Journal of
Water & Climate Change

© 2024 The Authors
Journal of Water and Climate Change Vol 15 No 9, 4561 doi: 10.2166/wcc.2024.180

A segmented trial-and-error algorithm for optimized operation of water storage projects

Xinya Jin[a], Hailong Zhou[b], Yuelai Yao[a], Tangsong Luo[c] and Yu Zhang[d,*]
[a] Zhejiang Province Hydrological Management Center, Hangzhou 310009, China
[b] Jiangshan Water Conservancy Bureau of Zhejiang Province, Jiangshan 324100, China
[c] Zhejiang Anlan Engineering Technology Co., Ltd, Hangzhou 310051, China
[d] Nanjing Hydraulic Research Institute, Nanjing 210029, China
*Corresponding author. E-mail: zhangyu74@163.com; yuzhang@nhri.cn

ABSTRACT

Mathematical programming methods and modern intelligent algorithms are used to solve the optimized operation models of water storage projects. Classical mathematical programming methods are prone to the curse of dimensionality when the size of the system increases. Intelligent algorithms improve the computational efficiency to a certain extent, but still suffer from defects such as unstable optimized solutions and easy to fall into local optimizers. In this article, a segmented trial-and-error algorithm is proposed to obtain the global optimizer while considering computational efficiency. First, a water balance constraint is introduced into the objective function and a Lagrangian function is constructed to derive the ideal optimizer. Constraints are then gradually introduced and the optimized model is solved by iterative trial-and-error calculations. By approximating the ideal optimizer by segments in this way, the global optimizer is finally obtained. Numerical experiments were carried out in a water supply reservoir. The results show that the segmented trial-and-error algorithm can obtain the global optimizers in different situations with objective functions that are 0.0028–0.0076 lower than those of the genetic algorithm, implying less and more uniform water shortages. The segmented trial-and-error algorithm requires less than 1% of the computational time of the dynamic programming.

Key words: global optimizer, optimized operation, trial-and-error algorithm, water storage projects, water supply operation

HIGHLIGHTS

- A segmented trial-and-error algorithm is proposed for the optimized operation of water storage projects.
- A water balance constraint is introduced into the objective function, and a Lagrangian function is constructed to derive the ideal optimized solution.
- The segmented trial-and-error algorithm obtains the global optimizer in different scenarios and requires less than 1% of the computation time of the dynamic programming.

1. INTRODUCTION

Water storage projects such as reservoirs and lakes are important tools for water resources allocation. The operation of water storage projects redistributes water resources in time and space according to human needs. It is an important means to alleviate the contradictory relationship between the uneven distribution of water resources and the water demand of human economy, society, and environment (Shiau 2021). However, due to the impact of global climate change, the spatiotemporal distribution patterns of river runoff have changed significantly. Statistical characteristics of runoff such as mean, variance, and extreme values have exhibited noticeable alterations. The hydrological consistency has been disrupted, increasing the uncertainty surrounding water resources and their development and utilization. Hydrological consistency is a fundamental assumption in traditional water resources planning and management. The design and operation of water storage projects are based on this assumption. The emergence of inconsistency undoubtedly affects the operation modes and overall benefits of water storage projects and may even threaten their safety. The ability of water storage projects to operate safely and maintain their designed benefits under climate change remains uncertain. To address the challenges posed by climate change, researchers have developed adaptive scheduling models for water storage projects and sought new scheduling patterns through solving these models. The optimized operation of water storage projects under climate change has received

This is an Open Access article distributed under the terms of the Creative Commons Attribution Licence (CC BY-NC-ND 4.0), which permits copying and redistribution for non-commercial purposes with no derivatives, provided the original work is properly cited (http://creativecommons.org/licenses/by-nc-nd/4.0/).

Downloaded from http://iwaponline.com/jwcc/article-pdf/15/9/4561/1489228/jwc2024180.pdf
by guest

widespread attention. Its optimization model construction and solution are hot spots in academic research and a focus of attention in practice (Chen *et al.* 2023).

Mathematical programming methods are usually used to solve optimization problems. Linear programming (LP), nonlinear programming (NP), and dynamic programming (DP) are representative methods (Yurtal *et al.* 2005). Compared with LP and NP, DP has the advantages of accurate calculation results, high operational efficiency, and high applicability in optimized operation. DP has been widely used in solving the optimized operation models of water storage projects and has achieved remarkable results (Haguma *et al.* 2018). Mousavi *et al.* (2004) developed DP optimization and Hydrologic Engineering Center-5 (HEC-5) simulation models for planning the long-term operation of the Karoon-Dez multireservoir system in Iran. The DP results were better than those of HEC-5 in terms of meeting system operating targets and energy generation, but HEC-5 as a simulation model demands much less computer time and memory. Kim *et al.* (2007) use sampling stochastic DP to derive a monthly joint operating policy during the drawdown period of the Geum River multireservoir system in Korea. A cross-validation test of 1,900 simulation runs demonstrates that the updating policy is more appropriate in this reservoir system.

Most water storage projects, especially large reservoirs, are usually designed as multiobjective reservoirs providing functions such as flood control, hydropower generation, navigation, urban water supply, agricultural irrigation, and ecological flow maintenance. They generate multiple benefits in economic, social, ecological, and environmental terms (Reed *et al.* 2013). These objectives are usually in competition with each other, meaning that the achievement of one objective is usually at the expense of other objectives (Zhang *et al.* 2021). As the number of reservoirs and operation objectives increase, the optimization problem of reservoir operation becomes complex and high dimensional. It makes the computational cost grow exponentially and poses a huge challenge to reservoir operation, thus making DP vulnerable to the curse of dimensionality (Zhang *et al.* 2015; Xu *et al.* 2023). To alleviate the curse of dimensionality, many improved algorithms of DP have been proposed and applied in the optimization problem of reservoir operation such as the incremental dynamic programming (Kumar & Baliarsingh 2003) and discrete differential DP (Feng *et al.* 2017). These algorithms alleviate the curse of dimensionality to some extent, but they lose the ergodicity of DP and often obtain only local optimizers.

With the development of modern optimization techniques, the emergence of intelligent algorithms, such as genetic algorithm (GA), differential evolution, ant colony optimization, simulated annealing algorithm, and particle swarm optimization, has provided new ways to solve such optimization problems (Chen *et al.* 2023). GA is an algorithm for searching optimized solutions, which draws on natural selection and genetic mechanisms in biology and outperforms mathematical optimization algorithms such as LP, NP, and stochastic DP in terms of convergence speed, diversity of solution set space, and optimality-seeking ability. It is the first evolutionary algorithm applied to the field of optimized operation (Wang *et al.* 2022). The intelligent algorithms improve the computational efficiency to a certain extent, but still suffer from defects such as unstable optimized solutions and easy to fall into local optimizers (Ibrahim *et al.* 2021). Improved algorithms for known flaws of intelligent algorithms are also being studied and proposed. For example, when applying traditional GA to solve multireservoir system optimization problems, crossover and mutation operators may violate constraints such as water balance equations, hydraulic continuity relationships, and power system load demands. This can reduce the efficiency of the algorithm in searching for a feasible region or even leads to a convergence on an infeasible chromosome within the expected generations (Wang *et al.* 2023). Xu *et al.* (2012) proposed a modified GA taking stochastic operators within the feasible region of variables. The experimental results show that compared with GA adopting a penalty function or pairwise comparison in constraint handling, the proposed modified GA improves the refinement of the quality of a solution in a more efficient and robust way.

In this article, a segmented trial-and-error algorithm is proposed to solve the optimized operation model of the water storage project to obtain a global optimizer while taking into account the computational efficiency. First, a water balance constraint is introduced into the objective function, and a Lagrangian function is constructed to derive the ideal optimized solution, i.e., the optimized solution without considering other constraints. Then, constraints such as water supply, water demand, and water storage are gradually introduced, and the optimized model is solved by iterative trial-and-error calculations. By approximating the ideal optimized solution by segments in this way, the global optimizer is finally obtained. Numerical experiments were conducted to evaluate the performance of the segmented trial-and-error algorithm for optimization of a water supply reservoir, and compared with DP and GA.

Downloaded from http://iwaponline.com/jwcc/article-pdf/15/9/4561/1489228/jwc2024180.pdf
by guest

2. OPTIMIZED OPERATION MODEL OF WATER STORAGE PROJECTS

2.1. Objective function

The optimized operation of the water storage projects aims to make full use of the regulating capacity of the projects, so that the water supply is distributed in time with a balance of minimum water shortage and uniform water shortage, avoiding the concentrated destruction of the water supply. For the convenience of expression, a reservoir is used as a representative of the water storage project. The objective function for optimized operation of water supply reservoirs has two common forms, as shown in Equations (1) and (2) (Tu *et al.* 2008), respectively:

$$\min F = \sum_{t=1}^{m} (G(t) - X(t))^2 \tag{1}$$

$$\min F = \sum_{t=1}^{m} \left(\frac{G(t) - X(t)}{X(t)} \right)^2 \tag{2}$$

where $G(t)$ is the water supply from the reservoir at the tth time period; $X(t)$ is the water demand from the reservoir at the tth time period; and m is the number of time periods.

For water supply reservoirs with a relatively uniform distribution of water demand over time, the results of Equations (1) and (2) are similar, and it is relatively simple to use Equation (1) as the objective function. For water supply reservoirs with strong seasonality of water demand, such as agricultural irrigation, because of the strong correlation between the growth stages of crops, a concentrated water shortage at any growth stage may cause crop failure. Although Equation (1) can obtain a relatively uniform absolute water shortage over time, it may lead to a large difference in the relative water shortage (or supply/demand ratio) in each time period, and it is more scientific and reasonable to use Equation (2) as the objective function (Tu *et al.* 2008).

2.2. Constraint conditions

Six constraints are considered as follows (Tu *et al.* 2008; Wang *et al.* 2022; Chen *et al.* 2023):

(1) Water balance constraint: Ensures that the water input to the system equals the water output and maintains the water balance of the water resource system:

$$V(t) = V(t-1) + Y(t) - G(t) \tag{3}$$

(2) Water supply capacity constraint: Limits the maximum amount of water that can be supplied to the system to ensure that the water supply does not exceed its carrying capacity:

$$G(t) \leq M \tag{4}$$

(3) Water demand constraint: The amount of water supplied does not exceed the water demand:

$$G(t) \leq X(t) \tag{5}$$

(4) Minimum water supply constraint: Ensures that the water supply to the system does not fall below a certain minimum limit such as domestic and minimum ecological water demand:

$$G(t) \geq X'(t) \tag{6}$$

(5) Reservoir storage lower limit constraint: Limits the amount of water stored in the reservoir to not fall below a certain lower limit:

$$V(t) \geq V\min(t) \tag{7}$$

Downloaded from http://iwaponline.com/jwcc/article-pdf/15/9/4561/1489228/jwc2024180.pdf
by guest

(6) Reservoir storage upper limit constraint: Limits the amount of water stored in a reservoir to not exceed a certain upper limit value to avoid reservoir overflow or other undesirable consequences:

$$V(t) \leq V\max(t) \tag{8}$$

where $V(t)$ and $V(t-1)$ are the reservoir storage at the end and beginning of the tth time period, $Y(t)$ is the amount of water inflow to the reservoir the tth time period, M is the water supply capacity of the reservoir, $X'(t)$ is the basic water demand of the reservoir the tth time period, and $V\min(t)$ and $V\max(t)$ are the lower and upper limits of allowable reservoir storage at the end of the tth time period.

3. SEGMENTED TRIAL-AND-ERROR ALGORITHM

The water balance constraint Equation (3) is initially incorporated into the objective function, and a Lagrangian function is formulated to obtain the ideal optimized solution. Subsequently, the remaining constraints Equations (4)–(8) are sequentially integrated, and the optimized model is iteratively solved through trial-and-error computations. By segmenting the approximation of the ideal optimized solution in this manner, the global optimizer is ultimately achieved. The flow of the segmented trial-and-error algorithm is shown in Figure 1.

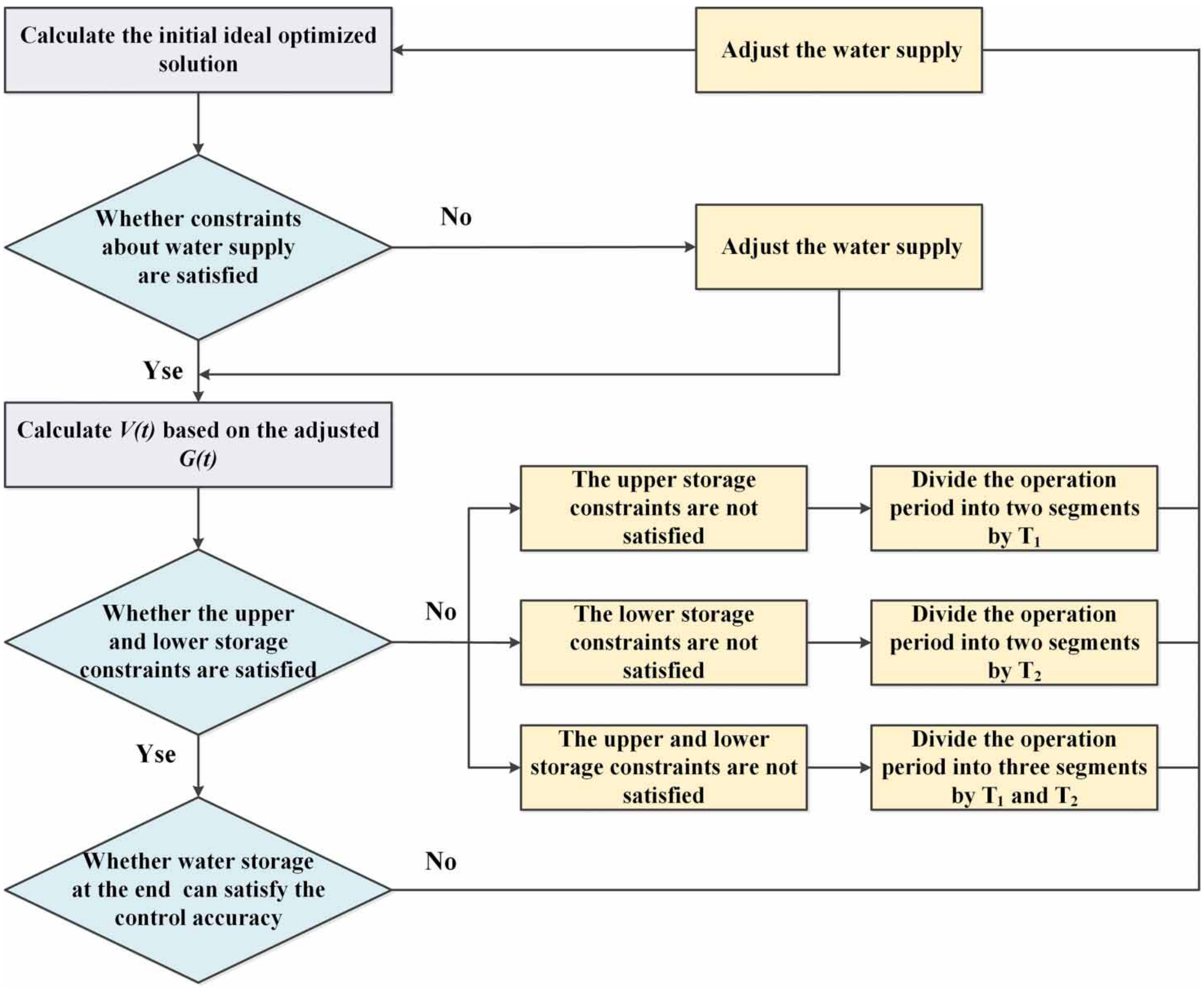

Figure 1 | Flowchart of the segmented trial-and-error algorithm.

Downloaded from http://iwaponline.com/jwcc/article-pdf/15/9/4561/1489228/jwc2024180.pdf
by guest

3.1. Ideal optimized solution

The following equation can be derived from the water balance constraint Equation (3) during the full operation period:

$$\sum_{t=1}^{m}(G(t)-Y(t))=Vo-Ve \tag{9}$$

where Vo and Ve are the reservoir storage at the end and beginning of the full operation period.

An auxiliary Lagrangian function is constructed from the objective function Equations (2) and (9):

$$L(G(1),G(2)\ldots G(m),\lambda)=\sum_{t=1}^{m}\left(\frac{G(t)-X(t)}{X(t)}\right)^2+\lambda\left[\sum_{t=1}^{m}(G(t)-Y(t))-(Vo-Ve)\right] \tag{10}$$

According to the dual principle, the necessary condition for the existence of an optimized solution for this constrained non-linear optimization problem is that the (partial) derivative is zero, and the set of equations is obtained as follows:

$$\begin{cases} L_{G(1)}=2\dfrac{G(1)-X(1)}{X^2(1)}+\lambda=0 \\ L_{G(2)}=2\dfrac{G(2)-X(2)}{X^2(2)}+\lambda=0 \\ \ldots \\ L_{G(m)}=2\dfrac{G(m)-X(m)}{X^2(m)}+\lambda=0 \\ L_{\lambda}=\sum\limits_{t=1}^{m}(G(t)-Y(t))-(Vo-Ve)=0 \end{cases} \tag{11}$$

Solving Equation (11) yields $G(t)$, where $t=1,2,\ \ldots,m$:

$$G(t)=X(t)-X^2(t)\frac{\sum\limits_{i=1}^{m}(X(i)-Y(i))-(Vo-Ve)}{\sum\limits_{i=1}^{m}X^2(i)} \tag{12}$$

Equation (12) is the ideal optimized solution considering only the water balance constraint.

If the reservoir water supply process derived from Equation (12) satisfies all the remaining constraints, the water supply process is the result of optimized operation, which is often not the actual case. Therefore, a segmented trial-and-error algorithm is proposed to adjust the water supply process in segments to satisfy all constraints.

3.2. Segmented trial and error

The following are the steps of segmented trial and error:

Step 1: Input the datasets including reservoir utilizable capacity, dead storage capacity, storage upper limit, storage at the beginning and end of the operation period, water supply capacity, and water demand process. Calculate the initial ideal optimized solution $G(t)$ considering the water balance constraint according to Equation (12).

Step 2: Check by time step whether the water supply capacity constraint, water demand constraint, and minimum water supply constraint are satisfied; if the constraint is satisfied, then go to Step 3, otherwise adjust the water supply according to the following method:

(i) If $G(t)>X(t)$, then $G(t)=X(t)$.
(ii) If $G(t)>M$, then $G(t)=M$.
(iii) If $G(t)<X'(t)$, then $G(t)=X'(t)$.

Step 3: Calculate $V(t)$ ($t=1,2,\ldots m$) based on the adjusted $G(t)$; calculate $\Delta V(t)=V(t)-V\max(t)$; find the maximum value $\Delta V(T_1)$ in $\Delta V(t)$ and the minimum value $V(T_2)$ in $V(t)$; and check whether the upper and lower storage constraints are satisfied. If the constraint is satisfied (Figure 2(a)), then go to Step 6, otherwise adjust the water supply according to the following

Downloaded from http://iwaponline.com/jwcc/article-pdf/15/9/4561/1489228/jwc2024180.pdf
by guest

method:

(i) If $\Delta V(T_1) > 0 \cap V(T_2) \geq V\min(T_2)$ (Figure 2(b)), then go to Step 4.
(ii) If $\Delta V(T_1) \leq 0 \cap V(T_2) < V\min(T_2)$ (Figure 2(c)), then go to Step 4.
(iii) If $\Delta V(T_1) > 0 \cap V(T_2) < V\min(T_2)$ (Figure 2(d)), then go to Step 5.

Step 4: Divide the operation period into two segments, namely, T_1 and T_2. If $V(T_1)$ does not satisfy the constraint, the segment is bounded by T_1, $T_l = T_1$, and $V_l = V\max(T_1)$. If $V(T_2)$ does not satisfy the constraint, the segment is bounded by T_2, $T_l = T_2$, and $V_l = V\min(T_2)$. Adjust the optimized solution according to Equation (12):

$$\begin{cases} G(t) = X(t) - X^2(t)\dfrac{\sum_{i=1}^{T_l}(X(i) - Y(i)) - (Vo - V_l)}{\sum_{i=1}^{T_l} X^2(i)}, t \in [1, T_l] \\ G(t) = X(t) - X^2(t)\dfrac{\sum_{i=T_l+1}^{m}(X(i) - Y(i)) - (V_l - Ve)}{\sum_{i=T_l+1}^{m} X^2(i)}, t \in [T_l + 1, m] \end{cases} \quad (13)$$

Go to Step 2.

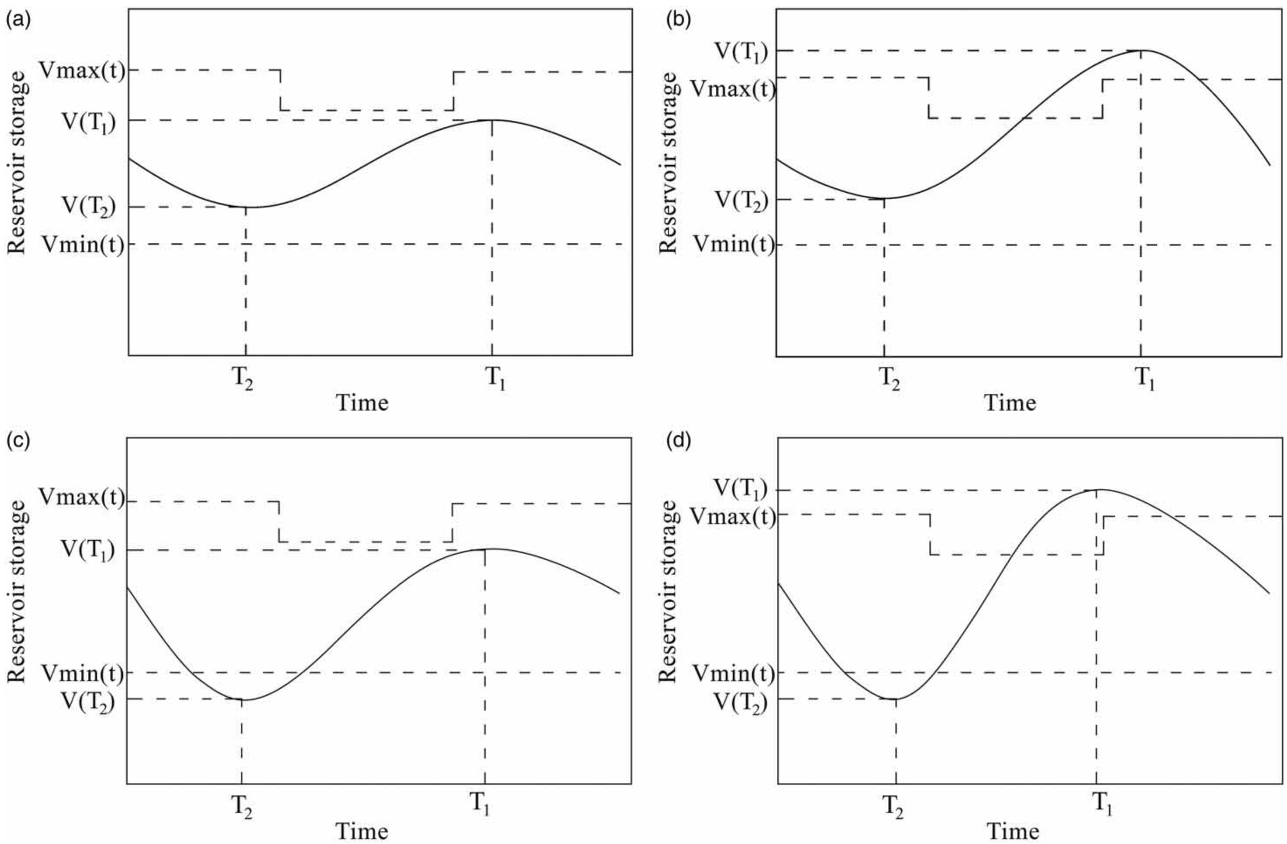

Figure 2 | Diagram of the relationship between the calculated water storage capacity and the upper/lower limits of water storage.

Downloaded from http://iwaponline.com/jwcc/article-pdf/15/9/4561/1489228/jwc2024180.pdf
by guest

Step 5: Divide the operation period into three segments by T_1 and T_2. Adjust the optimized solution according to Equation (12) for each segment:

If $T_1 < T_2$, then $T_a = T_1$, $T_b = T_2$, $V_a = V\max(T_1)$, and $V_b = V\min(T_2)$.

If $T_2 < T_1$, then $T_a = T_2$, $T_b = T_1$, $V_a = V\min(T_2)$, and $V_b = V\max(T_1)$.

$$\begin{cases} G(t) = X(t) - X^2(t)\dfrac{\sum_{i=1}^{T_a}(X(i) - Y(i)) - (Vo - V_a)}{\sum_{i=1}^{T_a} X^2(i)}, & t \in [1, T_a] \\ G(t) = X(t) - X^2(t)\dfrac{\sum_{i=T_a+1}^{T_b}(X(i) - Y(i)) - (V_a - V_b)}{\sum_{i=T_a+1}^{T_b} X^2(i)}, & t \in [T_a + 1, T_b] \\ G(t) = X(t) - X^2(t)\dfrac{\sum_{i=T_b+1}^{m}(X(i) - Y(i)) - (V_b - Ve)}{\sum_{i=T_b+1}^{m} X^2(i)}, & t \in [T_b + 1, m] \end{cases} \tag{14}$$

Go to Step 2.

Step 6: Check whether the water storage at the end of the operation period can satisfy $|V(m) - V_e| < \varepsilon$, where ε is the control accuracy. If it satisfies, the calculation results are collated, and the calculation is ended; otherwise $G(t) \Leftarrow G(t) + (V(m) - V_e)X^2(t)/\sum_{i=t_0}^{m} X^2(i)$, $t \in [t_0, m]$.

If the operation period is divided into two segments, then $t_0 = T_l + 1$, and if the operation period is divided into three segments, then $t_0 = T_b + 1$, otherwise $t_0 = 1$. Go to Step 2.

4. NUMERICAL EXPERIMENT

4.1. Water storage project

An annual regulated water supply reservoir was selected as the case study. Its utilizable capacity and dead storage capacity are 26×10^6 m^3 and 5×10^6 m^3, respectively. The upper limit of reservoir storage from May to July is 25×10^6 m^3. The reservoir storage at the beginning and the end of the operation period is 15×10^6 m^3. The monthly water supply capacity of the reservoir is 10×10^6 m^3. The water demand process for a year is shown in Table 1.

4.2. Experiment setting

In this article, DP and GA are selected and their solutions are used as comparisons to verify the rationality of the segmented trial-and-error algorithm for optimized operation of water storage projects. The stage variable t in DP is taken as 12 time periods, the state variable is the reservoir storage volume $V(t)$, the number of states in each time period is 3000, and the decision variable is the water supply volume $G(t)$.

Inflows to the reservoir during 3 years with different degrees of drought (exceedance probability $P = 95$, 90, and 75%) were selected as three scenarios, which are designated as No. 1, No. 2, and No. 3, respectively. The corresponding annual inflow of water in these 3 years was 87.57×10^6 m^3, 97.53×10^6 m^3, and 102.74×10^6 m^3, respectively. The specific inflow process is shown in Table 2, where $Y^{(1)}(t)$, $Y^{(2)}(t)$, and $Y^{(3)}(t)$ are inflow processes of Scenarios No. 1, No. 2, and No. 3. The inflow processes of these 3 years are used as inputs of the established optimized operation model and solved by the segmented trial-and-error algorithm, DP, and GA to verify the adaption.

Table 1 | Water demand process of the selected water supply reservoir (unit: $\times 10^6$ m^3)

Month	1	2	3	4	5	6	7	8	9	10	11	12
$X(t)$	7.00	7.50	8.20	10.00	12.53	13.00	12.75	12.02	11.02	9.50	8.80	8.20

Downloaded from http://iwaponline.com/jwcc/article-pdf/15/9/4561/1489228/jwc2024180.pdf
by guest

Table 2 | Inflow processes of different scenarios (unit: $\times$ 10^6 m^3)

Month	1	2	3	4	5	6	7	8	9	10	11	12
$Y^{(1)}(t)$	1.87	2.15	5.50	6.92	14.92	10.65	19.00	7.86	6.72	4.79	3.48	3.70
$Y^{(2)}(t)$	2.99	4.28	6.15	6.36	15.84	14.40	19.30	8.35	7.13	5.09	3.70	3.93
$Y^{(3)}(t)$	2.15	2.47	6.32	6.51	17.16	13.41	24.16	9.04	7.73	5.52	4.01	4.26

5. RESULTS AND DISCUSSION

5.1. Algorithm rationality and adaption analysis

The segmented trial-and-error algorithm, DP, and the GA are used to calculate the aforementioned scenarios simultaneously. The calculation results of optimized operation in different inflow scenarios are shown in Table 3, where $G^{(0)}(t)$ is the initial ideal optimized solution at the tth time period, $V^{(0)}(t)$ is the water storage calculated by the initial ideal optimized solution at the tth time period, $G(t)$ is the water supply calculated by the segmented trial-and-error algorithm at the tth time period, $R(t)$ is the corresponding time period water shortage rate at the tth time period, $G_{\mathrm{D}}(t)$ is the water supply calculated by DP at the tth time period, and $G_{\mathrm{G}}(t)$ is the water supply calculated by GA at the tth time period.

The optimized objective function values of reservoir water supply obtained by the three algorithms under different scenarios are listed in Table 4, where F, F_D, and F_G are the optimized objective function values calculated by the segmented trial-and-error algorithm, DP, and GA, respectively (using Equation (2)).

According to Table 3, the operation processes obtained by the segmented trial-and-error algorithm is shown in Figures 3–5.

As can be seen from Table 3, the water supply processes obtained by the segmented trial-and-error algorithm and DP are the same for the three different scenarios, indicating that the segmented trial-and-error algorithm yields a global optimizer. The segmented trial-and-error algorithm can replace DP for generating water supply reservoir operation schemes. As can

Table 3 | Results of optimized operation in different inflow scenarios (unit: $\times$ 10^6 m^3)

Month		1	2	3	4	5	6	7	8	9	10	11	12
$X(t)$		7.00	7.50	8.20	10.00	12.53	13.00	12.75	12.02	11.02	9.50	8.80	8.20
Scenario No. 1	$Y^{(1)}(t)$	1.87	2.15	5.50	6.92	14.92	10.65	19.00	7.86	6.72	4.79	3.48	3.70
	$G^{(0)}(t)$	5.72	6.03	6.44	7.39	8.43	8.59	8.50	8.25	7.85	7.14	6.78	6.44
	$V^{(0)}(t)$	11.15	7.27	6.32	5.85	12.34	14.40	24.90	24.51	23.38	21.03	17.74	14.99
	$G(t)$	5.72	6.03	6.44	7.39	8.43	8.59	8.50	8.25	7.85	7.14	6.78	6.44
	$V(t)$	11.15	7.27	6.32	5.85	12.34	14.40	24.90	24.51	23.38	21.03	17.74	14.99
	$R(t)$	18%	20%	21%	26%	33%	34%	33%	31%	29%	25%	23%	21%
	$G_{\mathrm{D}}(t)$	5.72	6.03	6.44	7.39	8.43	8.59	8.50	8.25	7.85	7.14	6.78	6.44
	$G_{\mathrm{G}}(t)$	5.68	6.02	6.40	7.32	8.40	8.62	8.49	8.25	7.91	7.20	6.71	6.50
Scenario No. 2	$Y^{(2)}(t)$	2.99	4.28	6.15	6.36	15.84	14.40	19.30	8.35	7.13	5.09	3.70	3.93
	$G^{(0)}(t)$	6.11	6.47	6.97	8.18	9.67	9.92	9.79	9.39	8.81	7.86	7.39	6.97
	$V^{(0)}(t)$	11.88	9.69	8.86	7.05	13.22	17.70	27.21	26.17	24.50	21.73	18.04	15.00
	$G(t)$	6.39	6.80	7.37	8.76	10.00	10.00	10.00	8.75	8.27	7.45	7.05	6.68
	$V(t)$	11.60	9.08	7.86	5.46	1.130	15.70	25.00	24.60	23.46	21.10	17.75	1,500
	$R(t)$	9%	9%	10%	12%	20%	23%	22%	27%	25%	22%	20%	19%
	$G_{\mathrm{D}}(t)$	6.39	6.80	7.37	8.76	10.00	10.00	10.00	8.75	8.27	7.45	7.05	6.68
	$G_{\mathrm{G}}(t)$	6.28	6.89	7.32	8.79	10.00	10.00	9.95	8.77	8.11	7.61	6.99	6.75
Scenario No. 3	$Y^{(3)}(t)$	2.15	2.47	6.32	6.51	17.16	13.41	24.16	9.04	7.73	5.52	4.01	4.26
	$G^{(0)}(t)$	6.31	6.71	7.25	8.59	10.32	10.62	10.46	9.98	9.31	8.23	7.71	7.25
	$V^{(0)}(t)$	10.84	6.60	5.68	3.60	10.44	13.23	26.93	25.99	24.41	21.70	17.99	15.00
	$G(t)$	6.06	6.42	6.90	8.07	10.00	10.00	10.00	9.43	8.84	7.88	7.41	7.00
	$V(t)$	11.09	7.14	6.56	5.00	12.16	1,557	25.00	24.61	23.50	21.14	17.74	15.00
	$R(t)$	13%	14%	16%	19%	20%	23%	22%	27%	25%	22%	20%	19%
	$G_D(t)$	6.06	6.42	6.90	8.07	10.00	10.00	10.00	9.43	8.84	7.88	7.41	7.00
	$G_G(t)$	6.05	6.43	7.01	8.02	9.96	10.00	10.00	9.38	8.80	7.85	7.40	7.03

Downloaded from http://iwaponline.com/jwcc/article-pdf/15/9/4561/1489228/jwc2024180.pdf
by guest

Table 4 | Results of optimized operation in different inflow scenarios

Inflow scenario	Scenario No. 1	Scenario No. 2	Scenario No. 3
F	0.8609	0.4392	0.4027
F_D	0.8609	0.4392	0.4027
F_G	0.8643	0.4416	0.4055

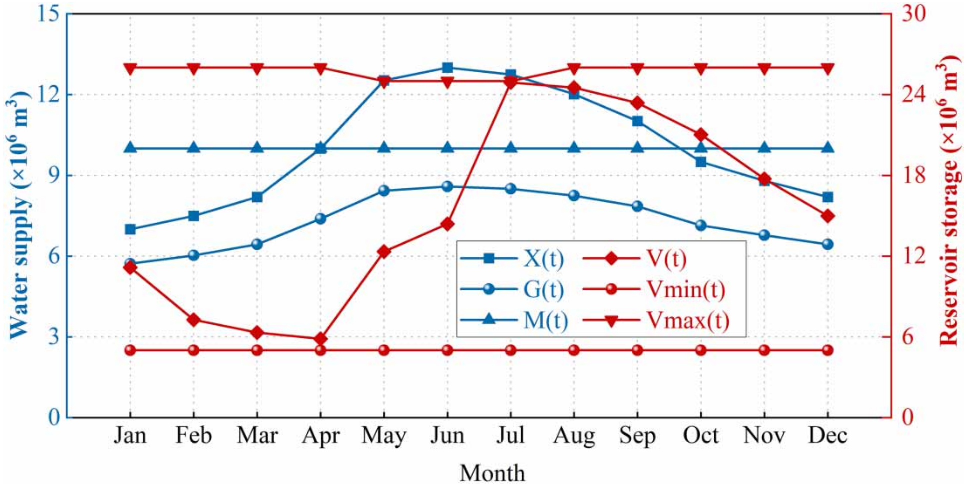

Figure 3 | Operation processes of Scenario No. 1 obtained by the segmented trial-and-error algorithm (initial ideal optimized solution of Scenario No. 1).

be seen from Table 4, the optimized objective function values obtained by the segmented trial-and-error algorithm and DP are slightly lower than that calculated by GA (the lower the value of the objective function, the better the water supply strategy), which are more reasonable compared with that calculated by GA. The segmented trial-and-error algorithm proposed in this article performs better than GA in terms of computational accuracy.

As can be seen from Figure 3, the initial ideal optimized solution as well as the calculated water storage volume under Scenario No. 1 satisfies all constraints, which means that the initial ideal optimized solution is the final calculation result of the segmented trial-and-error algorithm.

From Figure 4(a), it can be seen that the maximum storage volume obtained from the initial ideal optimized solution under Scenario No. 2 does not satisfy the reservoir storage upper limit constraint. Therefore, according to the segmented trial-and-error algorithm, the operation period is divided into two segments using July as the boundary, and the regulation and calculation are performed separately. Due to the water supply capacity constraint, the water supply from May to July is 10×10^6 m^3 per month (water supply capacity). As can be seen from Figure 4(b), the adjusted reservoir water supply as well as the storage volume satisfy all constraints, and the optimized solution is obtained.

As can be seen from Figure 5(a), the maximum and minimum storage volumes calculated by the initial ideal optimized solution under Scenario No. 3 do not satisfy the reservoir storage lower and upper limit constraints. Therefore, according to the segmented trial-and-error algorithm, the operation period is divided into three segments with April and July as the boundary, and the regulation and calculation are performed separately. Due to the water supply capacity constraint, the water supply from May to July is 10×10^6 m^3 per month (water supply capacity). From Figure 5(b), it can be seen that the adjusted reservoir water supply as well as the storage volume satisfy all constraints, and the optimized solution is obtained.

The optimized operation of water supply reservoirs makes full use of the regulating capacity of reservoirs and makes the water shortage rate relatively uniform in time distribution, avoiding the occurrence of concentrated damage due to concentrated water shortage. The aforementioned operation results are consistent with the characteristics of water supply reservoir scheduling.

Downloaded from http://iwaponline.com/jwcc/article-pdf/15/9/4561/1489228/jwc2024180.pdf
by guest

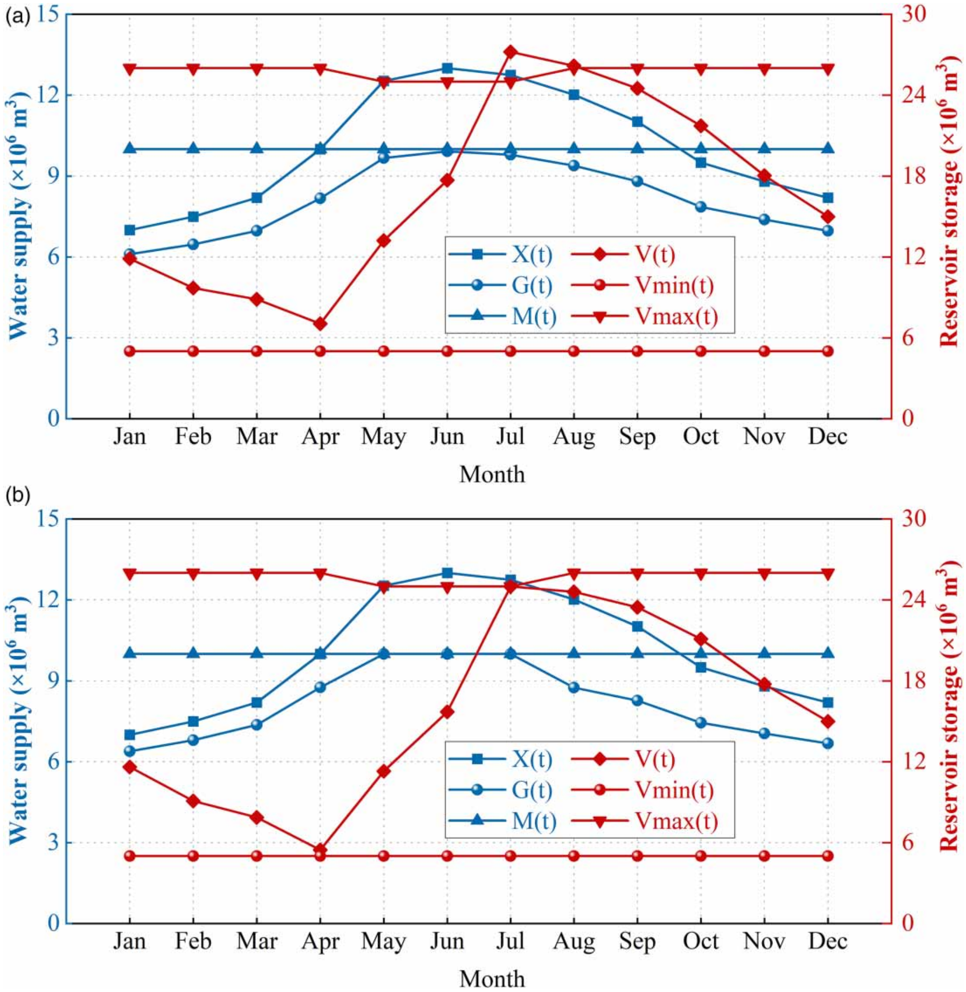

Figure 4 | Operation processes of Scenario No. 2 obtained by the segmented trial-and-error algorithm: (a) initial ideal optimized solution of Scenario No. 2 and (b) final optimized solution Scenario No. 2.

5.2. Computational efficiency analysis

The segmented trial-and-error algorithm and DP programs were run separately on a Pentium(R) Dual-Core CPU E6600 @ 3.06 GHz PC configuration. The average time taken to run the DP program is about 46 s, while the average time taken for the segmented trial-and-error algorithm is about 42 ms. The computational efficiency of the segmented trial-and-error algorithm is much greater than that of DP.

6. CONCLUSIONS

To obtain the global optimizer while considering the computational efficiency, a segmented trial-and-error algorithm is proposed in this article for the optimized operation models of water storage projects. Numerical experiments were conducted to evaluate the performance of the segmented trial-and-error algorithm for optimization of a water supply reservoir. The main conclusions obtained are as follows:

(1) The designed scenarios cover all possibilities for the initial optimized solution to break the constraints and also validate each step proposed by the segmented trial-and-error algorithm. The operation scheme obtained by the segmented trial-and-error algorithm makes full use of the regulating capacity of reservoirs and makes the water shortage rate relatively uniform in time distribution, avoiding the occurrence of concentrated water shortage.

(2) The segmented trial-and-error algorithm yields global optimizers in different scenarios. The segmented trial-and-error algorithm can replace DP for generating water supply reservoir operation schemes.

Downloaded from http://iwaponline.com/jwcc/article-pdf/15/9/4561/1489228/jwc2024180.pdf
by guest

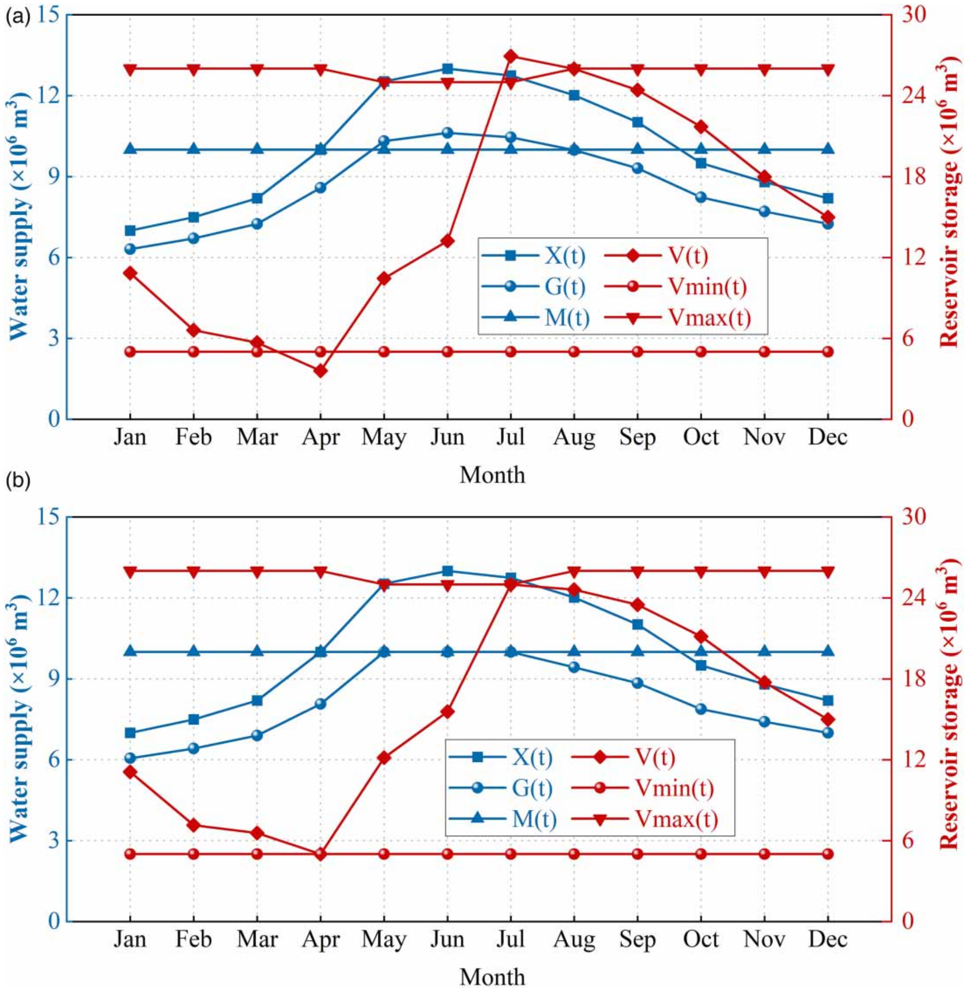

Figure 5 | Operation processes of Scenario No. 3 obtained by the segmented trial-and-error algorithm: (a) initial ideal optimized solution of Scenario No. 3 and (b) final optimized solution Scenario No. 3.

(3) The values of the optimized objective function obtained by the segmented trial-and-error algorithm for different scenarios are slightly lower than those calculated by the GA, which are more reasonable compared with that calculated by GA. The segmented trial-and-error algorithm performs better than GA in terms of computational accuracy.

(4) Under the same computer conditions, the segmented trial-and-error algorithm requires less than 1% of the computation time of the DP. The computational efficiency of the segmented trial-and-error algorithm is much greater than that of DP.

(5) The proposed algorithm is constructed based on the objective function (Equation (2)), and the constraints are introduced step by step to arrive at the optimized solution. In practical applications, the objective function and constraints are sometimes different, the solution ideas are applicable, and the proposed algorithm needs to be deformed accordingly.

AUTHORS CONTRIBUTIONS

Conceptualization: Yu Zhang; methodology: Xinya Jin and Hailong Zhou; formal analysis and investigation: Xinya Jin, Hailong Zhou, Yuelai Yao, and Tangsong Luo; writing – original draft preparation: Xinya Jin, Hailong Zhou, Yuelai Yao, and Tangsong Luo; writing – review and editing: Xinya Jin, Hailong Zhou, and Yu Zhang; funding acquisition: Yu Zhang; resources: Yu Zhang; supervision: Yu Zhang.

Downloaded from http://iwaponline.com/jwcc/article-pdf/15/9/4561/1489228/jwc2024180.pdf
by guest

FUNDING

This work was supported by National Natural Science Foundation of China (Grant No. 52209032), Water Conservancy Science and Technology Program of Zhejiang Province (Grant Nos. RA1801 and RA2003), and Zhejiang Province Emergency Management Research and Development Technology Project (Grant No. 2024YJ017).

DATA AVAILABILITY STATEMENT

All relevant data are included in the paper or its Supplementary Information.

CONFLICT OF INTEREST

The authors declare there is no conflict.

REFERENCES

Chen, Y. B., Wang, M. L., Zhang, Y., Lu, Y., Xu, B. & Yu, L. 2023 Cascade hydropower system operation considering ecological flow based on different multi-objective genetic algorithms. *Water Resour. Manage.* https://doi.org/10.1007/s11269-023-03491-3.

Feng, Z. K., Niu, W. J., Cheng, C. T. & Liao, S. L. 2017 Hydropower system operation optimization by discrete differential dynamic programming based on orthogonal experiment design. *Energy* **126**, 720–732. https://doi.org/10.1016/j.energy.2017.03.069.

Haguma, D., Leconte, R. & Cote, P. 2018 Evaluating transition probabilities for a stochastic dynamic programming model used in water system optimization. *J. Water Resour. Plann. Manage.* **144** (2), 04017090. https://doi.org/10.1061/(ASCE)WR.1943-5452.0000883.

Ibrahim, K. S. M. H., Huang, Y. F., Ahmed, A. N., Koo, C. H. & El-Shafie, A. 2021 A review of the hybrid artificial intelligence and optimization modelling of hydrological streamflow forecasting. *Alexandria Eng. J.* **61** (1), 279–303. https://doi.org/10.1016/j.aej.2021.04.1001110-0168.

Kim, Y. O., Eum, H., Lee, E. G. & Ko, I. H. 2007 Optimizing operational policies of a Korean multi-reservoir system using sampling stochastic dynamic programming with ensemble streamflow prediction. *J. Water Resour. Plann. Manage.* **133** (1), 4–14. https://doi.org/10.1061/(ASCE)0733-9496(2007)133:1(4).

Kumar, D. N. & Baliarsingh, F. 2003 Folded dynamic programming for optimal operation of multireservoir system. *Water Resour. Manage.* **17** (5), 337–353. https://doi.org/10.1023/A:1025894500491.

Mousavi, S. J., Zanoosi, A. G. & Afshar, A. 2004 Optimization and simulation of a multiple reservoir system operation. *J. Water Supply Res. Technol.* **53** (6), 409–424. https://doi.org/10.2166/aqua.2004.0032.

Reed, P. M., Hadka, D., Herman, J. D., Kasprzyk, J. R. & Kollat, J. B. 2013 Evolutionary multiobjective optimization in water resources: The past, present, and future. *Adv. Water Resour.* **51**, 438–456. https://doi.org/10.1016/j.advwatres.2012.01.005.

Shiau, J. T. 2021 Analytical water shortage probabilities and distributions of various lead times for a water supply reservoir. *Water Resour. Manage.* **35** (11), 3809–3825. https://doi.org/10.1007/s11269-021-02921-4.

Tu, M. Y., Hsu, N. S., Tsai, F. T. C. & Yeh, W. W. G. 2008 Optimization of hedging rules for reservoir operations. *J. Water Resour. Plann. Manage.* **134** (1), 3–13. https://doi.org/10.1061/(ASCE)0733-9496(2008)134:1(3).

Wang, M. L., Zhang, Y., Lu, Y., Wan, X. Y., Xu, B. & Yu, L. 2022 Comparison of multi-objective genetic algorithms for optimization of cascade reservoir systems. *J. Water Clim. Change* **13** (11), 4069–4086. https://doi.org/10.2166/wcc.2022.290.

Wang, M. L., Zhang, Y., Lu, Y., Gao, L. & Wang, L. Z. 2023 Attribution analysis of streamflow changes based on large-scale hydrological modeling with uncertainties. *Water Resour. Manage.* **37** (2), 713–730. https://doi.org/10.1007/s11269-022-03396-7.

Xu, B., Zhong, P. A., Wan, X. Y., Zhang, W. G. & Chen, X. 2012 Dynamic feasible region genetic algorithm for optimal operation of a multi-reservoir system. *Energies* **5** (8), 2894–2910. https://doi.org/10.3390/en5082894.

Xu, Y. S., Chen, Y. B., Ren, Y. F., Tang, Z. Y., Yang, X. & Zhang, Y. 2023 Attribution of streamflow changes considering spatial contributions and driver interactions based on hydrological modeling. *Water Resour. Manage.* **37**, 1859–1877. https://doi.org/10.1007/s11269-023-03459-3.

Yurtal, R., Seckin, G. & Ardiclioglu, M. 2005 Hydropower optimization for the Lower Seyhan System in Turkey using dynamic programming. *Water Int.* **30** (4), 522–529. https://doi.org/10.1080/02508060508691896.

Zhang, Y. K., Jiang, Z. Q., Ji, C. M. & Sun, P. 2015 Contrastive analysis of three parallel modes in multi-dimensional dynamic programming and its application in cascade reservoirs operation. *J. Hydrol.* **529**, 22–34. https://doi.org/10.1016/j.jhydrol.2015.07.017.

Zhang, Y., Yu, L., Wu, S. Q., Wu, X. F., Dai, J. Y., Xue, W. Y. & Yang, Q. Q. 2021 A framework for adaptive control of multi-reservoir systems under changing environment. *J. Cleaner Prod.* **316**, 128304. https://doi.org/10.1016/j.jclepro.2021.128304.

First received 6 February 2024; accepted in revised form 14 June 2024. Available online 30 August 2024

Downloaded from http://iwaponline.com/jwcc/article-pdf/15/9/4561/1489228/jwc2024180.pdf
by guest