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Multiobjective Reservoir Operation Optimization Using Improved Multiobjective Dynamic Programming Based on Reference Lines

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ABSTRACT Reservoir optimal operation (ROO) needs to coordinate various profit-making objectives, which is a typical multiobjective optimization problem (MOP) with complex constraints. With the development of multiobjective evolutionary algorithms (MOEAs) in the past decades, more and more research has focused on MOEAs to solve MOP. Considering that multiobjective ROO is also a typical multi-stage Markov decision-making problem, this paper introduces the application of multiobjective dynamic programming (MODP) for multiobjective ROO in detail. On this basis, an improved MODP with selection mechanism of non-dominated solutions based on reference lines (MODP-BRL) is proposed to improve the convergence efficiency of MODP. The experimental results show that the proposed MODP-BRL is a reliable and effective tool in solving multiobjective ROO. In addition, MODP-BRL has better performance in convergence effect and efficiency in comparison experiments with NSGAII, NSGAIII, and SPEA2. It is noteworthy that MODP and MODP-BRL are very sensitive to the discrete step. With the decrease of the discrete step (the higher the discrete precision), the computing time increases nonlinearly. The appropriate discrete step of the state variable is key presets to balance the superiority and computational efficiency of non-dominated solutions with the application of MODP and MODP-BRL.

INDEX TERMS Reservoir operation optimization (ROO), multiobjective optimization, multiobjective dynamic programming (MODP), reference lines.

I. INTRODUCTION

Reservoir operation optimization (ROO) facilitates flood control, agriculture irrigation, hydropower generating and shipping [1], [2], which serves human by optimizing benefit through meeting societal demand [3]. These structures and their catchments need an efficient and stable solving tool to handle their complexity in terms of non-linearity, multimodal, conflicting objectives and multiple constraints. In the past decades, with the development of multiobjective optimization methods, lots of related research [4]–[8] on multiobjective ROO have been done. In these studies, water is allocated as a limited resource to meet various profit-making needs, resulting in conflicts among various dispatch objectives [9], [10]. It means that ROO with multiple conflicting objectives is a multiobjective optimization problems (MOP). During the past decades, various multiobjective evolutionary algorithms (MOEAs) based on Pareto dominance have been proposed like Multiobjective Genetic Algorithm (MOGA) [5], [11], the Improved Strength Pareto Evolutionary Algorithm (SPEA2) [12], Nondominated Sorting Genetic Algorithm II (NSGAII) [13]–[15], Multiobjective Particle Swarm Optimization (MOPSO) [6], [16], Multiobjective Evolutionary Algorithm based on Decomposition

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(MOEA/D) [17], [18] and Nondominated Sorting Genetic Algorithm III (NSGAIII) [19], [20]. With the development of MOEAs, more and more researchers have begun to focus on the application of MOEAs in multiobjective ROO, and achieved good performance [21]–[23]. MOEAs have achieved good performance in testing with benchmark function. However, there are still some drawbacks in the application of MOEAs to ROO: the randomness of convergence results and the gap between the obtained non-dominated solutions and the Pareto optimal solutions.

It is noteworthy that ROO is also a multi-stage Markov decision-making problem [24]. As a classical solving method of multi-stage Markov decision problem, dynamic programming (DP) can efficiently address linear or nonlinear, convex or non-convex objective functions, and deal with a variety of complicated constraints [25]. In addition, DP can obtain global optimal solution in most cases, which makes DP widely used in quite a lot fields. In some literatures [26], [27] about solving multiobjective ROO via DP, the preferences or weights are often required. These methods cannot effectively solve practical problems, nor can they get Pareto-optimal solutions of MOP. Tauxe *et al.* [28] treated secondary objectives as state variables in DP and applied it to multiobjective ROO. Then Daellenbach & Dekluyver [29] proposed the multiobjective DP (MODP), which retains all the Pareto-optimal solutions based on non-dominated policy in recursive computation, resulting in an exponentially increasing computational burden with the length of study horizon. Zhao and Zhao [30] propose an improved MODP (IMODP) incorporated the ranking technique with crowding distance to select a representative set of Pareto-optimal solutions (instead of retaining all solutions). However, the ranking technique with the crowding distance makes some crowded solutions easy to be ignored because of the smaller crowding distance. NSGA-III [19] is aided by a new selection mechanism with well-spread reference points to maintain population diversity. This selection mechanism can be introduced into MODP to improve its convergence efficiency and effect.

In this paper, a multiobjective dynamic programming based on the reference lines (MODP-BRL) is proposed to solve ROO of Three Gorges Reservoir (TGR) with two objectives. Major contributions are outlined as follows:

1) The multiobjective dynamic programming (MODP) based on principle of Pareto-optimality is introduced in detail, which extended single-objective DP with non-dominated policy to solve MOP.
2) A new MODP based on reference lines of normalized reference plane named MODP-BRL is proposed. The MODP-BRL combines the advantages of MODP and NSGAIII and shows its high performance in multiobjective ROO.

The remainder of this paper is organized as follows: Section II introduces the formulation of ROO with two objectives. In Section III, the detail of MODP and MODP-BRP are presented. In Section IV, MODP and MODP-BRP are applied to solve ROO for TGR, then the results are analyzed. Finally, conclusions are summarized in Section V.

II. PROBLEM FORMULATION

This section introduces the details of multiobjective ROO, mainly including the mathematical model with multiobjective and several constraints.

A. OBJECTIVE FUNCTION

The primary objective of ROO is to maximize the comprehensive benefit of water resources utilization. The maximization of power generation, minimum output of TGR are selected as objectives. The maximization of power generation and minimum output are conflicting under the premise of limited water resources. The tradeoff between power generation and minimum output for multiobjective ROO are focused in many related literatures [30], [31]. The power generation reflects direct economic benefits, which can be expressed as follows.

$$\max f_1 = \max \sum\nolimits_{t=1}^{T} N_t \Delta t \tag{1}$$
$$N_t = A\, H_t Q_t \tag{2}$$

where T is the number of periods; A is output coefficient of TGR; Δt shows interval of scheduling term; N_t, H_t and Q_t denote output, pure water head and generating discharge in t period, respectively.

The minimum output determines the power quality of power plants, and it determines the competitiveness of power plants participating in the electricity market. It can be expressed as follows.

$$\max f_2 = \max \left\{ \min_{\forall t=1,2,\ldots,T} (N_t) \right\} \tag{3}$$

B. CONSTRAINTS

In ROO, the following constraints of hydropower station should be considered.

1) Water balance constraint.

$$V_t = V_{t-1} + (I_t - O_t)\,\Delta t,$$
$$O_t = Q_t + S_t \tag{4}$$

where V_t is reservoir storage at t period; I_t is inflow at t period; O_t, Q_t and S_t stands for outflow, generating discharge and deserted outflow, respectively.

2) Water head equation.

$$H_t = (Z_{t-1} + Z_t)/2 - Z_t^{\text{down}} \tag{5}$$
$$Z_t^{down} = SDR\,(O_t) \tag{6}$$

where H_t stands for the water head; Z_t is the upstream water level at t period; Z_t^{down} is tail water level described in formula (6); The function $SDR()$ represents the hydraulic connection between Z_t^{down} and O_t.

3) Water level constraint.

$$Z_t^{\min} \le Z_t \le Z_t^{\max} \tag{7}$$
$$|Z_t - Z_{t+1}| \le \Delta Z \tag{8}$$

where $Z_t^{\min}$ and $Z_t^{\max}$ are the minimum and maximum water level limits; and ΔZ is the maximum amplitude of water level variation.

4) Power generating constraint.

$$N_t^{\min} \leq N_t \leq N_t^{\max}(H_t) \tag{9}$$

where $N_t^{\max}(H_t)$ represents the maximum output limit, which is a function of water head; $N_t^{\min}$ is the minimum output limit.

5) Outflow constraint.

$$O_t^{\min} \leq O_t \leq O_t^{\max} \tag{10}$$

where $O_t^{\min}$ and $O_t^{\max}$ represent respectively the minimum and maximum outflow limit.

6) Boundary condition.

$$Z_0 = Z_{\text{begin}}, \quad Z_T = Z_{\text{end}} \tag{11}$$

where Z_{begin} and Z_{end} are initial water level and terminal water level of hydropower station, respectively.

III. MODP-BRL

This section introduces standard DP, then some basic concepts related to the MODP algorithm is described in detail. Finally, the details of MODP-BRL will be listed.

A. DP

DP is one of the most well-known and effective methods to handle multi-stage Markov decision-making problem, which is first introduced by Bellman in 1962. It is extremely effective for DP to deal with nonlinear objective functions and reservoir operation constraints in ROO [24], [32], [33]. In ROO, reservoir capacity or water level are often chosen as state variable, and outflow is chosen as decision variable. According to the principle of optimality, the recursive function for single objective ROO in DP can be expressed as below.

$$R_t(V_{t-1,i}) = \max_{V_{t,j}\in\{V_t\}} \left\{B_t(V_{t-1,i}, O^*_{t,j}, I_t) + R_{t+1}(V_{t,j})\right\} \tag{12}$$

where $O^*_{t,j}$ represents optimal decision or optimal control. Considering the water balance $O_t = (V_{t-1} - V_t)/\Delta t + I_t$ refer to (3), the decision can be expressed by the state V_{t-1} and V_t, $O^*_{t,j}$ in (11) can be expressed as follows.

$$R_t(V_{t-1,i}) = \max_{V_{t,j}\in\{V_t\}} \{B_t(V_{t-1,i}, V_{t,j}, I_t) + R_{t+1}(V_{t,j})\} \tag{13}$$

$$Backtracking(V_{t-1,i}, t) = V_{t,j} \tag{14}$$

where $R_t(V_{t-1,i})$ represents the benefit of remaining period from t to T for state $V_{t-1,i}$, and $V_{t-1,i}$ is the reservoir capacity at the beginning of period t; $B_t(V_{t-1,i}, V_{t,j}, I_t)$ stands for single-period benefit function. The benefit of $R_t(V_{t-1,i})$ and $B_t(V_{t-1,i}, V_{t,j}, I_t)$ can be specified as many scheduling objectives in (12), such as power generation, flood control, water supply, …, etc. $Backtracking(V_{t-1,i}, t) = V_{t,j}$ represents the backtracking relationship between $V_{t-1,i}$ and $V_{t,j}$ with the optimal decision $O^*_{t,j}$.

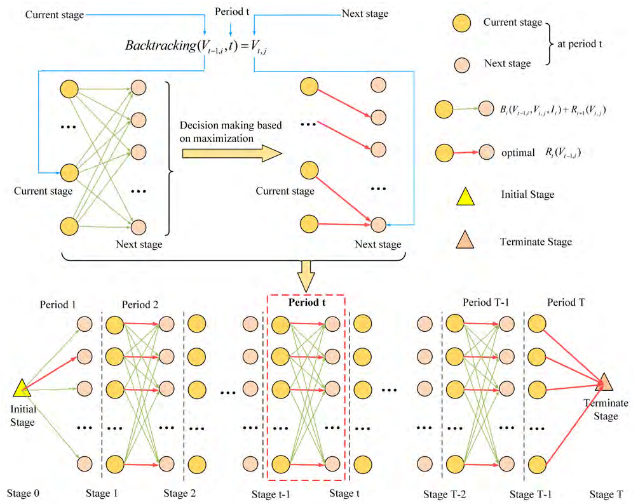


FIGURE 1. The decision making process of DP for reservoir operation.

FIGURE 1 shows the decision making process of DP for ROO. The reservoir capacity V is discretized into n values $\{V_{t,j}\}$. V_{begin} and V_{end} of TGR are set as a fixed value, which are usually specified by the dispatcher. Accordingly, there is only one state at the first and last period. At t period, the optimal state $V_{t,j}$ corresponding to optimal decision will be selected from $\{V_{t,j}\}$ to obtain the optimal $R_t(V_{t-1,i})$ for each $V_{t-1,i}$ in $\{V_{t-1,i}\}$, and save the backtracking relationship between $V_{t-1,i}$ and $V_{t,j}$. After recursive computation from T-1 to 1 period, the optimal benefit $R_1(V_{\text{begin}})$ and optimal state process $\{V^*_{t,j}\}$ can be obtained based on the backtracking relationship previously preserved.

B. MODP

The MODP algorithm extends DP using a multiobjective benefit evaluation function, and it searches for states with superior performance considering multiple objectives [34]. Daellenbach & Dekluyver [29] proposed MODP based on principle of Pareto-optimality. The principle of Pareto-optimality of MODP states that a non-dominated policy has the property that regardless of how the process entered a given state, the remaining decisions must belong to a non-dominated sub-policy [30]. Equation (13) and (14) for single objective of reservoir operation in DP can be extended to multiple objective problem as below.

$$\mathbf{MOR}_t(V_{t-1,i}) = \underset{[V_{t,j},y]\in MOR_t(V_{t,j})}{\text{non-dominated-select}} \left\{\mathbf{MOs}_t^1(V_{t-1,i}, V_{t,j}, y, I_t)\right\} \tag{15}$$

$$\begin{cases} \mathbf{F}(V_{t-1,i}) = \mathbf{MOR}_t(V_{t-1,i}) = \left\{\mathbf{MOR}_t(V_{t-1,i}, x)\right\} \\ \mathbf{MOR}_t(V_{t-1,i}, x) = \begin{bmatrix} MOR_t^1(V_{t-1,i}, V_{t,j}, y, I_t) \\ MOR_t^2(V_{t-1,i}, V_{t,j}, y, I_t) \\ \vdots \\ MOR_t^M(V_{t-1,i}, V_{t,j}, y, I_t) \end{bmatrix} \end{cases} \tag{16}$$

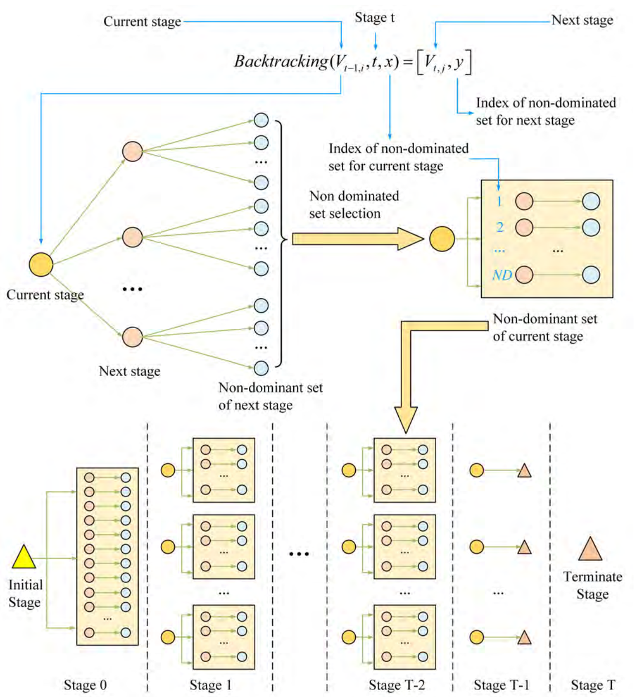


FIGURE 2. The decision making process of MODP for reservoir operation.

$$\mathbf{MOs}_t(V_{t-1,i}, V_{t,j}, y, I_t) = \begin{bmatrix} MOs_t^1(V_{t-1,i}, V_{t,j}, y, I_t) \\ MOs_t^2(V_{t-1,i}, V_{t,j}, y, I_t) \\ \vdots \\ MOs_t^M(V_{t-1,i}, V_{t,j}, y, I_t) \end{bmatrix} \tag{17}$$

$$MOs_t^m(V_{t-1,i}, V_{t,j}, y, I_t) = MOB_t^m(V_{t-1,i}, V_{t,j}, I_t) + MOR_{t+1}^m(V_{t,j}, y) \tag{18}$$

$$\begin{cases} Backtracking(t, [V_{t-1,i}, x]) = [V_{t,j}, y] \\ [V_{t-1,i}, x] \sim MOR_t(V_{t-1,i}, x) \\ [V_{t,j}, y] \sim MOR_{t+1}(V_{t,j}, y) \end{cases} \tag{19}$$

where $\mathbf{MOs}_t(V_{t-1,i}, V_{t,j}, y, I_t)$ represents general solutions (multiobjective evaluation vector) as formula (16) and (17). $\mathbf{MOR}_t(V_{t-1,i})$ represents the non-dominated solutions from t to T period for state $V_{t-1,i}$, and the reservoir capacity is $V_{t-1,i}$ at the beginning of t period. $\mathbf{MOR}_t(V_{t-1,i}, x)$ represents the multiple objective benefit vectors of x-th non-dominated solution in $\mathbf{MOR}_t(V_{t-1,i})$. $\mathbf{MOs}_t(V_{t-1,i}, V_{t,j}, y, I_t)$ and $\mathbf{MOR}_t(V_{t-1,i}, V_{t,j}, y, I_t)$ represent the multiobjective benefit vectors of general solutions and non-dominated solutions from t to T period for state $V_{t-1,i}$ to $V_{t,j}$with $\mathbf{MOR}_{t+1}(V_{t,j}, y)$. Equation (18) extends (13) from single objective to multiobjective, and M is the number of objectives. $Backtracking(t, [V_{t-1,i}, x]) = [V_{t,j}, y]$ represents the backtracking relationship between $\mathbf{MOR}_t(V_{t-1,i}, x)$ and$\mathbf{MOR}_{t+1}(V_{t,j}, y)$. $\mathbf{MOR}_t(V_{t-1,i}, x)$ and $\mathbf{MOR}_{t+1}(V_{t,j}, y)$ represents the multiobjective benefit vectors of x-th non-dominated solution in $\mathbf{MOR}_t(V_{t-1,i})$ for state $V_{t-1,i}$ and y-th non-dominated solution in $\mathbf{MOR}_{t+1}(V_{t,j})$ for state $V_{t,j}$. FIGURE 2 shows the decision making process of MODP for multiobjective ROO. Each state retain own non-dominated solutions, so $Backtracking(t, [V_{t-1,i}, x]) = [V_{t,j}, y]$ needs to specifies two index x, y for non-dominated solutions of state $V_{t-1,i}$ and $\{V_{t,j}\}$.

Algorithm 1 shows the process of MODP algorithm. The non-dominated policy and different record form of backtracking relationship were introduced to DP [29]. It enables MODP to obtain non-dominated solutions of MOP. And *non-dominated-select*{ } represents the method of obtaining and identifying $\mathbf{MOR}_t(V_{t-1,i})$ from $\mathbf{MOs}_t(V_{t-1,i}, V_{t,j}, y, I_t)$ in (15). The new record form of backtracking relationship $Backtracking(t, [V_{t-1,i}, x])$ select $[V_{t,j}, y]$ as backtracking index, because each state $V_{t,j}$ corresponds to $\mathbf{MOR}_{t+1}(V_{t,j})$. Any dominated solutions will not exist in $\mathbf{MOR}_t(V_{t-1,i})$. The backtracking relationships between $[V_{t-1,i}, x]$ and $[V_{t,j}, y]$ are saved when $\mathbf{MOR}_t(V_{t-1,i})$ is generated. And corresponding optimal state process $\{V_{t,j}^*\}$ can be obtained based on $Backtracking(t, [V_{t-1,i}, x]) = [V_{t,j}, y]$.

Algorithm 1 The Pseudocode of MODP Algorithm

Input:
V_{begin} and V_{end} and inflow series $\{I_t\}$
Initialization:
the states (reservoir capacity) are discretized
generate discrete set of states $\{V_{t,j}\}$
Calculation:
for $t = T$ to 1
  for i =1 to n select $V_{t-1,i}$
   for $j = 1$ to m select $V_{t,j}$
    for $np = 1$ to NP select $\mathbf{MOR}_{t+1}(V_{t,j}, y)$
     calculate $\mathbf{MOs}_t(V_{t-1,i}, V_{t,j}, y, I_t)$ as (17) and (18)
    end for
   end for
  obtain $\{\mathbf{MOs}_t(V_{t-1,i}, V_{t,j}, y, I_t)\}$ for state $V_{t-1,i}$
  non-dominated select $\{\mathbf{MOs}_t(V_{t-1,i}, V_{t,j}, y, I_t)\}$
   obtain $\mathbf{MOR}_t(V_{t-1,i})$ and save it for state $V_{t-1,i}$
   save $Backtracking(t, [V_{t-1,i}, x]) = [V_{t,j}, y]$
  end for
end for
Outflow:
non-dominated solutions $\mathbf{MOR}_1(V_{begin})$ and corresponding state (decision) process $\{V_t\}$

C. IMODP

MODP suffers a lot of computational burden because of state-based optimization and preservation of all the Pareto-optimal solutions in recursive computation. To improve the computational efficiency, Zhao [30] incorporates the ranking technique [13] into MODP and proposes an efficient IMODP algorithm. IMODP uses selection mechanism based on crowding distance to alleviate computational burden and involves a parameter K, that is, to select a representative set of K solutions from the whole set. The idea of IMODP is clarified by MOEA, which employs selection mechanism to control the size of non-dominated solutions and thus reduce the computational burden [35], [36].

The ranking technique uses the crowding distance to select representative solutions from the whole set, preserving the diversity of solutions [13]. It consists of two steps: assigning the crowding distance and sorting of the objective vectors. We denote the number of Pareto optimal objective vectors as N. In the steps of the calculation of crowding distance, first, the initial crowding distances are set to zero. Then, the distance for each of the objectives is calculated; the crowding distance is the sum of the difference of each objective function value of two adjacent individuals. After the crowding distance assignment, sorting of the non-dominated solutions is conducted. The non-dominated solutions are ranked based on the corresponding distance values in descending order, and the first K solutions are selected.

D. MODP-BRL

The number of non-dominated solutions needs to be reduced to prevent curse of computational burden, and the selected non-dominated solutions should be uniformly distributed. NSGA-III algorithm used reference points generated by a normalized reference plane to choose uniformly distributed non-dominated solutions. In MODP-BRL, a new selection mechanism based on reference lines referring to reference points in the NSGA-III is proposed to alleviate computational burden and ensure uniform distribution of selected non-dominant solutions.

1) REFERENCE POINTS

The reference points are evenly placed on a normalized reference plane proposed by Das and Dennis [37], which is generated by hypothetical extreme reference points. The total number of reference points (H) in an M-objective problem is calculated by (20).

$$H = \binom{M+p-1}{p} \tag{20}$$

For example, there are three hypothetical extreme reference points at (1, 0, 0), (0, 1, 0), (0, 0, 1) on normalized reference plane when the number of objective is three ($M = 3$) as FIGURE 3. If three divisions ($p = 3$) are selected for each axis that any two extreme reference points are connected, the reference point set will have 10 reference points including 3 extreme reference points. The reference points can be generated by Das and Dennis's [37] systematic approach that places points on a normalized hyper-plane.

2) NORMALIZATION

The reference points on normalized reference plane have been normalized, so multiobjective evaluation vector $\mathbf{f}_{np}$ also needs to be normalized as $\mathbf{nf}_{np}$. The standard 0-1 transformation is chosen for normalization, which can be described as follows.

$$\begin{cases} \mathbf{F}(V_{t-1,i}) = \mathbf{MOR}_t(V_{t-1,i}) \\ \mathbf{f}_{np} = \mathbf{MOR}_t(V_{t-1,i}, np) \end{cases} \tag{21}$$

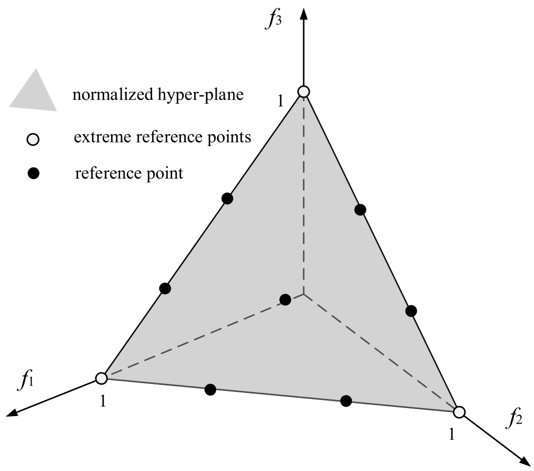


FIGURE 3. Reference points are shown on a normalized reference plane for a three-objective problem with p = 3.

$$\begin{cases} \mathbf{nF} = \text{normalize}(\mathbf{F}) \\ \mathbf{F} = \{\mathbf{f}_{np}\} \text{ before normalization} \\ \mathbf{nF} = \{\mathbf{nf}_{np}\} \text{ after normalization} \end{cases} \tag{22}$$

$$\begin{cases} \mathbf{f}_{np} = \left[f_{np}^1, f_{np}^2, \ldots, f_{np}^m, \ldots, f_{np}^M\right]^T \\ \mathbf{nf}_{np} = \left[nf_{np}^1, nf_{np}^2, \ldots, nf_{np}^m, \ldots, nf_{np}^M\right]^T \end{cases} \tag{23}$$

$$nf_{np}^m = \left(f_{np}^m - f_{\min}^m\right)/f_{\max}^m - f_{\max}^m \tag{24}$$

$$nf_{np}^m = \left(f_{\max}^m - f_{np}^m\right)/\left(f_{\max}^m - f_{\max}^m\right) \tag{25}$$

where $\mathbf{nF}$ and $\mathbf{F}$ represent non-dominated solutions before and after normalization operation as (21). $\mathbf{f}_{np}$ and $\mathbf{nf}_{np}$ represent np-th non-dominated solution in $\mathbf{nF}$ and $\mathbf{F}$, respectively. And they are multiobjective evaluation vector with M objectives. f_{np}^m and nf_{np}^m represent m-th objective in $\mathbf{f}_{np}$ and $\mathbf{nf}_{np}$, respectively. Equation (24) and (25) represent the benefit attribute and cost attribute respectively of standard 0-1 transformation. The maximization of power generation and minimum output can be regarded as beneficial attributes in this paper.

3) SELECTION BASED ON REFERENCE LINES

After the reference points on normalized reference plane generated, the rays from origin point (0, 0, 0) to reference points is taken as reference lines $\vec{\mathbf{R}} = \{\vec{r}_h\}$ as FIGURE 4. There are 10 reference lines generated from 10 reference points, and each $\vec{r}_h$ cover a range of objective space.

For massive $\mathbf{nf}_{np}$ in $\mathbf{nF}$, $\mathbf{nf}_{np}$ can be sorted according to the minimum value of distance from $\mathbf{nf}_{np}$ to $\vec{r}_h$ in $\vec{\mathbf{R}}$. The Euclidean distance is used in the distance $ED(\mathbf{nf}_{np}, \vec{r}_h)$ from $\mathbf{nf}_{np}$ to $\vec{r}_h$. $\mathbf{nf}_{np}$ with the first K smaller $ED(\mathbf{nf}_{np}, \vec{r}_h)$ should be retained into selected non-dominated solutions $\mathbf{snF}$, and each $\vec{r}_h$ holds only one $\mathbf{nf}_{np}$ with minimum $ED(\mathbf{nf}_{np}, \vec{r}_h)$. The number of $\mathbf{nf}_{np}$ retained in $\mathbf{snF}$ eventually depends on H and K. The pseudocode of selection based on reference lines for normalized non-dominated solutions in Algorithm 2.

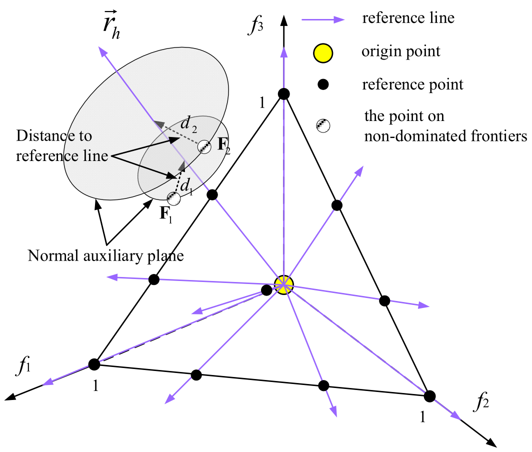


FIGURE 4. The reference lines and euclidean distance for a three-objective problem with p = 3.

Algorithm 2 Selection Based on Reference Lines

Input:

1: non-dominated solutions **F** and size(**F**) $= NP$

2: number of reference lines H and parameter K

3: reference lines $\vec{\mathbf{R}} = \{\vec{r}_h\}$

Initialization:

1: $\mathbf{nF} = \text{normalize}(\mathbf{F})$ as formula (21)-(24) in section 3.3.1

2: $\mathbf{snF} = \emptyset$ and $\mathbf{sF} = \emptyset$

Main loop:

1: **for** $h = 1$ to H select $\vec{r}_h$ in $\vec{\mathbf{R}}$

2: $EDs = \emptyset$//record Euclidean distance from $\mathbf{nf}_{np}$ to $\vec{r}_h$

3: **for** $np = 1$ to NP select $\mathbf{nf}_{np}$ in current **nF**

4: calculate $ED(\mathbf{nf}_{np}, \vec{r}_h)$

5: $EDs \leftarrow ED(\mathbf{nf}_{np}, \vec{r}_h)$

6: **end for**

7: ascending sort EDs according to $ED(\mathbf{nf}_{np}, \vec{r}_h)$

8: select index np with minimum $ED(\mathbf{nf}_{np}, \vec{r}_h)$

9: $\mathbf{snF} \leftarrow \mathbf{nf}_{np}$ and $\mathbf{sF} \leftarrow \mathbf{f}_{np}$

10: remove $\mathbf{nf}_{np}$ from **nF**

11: remove $\mathbf{f}_{np}$ from **F**

12: **end for**

13: **while** size(**sF**) $<$ K

14: select $\mathbf{nf}_{np}$ with $\max_{\mathbf{snf} \in \mathbf{snF}} ED(\mathbf{nf}_{np}, \mathbf{snf})$

15: $\mathbf{snF} \leftarrow \mathbf{nf}_{np}$ and $\mathbf{sF} \leftarrow \mathbf{f}_{np}$

16: **end**

Output:

The non-dominated solutions after selection **sF**

Algorithm 2 shows the process of selection based on reference lines. Firstly, **F** are normalized into **nF**, which make it suitable for normalized reference plane and reference lines $\vec{\mathbf{R}}$. The index np with minimum $ED(\mathbf{nf}_{np}, \vec{r}_h)$ will be find out for each $\vec{r}_h$ in $\vec{\mathbf{R}}$. Then $\mathbf{nf}_{np}$ and $\mathbf{f}_{np}$ will be added to **snF** and **sF**, and the backtracking relationships should be updated. The selection operation can reduce the number of elements from **F** to **sF**. It can effectively select **sF** to ensure the uniform distribution of solutions in the objective space. Combined with these steps, the pseudocode of MODP-BRL algorithm can be described as follows.

Algorithm 3 The Pseudocode of MODP-BRL Algorithm

Input:

1: V_{begin} and V_{end} and inflow series $\{I_t\}$

2: number of reference points H

Initialization:

1: generate discrete set of states $\{V_{t,j}\}$

2: H structured reference points, and $\vec{\mathbf{R}} = \{\vec{r}_h\}$ are generated

Calculation:

1: **for** $t = T$ to 1

2: **for** $i = 1$ to n select $V_{t-1,i}$

3: **for** $j = 1$ to m select $V_{t,j}$

4: **for** $np = 1$ to NP select $\mathbf{MOR}_{t+1}(V_{t,j}, y)$

5: calculate $\mathbf{MOs}_t(V_{t-1,i}, V_{t,j}, y, I_t)$ as (17) and (18)

6: **end for**

7: **end for**

8: obtain $\{\mathbf{MOs}_t(V_{t-1,i}, V_{t,j}, y, I_t)\}$ for state $V_{t-1,i}$

9: non-dominated select $\{\mathbf{MOs}_t\}$

10: obtain $\mathbf{MOR}_t(V_{t-1,i})$ and save it for state $V_{t-1,i}$

11: save $Backtracking(t, [V_{t-1,i}, x]) = [V_{t,j}, y]$

12: **if** size(**F**) $> K$

12: obtain **sF** after selection of **F** as **Algorithm 3**

13: **elseif**

14: $\mathbf{sF} = \mathbf{F}$

15: obtain $\mathbf{sMOR}_t(V_{t-1,i})$ according to **sF**.

16: update $Backtracking(t, [V_{t-1,i}, x]) = [V_{t,j}, y]$ according to $\mathbf{sMOR}_t(V_{t-1,i})$

17: **end for**

18: **end for**

Output:

selected non-dominated solutions $\mathbf{sMOR}_1(V_{begin})$ and corresponding state (decision) process $\{V_t\}$

IV. CASE STUDY

A. DESCRIPTION OF CASE STUDY

The Yangtze River is the third longest river in the world, the largest river in China. TGR is the key backbone of the Yangtze River Basin (See as FIGURE 5), and the operation and management of TGR will inevitably affect the river basin ecosystem of upper and lower reaches. The mainly parameters of TGR are listed in TABLE 1. The typical years are selected to be the inflow conditions according to historical runoff from 1959 to 2014: dry year (1969). In order to defend the coming flood in flood season, the TGR empties storage capacity, and its water level dropped to 145 at June 10. And the TGR begins to store water in September 1. Therefore, the scheduling period begins at June 10 and end at June 10 of next year. The time step was ten days (actually it is not a constant, and the end 10 days could be 8 or 9 days (February), 10 days and 11 days). The initial water level Z_i^{begin} and terminal water level Z_i^{end} are set to 145 m.

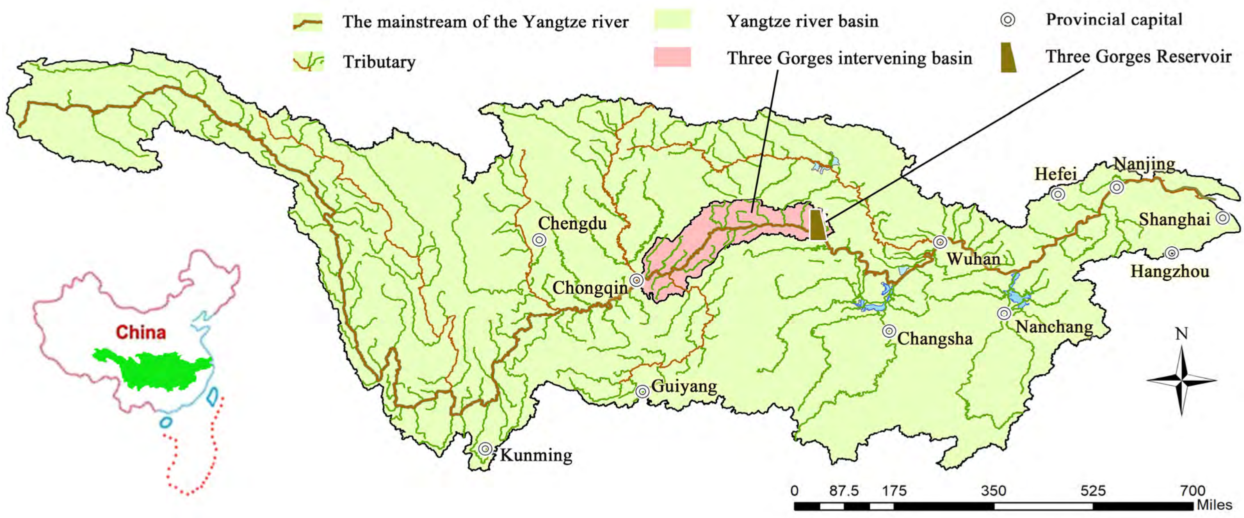


FIGURE 5. The location of the research area in china.

TABLE 1. The main parameters of TGR.

Parameter	TGR
Adjustment ability	Season
Total reservoir capacity (billion m^3)	39.30
Regulating storage (billion m^3)	16.50
Hydro plant discharge range(m^3/s)	[98800,4500]
Upriver water level range (m)	[175,145]
Installed capacity (MW)	22400
Normal water level (m)	175
Maximum water level amplitude(m/d)	0.6

B. PERFORMANCE METRICS

MODP retains all non-dominated solutions of each states in the process of recursion calculation. It means that MODP can obtain Pareto-optimal solutions with a specified discrete step of state. MODP-BRL and IMODP use different strategies to reduce the number of non-dominated solutions of each states so as to alleviate computational burden, but this makes the non-dominated solutions obtained by MODP-BRL and IMODP unable to guarantee Pareto-optimality. Therefore, several performance metrics are given to evaluate these algorithms.

The two most commonly used performance metrics are inverted generational distance (IGD) [38] and hypervolume (HV) [39]. IGD is selected in experiments rather than HV because of the complexity of HV calculation steps. As for IGD, we should compute a set $\mathbf{V} = [\mathbf{v}_1, \mathbf{v}_2, \ldots, \mathbf{v}_N]$; first, each of them is the intersection point of the true Pareto frontier with each weight vector. Then, the final non-dominated solutions $\mathbf{F} = \{\mathbf{f}_{np}\}$ is obtained by any algorithm. The IGD value of $\mathbf{F}$ is computed as:

$$\mathrm{IGD}(\mathbf{F}, \mathbf{V}) = 1/|\mathbf{V}| \sum_{i=1}^{|\mathbf{V}|} \min_{\mathbf{nf} \in \mathbf{nF}} d(\mathbf{v}_i, \mathbf{f}) \tag{26}$$

where $d(\mathbf{v}_i, \mathbf{f})$ is the Euclidean distance between $\mathbf{v}_i$ and $\mathbf{f}$ in $\mathbf{F}$, and $|\mathbf{V}|$, $|\mathbf{F}|$ is the cardinality of $\mathbf{V}$ and $\mathbf{F}$.

In this case, the Pareto frontier of the problem is unknown. MODP can obtain the Pareto-optimal solutions of Markov multi-stage decision making problem with specified discrete precision, so the non-dominated solutions obtained by MODP can be regarded as the true Pareto frontier $\mathbf{V}$ of the problem with specified discrete precision. For non-dominated solutions $\mathbf{F}1$ and $\mathbf{F}2$, the average number of dominated solutions (ANDS) of $\mathbf{F}1$ to $\mathbf{F}2$ is defined as follows.

$$\begin{cases} \mathrm{ANDS}(\mathbf{F}1, \mathbf{F}2) = 1/|\mathbf{F}1| \sum_{i=1}^{|\mathbf{F}1|} \sum_{j=1}^{|\mathbf{F}2|} \delta(\mathbf{f}1_i, \mathbf{f}2_j) \\ \delta(\mathbf{f}1_i, \mathbf{f}2_j) = \begin{cases} 1 & \mathbf{f}1_i \text{ is dominated by } \mathbf{f}2_j \\ 2 & \text{otherwise} \end{cases} \end{cases} \tag{27}$$

where $\delta(\mathbf{f}1_i, \mathbf{f}2_j)$ is a function of 0, 1. When $\mathbf{f}1_i$ is dominated by $\mathbf{f}2_j$, $\delta(\mathbf{f}1_i, \mathbf{f}2_j) = 1$; otherwise, $\delta(\mathbf{f}1_i, \mathbf{f}2_j) = 0$, and $|\mathbf{F}1|$, $|\mathbf{F}2|$ is the cardinality of $\mathbf{F}1$ and $\mathbf{F}2$. The smaller ANDS($\mathbf{F}1$, $\mathbf{F}2$), the smaller the degree that $\mathbf{F}1$ is dominated by $\mathbf{F}2$.

C. CASE 1

In this case, the model of multiobjective ROO of TGR is established with two objectives ($M = 2$). Then MODP-BRL and IMODP, MODP are used to solve this problem and test their performance. The water level is selected as state, and the discrete step of state is 0.1 m. The parameter K in IMODP and K, H in MODP-BRL are used to limit the number of non-dominated solutions of each states. In this case, K is set to 100, 80, 60, 40. In addition, the number of reference points also affects the performance of MODP-BRP. These experiments are made on a personal computer, Windows10, Intel(R) Core(TM) i7-8750H CPU@ 2.20GHZ, RAM 16.00 GB. The code language for experiments and models is java.

The ANDS for MODP-BRL, IMODP and MODP are presented in TABLE 2. ANDS of MODP-BRL to MODP are

TABLE 2. The ANDS for MODP-BRL, IMODP and MODP.

ANDS(F1,F2)		K			
F1	**F2**	40	60	80	100
IMODP	MODP	3.425	2.217	1.195	0.635
MODP-BRL		2.825	1.621	1.025	0.607
IMODP	MODP-BRL	0.350	0.567	0.351	0.323
MODP-BRL	IMODP	0.275	0.207	0.250	0.283

TABLE 3. The IGD and computing time for MODP-BRL, IMODP and MODP.

IGD				
K	40	60	80	100
IMODP	1.550E-02	9.912E-03	5.769E-03	3.645E-03
MODP-BRL	1.529E-02	8.532E-03	5.225E-03	3.185E-03
Computing time (s)				
MODP	11.311			
K	40	60	80	100
IMODP	2.402	3.293	4.792	6.104
MODP-BRL	2.917	4.187	5.990	8.351

less than ANDSof IMODP to MODP with K = 40, 60, 80, 100. It means that the number of the non-dominated solutions of MODP-BRL dominated by MODP is less than that of IMODP dominated by MODP. The non-dominated obtained of MODP-BRL is closer to that of MODP than that of IMODP. These indicate that MODP-BRL outperforms IMODP in ANDS.

Table 3 shows the IGD and computing time for MODP-BRL, IMODP and MODP. The non-dominated solutions of MODP is treated as true Pareto frontier in the calculation of IGD. Obviously, the IGD of MODP-BRL is less than that of IMODP when K = 40, 60, 80, 100. This is mainly due to the fact that the crowded solutions are not selected to representative solutions from the whole solutions according to the crowding distance in IMODP. The crowding distance cannot really reflect the aggregation degree of the solutions. In addition, some solutions with very small congestion distance may be in a position with better spatial distribution uniformity. MODP-BRL chooses representative solutions based on uniformly distributed reference lines on the normalized hyperplane, and MODP-BRL uses Euclidean distance instead of crowding distance. But the computational cost of Euclidean distance makes the computational time of MODP-BRL slightly longer than that of IMODP. To sum up, MODP-BRL performs better on ANDS and IGD than IMODP, which fully demonstrates that MODP-BRL is also reliable and effective tool in solving problems.

D. CASE 2

Then, the NSGAII, NSGAIII and SPEA2 are applied to verify the convergence efficiency of MODP-BRL in multiobjective ROO of TGR. The code of NSGAII, NSGAIII and SPEA2 are obtained by jMetal [40], which is an object-oriented Java-based framework for multiobjective optimization with metaheuristics. The parameters of NSGAII, NSGAIII and SPEA2 are set as Table 4. The parameter *D* in Table 6 represents the dimension of the problem (D = 36 in this problem). The parameter settings of MODP and MODP-BRP are the same as those of case 1 except K = 100 in MODP-BRP. FIGURE 6 shows the non-dominated solutions obtained by different methods when the iterations = 1000 and 2000. Table 5 gives the calculation time of different methods under different conditions.

TABLE 4. The main parameters of NSGAII, NSGAIII and SPEA2.

	NSGAII	NSGAIII	SPEA2
Population size	Population size = 100		
Crossover	Simulated Binary Crossover		
	Crossover Probability = 1.0; Crossover Distribution Index = 20.0		
Mutation	Polynomial Mutation		
	Mutation Probability = 1.0 / D Mutation Distribution Index = 20.0		
Selection	Binary Tournament Selection		
Constraint handling method	Superiority of feasible solutions [41]		

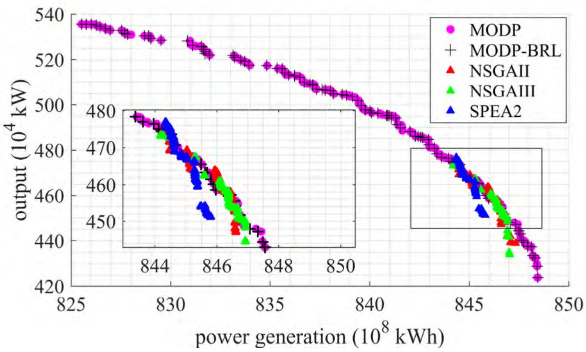
TABLE 5. The computing time for different methods.

Method	MODP	MODP -BRL	Iteration	NSGAII	NSGAIII	SPEA2
Computing time (s)	11.311	8.351	1000	9.052	9.851	12.656
			2000	17.634	19.483	24.631

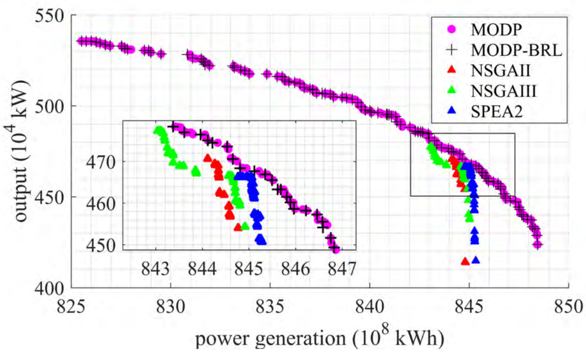
As can be seen from FIGURE 6, most of the non-dominated solutions of NSGAII, NSGAIII, SPEA2 are dominated by the non-dominated solutions of MODP and MODP-BRP when iterations = 1000. The non-dominated solutions of NSGAII, NSGAIII, SPEA2 are close to those of MODP and MODP-BRP when iterations = 2000. However, the non-dominated solutions of NSGAII, NSGAIII, and SPEA2 are crowded, and the non-dominated solutions of MODP and MODP-BRP are more widely distributed. In addition, NSGAII, NSGAIII, and SPEA2 take longer time to compute than MODP-BRP and MODP. It should be noted that, MODP-BRP and MODP only need to check constraints and abandon the states and decisions that violate the constraints, instead of conceiving constraints handling technology for MOEAs in practical engineering problems with complex constraints. In conclusion, MODP-BRP is superior to NSGAII, NSGAIII, and SPEA2 in both convergence effect and convergence efficiency in multiobjective ROO problems.

E. CASE 3

Finally, the influence of discrete step of MODP-BRP on problem solving is analyzed. The discrete step of state is set to 1, 0.5, 0.2, 0.1, 0.05, 0.02, 0.01 m for MODP-BRP



(a). Iteration = 1000



(b). Iteration = 2000

FIGURE 6. The non-dominated solution obtained by different methods.

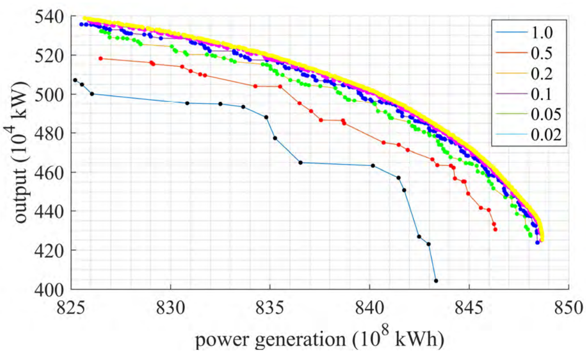


FIGURE 7. The non-dominated solutions obtained by MODP with different discrete step.

and MODP, and K = 100 in MODP-BRP. FIGURE. 7 and FIGURE 8 shows the non-dominated solutions obtained by MODP and MODP-BRP with different discrete step, respectively. Table 6 shows the computing time of MODP and MODP-BRP in different discrete step.

FIGURE. 7 shows that the smaller the discrete step, the better the non-dominated solutions of MODP can be obtained. It also reflects that even though MODP can obtain Pareto optimal solution, only when the discrete step size approaches infinitesimal, can MODP obtain true Pareto frontier. However, with the decrease of discrete step, the corresponding computing time increases nonlinearly as shown in Table 6. The corresponding computing time increases sharply from 11.3 s to 174.8 s when the discrete step size changes from

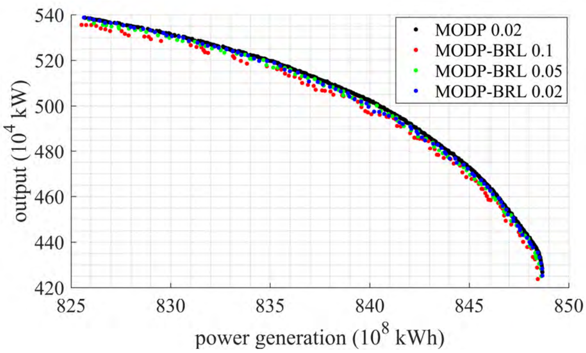


FIGURE 8. The non-dominated solutions obtained by MODP-BRL with different discrete step.

TABLE 6. The calculation time of MODP and MODP-BRP with different discrete step.

	Computing time (s)		solutions size	
discrete step	MODP	MODP-BRL	MODP	MODP-BRL
1	0.056	0.056	15	0.056
0.5	0.162	0.162	29	0.162
0.2	1.16	1.16	89	1.16
0.1	11.311	8.351	174	97
0.05	174.774	44.693	326	100
0.02	6615.457	440.305	881	100
0.01	>24h	2730.219	-	100

0.1 to 0.05 m. Then the discrete step is further reduced to 0.02 m, the corresponding computing time will increase to 6615.5 s. FIGURE 7 shows the non-dominated solutions obtained by MODP is closer when the discrete precision is 0.1 m and 0.02 m. In addition, the non-dominated solutions of MODP-BRL with discrete step = 0.1 m is close to that of MODP with the discrete step = 0.02 m as shown in FIGURE 8. Therefore, it is appropriate to set the discrete step to 0.1 m when solving this problem.

When the size of non-dominated solutions is smaller than K, MODP and MODP-BRL are equivalent. Therefore, the calculation results of MODP and MODP-BRL in Table 6 are the same when the discrete step size is 1, 0.5, and 0.2. When the discrete step of state is 0.1, 0.05, and 0.02 m, the computing time and obtained solutions size of MODP-BRL are less than those of MODP. Compared with MODP in the computing time, MODP-BRL decreases by 26.1%, 74.4% and 93.3% respectively when the discrete step is 0.1 m, 0.05 m and 0.02 m. FIGURE 9 shows that the number of non-dominated solutions of MODP-BRL and MODP of all state in any periods. The maximum of the number of non-dominated solutions is 1219095 at 21 periods in the result of MODP with discrete step = 0.02 m. The size of solutions obtained by MODP-BRL is much smaller than that of MODP with the same discrete step size. It is mainly due to the reference lines in MODP-BRL to select representative solutions from a large number of non-dominated solutions.

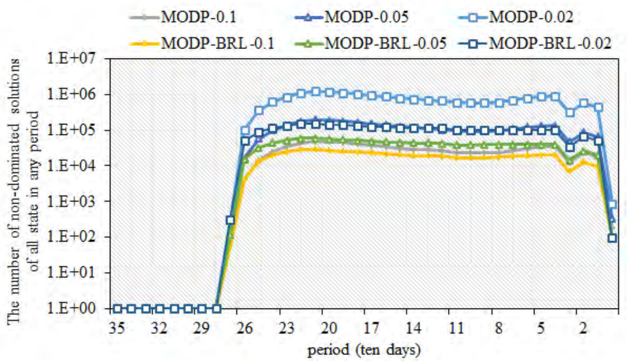


FIGURE 9. The number of non-dominated solutions obtained by MODP-BRL and MODP of all state in any periods.

In summary, the following conclusions can be obtained from Case 3: (a) MODP and its improved version are very sensitive to the discrete step. With the decrease of the discrete step (the higher the discrete precision), the computing time increases nonlinearly; (b) the smaller the discrete step, the better the non-dominated solutions can be obtained. And the effect of continuing to reduce the discrete step on the non-dominated solutions is negligible when the discrete step is small enough. (c) MODP-BRL alleviates computational burden by reducing the size of reserved solutions based on the reference lines.

V. CONCLUSION

In this paper, an improved MODP named MODP-BRL is proposed with new selection mechanism of non-dominated solutions based on reference lines. To test its performance on multiobjective ROO, the model of multiobjective ROO of TGR with two objectives is established. These experimental results show the following conclusions: (a) MODP-BRL performs better on ANDS and IGD than IMODP, which fully demonstrates that MODP-BRL is also reliable and effective tool in solving multiobjective ROO. (b) MODP-BRL is superior to NSGAII, NSGAIII, and SPEA2 in both convergence effect and convergence efficiency in multiobjective ROO problems. And MODP-BRP and MODP only need to check constraints and abandon the states and decisions that violate the constraints, instead of conceiving constraints handling technology for MOEAs. (c) MODP and its improved version are very sensitive to the discrete step. With the decrease of the discrete step (the higher the discrete precision), the computing time increases nonlinearly. (d) MODP-BRL alleviates computational burden by reducing the size of reserved solutions based on the reference lines. (e) Choosing appropriate discrete step can balance the need for superiority and computational efficiency of non-dominated solutions when using MODP and its improved versions are used to solve multiobjective ROO.

In summary, the proposed MODP-BRL can be used as an effective and reliable tool to solve multiobjective ROO, MODP-BRL can also be extended to multiobjective multi-stage Markov decision-making problem with complicated constraints. It should be noted that it is necessary to set the appropriate discrete step of state to balance the superiority and computational efficiency of non-dominated solutions in the application of MODP-BRL.

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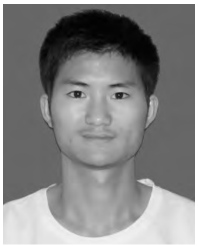

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