# An enhanced DP-POA algorithm for reservoir flood control optimization operation

**Yawei Ning[1,2*], Minglei Ren[1,2], Junbin Zhang[1,2,3], Rong Tang[1,2], Liping Zhao[1,2], and Gang Wang[1,2]**

China Institute of Water Resources and Hydropower Research, Beijing, China[1]
Engineering and Technology Research Center for Flood Control, Drought Mitigation and Disaster Reduction (Flood and Drought Disaster Defense Center), Ministry of Water Resources, Beijing, China[2]
Shenyang Agricultural University, Shenyang, China[3]

* Correspondence: Yawei Ning, ningyw@iwhr.com
Address: A-1, Fuxing Road, Haidian District, Beijing 100038, People's Republic of China

**ABSTRACT**

The computational efficiency of reservoir optimal operation algorithms is critical for real-time flood control. While traditional DP-POA (Dynamic Programming-Progressive Optimization Algorithm) delivers high-quality solutions, its computational demands are substantial. This study proposes an enhanced DP-POA algorithm that significantly reduces computational load and accelerates computation by simplifying the objective function. Using China's Yuecheng Reservoir as a case study, we conducted comparative analyses of five algorithms: enhanced DP-POA, traditional DP-POA, enhanced POA, traditional POA, and PSO (Particle Swarm Optimization). Results demonstrate that the enhanced DP-POA achieves superior computational efficiency while maintaining solution quality. During the 2021 flood event, it reduced runtime from approximately 30 minutes to less than 5 minutes compared to traditional DP-POA. Moreover, the solutions generated by the enhanced DP-POA either outperformed or matched those of all benchmark methods.

**KEYWORDS:** Optimal operation algorithm; Flood control; Reservoir operation; Computational efficiency

## 1 INTRODUCTION

Flood disasters are among the most frequent and destructive natural hazards worldwide, causing losses that include not only casualties and property damage but also long-term socioeconomic impacts(Schaum et al. 2025). Reservoir flood regulation is a critical non-engineering measure for flood mitigation and disaster reduction. Through scientifically and reasonably managing reservoir operations, flood damage both upstream and downstream can be reduced while ensuring the safety of the dam. However, improper regulation may increase flood risks(Ding et al. 2023b). Therefore, reservoir flood regulation has always been a prominent research topic in the field of flood control.

Common regulation methods include conventional operation and optimized operation (Zhou et al. 2018; Xu et al. 2020; Ding et al. 2023a). Conventional operation is simple and easy to implement but often falls short in meeting complex flood control requirements. In contrast, optimized operation can fully utilize the storage capacity of reservoirs, offering significant advantages (Stedinger et al. 1984; Zhou et al. 2018; Zhu et al. 2021; Wu et al. 2024). This technology typically begins with establishing an optimization model and then employs optimization algorithms to search for the optimal solution under multiple constraints, providing scientific decision support for managers. Due to the substantial computational demands and challenges in finding optimal solutions, exploring efficient and reliable algorithms for solving optimization models is of great importance for enhancing reservoir flood control benefits (Feng et al. 2023; Ning et al. 2024; Wu et al. 2024).

Reservoir optimization solution algorithms can be broadly categorized into linear programming, intelligent optimization algorithms, and dynamic programming (Lai et al. 2022b, a; Feng et al. 2023). Linear programming is relatively mature but limited to linear models. Intelligent optimization methods have gained widespread attention due to their strong capability in handling nonlinear problems and high computational efficiency (Mansouri et al. 2022; Ding et al. 2023a). These mainly include the Particle Swarm Optimization (PSO) algorithm(Wu et al. 2024), Genetic Algorithm (GA) (Zhang et al. 2024), and Simulated Annealing (SA) algorithm (Vasan and Raju 2009). However, intelligent algorithms often face issues such as dependency on initial solutions and premature convergence (Nourani et al. 2020; Ning et al. 2024). Dynamic programming is well-suited for solving reservoir operation problems due to its capability to handle multi-stage decision processes. This includes basic Dynamic Programming (DP) and modified or improved methods based on DP, such as Progressive Optimization Algorithm (POA) and Dynamic Programming Successive Approximation (DPSA) (Stedinger et al. 1984; Zhao et al. 2014). Among the various optimization algorithms, the DP-POA algorithm (Zhu et al. 2021), which combines dynamic programming and progressive optimization, has attracted significant attention for its advantages in handling complex constraints and multi-objective optimization problems. The DP-POA hybrid algorithm integrates the strengths of Dynamic Programming (DP) and Progressive Optimization Algorithm (POA). This algorithm first uses DP to obtain a high-quality initial solution and then introduces POA for further refinement (Zhu et al. 2021). By decomposing multi-stage decision problems into a series of two-stage subproblems, the DP-POA algorithm significantly reduces computational complexity and avoids the "curse of dimensionality" commonly associated with DP. However, the traditional DP-POA algorithm still faces issues such as low computational efficiency and slow convergence in practical applications (Zhou et al. 2018; Zhu et al. 2021; Chen 2021).

To address these limitations, this paper proposes improvements to the traditional DP-POA algorithm by simplifying the objective function during the computational process. This approach aims to reduce the computational load in each iteration and shorten convergence time. Using the Yuecheng Reservoir in northern China as a case study, the performance of the enhanced DP-POA algorithm is compared with four other algorithms to validate its effectiveness.

## 2 RESEARCH METHODS

### 2.1 Reservoir optimal operation model

#### 2.1.1 Objective functions and main constraints

Case 1: Minimize the maximum flow at downstream protection section

The objective of this function is to maximize flood retention under the premise of ensuring reservoir safety, thereby reducing the flood peak for the downstream flood control section. By imposing a hard constraint to ensure the reservoir water level does not exceed the allowable value, it minimizes the maximum flow at the downstream control section. Its mathematical expression is:

$$obj1 = \min\{\max[Q_{down}(t)\}, t = 1, 2, \ldots T \tag{1}$$

Where: $Q_{\text{down}}(t)$ is the flow at the downstream flood control section at time $t$; $T$ is the total operation period.

Case 2: Minimize the highest reservoir flood regulation water level

This objective function aims to maximize water release while ensuring the safety of the downstream control section and maintaining dam safety. By imposing a hard constraint that the maximum flow at the downstream section does not exceed the allowable value, the optimization algorithm determines the minimum highest reservoir water level, thereby reducing the reservoir's flood risk. Its mathematical expression is:

$$obj2 = \min\{\max[Z(t)]\}, t = 1, 2, \ldots T \tag{2}$$

Where: Z($t$) is the reservoir water level at time $t$.

**2.1.2 Other constraints**

(1) Water balance constraint

$$V(t+1) = V(t) + [q_{in}(t) - q_{out}(t)] \times \Delta t \tag{3}$$

Where: V($t$) and V($t$+1) represent the reservoir storage volume at times $t$ and $t$+1, respectively; $q_{in}(t)$ is the reservoir inflow at time t; $q_{out}(t)$ is the reservoir release discharge at time $t$; and $\Delta t$ is the time step length.

(2) Reservoir water level constraint

$$Z_{\min} \le Z(t) \le Z_{\max} \tag{4}$$

Where: $Z_{\min}$ and $Z_{\max}$ are the minimum and maximum allowable reservoir water levels, respectively.

(3) Release discharge constraint

$$q_{\min} \le q_{out}(t) \le q_{\max} \tag{5}$$

Where: $q_{\min}$ and $q_{\max}$ are the minimum and maximum allowable reservoir release discharges, respectively.

(4) Release capacity constraint

$$q_{out}(t) \le q_{out}^{\max}(t) \tag{6}$$

Where: $q_{out}^{\max}(t)$ is the maximum release capacity corresponding to the water level at time $t$.

(5) Flow variation amplitude constraint

$$q_{out}(t) - q_{out}(t-1) \le \varepsilon^{*} \tag{7}$$

Where: $\varepsilon^*$ is the maximum allowable flow variation amplitude.

(6) Non-negativity constraint

All variables, including water level, storage volume, and flow, are non-negative.

## 2.2 River flood routing model

A river flood routing model based on the Muskingum method was used, aiming to accurately simulate the nonlinear propagation process of flood waves along the river channel in the context of reservoir optimal operation. The river reach is divided into $n$ sub-reaches, and the Muskingum method is applied $n$ times for routing. The model parameter system includes characteristic parameters for each sub-reach: storage coefficient $K_l$, flow weighting factor $x_l$, and calculation step length $\Delta t$.

## 2.3 Traditional DP-POA algorithm for solving the optimal operation model

The purpose of the Progressive Optimality Algorithm (POA) is to decompose a multi-stage decision problem into a series of two-stage sub-problems, iteratively optimizing decision variables for adjacent time periods to eventually approximate the global optimal solution. However, the traditional POA algorithm also has limitations, the most notable being its high sensitivity to the initial solution. To overcome this limitation, the DP algorithm is used to solve the initial solution for reservoir optimal operation, and then the POA algorithm is applied for further refinement and adjustment. This enhances the quality of the initial solution and improves the overall algorithm's robustness. The procedure of the DP-POA algorithm is as follows:

(1) Initialization: Set an initial solution set $\{H_t^n\}$ for the entire operation period $T$, where $t \in \{1, 2, ..., T\}$, $n$ denotes the iteration number, initially set to 0.

(2) Iterative Optimization: For time periods $t$ = 2 to $T$-1, fix $H_{t-1}^n$ and $H_{t+1}^n$. Find the optimal $H_t^n$ between $H_{t-1}^n$ and $H_{t+1}^n$ that optimizes the objective function. During the search for the optimal $H_t^{n+1}$, the discrete water level values replace the original operational curve's water levels to form a new operational

curve. Then, the downstream section hydrograph is calculated using the Muskingum segmented flow routing method. The objective function value is computed to obtain the optimal $H_t^{n+1}$.

(3) Convergence check: Define the newly obtained solution set as $\{H_t^{n+1}\}$. Next, calculate the maximum absolute $\max|H_t^{n+1} - H_t^n| = \varepsilon$. If $\varepsilon \leq \xi$ (where $\xi$ is a predefined precision threshold) or if the maximum number of iterations is reached, terminate the algorithm. Otherwise, set $n = n + 1$ and return to step (2). When the algorithm converges or reaches the maximum iteration count, output the optimized water level sequence $\{H_t^n\}$.

## 2.4 Enhanced DP-POA algorithm for solving the optimal operation model

The enhanced DP-POA algorithm primarily optimizes the calculation of the hydrograph at the downstream flood control section compared to the traditional DP-POA algorithm. Based on the core characteristic of the POA algorithm, when optimizing the decision variable for time *t*, the decision variables for other times remain unchanged (i.e., maintaining their state from the previous iteration). Traditionally, calculating the hydrograph at the downstream section requires computing the entire flow process. However, this increases the computational load, especially for the downstream peak reduction objective function, which typically involves calculating the sum of squared flow values over the entire hydrograph at the downstream section, making it even more computationally intensive. Since the POA algorithm does not modify decision variables at other times when optimizing the decision variable for the current time step, only the segment of the downstream hydrograph affected by modifying the current decision variable needs to be identified during calculation. The objective function is then calculated based on this modified portion of the flow process. This improvement can significantly shorten the runtime and reduce the algorithm's computational load.

Assume that in the Muskingum method, a change in discharge at the upstream section at a given time causes the length of the range over which the hydrograph at the downstream section varies to be *S*. Therefore, when optimizing the decision variable at time *t*, only the flows within the time interval [*t*-1, *t*+*S*-1] at the downstream section change. Therefore, when the optimization objective is downstream peak shaving, it is only necessary to calculate the sum of squared flow values within this time interval and minimize this sum. For the objective of minimizing the maximum reservoir water level, to calculate the maximum flow at the downstream flood control section, it is only necessary to find the maximum flow within this modified time interval, thereby ensuring it remains below the allowable maximum flow. This method is particularly effective when the inflow sequence is long, significantly reducing the computational load as it focuses only on the portion of the flow process that actually changes, rather than the entire time series.

This improvement approach, based on the stepwise optimization nature of the POA algorithm, is only applicable to POA and its variants. If there is no downstream flood control requirement or other flow routing methods are adopted, the key is still to utilize the stepwise optimization nature of POA or its improvements by separating the changed and unchanged parts of the calculation process and only considering the changed portion. In this way, the computational efficiency of POA and its variants can be greatly improved. This localized calculation method significantly improves the algorithm’s runtime efficiency and also offers a reference for the real-time optimal operation of large-scale complex water conservancy systems. The flowchart for the enhanced DP-POA algorithm is shown in **Figure 1**.

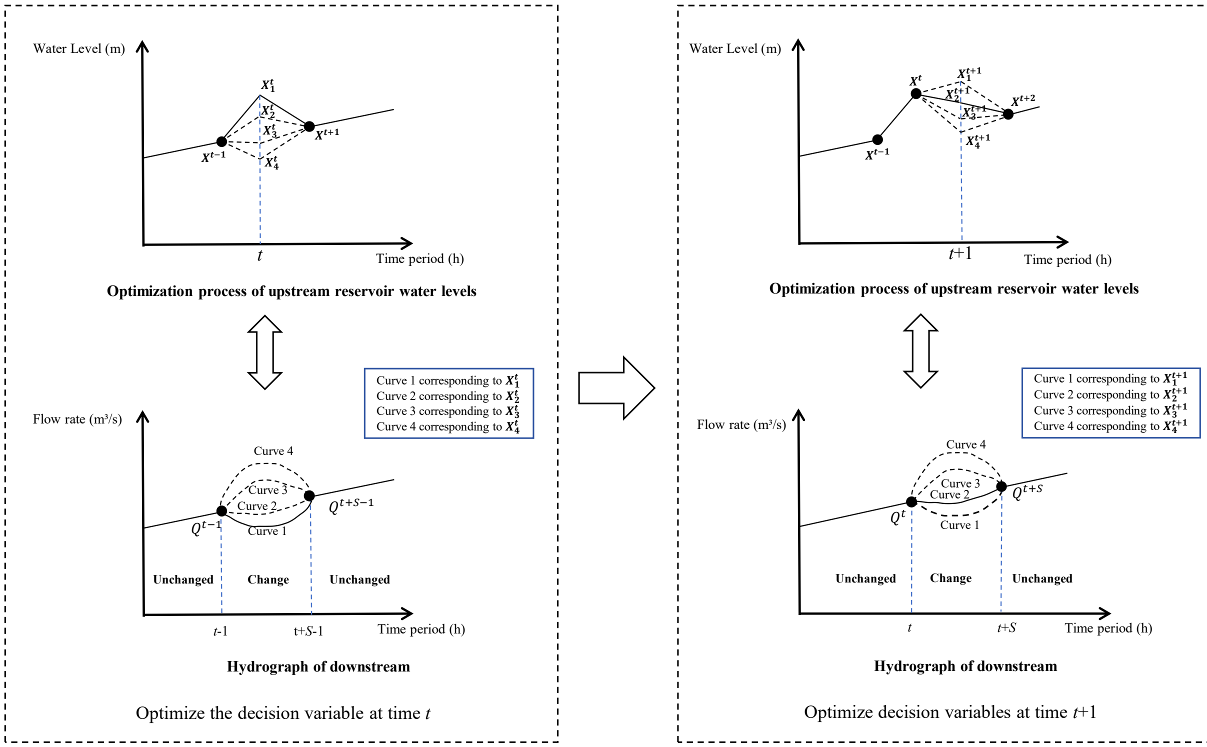


Figure 1 Process diagram of enhanced DP-POA algorithm

## 3 STUDY AREA

The analysis presented in this paper focuses on the flood control operation of Yuecheng Reservoir, having two main objectives: reservoir safety and the safety of the downstream flood control section. Yuecheng Reservoir, located in Ci County, Handan City, Hebei Province, is a key control project within the Zhang-Wei River system of the Haihe River Basin. It was constructed in 1959, and controls a catchment area of 18,100 $km^2$. Its total storage capacity is $1.3 \times 10^9$ $m^3$, with design and check flood standards of the 1000-year and 2000-year floods, respectively. It serves multiple functions, including flood control, irrigation, urban water supply, and power generation. By regulating and storing upstream inflows and optimizing downstream releases, the reservoir ensures the safety of the vast downstream plain and several important transportation arteries.

The reservoir's outflow propagates along the Zhang River to the downstream Nantao flood control section, with no significant inflows from surrounding drainage area. The analysed river system is shown in **Figure 2**. Additionally, **Table 1** summarizes the key characteristic parameters of the reservoir, providing an essential basis for subsequent analysis.

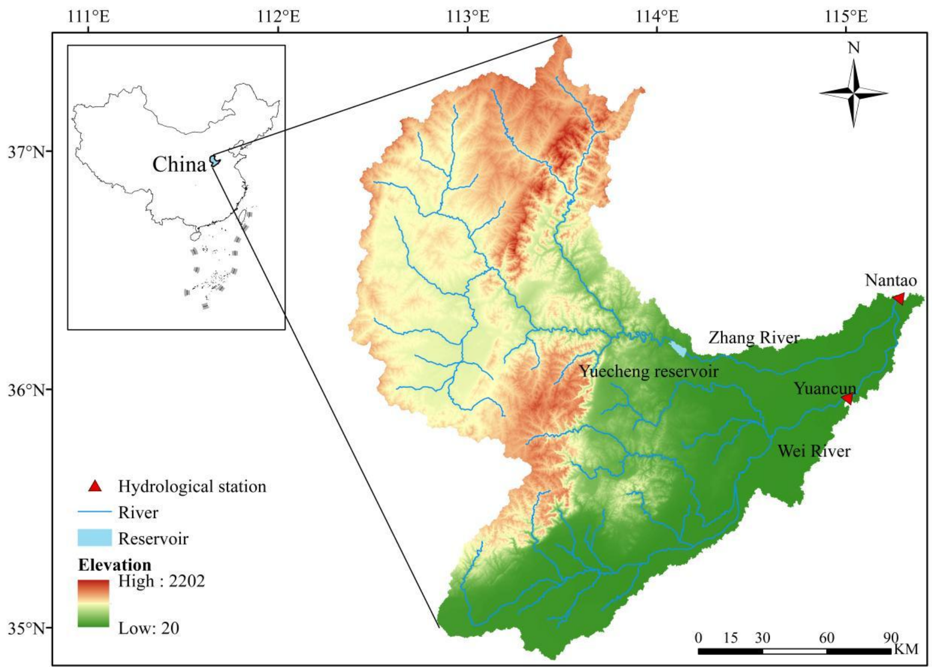


Figure 2: River system of Yuecheng Reservoir.

Table 1 Reservoir characteristic parameters

| **Minimum operating level (m)** | **Flood limited water level (m)** | **Normal storage level (m)** | **Design flood level (m)** | **Control flood level (m)** |
|---|---|---|---|---|
| 120.00 | 134.00 | 148.50 | 157.45 | 159.21 |

## 4 RESEARCH RESULTS

### 4.1 Parameter settings

The measured flood hydrograph of Yuecheng Reservoir from July 2021 was used as input for the reservoir operation model. Key parameters such as characteristic water levels, flow rates, and stage-storage-discharge relationships have been collected and systematically organized. To ensure data continuity and completeness, linear interpolation is used to supplement missing data.

To comprehensively evaluate operation performance, five algorithms are employed: traditional DP-POA, enhanced DP-POA, traditional POA, enhanced POA, and PSO. The only differences between these algorithms are calculation process and the type of initial operational curve; all other conditions remained consistent, as shown in **Table 2**.

The convergence criterion for the algorithms is defined as the objective function value remaining unchanged for 30 consecutive iterations. The maximum number of iterations is set to 5000. The initial and final water levels are both set to the flood limited water level of 134 m. In the case of minimizing the peak flow at the Nantao section, the maximum water level constraint for Yuecheng Reservoir is set to the maximum water level under rule-based operation (137.7 m). In the case of minimizing the maximum water level of Yuecheng Reservoir, the maximum flow constraint at the Nantao section is set to the maximum flow at the Nantao section under rule-based operation (2435.4 $m^3/s$). The particle number for the PSO algorithm is set to 100.

The aim of this analysis is to assess the performance advantages of the enhanced POA and enhanced DP-POA algorithms and explore their application potential in practical reservoir flood control operation by comparing the results of different algorithms.

Table 2 Basic conditions of algorithms

| Algorithm | Improved calculation process | Initial operational curve |
|---|---|---|
| Traditional DP-POA algorithm | No | DP initial operational curve |
| Enhanced DP-POA algorithm | Yes | DP initial operational curve |
| Traditional PSO algorithm | No | Random initial operational curve |
| Traditional POA algorithm | No | Random initial operational curve |
| Enhanced POA algorithm | Yes | Standard water level sequence |

## 4.2 Computation results

The objectives of optimal operation models were: minimizing the peak flow at the Nantao section (Case 1) and minimizing the highest water level of Yuecheng Reservoir (Case 2). The calculation results are analyzed in greater detail below, covering: a comparison of computation times between the traditional and improved algorithms, the influence of employing different initial operational curves within the same algorithm, and a detailed analysis of the optimization outcomes produced by the five algorithms.

### 4.2.1 Computation time comparison

According to the computation time comparison results (**Figure 3**), enhanced POA and enhanced DP-POA require less computation time than their traditional equivalents. Under Case 1 conditions, the computation times of enhanced POA, traditional POA, enhanced DP-POA, traditional DP-POA, and PSO are 984 s, 1573 s, 961 s, 1555 s, and 292 s, respectively. Under Case 2 conditions, the corresponding computation times are 867 s, 1396 s, 943 s, 1386 s, and 189 s. The results indicate that improved algorithms significantly accelerate computation speed compared to traditional ones. PSO is the fastest in terms of computation speed, but in terms of solution effectiveness, its solutions are not optimal.

### 4.2.2 Impact of initial solution

According to the calculation results (**Table 3**), the initial solution has a significant impact on the performance of POA-based algorithms. The traditional POA algorithm uses rule-based operational scheme as the initial solution, while the DP-POA algorithm uses the solution obtained by the DP algorithm in the initial step. The two algorithms exhibit a significant difference in convergence speed. Under Case 1, the traditional POA algorithm converges and exits after 111 iterations, whereas the traditional DP-POA algorithm converges after only 43 iterations, substantially reducing the computation time.

### 4.2.3 Comparison of calculation results

Based on the final calculation results, the traditional POA, enhanced POA, traditional DP-POA, and enhanced DP-POA algorithms converge to the same optimal solution. However, there are differences in their computation time and number of iterations: the enhanced DP-POA algorithm converges to this optimum with less iterations and faster than others. The PSO algorithm exhibits some randomness, and its convergence performance is inferior to other algorithms. The figures illustrate that the final calculation results of these four algorithms after convergence are essentially identical, indicating the stability of POA-based algorithms. Details of the calculation results are presented in **Table 3**, **Figures 6** and **7**.

Table 3 Calculation results under different algorithms

| Algorithm | Case1 | | | | Case2 | | | |
|---|---|---|---|---|---|---|---|---|
| | Iterations | Runtime (s) | Nantao Max Flow (m³/s) | Yuecheng Max Level (m) | Iterations | Runtime (s) | Nantao Maximum Flow (m³/s) | Yuecheng Max Level (m) |
| Traditional POA | 111 | 37.3 | 2083.0 | 137.70 | 263 | 71.5 | 2435.4 | 137.03 |
| Traditional DP-POA | 43 | 20.2 | 2083.0 | 137.70 | 87 | 30.4 | 2435.3 | 137.02 |
| Enhanced POA | 110 | 23.0 | 2083.0 | 137.70 | 263 | 44.3 | 2435.4 | 137.03 |
| Enhanced DP-POA | 43 | 15.4 | 2082.9 | 137.70 | 87 | 23.5 | 2435.3 | 137.02 |
| PSO | 1080 | 66.7 | 2107.0 | 137.70 | 1167 | 50.7 | 2416.0 | 137.22 |

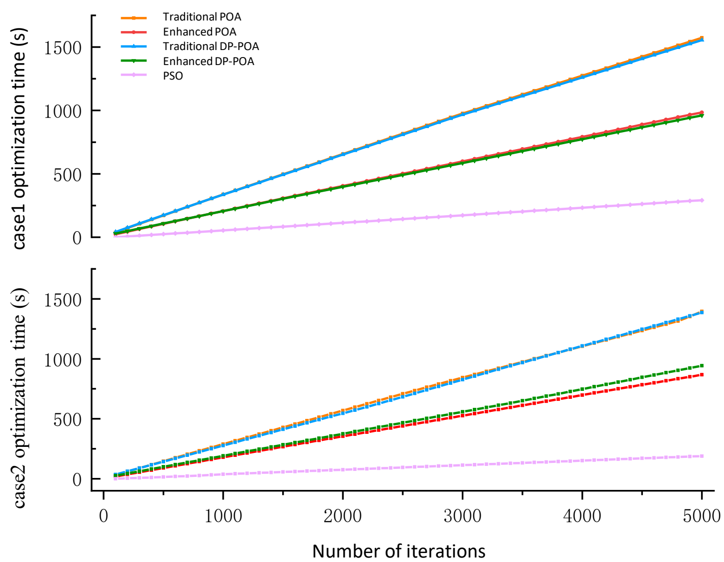


Figure 3: Computation time comparison.

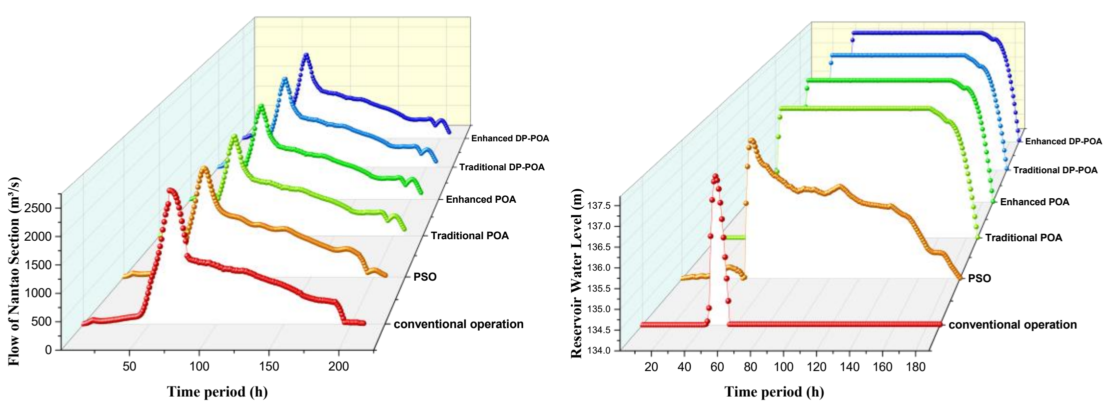


Figure 4: Operation hydrograph for Case 1.

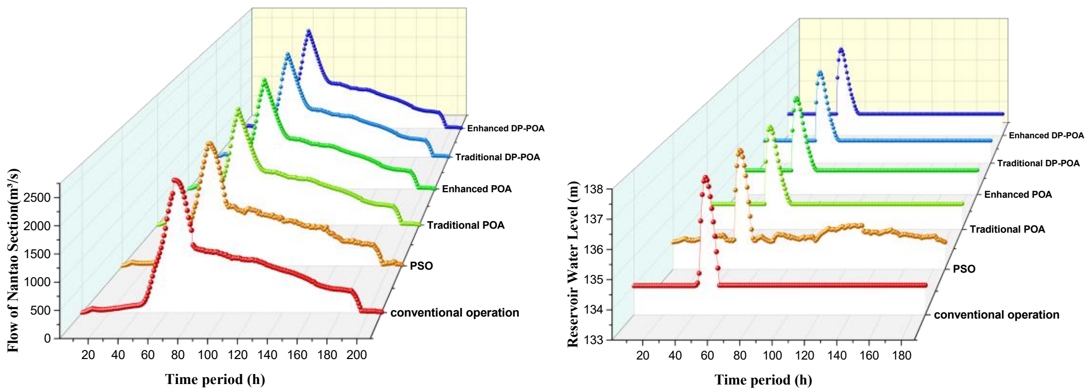


Figure 5: Operation hydrograph for Case 2.

## 5 CONCLUSIONS

Based on a case study of Yuecheng Reservoir, the following main conclusions on algorithms for optimization of reservoir flood control operation are drawn:

(1) The enhanced DP-POA algorithm demonstrates outstanding performance in computational efficiency. Compared to traditional algorithms, it saves 30-38% of computation time for both objective functions (Case1 and Case2). This significant efficiency improvement makes the algorithm more suitable for practical reservoir flood control operation decision support systems, especially in emergencies requiring rapid response.

(2) The initial solution has a significant impact on the performance of POA algorithms. The DP-POA algorithm, due to its use of a high-quality initial solution, shows markedly better convergence speed and efficiency than the traditional POA algorithm. Under the Case 1 objective function, the DP-POA algorithm reduces the number of iterations by 61% and shortens computation time by nearly 46%. This highlights the importance of selecting an appropriate initial solution in reservoir operation optimization.

(3) Regarding solution quality, traditional POA, enhanced POA, traditional DP-POA, and enhanced DP-POA all converge to the same or very similar optimal solutions. This indicates good stability and reliability of these algorithms. In contrast, the PSO algorithm yields slightly inferior solution quality compared to the other four algorithms.

(4) The results of this study emphasize the need to balance multiple key factors, such as accuracy, computation speed, and result stability, when selecting reservoir optimization operation algorithm. The enhanced DP-POA algorithm performs well in all these aspects, providing an effective solution for reservoir flood control operation optimization.

## 6 ACKNOWLEDGEMENTS

This study is supported by National key R&D program (No. 2024YFC3212800) and Key Scientific and Technological Programs of the Ministry of Emergency Management (No. 2024EMST050501).

## REFERENCES

Chen J (2021) Long-Term Joint Operation of Cascade Reservoirs Using Enhanced Progressive Optimality Algorithm and Dynamic Programming Hybrid Approach. Water Resour Manag 35:2265–2279. https://doi.org/10.1007/s11269-021-02846-y

Ding W, Wei G, Zhou H (2023a) Improving flood resilience through optimal reservoir operation. J Hydrol 620:129494. https://doi.org/10.1016/j.jhydrol.2023.129494

Ding W, Zhang C, Lin J, et al (2023b) Flood Risk Quantification, Transmission, and Propagation Analysis for Flood Water Utilization of Parallel Reservoirs. J Hydrol 618:129202. https://doi.org/10.1016/j.jhydrol.2023.129202

Feng Z, Luo T, Niu W, et al (2023) A LSTM-based approximate dynamic programming method for hydropower reservoir operation optimization. J Hydrol 625:130018. https://doi.org/10.1016/j.jhydrol.2023.130018

Lai V, Essam Y, Huang YF, et al (2022a) Investigating dam reservoir operation optimization using metaheuristic algorithms. Appl Water Sci 12:280. https://doi.org/10.1007/s13201-022-01794-1

Lai V, Huang YF, Koo CH, et al (2022b) A Review of Reservoir Operation Optimisations: from Traditional Models to Metaheuristic Algorithms. Arch Comput Methods Eng 29:3435–3457. https://doi.org/10.1007/s11831-021-09701-8

Mansouri M, Safavi HR, Rezaei F (2022) An improved MOPSO algorithm for multi-objective optimization of reservoir operation under climate change. Environ Monit Assess 194:261. https://doi.org/10.1007/s10661-022-09909-6

Ning Y, Ren M, Guo S, et al (2024) An Advanced Multi-Objective Ant Lion Algorithm for Reservoir Flood Control Optimal Operation. Water 16:852. https://doi.org/10.3390/w16060852

Nourani V, Rouzegari N, Molajou A, Hosseini Baghanam A (2020) An integrated simulation-optimization framework to optimize the reservoir operation adapted to climate change scenarios. J Hydrol 587:125018. https://doi.org/10.1016/j.jhydrol.2020.125018

Schaum S, Stenger-Wolf S, Schüttrumpf H, Jüpner R (2025) An Overview of Long-Term Temporaries After Flood Disasters. J Flood Risk Manag 18:e70109. https://doi.org/10.1111/jfr3.70109

Stedinger JR, Sule BF, Loucks DP (1984) Stochastic dynamic programming models for reservoir operation optimization. Water Resour Res 20:1499–1505. https://doi.org/10.1029/WR020i011p01499

Vasan A, Raju KS (2009) Comparative analysis of Simulated Annealing, Simulated Quenching and Genetic Algorithms for optimal reservoir operation. Appl Soft Comput 9:274–281. https://doi.org/10.1016/j.asoc.2007.09.002

Wu X, Shen X, Wei C, et al (2024) A Hybrid Particle Swarm Optimization-Genetic Algorithm for Multiobjective Reservoir Ecological Dispatching. Water Resour Manag 38:2229–2249. https://doi.org/10.1007/s11269-024-03755-6

Xu C, Xu Z, Yang Z (2020) Reservoir operation optimization for balancing hydropower generation and biodiversity conservation in a downstream wetland. J Clean Prod 245:118885. https://doi.org/10.1016/j.jclepro.2019.118885

Zhang R, Zhang S, Wen X, et al (2024) Optimization of short-term hydropower scheduling with dynamic reservoir capacity based on improved genetic algorithm and parallel computing. J Hydrol 636:131238. https://doi.org/10.1016/j.jhydrol.2024.131238

Zhao T, Zhao J, Yang D (2014) Improved Dynamic Programming for Hydropower Reservoir Operation. J Water Resour Plan Manag 140:365–374. https://doi.org/10.1061/(ASCE)WR.1943-5452.0000343

Zhou C, Sun N, Chen L, et al (2018) Optimal Operation of Cascade Reservoirs for Flood Control of Multiple Areas Downstream: A Case Study in the Upper Yangtze River Basin. Water 10:1250. https://doi.org/10.3390/w10091250

Zhu D, Mei Y, Xu X, et al (2021) Optimal Operation of a Parallel Multireservoir System for Flood Control using a Stagewise Compensation Method. Water Resour Manag 35:1689–1710. https://doi.org/10.1007/s11269-021-02803-9