A novel multi-objective electromagnetism-like mechanism algorithm with applications in reservoir flood control operation

Shuo Ouyang, Jianzhong Zhou, Hui Qin, Xiang Liao and Hao Wang

ABSTRACT

Reservoir flood control operation (RFCO) is a complex problem that involves various constraints and purposes, which include the safety of the dam, watershed flood control and navigation. These objectives often conflict with each other. Thus, traditional methods have difficulty in solving the multi-objective problem efficiently. In this paper, a multi-objective self-adaptive electromagnetism-like mechanism (MOSEM) algorithm is introduced in the local searching operation of the proposed method. To enhance the optimization ability of EM, a self-adaptive parameter is applied in the local search operation of MOSEM for adjusting the values of parameters dynamically. Moreover, MOSEM is tested by several benchmark test problems and compared with some well-known multi-objective evolutionary algorithms. A case study is also used for solving RFCO problems of the Three Georges Reservoir by using the multi-objective cultured differential evolution (MOCDE), non-dominated sorting genetic algorithm-II (NSGA-II) and proposed MOSEM methods. The study results reveal that MOSEM can provide alternative Pareto-optimal solutions (POS) with better convergence properties and diversification.

Key words | electromagnetism-like algorithm, multi-objective optimization, reservoir flood control operation, self-adaptive

INTRODUCTION

Flood disasters lead to tremendous damage worldwide scope. Especially in China, the enormous population increase and rapid economic development have aggravated the harm caused by floods in a valley. Flood control projects are therefore needed to alleviate these disaster situations. Reservoir flood control is one of the most important optimization problems in hydropower system operation, as it determines the water releases of reservoirs to meet flood control requirements (Wei & Hsu 2009). Typically, reservoir flood control operation (RFCO) is a complex problem that has multiple purposes. The purposes include the safety of the dam, watershed flood control and navigation. These objectives often conflict with each other. Hence, it is more difficult to solve a multipurpose problem than a single-purpose problem for RFCO.

Many traditional methods have been proposed for solving the RFCO problem in the past decades. The RFCO problem is resolved using a linear programming method (Windsor 1973) by considering one objective at a time while converting other objectives into constraints to simplify the problem. A linear quadratic Gaussian control method (Wasimi & Kitanidis 1983) has also been proposed. However, these methods may have difficulty in dealing with multiple objectives simultaneously as well as generating all the Pareto-optimal solutions in a single run.

In recent years, the situation of multipurpose reservoir operation problems using outdated and highly subjective technology has been ameliorated by some researchers through the adoption of many intelligent methods, such as non-dominated sorting genetic algorithm-II (NSGA-II) (Deb et al. 2002), enhanced strength Pareto evolutionary algorithm (SPEA2) (Zitzler et al. 2001), multi-objective particle swarm optimization algorithm (MOPSO) (Coello et al. 2004) and multi-objective differential evolution algorithm (MODE) (Reddy & Kumar 2006). These algorithms, in the field of multipurpose reservoir operation problems, have achieved various degrees of success (Kim et al. 2006; Alexandre & Darrell 2008). Nevertheless, these methods...
seem to lack the ability to find true Pareto-optimal fronts when applied to the RFCO problem. NSGA-II and SPEA2, which are both based on GA (Ebner et al. 2010; Delelegn et al. 2011), still suffer from genetic drifting, and the search progress may be biased to some particular regions, which will result in premature convergence. The fast convergence rate of particle swarm optimization (PSO) and differential evolution (DE) often decreases the diversity of population rapidly, which may lead to the optimization progress of MOPSO and MODE methods to the local Pareto-optimal front. Thus, the improvement of current optimization algorithms and the exploration of new techniques for solving the RFCO problem are of great significance.

The electromagnetism-like mechanism (EM), proposed by Birbil and Fang in 2003, is a novel random-search globally optimum algorithm, which has all the desired properties necessary for dealing with complex problems. This method is a flexible and effective population-based algorithm to solve mathematical programming problems (Birbil et al. 2004). EM has been used to solve various single-objective optimization problems successfully, such as the applications cover areas of electronics (Lee & Jhang 2008), machine scheduling (Chang et al. 2009), and cellular manufacturing (Nai-Chieh et al. 2012).

However, there is less research on the applications of multi-objective electromagnetism-like meta-heuristic (MOEM) for the RFCO problems. Therefore, this paper proposes a multi-objective self-adaptive electromagnetism-like mechanism (MOSEM) algorithm in consideration of multiple objectives. In this algorithm, a self-adaptive parameter is applied in a local search operation to adjust the values of parameters dynamically. Meanwhile, the modified operation can adjust the obtained Pareto-optimal solutions (POS) to help MOSEM escape from local Pareto-optimal fronts. A solution is Pareto optimal if there exists no feasible solution for which an improvement in one objective does not lead to a simultaneous degradation in one (or more) of the other objectives. That is, a Pareto-optimal solution cannot be improved without harming at least one other objective. In addition, considering the complicated constraints and objectives of the RFCO problem, external archive set and selection strategies are adopted to keep a good diversity and uniformity of POS. In order to verify its effectiveness, MOSEM is tested, first on several benchmark test problems and compared with some well-known multi-objective evolutionary algorithms. After that, a case study is implemented for solving the RFCO problem of the Three Georges Reservoir by comparing the convergence properties and diversification of POS obtained by the proposed MOSEM method and those of MODE and NSGA-II. The study results reveal that MOSEM can provide alternative POS with better convergence properties and diversification.

This paper is organized as follows. The ‘Model formulation of RFCO’ section introduces the flood control operation problem. The ‘Multi-objective self-adaptive electromagnetism-like mechanism algorithm’ section briefly describes the EM scheme that MOSEM is based on, details the procedures of MOSEM and outlines the comparison results with some multi-objective evolutionary algorithms. Afterward, in the ‘Case-study: Multi-objective flood control operation of Three Gorges Reservoir’ section, the computational results of a practical RFCO problem are shown and compared with multi-objective cultured differential evolution (MOCDE) (Qin et al. 2010) and NSGA-II.

MODEL FORMULATION OF RFCO

An RFCO problem is a difficult task because of high dimensionality, complicated constraints and multiple objectives. Generally, the main objective of RFCO is to meet the safety requirement of dams, the flood control requirement of the upstream area and the flood control requirement of the downstream protected area. RFCO goals do not mutually promote each other. In our investigation, we establish a multi-objective flood control optimization model by minimizing the maximum upstream water level and the maximum water discharge volume as two main objectives to consider simultaneously for the safety requirement of dams, the flood control requirement of the upstream area and the flood control requirement of the downstream area. The objectives and corresponding constraints are expressed as follows.

Objective function

(1) Minimize the maximum upstream water level to ensure the safety of the dam and upstream area.

\[ \min F_1 = \min \{ \max (Z_t), t = 1, 2, \cdots T \} \]  \hfill (1)

(2) Minimize the maximum water discharge to keep the downstream area from being submerged.

\[ \min F_2 = \min \{ \max (Q_t), t = 1, 2, \cdots T \} \]  \hfill (2)
where $Z_t$ is the upstream water level in the $t$-th period, $T$ is the number of operational periods, $Q_t$ is the water discharge volume in the $t$-th period.

**Constraints**

1. Upstream water level limit
   \[ Z_{t,\min} \leq Z_t \leq Z_{t,\max}; \quad t = 2, 3, \cdots, T \]  
   \[ (3) \]

2. Water balance equation
   \[ V_t = V_{t-1} + (I_t - Q_{out,t})\Delta t; \quad t = 2, 3, \cdots, T \]  
   \[ (4) \]

3. Water discharge capability limit corresponding to different water levels, reservoir spillway facilities have unlike water discharge capabilities.
   \[ Q_{out,t} \leq Q_{\max}(Z_t); \quad t = 2, 3, \cdots, T \]  
   \[ (5) \]

4. Water discharge limit
   \[ Q_{\max} \geq Q_{out,t} \geq Q_{\min}; \quad t = 2, 3, \cdots, T \]  
   \[ |Q_{out,t} - Q_{out,t-1}| \leq \Delta Q; \quad t = 2, 3, \cdots, T \]  
   \[ (7) \]

where $Z_{t,\min}$ and $Z_{t,\max}$ are the minimum and maximum limits of the upstream water level of the reservoir at the $t$-th period; $V_t$, $I_t$ and $Q_{out,t}$ are the reservoir storage, flood inflow and water release volume in the $t$-th period respectively; $\Delta t$ is the time interval of a period; $Q_{\max}(Z_t)$ is the water discharge capability of the dam for the corresponding water level in the $t$-th period; $Q_{\min}$ and $Q_{\max}$ are the minimum and maximum limits of water discharge volume; $\Delta Q$ is the maximum water discharge diurnal amplitude of the dam.

**MOSEM**

**Foundation EM**

EM is a population-based stochastic algorithm that is quite simple, robust, significantly fast and effective. EM originates from the electromagnetism theory of physics by considering each sample point as a charged particle spreading around the solution space (Tsou & Kao 2008). The fundamental procedures of EM include initialization of population, local search, calculation of total force, and movement of particles. The basic strategy of EM can be described as follows.

**Initialization of population – Initialize()**

The initialization starts to ensure some parameters such as the population size $N$, dimensionality $D$ of decision variable $X^i$ and the bound of initial solution. Afterwards, the initialization is used to sample a population $X$ randomly from the feasible domain. The operation of the initialization is shown as:

\[ X_k^i = L_k + \lambda \cdot (U_k - L_k) \]  
\[ i = 1, 2, 3, \cdots, N; \quad k = 1, 2, 3, \cdots, D \]  
\[ (8) \]

where $X_k^i$ denotes the $k$-th of the $X^i$; $i$ is the index of the generation; $U_k$ and $L_k$ are the upper and lower bound of $X_k^i$ respectively; $\lambda$ is a uniform distributed random parameter.

**Local search – LocalSearch()**

The local search procedure is used to advance the convergence accuracy and population diversification of EM. In this procedure, the operation provides many valuable alternative schemes for changing $X^i$ by using the equiprobable mode, as follows:

\[ X_k^i = \begin{cases} 
X_k^i + \lambda_1(\delta \max(U_k - L_k)) & \text{if } mdl() > 0.5 \\
X_k^i - \lambda_1(\delta \max(U_k - L_k)) & \text{otherwise} 
\end{cases} \]  
\[ (9) \]

where $mdl()$ and $\lambda_1$ are uniform random numbers between [0, 1]; the size of $\delta$ determines the step of the local search.

**Calculation of total force – CalF()**

Total force vector $F^i$ of $X^i$ is calculated to confirm the moving direction and degree of $X^i$, as follows:

\[ F^i = \sum_{j=i}^{N} \begin{cases} 
q^j q^i |X^i - X^j|^2 & \text{if } \cal{f}(X^j) < \cal{f}(X^i) \\
q^j q^i |X^j - X^i|^2 & \text{if } \cal{f}(X^j) \geq \cal{f}(X^i) 
\end{cases} \]  
\[ \forall i \]  
\[ (10) \]
where $f(X^i)$ is the objective function value of $X^i$; and $q^i$ denotes the quantity charge of $X^i$:

$$q^i = \exp \left( -D \frac{f(X^i) - f(X^\text{best})}{\sum_{k=1}^{N} (f(X^k) - f(X^\text{best}))} \right), \forall i$$

where $X^\text{best}$ is the best point of $X$. According to the above equation, EM represents the distance of $X^i$ from $X^\text{best}$. When the target of $f(X^i)$ is at its minimum, the greater $q^i$ is, the smaller the distance.

**Movement of particles – Move()**

According to the $F^i$ of $X^i$, the operation acquires the next generation by moving and evolving $X^i$:

$$X^{i+1} = X^i + \lambda \frac{F^i}{|F^i|} \cdot \lambda = \text{round}(\cdot) ; i = 1, 2, \cdots, N$$

where $\lambda$ is a uniform random number between $[0, 1]$.

**MOSEM**

EM is primarily proposed for solving single-objective optimization problems. Thus, EM needs to modify some of its operations for dealing with multiple-objective problems, so as to optimize all objectives simultaneously. Hence, in MOSEM, we mainly focus on the preservation of POS, the modification of EM operations and the avoidance of premature convergence to try to achieve a successful application in dealing with multi-objective optimization problems.

**External archive updating**

Generally, multi-objective optimization algorithms are expected to find a set of POS when considering all the objectives simultaneously. External archive set (denoted as $Qset$) is adopted by the proposed method to keep a good diversification and uniformity of POS. Because of computational limitations, the size $M$ of $Qset$ is usually a constant. In archiving strategy, crowding distance (Deb et al. 2002) is often used to calculate the sharing fitness of POS.

**Modification of EM operations**

The local search procedure moves the solutions toward the local minimums that are near them. The method used in this procedure is very simple. In this paper, a self-adaptive mechanism is added to the local search operation. The new operation improves the accuracy of solutions and avoids premature convergence. The modification of this step revises the evolution step of EM, as follows:

$$X^*_k = \begin{cases} X^*_k + \lambda \cdot \text{Selfadapt}(g) \cdot \max(U_k - L_k) & \text{if } \text{rand}() > 0.5 \\ X^*_k - \lambda \cdot \text{Selfadapt}(g) \cdot \max(U_k - L_k) & \text{otherwise} \end{cases}$$

where $\text{Selfadapt}(g)$ is the $g$-th self-adaptive function; $g$ is the index of the generation:

$$\text{Selfadapt}(g) = \begin{cases} \delta \cdot \exp(-\alpha \cdot \text{count} \cdot g/G) & \text{if } \text{count} > r \\ \delta \cdot \exp(-g/G) & \text{otherwise} \end{cases}$$

where $G$ denotes the total evolution number; $\alpha$ is the self-adaptive parameter; $\text{count}$ and $r$ are the number and threshold value of stagnation, respectively.

In general, a multi-objective optimization problem does not have a single solution that could optimize all objectives simultaneously. Hence, the calculation for the charge of $i$-th particle is modified (Tsou & Kao 2006). To keep the diversification of the solution for a multi-objective optimization problem, there are some changes in the method, revised by Tsou and Kao in 2008, while the external archive set has been joined in the algorithm:

$$q^i = \exp \left( -D \frac{\text{Aprox}(X^i) - \text{Aprox}(X^\text{best})}{\sum_{k=1}^{N} (\text{Aprox}(X^k) - \text{Aprox}(X^\text{best}))} \right), \forall i$$

where $\text{Aprox}(X^i)$ is minimum distance of $X^i$ from $Qset$; $X^\text{best}$ is the nearest one to $Qset$; as follows:

$$\text{Aprox}(X^i) = \min_{Y \in Qset} (||f(X^i) - f(Y)||)$$

$$X^\text{best} = \arg \min_i (\text{Aprox}(X^i)), \quad i = 1, 2, \cdots, N$$

The dominance relationship of two particles is indeterminate, which can be judged by the distance of $X^i$ to $Qset$: (1) if $\text{Aprox}(X^i) < \text{Aprox}(X^j)$, $X^i$ is attracted by $X^j$; (2) if $\text{Aprox}(X^i) > \text{Aprox}(X^j)$, the relationship changes. The
function for calculating the total force is modified into the following equation.

$$F^i = \sum_{j=1}^{N} \begin{cases} \frac{q^j q^i}{|X^j - X^i|^{2}} & \text{if } \text{Aprox}(X^j) < \text{Aprox}(X^i) \\ \frac{q^j q^i}{|X^j - X^i|^{2}} & \text{if } \text{Aprox}(X^j) > \text{Aprox}(X^i) \end{cases} \forall i$$

(18)

**Procedures of MOSEM**

The flow chart for MOSEM is shown in Figure 1.

**Numerical simulation**

**Test functions and performance measures.** In order to verify the effectiveness of MOSEM for dealing with multi-objective optimization problems, the optimization performance of MOSEM is measured by adopting four well-known test functions (denoted as ZDT2, ZDT3, ZDT4 and ZDT6) of the Zitzler-Deb-Thiele series in this paper. It is different from the main characters of the true optimal Pareto fronts obtained by the four test functions. Among them, ZDT2 has a non-convex Pareto front; the true Pareto-optimal front of ZDT3 consists of a number of non-smooth Pareto-fronts; the true optimal Pareto front of ZDT4 is non-convex, but there are a lot of local optimal fronts in its solution space; ZDT6 has a non-convex Pareto optimal front, and it is hard to locate its true Pareto-optimal front due to the large amount of local optimal fronts around it. The features described above are summarized in Table 1.

Generally, there are two types of measure, convergence measures and diversity measures, for verifying the performance of multi-objective optimization algorithms. According to the correlative literature (Deb et al. 2002), this paper applies two widely used performance indicators to verify the performance of the propose MOSEM: convergence metric $\gamma$ and diversity metric $\Delta$, and their expressions are as follows:

$$\gamma = \sum_{i=1}^{n} \frac{D_i}{n}$$

(19)

$$\Delta = \frac{d_i + d_i + \sum_{i=1}^{n-1} |d_i - \tilde{d}|}{d_i + d_i + (n - 1)\tilde{d}}$$

(20)

**Table 1**

<table>
<thead>
<tr>
<th>Test function</th>
<th>Dimension</th>
<th>Variable bounds</th>
<th>Objective functions (and constraints)</th>
<th>Optimal solutions</th>
<th>Main characters</th>
</tr>
</thead>
</table>
| ZDT2          | 30        | [0,1]           | $f_1(x) = x_1, f_2(x) = g[1 - (f_1/g)^2]$, $g(x) = 1 + 9(\sum_{i=2}^{n} x_i)/(n - 1)$ | $x_1 \in [0, 1], x_1 = 0$ | Non-convex |}
|               |           |                 |                                       | $i = 2, 3, \ldots, n$ |               |
| ZDT3          | 30        | [0,1]           | $f_1(x) = x_1, f_2(x) = g[1 - \sqrt{f_1/g}] - (f_1/g) \sin(10\pi f_1)$, $g(x) = 1 + 9(\sum_{i=2}^{n} x_i)/(n - 1)$ | $x_1 \in [0, 1], x_1 = 0$ | Convex, discontinuous |
|               |           |                 |                                       | $i = 2, 3, \ldots, n$ |               |
| ZDT4          | 10        | $x_1 \in [0, 1]$, $x_1 \in [-5, 5]$ | $f_1(x) = x_1, f_2(x) = g[1 - \sqrt{f_1/g}]$, $g(x) = 1 + 10(n - 1) + \sum_{i=2}^{n} [x_i^2 - 10 \cos(2\pi x_i)]$ | $x_1 \in [0, 1], x_1 = 0$ | Non-convex and many local optimal fronts |
|               |           |                 |                                       | $i = 2, 3, \ldots, n$ |               |
| ZDT6          | 10        | [0,1]           | $f_1(x) = 1 - \exp(-4x_1^2) \sin^2(6\pi x_1), f_2(x) = g[1 - (f_1/g)^2], g(x) = 1 + 9(\sum_{i=2}^{n} x_i)/(n - 1)^{0.25}$ | $x_1 \in [0, 1], x_1 = 0$ | Non-convex and non-uniform |
Simulation results and comparison. To solve the four test functions, the main parameters of MOSEM are set as follows in this paper: the population size $N = 100$; the size of archive set $Qset = 50$; the maximum number of generations $G = 200$, the maximum iteration number for the local search operation $LocalNum = 10$, the threshold value of stagnation $r = 5$, the local search parameter $\delta = 0.1$ and the self-adaptive parameter $\alpha = 0.8955$. Moreover, in trying to prove the optimizing performance of MOSEM, the experimental results of these four test functions obtained by NSGA-II (Deb et al. 2002), SPEA2 (Zitzler et al. 2001), adaptive differential evolution algorithm (ADEA) (Qian & Li 2008) and MOCDE (Qin et al. 2010) are also summarized for convenience of comparison.

Figure 2 and Table 2 show the optimal solutions and their technical indexes, $\gamma$ and $\Delta$. In Table 2, the mean and

<table>
<thead>
<tr>
<th>Measures</th>
<th>Test functions</th>
<th>NSGA-II</th>
<th>SPEA2</th>
<th>ADEA</th>
<th>MOCDE</th>
<th>MOSEM</th>
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<td>$\gamma$</td>
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<tr>
<td>$\Delta$</td>
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variance values are shown in the upper and lower rows respectively, and values smaller than $10^{-6}$ are denoted as 0.

From Figure 2 we can see that the results acquired by MOSEM are excellent for the four test problems. Because the results of MOSEM attain the true Pareto-optimal front accurately, the $\gamma$ of MOSEM method is quite well attested.

From Table 2, it can be seen that MOSEM can achieve a better performance than other comparative methods when dealing with these ZDT test problems, except ZDT3. For ZDT3, the result of MOSEM is better than NSGA-II, SPEA2 and ADEA, but the result of MOCDE is equally good. MOSEM can obtain excellent $\gamma$ and $\Delta$ compared to other comparative methods.

CASE STUDY: MULTI-OBJECTIVE FLOOD CONTROL OPERATION OF THE THREE GORGES RESERVOIR

Description of the systems

The Three Gorges Project (TGP), located in the middle of the Yangtze River, is the biggest water conservancy project in the world. The comprehensive utilization of TGP includes flood control, hydropower production and navigation, while the foremost aim of the TGP system is minimizing flood risk.

The flood control of TGP is extremely important for the safety of the areas around the Yangtze River. The planning department of TGP has set out some regulations to guide the flood control operation of TGP, and the main points are as follows:

1. If the flood frequency is no more than 1%, the water discharge is kept under 55,000 m$^3$/s.
2. If the flood frequency is between 1% and 0.1%, the water discharge is kept under 78,000 m$^3$/s.
3. The maximum upstream water level limit is 175 m, and if the upstream water level reaches 175 m, then all the inflows will be discharged to ensure the safety of TGP.

Parameter settings

MOSEM is implemented to solve RFCO problems of TGP, and the parameters of MOSEM are set as follows: $N = 50$, $Q_{set} = 30$, $G = 1,000$, $LocalNum = 100$, $r = 5$, $\delta = 0.29$ and $\alpha = 0.8955$. To verify the effectiveness of MOSEM, NSGA-II (Deb et al. 2002) and MOCDE (Qin et al. 2010) are also implemented. The parameter settings for the MOCDE method are as follows: $F = 0.2$, $CR = 0.1$, $N = 50$, $Q_{set} =$
<table>
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<tr>
<th>Scheme index</th>
<th>MOSEM Objectives values</th>
<th>MOCDE Objectives values</th>
<th>NSGA-II Objectives values</th>
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<td>max Q_t (m^3/s)</td>
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Table 3 | Details of POS for typical flood 2

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30, \( G = 1,000 \). Moreover, the parameter settings for NSGA-II are as follows: \( N = 100 \), \( Q_{\text{set}} = 30 \), the mutation probability \( P_m \) and crossover probability \( P_c \) are set as 0.8 and 0.02 respectively; \( G = 1,000 \).

**Results and comparison**

With the parameter settings mentioned above, MOSEM and other comparative methods are implemented to solve the RFCO problem of TGP. The 5% frequency flood in 1998 (typical flood 1) and 0.5% frequency flood in 1981 (typical flood 2) are adopted as typical flood inflows. **Figure 3** displays the solutions of MOSEM and the other comparison methods. The results of typical floods 1 and 2 are shown in the **Figures 3(a) and 3(b)** respectively. For the convenience of comparison between the other methods, **Table 3** details the flood control operation results, and **Figure 5(b)**, the results of typical flood 2 obtained with NSGA-II, MOCDE and MOSEM. In this way, the feasibility and effectiveness of MOSEM for solving the RFCO problem is immediately clear.

In **Figure 3**, it can be inferred that the distance from solutions obtained by MOSEM to the true Pareto-optimal front is closer compared to the distances obtained by the other comparative methods. Hence, it can be concluded that the convergence property of MOSEM is better than other methods. Meanwhile, compared to MOCDE and NSGA-II, we can see that the POS obtained by MOSEM and distributed on the front are good, with good diversity compared to MOCDE and NSGA-II. From **Table 3**, it can be seen that, for the POS of typical flood 2, the minimum of maximum upstream water levels (max \( Z_t \)) obtained by MOSEM methods is 150.39 m, which is slightly lower than 151.99 m for MOCDE and slightly higher than 149.431 m for NSGA-II. On the other hand, the minimum peak water discharges (max \( Q_t \)) obtained by MOSEM is 39,613 m\(^3\)/s, which is also much lower than 43,394 m\(^3\)/s for MOCDE and 46,661 m\(^3\)/s for NSGA-II. The peak water discharges and the maximum water levels, which do not exceed 78,000 m\(^3\)/s and 175 m respectively, are both in the feasible region.

A lower max \( Z_t \) would result in a larger maximum discharge; conversely, a higher max \( Z_t \) would result in a lower maximum discharge. For example, a lower max \( Z_t \) can reduce the overtopping risk of the cascade reservoirs while it sacrifices the safety of the downstream protected area. Instead, an increased max \( Z_t \) means a raised risk to dams and upstream areas, an increased capacity of flood storage and therefore a reduced flood risk in the downstream protected area. From **Figure 3**, it is clear that all the typical operation schemes obtained by MOSEM can reduce the flood peaks effectively and keep the upstream water level at a lower level. It means that these schemes can meet the safety requirement of dams, and the flood control requirements of the upstream area and downstream protected area better than the solutions obtained by other methods. Hence, from the analysis above, we can infer that MOSEM can make better POS, which can satisfy all kinds of constraints and get better fitness values in both objectives of the RFCO problem of TGP, with better convergence and diversity properties. Thus, it can provide better operation schemes for decision-makers to help them set up a better flood control schedule.

**CONCLUSIONS**

To solve the RFCO problem, a novel algorithm, MOSEM, is proposed. In this method, a self-adaptive mechanism is added to the local search operation for adjusting the values of parameters dynamically. Meanwhile, the modified procedure can tune the obtained POS to overcome the premature convergence problem of EM and improve the algorithm’s convergence speed. Objective function normalization is applied to the different dimensions of multiple purposes. Considering the complicated constraints and objectives of the RFCO problem, external archive set and selection strategies are adopted in MOSEM to keep a good diversity and uniformity of POS. Compared with other well-known multi-objective evolutionary algorithms, MOSEM can avoid premature convergence effectively and get better Pareto-optimal results for solving several typical benchmark problems. Finally, we applied MOSEM to a case study multi-objective flood control for the Three Gorges Reservoir. It was found that MOSEM can provide decision-makers with better flood control operational schemes with a lower maximum upstream water level and smaller maximum water discharge volume along with better solution qualities and distribution properties.

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REFERENCES


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