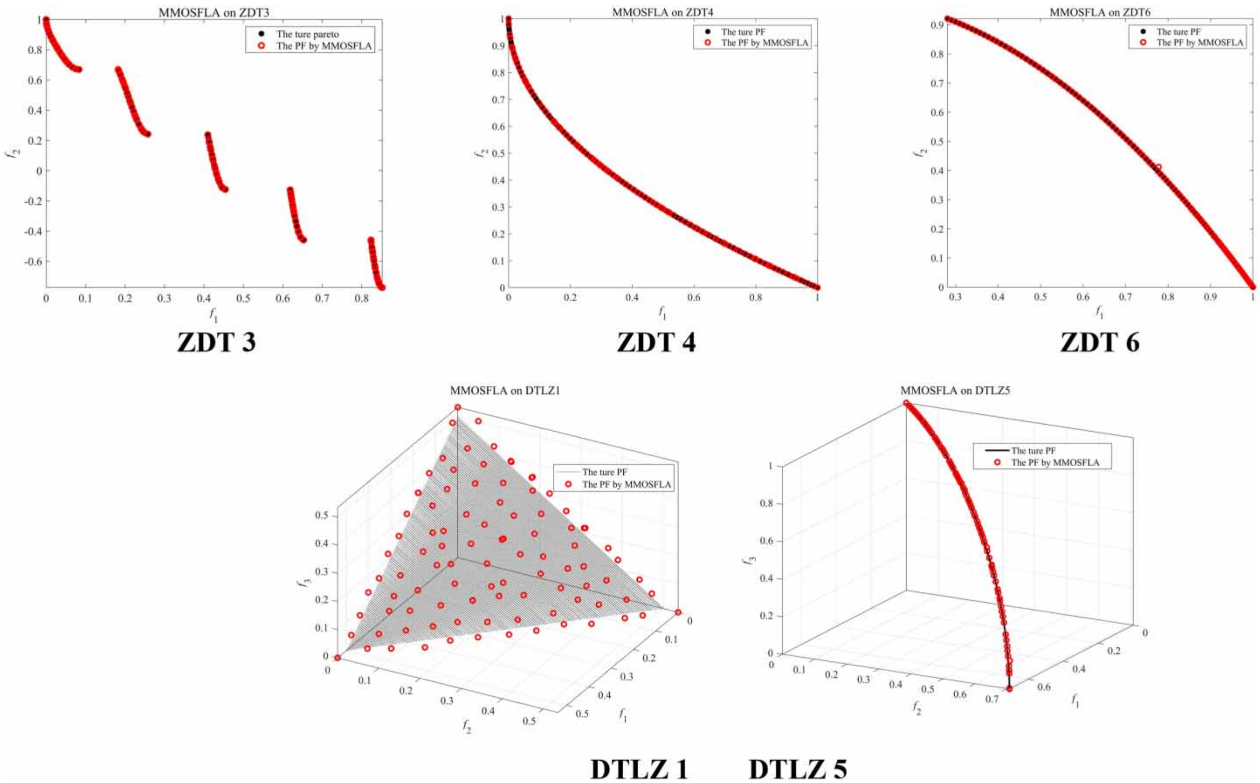

Figure 3 | The partial iteration curves of the optimal Pareto front.

CASE STUDY

The overview of cascade reservoirs located in Qingjiang River

Qingjiang River is the largest tributary of the middle Yangtze River between Yichang and Jingjiang. It is 423 km long with a basin area of 17,000 km^2 which flows through Enshi, Badong, Changyang and Yidu located in Hubei province. Along the river, there are three hydropower stations with large hydro-unit capacity and reservoir regulation storage.

The Shuibuya Reservoir, characterized with multi-year regulating storage and the largest installed capacity of three hydropower stations, is the most important stage of the cascade development in Qingjiang River basin. The hydropower station of Geheyan, located in Changyang county, is a huge water conservancy project with the major function of power generation, flood control and shipping benefit. Gaobazhou Reservoir, which is situated in the lower reaches of the Qingjiang River, plays a role on the reverse regulation of the upstream Geheyan Reservoir. The main characteristics of the water level of cascade reservoirs and power station parameters are shown in Table 3. The generalization of cascade reservoirs system in Qingjiang River catchment is illustrated in Figure 4.

Ecological flow acquisition

The stream ecological base flow is defined as the basic water amount needed to maintain the stability of the biocenosis in the river, and protect the river's ecological environment and functions from damage. The concept of ecological or environmental flows was historically developed as a response to the degradation of aquatic ecosystems caused by human interventions (Tegos *et al.* 2018). In this paper, the annual runoff and ecological health extent is considered to determine the basic, suitable and ideal ecological flow of the control section located in Geheyan and Gaobazhou reservoirs.

For acquiring the basic ecological flow in non-flood seasons, we adopt the Tennant method with 10% average

Table 1 | The mean and standard deviation (STD) of the IGD index

Test function	Algorithm NSGAII	MOEAD	dMOPSO	MOEADDE	MOPSO	MMOSFLA
ZDT1	2.3375×10^{-1} (1.16×10^{-1})	1.7506×10^{-1} (5.03×10^{-2})	2.6954×10^{-2} (1.11×10^{-2})	3.8550×10^{0} (2.28×10^{0})	4.2108×10^{1} (8.73×10^{0})	$\mathbf{5.1653\times10^{-3}}$ $\mathbf{(2.67\times10^{-4})}$
ZDT2	5.4347×10^{-1} (1.40×10^{-1})	3.6358×10^{-1} (1.99×10^{-1})	4.9077×10^{-1} (2.38×10^{-1})	5.2994×10^{0} (2.41×10^{-1})	4.6156×10^{1} (1.08×10^{1})	2.3943×10^{-2} (7.18×10^{-2})
ZDT3	1.7938×10^{-1} (1.12×10^{-1})	2.3082×10^{-1} (1.05×10^{-1})	1.2439×10^{-1} (2.07×10^{-1})	4.5374×10^{0} (1.87×10^{0})	4.3630×10^{1} (1.00×10^{1})	$\mathbf{2.2902\times10^{-2}}$ $\mathbf{(9.42\times10^{-2})}$
ZDT4	2.6914×10^{0} (2.24×10^{0})	4.6781×10^{-1} (2.28×10^{-1})	5.7986×10^{-1} (2.37×10^{-1})	3.5171×10^{0} (1.42×10^{0})	1.8812×10^{1} (7.62×10^{0})	$\mathbf{2.5576\times10^{-1}}$ $\mathbf{(1.52\times10^{-1})}$
ZDT6	8.1677×10^{-2} (3.31×10^{-2})	9.3728×10^{-2} (5.84×10^{-2})	4.2025×10^{-3} (1.49×10^{-3})	4.7737×10^{-2} (9.57×10^{-2})	1.3558×10^{0} (2.58×10^{0})	$\mathbf{3.5911\times10^{-3}}$ $\mathbf{(2.03\times10^{-4})}$
DTLZ1	$\mathbf{2.1271\times10^{-1}}$ $\mathbf{(1.77\times10^{-1})}$	2.5625×10^{-1} (3.21×10^{-1})	7.2134×10^{0} (5.76×10^{0})	1.1982×10^{0} (2.06×10^{0})	1.0643×10^{1} (3.94×10^{0})	2.1795×10^{0} (1.70×10^{0})
DTLZ2	7.0013×10^{-2} (2.98×10^{-3})	$\mathbf{5.4862\times10^{-2}}$ $\mathbf{(1.84\times10^{-4})}$	1.4315×10^{-1} (1.03×10^{-2})	7.7725×10^{-2} (1.62×10^{-3})	1.0528×10^{-1} (1.25×10^{-2})	7.2267×10^{-2} (2.42×10^{-3})
DTLZ3	$\mathbf{8.8711\times10^{0}}$ $\mathbf{(5.11\times10^{0})}$	1.4796×10^{1} (9.72×10^{0})	4.7035×10^{1} (5.00×10^{1})	1.6801×10^{1} (1.81×10^{1})	1.4728×10^{2} (6.50×10^{1})	8.4056×10^{1} (3.13×10^{1})
DTLZ4	1.0072×10^{-1} (1.60×10^{-1})	3.8486×10^{-1} (3.21×10^{-1})	3.0915×10^{-1} $(3.36\times10^{-2}$	1.7320×10^{-1} (6.79×10^{-2})	3.4990×10^{-1} (1.42×10^{-1})	$\mathbf{1.0009\times10^{-1}}$ $\mathbf{(1.20\times10^{-1})}$
DTLZ5	$\mathbf{6.1237\times10^{-3}}$ $\mathbf{(3.56\times10^{-4})}$	3.2176×10^{-2} (1.05×10^{-3})	4.4669×10^{-2} (6.50×10^{-3})	1.4273×10^{-2} (3.35×10^{-4})	1.4772×10^{-2} (4.71×10^{-3})	6.5428×10^{-3} (5.30×10^{-4})
DTLZ6	6.8978×10^{-3} (8.34×10^{-4})	8.5158×10^{-2} (1.68×10^{-1})	3.2884×10^{-2} (8.37×10^{-4})	1.4065×10^{-2} (6.04×10^{-4})	2.8475×10^{0} (8.83×10^{-1})	$\mathbf{5.9284\times10^{-3}}$ $\mathbf{(3.58\times10^{-4})}$

Data in brackets are standard deviation; optimal results are in bold font; methods compared are from Tian *et al.* (2017).

annual runoff. In terms of the fish breeding season (May–October), which overlaps with the breeding season of fish in the reservoir and river, the ecological flow will be raised to 15% of average annual runoff to guarantee fish breeding (Yang *et al.* 2018). The suitable and ideal ecological flow are obtained based on the requirement level index. The requirement level index can represent effects exerted by factors including vegetation coverage, biological diversity, and water quality on the ecological flow (Lyu *et al.* 2016). The specific method to calculate the requirement level index of suitable and ideal ecological flow is shown as follows:

$$\begin{cases} \lambda_{suitable} = \lambda_{basic} + \theta_1 \chi_{adj} + \theta_2 \beta_{suitable} \\ \lambda_{ideal} = \alpha_1 \beta_{year} + \alpha_2 \beta_{ideal} \\ \sum \theta_i = 1, \ \sum \alpha_i = 1 \end{cases} \tag{20}$$

where λ_{basic}, $\lambda_{suitable}$ and λ_{ideal} denote the requirement level index of basic, suitable and ideal ecological flow, respectively. χ_{adj} is the correction coefficient of suitable ecological flow; $\beta_{suitable}$ represents the corresponding characteristic index; θ_1 and θ_2 signify the membership degree of variation coefficient and the characteristic index of suitable ecological flow to the requirement level index of suitable ecological flow. The membership degree can be acquired through the entropy evaluation method. β_{year} and β_{ideal} are annual variation coefficient and characteristic index of ideal ecological flow, respectively. α_1 and α_2 signify the membership degree of β_{year} and β_{ideal} to the requirement level index of ideal ecological flow.

After the requirement level indexes are determined, Equation (21) is adopted to calculate corresponding suitable and ideal ecological flow of the control section in Geheyan and Gaobazhou reservoirs. The ecological flow results are

Table 2 | The mean and standard deviation (STD) of the GD index

Test function	Algorithm NSGAII	MOEAD	dMOPSO	MOEADDE	MOPSO	MMOSFLA
ZDT1	1.1359×10^{-2} (6.66×10^{-3})	2.1418×10^{-2} (1.73×10^{-2})	2.8028×10^{-3} (1.18×10^{-3})	1.3408×10^{0} (6.29×10^{-1})	2.0180×10^{1} (1.94×10^{1})	**2.4647×10^{-5} (2.15×10^{-5})**
ZDT2	4.3380×10^{-2} (2.65×10^{-2})	1.6640×10^{-2} (1.86×10^{-2})	6.0982×10^{-4} (1.51×10^{-3})	1.7839×10^{0} (8.63×10^{-1})	4.2950×10^{1} (1.46×10^{1})	**1.4220×10^{-5} (2.56×10^{-5})**
ZDT3	8.2373×10^{-3} (4.32×10^{-3})	2.3681×10^{-2} (1.82×10^{-2})	1.6209×10^{-3} (9.81×10^{-4})	1.6517×10^{0} (6.22×10^{-1})	2.5155×10^{1} (2.06×10^{1})	**4.0986×10^{-5} (1.50 × 10–5)**
ZDT4	**2.3943×10^{-2} (2.32×10^{-2})**	7.0046×10^{-2} (4.47×10^{-2})	2.4815×10^{-2} (1.30×10^{-1})	4.3727×10^{0} (3.60×10^{0})	8.2611×10^{0} (7.91×10^{0})	7.3716×10^{-1} (8.90×10^{-1})
ZDT6	1.2204×10^{-2} (6.18×10^{-3})	1.1560×10^{-2} (4.90×10^{-3})	9.4839×10^{-5} (7.32×10^{-4})	4.7398×10^{-2} (5.41×10^{-2})	3.4847×10^{-1} (4.91×10^{-1})	**5.6006×10^{-5} (4.52×10^{-4})**
DTLZ1	**2.9925×10^{-2} (3.27×10^{-2})**	4.1773×10^{-2} (5.70×10^{-2})	8.9482×10^{0} (1.67×10^{0})	1.0263×10^{0} (7.03×10^{-1})	7.6957×10^{0} (1.42×10^{0})	4.5638×10^{-1} (3.59×10^{-1})
DTLZ2	1.3245×10^{-3} (1.58×10^{-4})	**6.2695×10^{-4} (4.89×10^{-5})**	2.0143×10^{-2} (2.63×10^{-3})	1.7718×10^{-3} (3.48×10^{-4})	8.5144×10^{-3} (3.41×10^{-3})	1.7365×10^{-3} (5.93×10^{-4})
DTLZ3	**1.4477×10^{0} (6.88×10^{-1})**	2.5282×10^{0} (1.88×10^{0})	5.2792×10^{1} (8.67×10^{1})	5.3161×10^{0} (4.37×10^{0})	5.3308×10^{1} (2.19×10^{1})	1.1846×10^{1} (3.45×10^{0})
DTLZ4	1.2615×10^{-3} (3.15×10^{-4})	1.6947×10^{-3} (9.89×10^{-4})	5.5364×10^{-2} (1.67×10^{-2})	1.3925×10^{-3} (6.92×10^{-4})	3.4345×10^{-2} (1.76×10^{-2})	**4.3859×10^{-4} (2.29×10^{-4})**
DTLZ5	2.8789×10^{-4} (5.77×10^{-5})	2.8383×10^{-4} (1.06×10^{-3})	3.3932×10^{-2} (1.12×10^{-2})	3.1252×10^{-4} (1.12×10^{-4})	1.3698×10^{-3} (1.39×10^{-3})	**2.0039×10^{-4} (6.57×10^{-5})**
DTLZ6	5.0088×10^{-6} (2.83×10^{-7})	1.4951×10^{-2} (3.48×10^{-2})	1.4138×10^{-2} (7.79×10^{-3})	4.7962×10^{-6} (2.53×10^{-7})	4.2219×10^{-1} (7.51×10^{-2})	**4.7883×10^{-6} (2.33×10^{-7})**

Table 3 | The main parameters and characteristic water level of cascade reservoirs and power station

Characteristic water level and parameters	Cascade reservoirs in Qingjiang Shuibuya	Geheyan	Gaobazhou
Normal storage water level (m)	400	200	80
Flood control level (m)	391.8	193.6	78.5
Dead water level (m)	350	160	78.09
Total storage capacity (10^8 m^3)	45.89	30.18	4.03
Beneficial reservoir capacity (10^8 m^3)	23.83	19.75	0.54
Installed capacity (MW)	1,840	1,212	270
Annual utilization hours of installed capacity (h)	2,450	2,533	3,563
Guaranteed output (MW)	310.0	241.0	77.3
Comprehensive efficiency coefficient	8.50	8.50	8.40
Maximum water head (m)	203.0	121.6	40.0
Minimum water head (m)	147.0	80.7	22.3
Mean water head (m)	186.6	112.0	35.4

shown in Table 4:

$$\begin{cases} Q_{suitable} = \lambda_{suitable} Q_{avg} \\ Q_{ideal} = \lambda_{ideal} Q_{avg} \end{cases} \tag{21}$$

where $Q_{suitable}$, Q_{ideal} denotes suitable ideal ecological flow of the control sections; Q_{avg} is average monthly runoff.

The scheduling scenarios

In this paper, two scheduling scenarios are proposed based mainly on power generation of the cascade reservoirs and the different ecological flow requirements of Geheyan and Gaobazhou control sections are considered simultaneously. The conflict relationship between power generation and ecological water spill and shortage under each ecological flow requirement are discussed. The specific scenarios are described as follows:

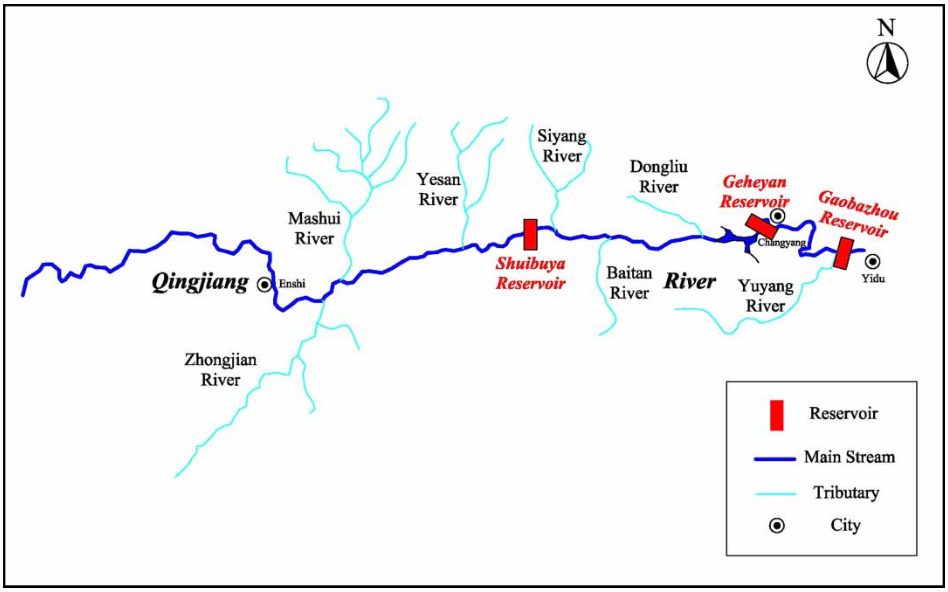

Figure 4 | The generalization of Qingjiang River and cascade reservoirs system.

Table 4 | The basic, suitable and ideal ecological flow in Geheyan and Gaobazhou control sections m³/s

		Control section					
		Geheyan			Gaobazhou		
Scheduling period	Month	Basic	Suitable	Ideal	Basic	Suitable	Ideal
Fish breeding	May	93.08	229.63	363.41	77.86	214.04	336.92
	June	105.62	263.35	419.64	94.66	254.58	405.82
	July	133.65	332.32	521.29	87.80	237.92	380.78
	August	76.37	186.71	295.88	61.30	167.36	268.08
	September	65.87	166.41	263.83	44.00	120.49	192.03
	October	52.37	126.51	201.01	37.21	100.18	159.99
Common water use (non-flood season)	November	23.03	56.04	87.98	20.94	56.26	89.53
	December	10.85	26.34	41.73	19.08	52.24	83.64
	January	8.09	19.96	31.46	21.90	58.46	93.18
	February	11.72	27.62	47.94	19.31	51.41	81.86
	March	22.34	54.79	86.94	28.34	76.47	122.01
	April	41.06	99.86	156.48	37.41	100.87	161.90

Scenario 1: The cascade reservoirs focus on power generation and take suitable ecological water requirements of Geheyan and Gaobazhou into consideration.

Scenario 2: The cascade reservoirs focus on power generation and take ideal ecological water requirements of Geheyan and Gaobazhou into consideration.

The encoding method and constraint handling

The encoding method

The multi-objective ecological operation for cascade reservoirs (MOEOCR) is complex non-linear optimization. In consideration of the complex encoding process and multi-constraint in the MOEOCR problem, the water level at each scheduling period is used as the decision variable to encode. It can directly reflect the temporal characteristic of decision variables. Each frog in the population represents a water level sequence for cascade reservoirs as follows (the dimensions are related to the number of scheduling periods and the reservoir):

$$W_l = (H_{i,1}, H_{i,2}, \ldots H_{i,T}, H_{j,1}, H_{j,2}, \ldots H_{j,T}, H_{k,1}, H_{k,2}, \ldots H_{k,T}) \tag{22}$$

where i, j, k denote the reservoirs of Shuibuya, Geheyan and Gaobazhou, respectively. $H_{k,T}$ denotes the water level of the kth reservoir at the Tth period.

In addition, the objective functions shown in Equations (1) and (2) belong to data with different dimensions. Thus the objective function value needs to normalize in order to calculate the solution distribution indicator conveniently. The normalization measure is elaborated in Equation (23):

$$\begin{aligned} f_{nor}\,(E_{LEC}) &= \frac{E_{LEC} - E_{LEC,\min}}{E_{LEC,\max} - E_{LEC,\min}} \\ f_{nor}\,(W_{YS}) &= \frac{W_{YS} - W_{YS,\min}}{W_{YS,\max} - W_{YS,\min}} \end{aligned} \tag{23}$$

where $E_{LEC,\max}$ and $E_{LEC,\min}$ are the maximum and minimum power generation among all scheduling solutions, respectively. Likewise, $W_{YS,\max}$, $W_{YS,\min}$ are the upper and lower bounds corresponding to ecological water spill and shortage.

The constraint handling

It is critical to effectively solve the MOEOCR problem with rational constraint handling. For this purpose, we propose the water level corridor combined with a penalty function to handle constraint.

For the reservoir water level constraint, the frog locations (water level) generated are restricted within a feasible zone. With regard to the discharge flow and output constraints which are an implicit function of reservoir water level, we can convert those constraints to a single water level constraint by use of a water level corridor. The specific conversion processes are as follows:

1. If the final scheduling water level is undetermined, start forward recursion from the water level at the initial period until the final scheduling period. Then the upper and lower bound of water level at each period can be obtained. Next, we can build a positive corridor of water level constraint.
2. By contrast, start reverse recursion from the water level at the final scheduling period until the initial period if the initial water level is unknown. Similarly, we can build a corresponding reverse corridor.
3. The forward and reverse water level corridors are intersected to obtain a feasible zone of reservoir water level.

The convergent speed can be boosted when the search zone is narrowed into the water level corridor. However, the frog locations generated in the corridor are still possible to be unfeasible (Zhou *et al.* 2010). Therefore, the penalty function is used to further improve the frog quality. A larger or smaller value is given to the objective function to make feasible frogs generate.

The main parameter settings for MMOSFLA

Fewer parameters are controlled in MMOSFLA, and the control parameters are selected as follows with contrastive analysis.

The total iterations of chaotic mapping initialization are set to 100, the frog population size M is 200 and the corresponding sub-population or memeplex size P is predefined as 20. The number of frogs in each sub-population n is 10 accordingly. The upper and lower bound of frog leap step is set to [–4,4]. Initial and terminal adjustment coefficient θ_s, $\theta_e = 0.90$ and 0.40, controlling factor φ is 0.60. The number of local iterations in the sub-population and global shuffling iteration are set to 20 and 200, respectively.

RESULTS AND DISCUSSION

In this paper, the inflow processes of the Qingjiang cascade reservoirs corresponding to the typical wet, normal and dry years are selected as the scheduling model input. Then, the

MMOSFLA proposed is applied to optimize the multi-objective scheduling model for cascade reservoirs. The initial and terminal scheduling water level of Shuibuya, Geheyan and Gaobazhou reservoirs are 400, 200 and 80 m, respectively. The spatial distribution of multi-objective optimal scheduling solution set (Pareto front) corresponding to scenario 1 and 2 is displayed in Figure 5. Take the scheduling scenario 2 which considers the ideal ecological flow requirement of Geheyan and Gaobazhou for instance, the partial representative scheduling solutions are compared in Table 5.

In Figure 5 it is demonstrated that power generation in Qingjiang cascade reservoir and ecological water spill and shortage present an interactional and mutually contradictory relationship. It is manifest that maximum power generation and ecological benefits cannot be achieved simultaneously and the competition between the two goals is clear. Therefore, it is difficult to find a single optimal scheduling solution. Instead, the multi-objective solutions exist in the form of the Pareto front (trade-off) and the solutions acquired have better space distribution and diversity. Moreover, the power generation varies at the most by 1% within each Pareto front set of solutions in Figure 5. It seems that the problem can be solved as a single objective ecological problem with constrained fixed power generation. However, multiple calculations are required for this method to obtain

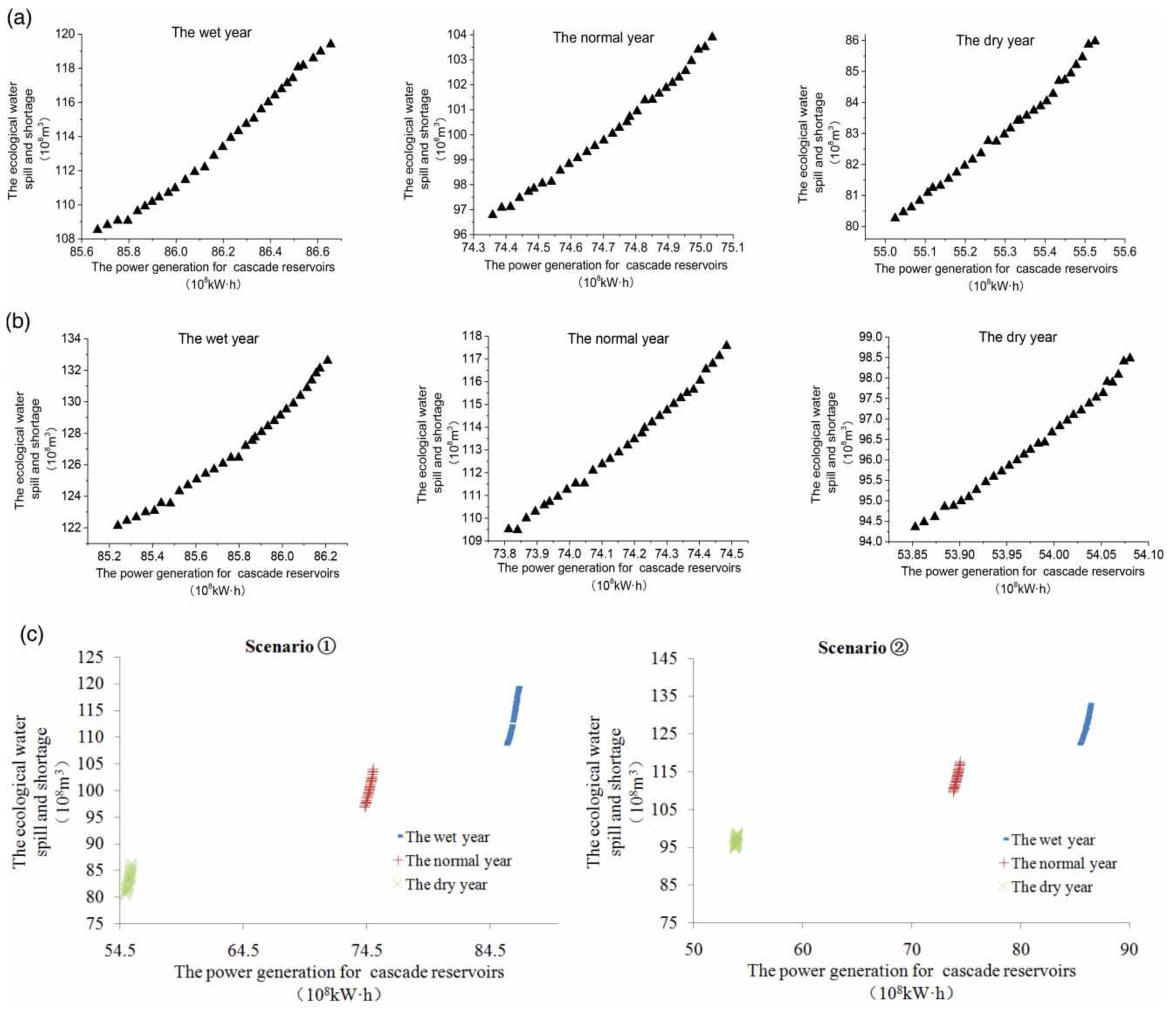

Figure 5 | The Pareto front of total power generation and ecological water spill and shortage corresponding to scenarios 1 and 2. (a) Scheduling scenario 1 (considering suitable ecological water requirement). (b) Scheduling scenario 2 (considering ideal ecological water requirement). (c) Comparison between typical years.

Table 5 | The typical scheduling solutions comparison corresponding to scheduling scenario 2

The solution number	The wet year		The normal year		The dry year	
	Power generation (10^8 kW·h)	Ecological water spill and shortage (10^8 m^3)	Power generation (10^8 kW·h)	Ecological water spill and shortage (10^8 m^3)	Power generation (10^8 kW·h)	Ecological water spill and shortage (10^8 m^3)
1	85.24	122.13	73.81	109.51	53.85	94.36
15	85.80	126.46	74.18	113.20	53.98	96.40
30	86.21	132.62	74.48	117.57	54.08	98.48

a multi-objective non-inferior solution set. Besides, the weight setting between each objective and constraints handling are subjective which results in the large error between the true Pareto front and inferior solutions we obtain. Furthermore, in fact, it is difficult to pursue the fixed power generation for the hydropower station due to the long-term development and the gradual increase in electricity consumption. The decision makers need to evaluate the scheduling solution and select the best one within acceptable limits. For this purpose, it is necessary to provide a set of solutions for them to make a decision.

From Table 5 we can find that scheduling solution 1 is the most representative scheduling solution focusing on ecological benefit, by contrast solution 30 is aimed at the maximum power generation with less attention to ecological objective. As a trade-off, solution 15 contributes to maintaining the balance between the multiple objectives.

Furthermore, we demonstrate the scheduling solution set (shown in Table 6) of Geheyan Reservoir in scenario 2. The results in Table 6 similarly indicate the competitive relation between power generation and ecological benefit. The value ranges corresponding to the normal and dry years are less than that to the wet year. Hence, under circumstances of relative abundant reservoir inflow, the cascade reservoirs have more space to coordinate the optimal scheduling. The specific scheduling processes including water level, unit output and water release in Geheyan Reservoir corresponding to the typical years are presented in Figure 6.

It can be seen from Figure 6 that the optimization space of the water level in the major flood season (June and July) is smaller than that in other months due to the flood control task conducted by Geheyan Reservoir. The difference between each solution (Solutions 1, 15 and 30) is mainly concentrated in the dry season and water supply period after the flood season. The water release process of Geheyan Reservoir indicates that a relatively abundant natural inflow in typical wet year results in a large water spill in May before the major flood season. However, the ecological water shortage in the dry season and water supply periods at the end of the flood season can be alleviated. For the typical normal year, the ecological impact is mainly reflected in the form of water shortage in the later stage of the flood season and dry season, especially April and May, while in June, July, August and September the form is converted into water spill. As for the typical dry year, the ecological water spill presents a downward trend in the major flood season and water shortage intensifies after September.

More information can be acquired from analyzing scheduling solutions in Figure 6. Due to the emphasis on the ecological benefit, solution 1 increases the quantity of release and lowers the water level quickly to alleviate an ecological water shortage in the earlier stage of the dry season. In the period of water level falling, the water level need to intensely lower is declined and water release is cut down to avoid excessive ecological water spill. During the flood season, the risk of downstream ecology destruction is reduced with a peak flood mitigation effect of the reservoir. The above measures play an important role in protecting the downstream ecological health of Geheyan Reservoir. However, the quick falling of the water level make the reservoir operate at a lower water level. The power generation cannot be centralized with water level falling so the power generation benefit obviously decreases.

Solution 30 focuses on pursuing the power generation benefit. For this purpose, it condenses the reservoir water release to maintain a higher operating water level. Because

Table 6 | The scheduling solution set of Geheyan Reservoir

	Wet year		Normal year		Dry year	
Solution number	Power generation (10^8 kW·h)	Ecological water spill and shortage (10^8 m³)	Power generation (10^8 kW·h)	Ecological water spill and shortage (10^8 m³)	Power generation (10^8 kW·h)	Ecological water spill and shortage (10^8 m³)
1	33.9825	55.4698	29.2178	40.7005	20.3696	23.3429
2	33.9990	55.6153	29.2288	40.7996	20.3773	23.3997
3	34.0164	55.7153	29.2394	40.8793	20.3847	23.4454
4	34.0336	55.8623	29.2504	40.9886	20.3923	23.5081
5	34.0498	55.9928	29.2614	41.0935	20.4000	23.5683
6	34.0624	56.1240	29.2678	41.1477	20.4084	23.5994
7	34.0792	56.2950	29.2780	41.2330	20.4155	23.6482
8	34.0958	56.4671	29.2889	41.3464	20.4231	23.7133
9	34.1114	56.6394	29.2996	41.4491	20.4306	23.7722
10	34.1277	56.8074	29.3103	41.5612	20.4381	23.8365
11	34.1442	56.9704	29.3207	41.6601	20.4453	23.8932
12	34.1598	57.0962	29.3320	41.7636	20.4532	23.9526
13	34.1761	57.2633	29.3416	41.8634	20.4598	24.0098
14	34.1908	57.4306	29.3524	41.9574	20.4674	24.0637
15	34.2050	57.6174	29.3630	42.0711	20.4748	24.1289
16	34.2179	57.7736	29.3712	42.1703	20.4805	24.1858
17	34.2300	57.9214	29.3805	42.2670	20.4870	24.2413
18	34.2352	58.0217	29.3838	42.3551	20.4938	24.3165
19	34.2473	58.1710	29.3928	42.4480	20.5001	24.3698
20	34.2590	58.3400	29.4021	42.5511	20.5066	24.4290
21	34.2707	58.4911	29.4112	42.6445	20.5129	24.4826
22	34.2819	58.6522	29.4194	42.7484	20.5186	24.5423
23	34.2930	58.8284	29.4279	42.8431	20.5245	24.5966
24	34.3060	58.9959	29.4355	42.9283	20.5299	24.6455
25	34.3188	59.2179	29.4435	43.0182	20.5354	24.6972
26	34.3313	59.4428	29.4514	43.1294	20.5410	24.7610
27	34.3397	59.6606	29.4586	43.2760	20.5459	24.8303
28	34.3478	59.8671	29.4668	43.4039	20.5515	24.9009
29	34.3546	60.0053	29.4750	43.5314	20.5572	24.9713
30	34.3691	60.2325	29.4837	43.6959	20.5633	25.0469

of centralized power generation and water supply task conducted by the reservoir at the end of the flood season, the ecological water shortage gap inevitably amplifies. Ecological benefit is lost with less consideration for ecology protection in solution 30. Solution 15, by contrast, is a trade-off solution in terms of power generation and ecological benefits. It contributes to achieving balanced development for economic and ecological benefits.

To verify the advantages of MMOSFLA in the MOEOCR problem, the scheduling solution Pareto front optimized by MMOSFLA is compared with MOPSO and MOEAD. The parameter settings, including population scale and maximum iterations, remain the same. The independent simulations are set to 20. Similarly, we choose the scheduling solutions under scenario 2 for comparison. The Pareto front of power generation for the cascade reservoir

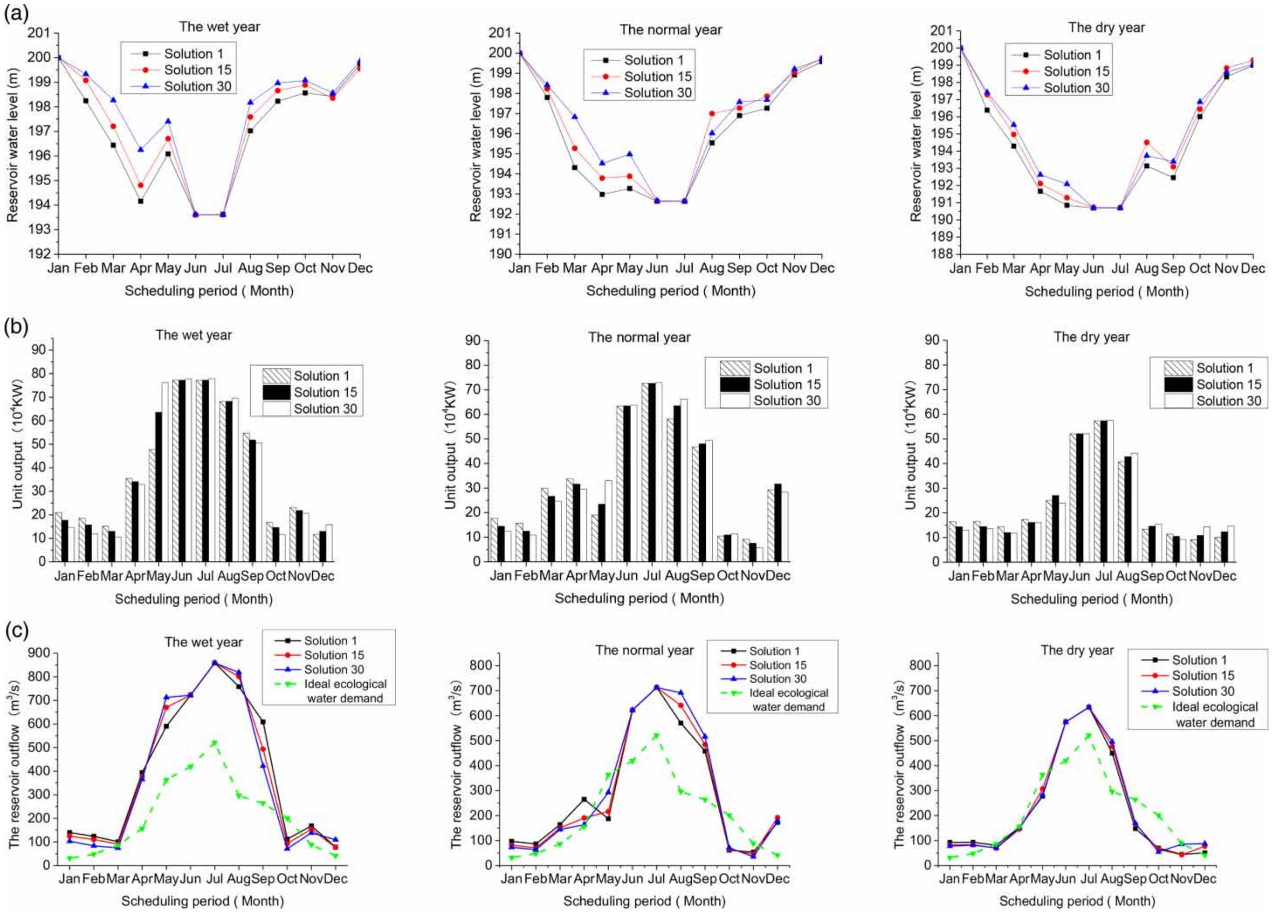

Figure 6 | Specific scheduling results in Geheyan Reservoir corresponding to typical wet, normal and dry years. (a) Water level process. (b) Output process. (c) Water release process.

and ecological water spill and shortage acquired by each method is displayed in Figure 7. In addition, the IGD and GD indexes are used to evaluate the solutions obtained by each algorithm. The results are listed in Tables 7 and 8.

On inspection of Figure 7 we find that the solutions that MMOSFLA converges to presents better diversity and distribution effect in comparison with other rivals (MOEAD, MOPSO). It is closer to the true Pareto front than others. According to the ecological controlling objective and measures issued by the administrative department, the reservoir decision maker should take ecology protection into consideration in the operation of the cascade reservoirs. For

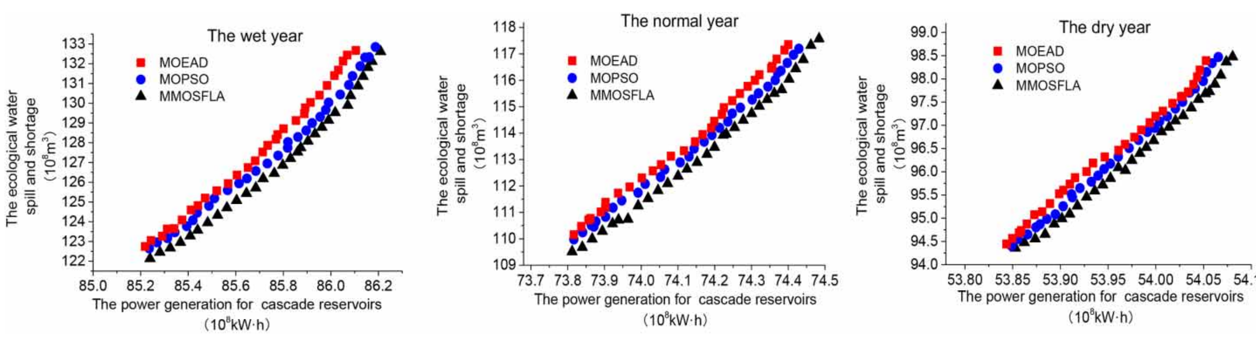

Figure 7 | The scheduling solution Pareto front comparison corresponding to different typical years.

Table 7 | The mean and standard deviation (STD) of the IGD index

Typical year	NSGAII	dMOPSO	MOEADDE	MMOSFLA
	The mean of IGD			
Wet year	2.95×10^{-1}	4.60×10^{-1}	4.84×10^{0}	$\mathbf{2.77 \times 10^{-1}}$
Normal year	7.04×10^{-1}	9.19×10^{-1}	8.18×10^{0}	$\mathbf{1.20 \times 10^{-1}}$
Dry year	5.86×10^{-1}	1.06×10^{0}	2.33×10^{-1}	$\mathbf{2.09 \times 10^{-1}}$
	STD of IGD			
Wet year	3.05×10^{-2}	$\mathbf{1.70 \times 10^{-3}}$	8.23×10^{-2}	2.03×10^{-3}
Normal year	6.10×10^{-3}	3.40×10^{-3}	2.16×10^{-1}	$\mathbf{1.08 \times 10^{-3}}$
Dry year	8.47×10^{-3}	4.12×10^{-3}	3.53×10^{-1}	$\mathbf{1.88 \times 10^{-3}}$

Table 8 | The mean and standard deviation (STD) of the GD index

Typical year	NSGAII	dMOPSO	MOEADDE	MMOSFLA
	The mean of GD			
Wet year	1.22×10^{-1}	9.24×10^{-2}	4.42×10^{-1}	5.60×10^{-2}
Normal year	4.66×10^{-2}	1.80×10^{-1}	3.18×10^{-1}	2.75×10^{-2}
Dry year	6.00×10^{-2}	2.07×10^{-1}	1.68×10^{-1}	3.53×10^{-2}
	The STD of GD			
Wet year	6.15×10^{-3}	7.32×10^{-2}	5.51×10^{-1}	4.52×10^{-3}
Normal year	1.23×10^{-2}	6.46×10^{-2}	6.19×10^{-1}	4.43×10^{-3}
Dry year	1.74×10^{-2}	9.77×10^{-2}	1.01×10^{-1}	7.86×10^{-3}

the decision maker or the end-users, it is difficult to sacrifice excessive economical benefits for ecology protection. The decision maker can choose an acceptable way where the reservoir is operated under given ecological water spill and shortage. For instance, the decision maker indicates that the ecological water spill and shortage should not exceed 112 (10^8 m^3) in terms of the normal year. Accordingly, they can determine a feasible and acceptable reservoir scheduling solution acquired by each algorithm and, apparently, the solution found by MMOSFLA has superiority in respect of total power generation than the compared methods.

It is shown in Tables 7 and 8 that for the normal year, the mean of IGD corresponding to each algorithm are 7.04×10^{-1}, 9.19×10^{-1}, 8.18×10^{0} and 1.20×10^{-1}. Similarly, mean of GD corresponding to each algorithm are 4.66×10^{-2}, 1.80×10^{-1}, 3.18×10^{-1} and 2.75×10^{-2}. It can be concluded that MMOSFLA performs better than other algorithms. The lower IGD and GD demonstrate that MMOSFLA is closer to true Pareto and has advantages in the solution convergence, distribution and diversity compared with other methods. Although the STD of IGD in the wet year is 2.03×10^{-3} is inferior to the dMOPSO (1.70×10^{-3}), the difference is controlled in a narrow range and MMOSFLA outperforms others at both the IGD and GD evaluation index. Therefore, we have reason to believe that MMOSFLA is more suitable for solving the MOEOCR problem. The decision maker can pursue relatively more power generation with consideration of ecological benefit.

CONCLUSIONS

In order to pursue higher economical and ecological benefits, multi-objective ecological operation for cascade reservoirs (MOEOCR) is conducted to give comprehensive consideration to water requirements in power generation and ecological health. For the high-dimensional MOEOCR problem with complex hydraulic constraints, the traditional single objective optimization method has difficulty demonstrating a mutually constrained relationship between objectives. For this purpose, we construct the multi-objective ecological operation model for cascade reservoirs and adopt the MMOSFLA proposed which converts SFLA into a multi-objective method to solve the model. The MMOSFLA introduces chaotic population initialization, renewed frog grouping method, local search method, and evolution for an elite frog set based on cloud model.

The test function results verify that MMOSFLA outperforms other methods at search capability, diversity and distribution uniformity for the Pareto solution set. For the ZDT3 and DTLZ 6, the mean and STD of IGD and GD obtained by MMOSFLA are 2.2902×10^{-2} (9.42×10^{-2}), 4.0986×10^{-5} (1.50×10^{-5}) and 5.9284×10^{-3} (3.58×10^{-4}), 4.7883×10^{-6} (2.33×10^{-7}), respectively. Finally, the proposed MMOSFLA is applied in an MOEOCR problem of hydropower stations in Qingjiang River. The results reflect a competing relationship between the power generation and ecological water spill and shortage. At the same time, with comparison with other methods, the solution optimized by MMOSFLA brings about more economical and ecological benefits conforming to suitable and ideal ecological water requirements. The less mean and STD of IGD and GD indexes demonstrate better solution distribution and diversity. It can provide a feasible scheduling solution set for decision makers to regulate a scheduling mode which coordinates cascade power generation and downstream ecological protection for Geheyan and Gaobazhou reservoirs. Therefore, we provide an effective measure for solving complex and high-dimensional MOEOCR problems.

Future study could emphasize on using stochastic rainfall and distributed run-off models to generate large amounts of inflow scenarios and test how the cascade reservoirs behave under all scenarios (Dimitriadis *et al.* 2016; Dimitriadis & Koutsoyiannis 2018). In addition, the expected Pareto front and its variability due to inflow uncertainty can also be estimated to determine more desirable reservoir operation rules.

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REFERENCES

Cai, W. J., Zhang, L. L., Zhu, X. P., Zhang, A. J., Yin, J. X. & Wang, H. 2013 Optimal reservoir operation to balance human and environmental requirements: a case study for the Three Gorges and Gezhouba Dams, Yangtze River basin, China. *Ecol. Inform.* **18**, 40–48.

Cao, J. 2014 *Research on the Unit Commitment Problems in Coal-Fired Power Plants Based on Shuffled Frog Leaping Algorithm*. Ningxia University, Yin Chuan, China.

Castelletti, A., Pianosi, F. & Soncini-Sessa, R. 2008 Water reservoir control under economic, social and environmental constraints. *Automatica* **44** (6), 1595–1607.

Cheng, C. T., Wang, W. C., Xu, D. M. & Chau, K. W. 2008 Optimizing hydropower reservoir operation using hybrid genetic algorithm and chaos. *Water Resour. Manage.* **22** (7), 895–909.

Dai, C. H., Zhu, Y. F., Chen, W. R. & Lin, J. H. 2007 Cloud model based genetic algorithm and its applications. *Acta Electron. Sin.* **35** (7), 1419–1424.

Dimitriadis, P. & Koutsoyiannis, D. 2018 Stochastic synthesis approximating any process dependence and distribution. *Stoch. Environ. Res. Risk Assess.* **9**, 1–23.

Dimitriadis, P., Tegos, A., Oikonomou, A., Pagana, V., Koukouvinos, A., Mamassis, N., Koutsoyiannis, D. & Efstratiadis, A. 2016 Comparative evaluation of 1D and quasi-2D hydraulic models based on benchmark and real-world applications for uncertainty assessment in flood mapping. *J. Hydrol.* **534**, 478–492.

Duan, Q., Sorooshian, S. & Gupta, V. 1992 Effective and efficient global optimization for conceptual rainfall-runoff models. *Water Resour. Res.* **28** (4), 1015–1031.

Eusuff, M. M. & Lansey, K. E. 2003 Optimization of water distribution network design using the shuffled frog leaping algorithm. *J. Water Resour. Plan. Manage.* **129** (3), 210–225.

Feng, Z. K., Niu, W. J., Zhou, J. Z., Cheng, C. T., Qin, H. & Jiang, Z. Q. 2017 Parallel multi-objective genetic algorithm for short-term economic environmental hydrothermal scheduling. *Energies* **10** (2), 1–22.

He, Y., Xu, Q., Yang, S. & Liao, L. 2014 Reservoir flood control operation based on chaotic particle swarm optimization algorithm. *Appl. Math. Model.* **38** (17–18), 4480–4492.

Hu, M., Huang, G. H., Sun, W., Li, Y. P., Ding, X. W., An, C. J. & Zhang, X. F. 2014 Multi-objective ecological reservoir operation based on water quality response models and improved genetic algorithm. *Eng. Appl. Artif. Intell.* **36** (C), 332–346.

Jager, H. I. & Smith, B. T. 2010 Sustainable reservoir operation: can we generate hydropower and preserve ecosystem values? *River Res. Appl.* **24** (3), 340–352.

Jia, B., Simonovic, S. P., Zhong, P. & Yu, Z. B. 2016 A multi-objective best compromise decision model for real-time flood mitigation operations of multi-reservoir system. *Water Resour. Manage.* **30** (10), 3363–3387.

Kang, L., Huang, Y. Y., Yang, Z. X. & Zhang, X. M. 2010 Reservoir ecological operation model and its application. *J. Hydraul. Eng.* **41** (2), 134–141.

Labadie, J. W. 2014 Optimal operation of multireservoir systems: state-of-the-art review. *J. Water Resour. Plan. Manage.* **130** (2), 93–111.

Li, F. L. 2016 *Study on Ecological Power Generation for Cascade Hydropower Stations in Multi Objective Optimization Scheduling Model*. Lanzhou University of Technology, Lanzhou, China.

Li, F. F. & Qiu, J. 2016 Incorporating ecological adaption in a multi-objective optimization for the Three Gorges Reservoir. *J. Hydroinform.* **18** (3), 564–578.

Li, H. & Yin, Y. M. 2014 An improved SFLA algorithm for economic operation of hydroelectric plant. *Water Conserv. Sci. Technol. Econ.* **20** (2), 127–130 (in Chinese).

Li, D. Y., Meng, H. J. & Shi, X. M. 1995 Membership clouds and membership cloud generators. *J. Comput. Res. Dev.* **32** (6), 15–20.

Long, F. & Mei, Y. D. 2017 A study of ecological operation of Xiluodu-Xiangjiaba cascade reservoirs on the lower Jinsha River. *China Rural Water Hydropower* **3**, 81–84.

Lu, Y. L., Zhou, J. Z., Wang, H. & Zhang, Y. C. 2011 Multi-objective optimization model for ecological operation in Three Gorges cascade hydropower stations and its algorithms. *Adv. Water Sci.* **22** (6), 780–788.

Luo, J., Chen, C. & Xie, J. 2015a Multi-objective immune algorithm with preference-based selection for reservoir flood control operation. *Water Resour. Manage.* **29** (5), 1447–1466.

Luo, J., Li, X., Chen, M. R. & Liu, H. W. 2015b A novel hybrid shuffled frog leaping algorithm for vehicle routing problem with time windows. *Inf, Sci. Int. J.* **316** (C), 266–292.

Lyu, W., Wang, H., Yin, J. X. & Zhu, X. Y. 2016 On ecological operation of cascade hydropower stations along Wujiang River in Guizhou province. *Adv. Water Sci.* **27** (6), 918–927.

Ma, Y., Tian, W. J. & Fan, Y. Y. 2013 Quantum adaptive immune clone algorithm based on cloud model. *Chin. J. Comput. Phys.* **30** (4), 627–632 (in Chinese).

Mao, J., Zhang, P., Dai, L., Dai, H. C. & Hu, T. F. 2016 Optimal operation of a multi-reservoir system for environmental water demand of a river-connected lake. *Hydrol. Res.* **47** (S1), 206–224.

Moazenzadeh, R., Mohammadi, B., Shamshirband, S. & Chau, K. W. 2018 Coupling a firefly algorithm with support vector regression to predict evaporation in northern Iran. *Eng. Appl. Comput. Fluid Mech.* **12** (1), 584–597.

Reddy, J. & Kumar, D. 2006 Optimal reservoir operation using multi-objective evolutionary algorithm. *Water Resour. Manage.* **20** (6), 861–878.

Reddy, M. J. & Nagesh Kumar, D. 2007 Multi-objective particle swarm optimization for generating optimal trade-offs in reservoir operation. *Hydrol. Process.* **21** (21), 2897–2909.

Sun, P., Jiang, Z. Q., Wang, T. T. & Zhang, Y. K. 2016 Research and application of parallel normal cloud mutation shuffled frog leaping algorithm in cascade reservoirs optimal operation. *Water Resour. Manage.* **30** (3), 1019–1035.

Tegos, A., Schlüter, W. & Gibbons, N. 2018 Assessment of environmental flows from complexity to parsimony – Lessons from Lesotho. *Water* **10** (10), 1–17.

Tian, Y., Cheng, R., Zhang, X. Y. & Jin, Y. C. 2017 PlatEMO: a Matlab platform for evolutionary multi-objective optimization [Educational Forum]. *IEEE Comput. Intell. Mag.* **12** (4), 73–87.

Vogel, R. M., Sieber, J., Archfield, S. A., Smith, M. P., Apse, C. D. & Lee, A. H. 2007 Relations among storage, yield, and instream flow. *Water Resour. Res.* **43** (5), 909–918.

Wang, X. M., Zhou, J. Z., Ou, Y. S. & Zhang, Y. C. 2013 TGC eco-friendly generation multi-objective optimal dispatch model and its solution algorithm. *J. Hydraul. Eng.* **44** (2), 154–163.

Wu, X., Wei, X. & Guo, W. 2012 Multi-objective ecological operation model of cascade hydropower reservoirs. *Proc. Eng.* **29** (4), 3996–4001.

Yang, G., Guo, S. L. & Li, L. P. 2015 Flexible decision-making for cascade reservoir operation considering ecological flow. *J. Huazhong Univ. Sci. Technol. (Nat. Sci. Ed.)* **43** (9), 114–116 + 122.

Yang, Z., Yang, K., Hu, H. & Su, L. W. 2018 The cascade reservoirs multi-objective ecological operation optimization considering different ecological flow demand. *Water Resour. Manage.* **33** (1), 207–228.

Yin, Z. J., Yang, C. H. & Xu, J. J. 2013 Ecological regulation of cascade dams in the lower Jinsha river under different ecological flow constraints. *J. Hydroelectric Eng.* **32** (3), 66–70 + 81.

Zhang, G., He, R. & Liu, Y. 2008 An evolutionary algorithm based on cloud model. *Chin. J. Comput.* **31** (7), 1082–1091 (in Chinese).

Zhang, C. L., Yu, C. R., Jiang, S. H., Liu, Q. J., Wu, W. J. & Li, Y. M. 2012 Particle swarm optimization algorithm based on chaos cloud model. *J. Comput. Appl.* **32** (7), 1951–1954 (in Chinese).

Zhang, H., Zhou, J., Fang, N., Zhang, R. & Zhang, Y. C. 2013 Daily hydrothermal scheduling with economic emission using simulated annealing technique based multi-objective cultural differential evolution approach. *Energy* **50** (1), 24–37.

Zhang, Z., Zhang, W. & Liao, W. H. 2016 Model of multipurpose reservoir ecological operation based on ecological flow range and its application. *South-to-North Water Transf. Water Sci. Technol.* **14** (5), 96–101 + 123 (in Chinese).

Zhou, J. Z., Li, Y. H. & Xiao, G. 2010 Multi-objective optimal dispatch of cascade hydropower stations based on shuffled particle swarm operation algorithm. *J. Hydraul. Eng.* **41** (10), 1212–1219.

Zhu, F., Zhong, P., Sun, Y. & Yeh, W. W.-G. 2017 Real-time optimal flood control decision making and risk propagation under multiple uncertainties. *Water Resour. Res.* **53**, 10635–10654.

Zou, C. R., Zhang, X. D. & Zhao, L. 2012 Review of shuffled frog leaping algorithm. *Inform. Res.* **38** (5), 1–5.

Zou, Q., Wang, X. M., Li, A. Q., He, X. C. & Luo, B. 2016 Optimal operation of flood control for cascade reservoirs based on parallel chaotic quantum particle swarm optimization. *J. Hydraul. Eng.* **47** (8), 967–976.

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