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Intelligent Scheduling Method for Cascade Reservoirs Driven by Dual Optimization of Harris Hawks and Marine Predators

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Abstract

Cascade reservoir optimization faces significant challenges due to multi-dimensional, non-convex, and nonlinear characteristics with coupled constraints. As reservoir numbers increase, computational complexity escalates dramatically, limiting conventional optimization methods' effectiveness. This paper proposes HHONMPA, a hybrid algorithm combining Harris Hawks Optimization (HHO) with Marine Predators Algorithm (MPA). The method uses SPM chaotic mapping for population initialization to enhance diversity and integrates both algorithms' predatory behaviors. During exploration, it employs Brownian motion and improved Lévy flight strategies for global search, while exploitation uses enhanced HHO for local optimization. A novel Dual-Period Oscillation Attenuation Strategy dynamically adjusts parameters to balance exploration-exploitation. Performance validation using CEC2017 benchmark functions shows HHONMPA significantly outperforms the original HHO and MPA in solution accuracy and convergence speed, confirmed through statistical testing. Engineering validation applies the algorithm to the Lower Jinsha River—Three Gorges four-reservoir system, conducting experiments across various hydrological scenarios. Results demonstrate substantial improvements in search accuracy and convergence efficiency compared to existing methods. HHONMPA effectively addresses large-scale cascade reservoir optimization challenges, offering promising prospects for water resource management and hydropower scheduling applications.

Keywords: cascade reservoirs; optimal scheduling; Harris hawks optimization algorithm; marine predators algorithm; hybrid algorithm



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1. Introduction

As global fossil fuel resources become increasingly scarce and energy demand continues to grow, hydroelectric power's important position as a clean renewable energy source becomes increasingly prominent. The efficient development and utilization of hydroelectric power is of great significance for achieving “dual carbon” goals [1]. The optimal operation strategy of reservoirs is essentially to store or distribute inflow according to planned methods through their regulation function in order to maximize multiple benefits such as power generation demand, flood control, irrigation, water supply, and navigation [2]. Among these, the scientific scheduling of cascade reservoirs is key to improving the utilization efficiency of water energy resources [3].

However, the rapid expansion and development of multi-reservoir systems (OMRS) have brought unprecedented challenges to operational management [4]. The optimal scheduling of cascade reservoir groups is a high-dimensional, nonlinear, multi-stage complex optimization problem with numerous constraints. The complex electrical and hydraulic coupling relationships between hydropower stations, numerous decision variables, strict constraint conditions, and complex hydrological-energy conversion mechanisms make it extremely difficult to seek global optimal solutions, posing severe challenges to traditional optimization methods [5].

In terms of algorithm development, solving cascade reservoir optimal scheduling problems has undergone two stages: the early stage was dominated by traditional mathematical programming methods such as linear programming (LP) and dynamic programming (DP), which demonstrated good accuracy in simple problems [6]. However, when system scale expands, traditional methods often suffer from a sharp decline in computational efficiency due to the “curse of dimensionality” [2]. In recent years, metaheuristic algorithms such as particle swarm optimization (PSO), whale optimization algorithm (WOA), and genetic algorithm (GA) have become research hotspots [7]. These algorithms effectively circumvent gradient problems of objective functions by simulating natural behavioral patterns, significantly enhancing optimization capabilities under complex constraint conditions [8].

According to the “No Free Lunch” theorem, no single algorithm can effectively solve all types of optimization problems. Existing metaheuristic algorithms suffer from issues such as local optima trapping and imbalance between convergence speed and global exploration capability [9,10]. In complex coupled systems like cascaded reservoirs, algorithm stability and solution quality are particularly critical [11]. This study addresses these limitations by proposing an improved hybrid optimization strategy and validates its effectiveness through case studies, providing theoretical and technical support for hydropower scheduling systems.

Although the HHO algorithm performs well in various optimization problems, it still has limitations when handling large-scale complex tasks: susceptibility to local optima, insufficient parameter adjustment flexibility, and reduced search efficiency in high-dimensional spaces [12,13]. Research indicates that single algorithms struggle to balance exploration and exploitation capabilities, while combining algorithms with complementary advantages into hybrid forms can effectively overcome these limitations and significantly improve optimization performance [14].

The Marine Predators Algorithm (MPA) is a novel metaheuristic algorithm based on predator behaviors in marine ecosystems, which simulates the strategic selection, prey searching, and energy optimization behaviors of marine predators such as sharks and killer whales [15]. Since its introduction, improved versions of MPA have demonstrated strong application potential across multiple fields. Khan et al. applied an improved MPA with nonlinear parameter control to nonlinear model identification of heat exchanger systems, showing rapid convergence, high accuracy, stability, and robustness under various noise scenarios [16]. Makhadmeh et al. integrated crossover operators into MPA for feature selection in intrusion detection systems within IoT environments, demonstrating excellent feature optimization efficiency and algorithmic stability [17].

“While deterministic optimization methods such as gradient-based techniques and mathematical programming can guarantee global optimality for convex problems, they face significant limitations when addressing complex real-world optimization problems. Specifically, these methods: (1) often become computationally intractable for high-dimensional, non-convex, non-differentiable problems; (2) require explicit mathematical formulations that may not be available for complex engineering systems; (3) struggle with problems involving discrete variables, multiple conflicting objectives, and complex constraints; and

(4) may require prohibitive computational time for large-scale problems where near-optimal solutions within reasonable time frames are more valuable than exact solutions. Metaheuristic algorithms, while not guaranteeing global optimality, provide effective approximation methods for such NP-hard problems where exact methods are impractical.”

HHO and MPA, as two metaheuristic algorithms based on biological behaviors, have demonstrated significant potential in multi-domain optimization problems. However, when facing complex large-scale optimization tasks, single algorithms are often constrained by their inherent mechanisms and struggle to achieve optimal balance between global exploration and local exploitation [8]. This inherent imbalance limits their application effectiveness in high-dimensional complex problems. Specifically, HHO exhibits strong local exploitation capability by simulating the multi-stage dynamic position update mechanism of Harris hawks during hunting processes [18,19]. However, since the global search of original HHO relies on random strategies and lacks multi-directional exploration, it easily leads to insufficient population diversity [20]. The research community widely recognizes MPA’s advantages, including its algorithmic simplicity, ease of use, excellent convergence acceleration capability, outstanding optimization results, and good solving ability for continuous, multi-objective, and binary problems, making it typically superior to other famous optimization algorithms in the literature. However, like many metaheuristic algorithms [21], MPA and its variants sometimes exhibit common problems such as population diversity degradation and susceptibility to local optima when solving certain complex problems [22]. Given the inherent limitations of single algorithms in effectively balancing global exploration and local exploitation, combining two or more algorithms with complementary advantages according to specific rules to form hybrid approaches is an effective way to elevate algorithmic performance to new levels. Therefore, this study proposes HHONMPA, a hybrid algorithm aiming to integrate MPA’s powerful global search capability with HHO’s strong local exploitation ability. Furthermore, to enhance population diversity, further alleviate the imbalance between exploration and exploitation processes, and escape local optima traps, this study also introduces SPM chaotic mapping and dual-period fluctuation decay strategies for enhancement. The main contributions of this study are as follows:

- (1) SPM chaotic mapping is introduced for population initialization to enhance population diversity, expand the search range, and significantly improve the quality of initial solutions.
- (2) A dual-period fluctuation decay strategy is introduced to control parameters for balancing the algorithm’s exploration and exploitation capabilities, ultimately achieving effective balance between global search and local fine search.
- (3) This study proposes HHONMPA, a hybrid algorithm whose core combines the predatory behavior of Harris hawks and the search mechanism of marine predators, integrating HHO’s powerful local search capability with MPA’s global search ability.
- (4) Comparative experiments on 12 CEC2017 test functions demonstrate that HHONMPA outperforms five comparative algorithms in optimization performance.
- (5) In the optimization problem of four cascaded reservoirs in the Jinsha River basin, compared with HHO and MPA, HHONMPA achieves faster convergence speed and higher accuracy, highlighting its tremendous potential in practical engineering applications.

The remainder of this paper is organized as follows: Section 2 introduces HHO and MPA and describes the proposed HHONMPA. Section 3 presents experimental results and analysis on benchmark test functions and describes how to apply HHONMPA to solve the optimal scheduling problem of cascaded reservoirs in the Jinsha River basin. Section 4 presents the conclusions of this study.

2. Materials and Methods

2.1. Harris Hawk Optimization Algorithm

Harris Hawks Optimization (HHO) is a metaheuristic algorithm inspired by the cooperative hunting behavior of Harris hawks [23]. Hawks represent candidate solutions and the prey symbolizes the optimal target. The optimization process consists of three phases: global exploration for comprehensive search, transition phase for gradual convergence, and exploitation phase for precise capture and position updates. HHO features simple parameters, clear implementation logic, and strong local search performance, making it widely applicable to diverse optimization problems.

2.1.1. Exploration Phase

In the initial exploration phase of the Harris Hawks optimization process, the algorithm simulates the perching behavior of hawks and employs a dual mechanism to locate potential prey. Based on the current hawk population position information and randomly selected individual position information, respectively, the system switches between two modes with a 50% probability. Through this dual-track parallel exploration strategy, the algorithm can conduct comprehensive searches in the solution space, effectively avoiding the trap of falling into local optima. Its mathematical expression is as follows:

$$X(t+1) = \begin{cases} X_{rand}(t) - r_1 \cdot |X_{rand}(t) - 2r_2 \cdot X(t)| & q \geq 0.5 \\ (X_{prey}(t) - X_m(t)) - r_3 \cdot (Lb + r_4 \cdot (Ub - Lb)) & q < 0.5 \end{cases} \quad (1)$$

where $X(t+1)$ represents the position vector of the hawk during the $(t+1)$ -th iteration; $X_{rand}(t)$ represents the position vector of the hawk randomly selected from the t -th iteration; r_1, r_2, r_3, r_4 and q represent different random numbers uniformly distributed in the interval $[0, 1]$, respectively; $X_{prey}(t)$ represents the position vector of the tracked prey during the $(t+1)$ -th iteration; $X_m(t)$ represents the average position vector of the population at the t -th iteration, and its mathematical expression is as follows:

$$X_m(t) = \frac{1}{N} \sum_{i=1}^N X_i(t) \quad (2)$$

where N represents the number of hawks in the population.

2.1.2. Exploitation Phase

The Harris Hawks Optimization (HHO) algorithm utilizes four tactical encirclement strategies: soft and hard encirclement modes plus two hybrid strategies with progressive rapid diving. A random variable $p \in (0,1)$ quantifies prey escape probability, where $p < 0.5$ indicates potential escape, enabling adaptive hunting scheme selection through the coupling of escape energy E and probability parameter p . However, random parameters in exploration and exploitation phases reduce convergence efficiency and weaken global optimization performance. Reducing exploitation strategies from four to two significantly enhances overall algorithm performance [24].

When $0.5 \leq |E| < 1$ and $p \geq 0.5$, the prey retains escape capabilities and attempts to break free through random jumping. Harris hawks employ soft encirclement to gradually exhaust the prey's strength, creating favorable conditions for the final attack. When $|E| < 0.5$ and $p \geq 0.5$, the prey lacks escape energy and evasion opportunities. Hawks then implement hard encirclement, launching a direct decisive attack. The escape energy param-

eter E serves as the core basis for hawks' behavioral selection. The algorithm integrates soft and hard encirclement mechanisms to establish corresponding position update formulas:

$$X(t+1) = \Delta X(t) - E \left| JX_{prey}(t) - X(t) \right| - (1-E) \left| \Delta X(t) \right| \quad (3)$$

$$J = 2(1 - r_5) \quad (4)$$

where $\Delta X(t)$ is the position vector difference between the prey and the current hawk group in the k -th iteration. r_5 is a random number in $[0, 1]$, and J represents the jumping intensity of the prey in the random escape process in each iteration.

When $p < 0.5$ and $|E| \geq 0.5$, the prey has escape opportunities and sufficient energy to evade capture. The hawk swarm implements a composite strategy of progressive rapid diving combined with soft encirclement. When $|E| < 0.5$ and $p < 0.5$, the prey is exhausted but escape possibilities remain. Harris hawks adopt progressive rapid diving combined with hard encirclement to constrain the prey. The position update formula for this strategy is:

$$\begin{aligned} Y &= X_{prey}(t) - E * LF |JX_{prey}(t) - X(t)| \\ Z &= X_{prey}(t) - (1 - E) * LF |JX_{prey}(t) - X_m(t)| \end{aligned} \quad (5)$$

$$X(t+1) = \begin{cases} Y & \text{if } F(Y) < F(X(t)) \text{ and } F(Y) < F(Z) \\ Z & \text{if } F(Z) < F(X(t)) \text{ and } F(Z) \leq F(Y) \end{cases}$$

$$\begin{cases} LF = 0.01 \times \left| \frac{u \times \sigma}{v^{\frac{1}{\beta}}} \right| \\ \sigma = \left(\frac{\sin(\frac{\pi\beta}{2}) \times \Gamma(1+\beta)}{\beta \times 2^{(\frac{\beta-1}{2})} \times \Gamma(\frac{1+\beta}{2})} \right)^{\frac{1}{\beta}} \end{cases} \quad (6)$$

where $F(\cdot)$ symbols the fitness function, LF represents the Levy flight function, u and v are random values obtained randomly in $[0, 1]$; β is a constant, which is taken as 1.5 in this paper.

2.2. Marine Predators Algorithm

The Marine Predators Algorithm (MPA) is a metaheuristic optimization method inspired by marine organism hunting behaviors [15]. The algorithm comprises three core modules: population initialization, optimization iteration, and vortex effect with Fish Aggregating Device (FAD) influence. MPA constructs initial population matrices for predators and prey, then formulates spatial position adjustment strategies based on velocity relationships between predators and prey, incorporating marine vortex phenomena and artificial fish aggregating device mechanisms. Through iterative computation, the algorithm progressively searches for optimal predator positions that achieve optimal objective function values. In MPA, prey positions are represented by a matrix with the following mathematical expression:

$$\text{Prey} = \begin{bmatrix} x_{1,1} & \cdots & x_{1,d} \\ \vdots & \ddots & \vdots \\ x_{n,1} & \cdots & x_{n,d} \end{bmatrix}_{n \times d} \quad (7)$$

where n represents the population size and d denotes the dimension of the search space. $X_{i,j}$ represents the current position of the i -th prey in the j -th dimension. The individual

with the optimal fitness value is referred to as the top predator, which is used to construct the elite matrix with the same size as the prey matrix. Its mathematical expression is:

$$Elite = \begin{bmatrix} x_{1,1}^I & \cdots & x_{1,d}^I \\ \vdots & \ddots & \vdots \\ x_{n,1}^I & \cdots & x_{n,d}^I \end{bmatrix}_{n \times d} \quad (8)$$

where X^I represents the top predator vector, and the elite matrix is obtained by replicating this vector n times.

2.2.1. Exploration Phase

This phase occurs during the first third of the algorithm's execution, where the algorithm performs a global search process. During this period, the predator's movement rate exceeds that of the prey, and the mathematical expression for prey individual position adjustment is:

$$\begin{aligned} stepsize_i &= R_B \otimes (Elite_i - R_B \otimes Prey_i) \\ Prey_i &= Prey_i + P \times R \otimes stepsize_i \end{aligned} \quad (9)$$

where R_B is a random vector following a normal distribution, used to represent Brownian motion. $\otimes$ denotes element-wise multiplication, R is a random number between $[0, 1]$, and P is a constant with a value equal to 0.5.

2.2.2. Exploitation Phase

This phase covers the time period from $1/3$ to $2/3$ of the algorithm's iterative process, marking the transition stage from global search to local exploitation. During this phase, predators and prey maintain the same movement rate. The algorithm divides the current population into two parts: the first part is responsible for exploration tasks, where prey adopt Brownian motion as their movement pattern; the second part performs exploitation functions, where predators follow Lévy flight position update rules. The mathematical expression for this process is as follows:

$$\begin{aligned} &\text{While } \frac{1}{3}t_{\max} < t < \frac{2}{3}t_{\max} \\ &stepsize_i = R_L \otimes (Elite_i - R_L \otimes Prey_i) \\ &Prey_i = Prey_i + P \times R \otimes stepsize_i \end{aligned} \quad (10)$$

$$\begin{aligned} &\text{While } \frac{1}{3}t_{\max} < t < \frac{2}{3}t_{\max} \\ &stepsize_i = R_B \otimes (R_B \otimes Elite_i - Prey_i) \\ &CF = \left(1 - \frac{t}{t_{\max}}\right)^{\left(\frac{2t}{t_{\max}}\right)} \\ &Prey_i = Elite_i + P \times CF \otimes stepsize_i \end{aligned} \quad (11)$$

where RL is a random number vector based on Lévy distribution, and CF is an adaptive parameter that controls the predator's movement step size.

2.3. Proposed HHONMPA Algorithm

2.3.1. SPM Chaotic Mapping Strategy

The Sine mapping has a relatively small chaotic range [25], while the PWLCM chaotic mapping possesses better ergodicity [26]. Therefore, a new chaotic mapping SPM is

designed by combining the Sine chaotic mapping and PWLCM chaotic mapping for population initialization. The SPM mapping function expression is:

$$x(t+1) = \begin{cases} \max\left(\frac{x(t)}{\eta} + u \sin(\pi x(t)) + r, 1\right), & 0 \leq x(t) < \eta \\ \max((1-x_t)(1-\eta) + u \sin(\pi x(t)) + r, 1), & \eta \leq x(t) < 1 \end{cases} \quad (12)$$

where $\eta \in (0,1)$, $u \in (0,1)$, and r is a random disturbance parameter.

The combination of Sine mapping and PWLCM chaotic mapping provides complementary advantages: Sine mapping offers continuity and mathematical stability, while PWLCM contributes strong ergodicity and wider chaotic range [27]. This combination overcomes single Sine mapping limitations and enhances system complexity through PWLCM's piecewise characteristics, improving chaotic effects and application potential. As shown in Figure 1, SPM mapping covers the entire data range, generates more random values, and demonstrates superior ergodicity.

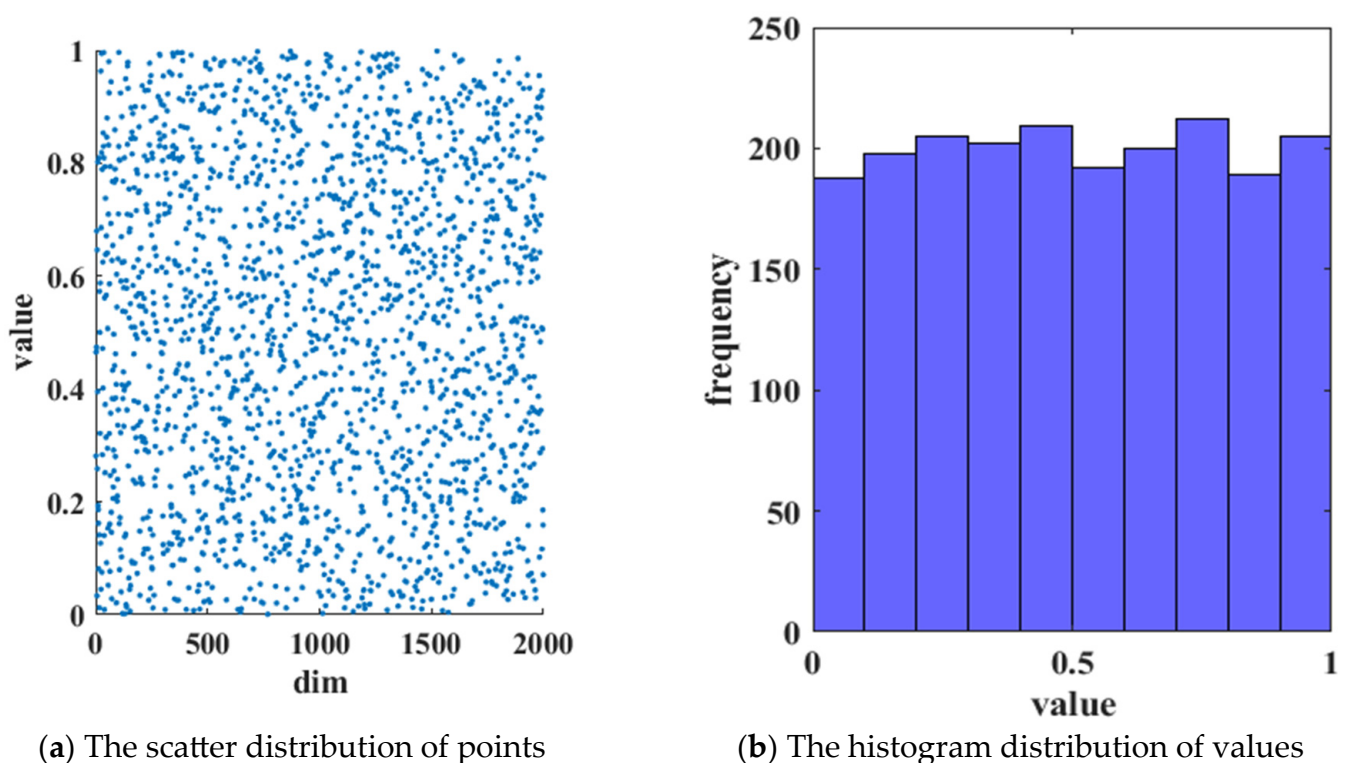


Figure 1. Visualization of SPM chaotic mapping.

2.3.2. Dual-Period Oscillation Attenuation Strategy

The dual-period oscillation decay strategy introduces controlled periodic fluctuations to traditional monotonic decay functions. It comprises two components: the base decay term ensures overall square decay trend for convergence, while the oscillation term creates periodic energy fluctuations with a “high-low-high” pattern. This dual time-scale design maintains convergence direction while providing periodic “energy boosts,” significantly enhancing escape from local optima. The mechanism effectively balances global exploration and local exploitation, improving solution performance and stability in complex multi-peak optimization problems. Its mathematical expression is:

$$E1 = \left(1 - \frac{t}{T}\right)^2 \times \left(0.5 + 0.5 \cdot \sin\left(\pi \times \frac{t}{T}\right)\right) \quad (13)$$

$$E0 = 2r - 1 \quad (14)$$

$$E = E0 \cdot E1 \quad (15)$$

where t represents the current iteration number; T denotes the maximum number of iterations; r is a random number distributed in the range $[0, 1]$; $E0$ is the initial escape energy, ranging from $[-1, 1]$; $E1$ is the escape energy with dual-cycle oscillatory attenuation; E is the final escape energy.

2.3.3. Update Rule Combining Levy and Differential Mutation Strategies

In the initial phase of MPA, the algorithm struggles to effectively balance global exploration and local exploitation, resulting in slow convergence. In this study, we introduce a differential mutation formula and integrate it with Lévy flight to establish a new update rule for the initial exploration phase. This modification aims to improve the algorithm's convergence speed during the early stages of the process. The update rule is shown in the equation:

$$\begin{aligned} &\text{While } \frac{1}{3}t_{\max} < t < \frac{2}{3}t_{\max} \\ &\alpha = \left(t - \frac{1}{3}t_{\max}\right) / \left(\frac{1}{3}t_{\max}\right) \\ &\text{stepsize}_{dif} = F(\text{Elite}_i - \text{Prey}_i) + F(\text{Prey}_{r1} - \text{Prey}_{r2}) \\ &\text{stepsize}_i = (1 - \alpha)[R_L \otimes (\text{Elite}_i - R_L \otimes \text{Prey}_i)] + \alpha \times \text{stepsize}_{dif} \\ &\text{Prey}_i = \text{Prey}_i + P \times R \otimes \text{stepsize}_i \end{aligned} \quad (16)$$

where r_1 and r_2 represent random indices of the Prey matrix; $\alpha \in [0, 1]$ is the progress factor; $F \in [0.4, 0.9]$ is the mutation factor.

2.3.4. HHONMPA

This hybrid optimization algorithm cleverly integrates the advantages of Harris Hawks Optimization (HHO) and Marine Predators Algorithm (MPA) to construct an adaptive optimization framework with balanced search capabilities. From the algorithmic structure perspective, it inherits HHO's diversified search strategy framework while incorporating MPA's efficient search mechanisms of Brownian motion and Levy flight. Specifically, during the exploration phase, it employs MPA's Brownian motion and improved Levy flight strategies for searching, while in the exploitation phase, it implements local fine-grained search through improved HHO exploitation strategies. Meanwhile, adaptive control parameters are used to balance the algorithm's exploration and exploitation capabilities, achieving an effective balance between global search and local fine-grained search. Additionally, an improved SPM chaotic mapping strategy is adopted to enhance initial population diversity. The overall architecture encompasses key phases, including initialization, exploration, and exploitation. Through the synergistic coordination of these phases, it demonstrates excellent problem adaptability and optimization performance. When handling complex optimization problems, the algorithm can adaptively adjust search strategies, effectively avoiding local optima traps while ensuring convergence accuracy. Its detailed flowchart is as follows (Figure 2):

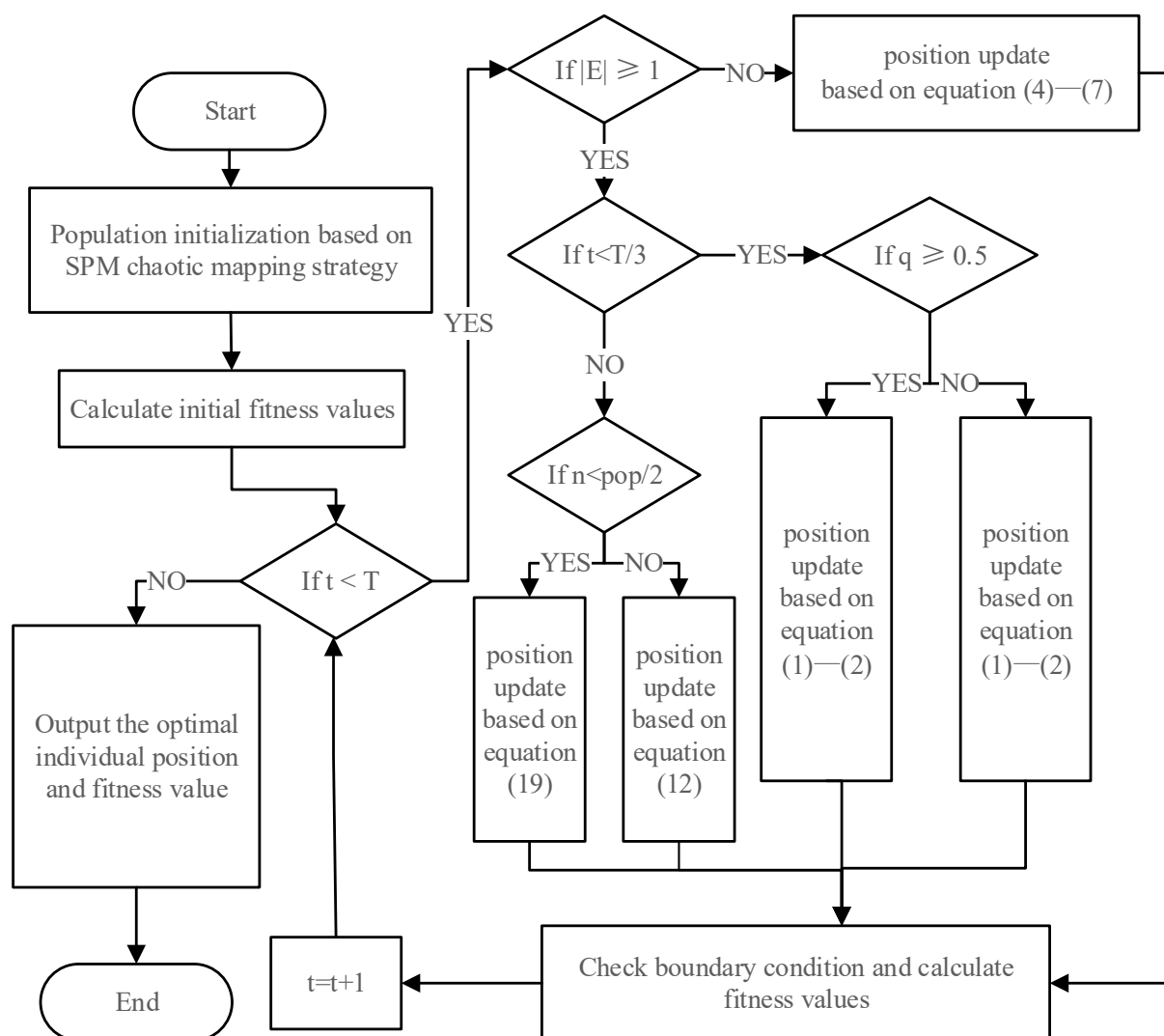


Figure 2. Flowchart of the proposed HHONMPA.

The proposed hybrid HHO-MPA operates through the following steps:

Step 1 (Initialization): The algorithm initializes a population of N individuals using an improved SPM chaotic mapping strategy to enhance initial diversity. Each individual's fitness is evaluated, and the best solution X_{best} is identified.

Step 2 (Parameter Update): At each iteration t , the energy parameter is updated as Equation (16), which controls the transition between exploration and exploitation phases. The algorithm also generates random parameters r and u for strategy selection.

Step 3 (Exploration Phase, $|E| \geq 1$): When $|E| \geq 1$, the algorithm employs MPA-based exploration strategies. The strategy selection depends on iteration progress: (i) If $t < T/3$, the algorithm checks condition $n < \text{pop}/2$ —when satisfied, Brownian motion Equation (19) performs random walks among individuals; otherwise, improved Levy flight Equation (12) is applied; (ii) If $t \geq T/3$, the algorithm checks condition $n > \text{pop}/2$ —when satisfied, Brownian motion Equation (19) is used; otherwise, improved Levy flight Equation (12) generates long-range movements toward the best solution.

Step 4 (Exploitation Phase, $|E| < 1$): When $|E| < 1$, the algorithm switches to HHO-based exploitation strategies. Four hunting behaviors are selected based on parameters q and $|E|$: (i) soft besiege using Equations (4)–(7) when $q \geq 0.5$ and $|E| \geq 0.5$; (ii) hard besiege using Equations (1) and (2) when $q \geq 0.5$ and $|E| < 0.5$; (iii) soft besiege with progressive rapid dives when $q < 0.5$ and $|E| \geq 0.5$; (iv) hard besiege with progressive

rapid dives when $q < 0.5$ and $|E| < 0.5$. The latter two strategies incorporate Levy flight to escape local optima.

Step 5 (Boundary Control and Selection): Each updated position is checked against boundary constraints. The fitness of new positions is evaluated, and greedy selection is applied: if the new position is better, it replaces the current one; otherwise, the current position is retained.

Step 6 (Termination): Steps 2–5 repeat until the maximum iteration T is reached. The algorithm then outputs the optimal solution X_{best} and its corresponding fitness value.

The key integration mechanism is the adaptive phase switching controlled by the energy parameter E , which enables a smooth transition from MPA's stochastic exploration in early iterations to HHO's deterministic exploitation in later iterations, achieving an effective balance between global search and local refinement.

3. Results and Discussion

3.1. Algorithm Convergence Validation

To ensure the scientific rigor and reproducibility of experimental results, the algorithm performance validation experiments in this study are divided into two main components: strategy effectiveness validation and algorithm convergence validation. All experiments are conducted under unified hardware and software environments, with the experimental platform utilizing a 64-bit Windows 10 operating system equipped with a 13th generation Intel Core i7-13700H processor (2.40 GHz base frequency; Intel Corporation, Santa Clara, CA, USA), and MATLAB R2023b serving as the simulation testing environment (The MathWorks, Inc., Natick, MA, USA). To facilitate comparative analysis, experimental results are presented in tabular format, with optimal performance indicators highlighted in bold. Furthermore, to guarantee experimental reliability and fairness, this study strictly follows the parameter configurations recommended in the original literature as shown in Table 1, which not only ensures experimental standardization but also provides a verifiable experimental benchmark for subsequent research.

Table 1. Detailed Parameter Settings for Each Algorithm.

Algorithm	Parameters
HHONMPA	Control coefficient $CF \in [2, 0]$; Initial state of the prey's energy $E_0 \in [-1, 1]$; Prey attack probability $FADs = 0.2$; Prey movement probability $p = 0.5$; Control coefficient $\omega \in [2, 0]$.
HHO	Constant $\beta = 1.5$; Random jump strength $J \in [0, 2]$; Chance of a prey in successfully escaping $q = 0.5$; Initial state of the prey's energy $E_0 \in [-1, 1]$.
MPA	Prey attack probability $FADs = 0.2$; Prey movement probability $p = 0.5$;
NCHHO	Control coefficient $CF \in [2, 0]$; Constant $\beta = 1.5$; Random jump strength $J \in [0, 2]$; Chance of a prey in successfully escaping $r = 0.5$; Initial state of the prey's energy $E_0 \in [-1, 1]$.
NMPA	Control coefficient $CF \in [2, 0]$; Prey attack probability $FADs = 0.2$; Prey movement probability $p = 0.5$.

To comprehensively evaluate the convergence performance of HHONMPA, this section selects the CEC 2017 standard test function suite as the validation benchmark. As shown in Table 2, the 12 CEC 2017 test functions employed in the experiments cover dif-

ferent types of optimization scenarios, including simple multimodal functions (F5, F7, F8, F10), hybrid functions (F12, F13, F15, F18), and composition functions (F22, F24, F26, F30). During the evaluation process, convergence performance is measured by the minimum convergence error, which is the difference between the optimization result's function value and the theoretical optimal value of the function. When this error is smaller than the preset threshold ϵ , the algorithm can be considered to have reached the optimal value of the function, meaning the convergence error approaches zero. To ensure the comparability of experimental results, all comparison algorithms adopt unified parameter configurations. Considering the complexity of the CEC 2017 test function suite, the experiment sets the maximum number of iterations to 1000, the population size to 50, and each test function runs independently 30 times to ensure statistical reliability. This study selects multiple representative state-of-the-art algorithms as comparison benchmarks, including the classical HHO [23], MPA [15], as well as recently proposed improved algorithms NCHHO [28], NMPA [16], and DBO [29]. Through performance comparison with these advanced algorithms, the convergence performance advantages of HHONMPA under different optimization scenarios can be comprehensively evaluated.

Table 2. 12 Test Functions in CEC2017 Test Function Experiment.

Type	No.	Description	F _i * (Optimal Value)
Simple Multimodal function	F5	Shifted and Rotated Rastrigin's Function	500
	F7	Shifted and Rotated Lunacek Bi-Rastrigin's Function	700
	F8	Shifted and Rotated Non-Continuous Rastrigin's Function	800
	F10	Shifted and Rotated Schwefel's Function	1000
Hybrid function	F12	Hybrid Function 7 (N = 3)	1200
	F13	Hybrid Function 10 (N = 3)	1300
	F15	Hybrid Function 10 (N = 4)	1500
	F18	Hybrid Function 10 (N = 5)	1800
Composition function	F22	Composition Function 2 (N = 3)	2200
	F24	Composition Function 4 (N = 4)	2400
	F26	Composition Function 6 (N = 5)	2600
	F30	Composition Function 8 (N = 6)	3000

Through convergence performance analysis of functions with different characteristics in the CEC2017 test set (as shown in Figure 3), HHONMPA demonstrates significant comprehensive performance advantages. The algorithm exhibits excellent convergence speed in the first 200 iterations, rapidly approaching the optimal solution. Particularly for complex functions such as F12, F13, F15, and F18, HHONMPA's optimization performance is significantly superior to comparative algorithms, demonstrating stronger solving capabilities, while the convergence curves exhibit good smoothness characteristics with minimal oscillation amplitude, reflecting excellent algorithm stability. Compared with classic algorithms such as HHO, MPA, NCHHO, NMPA, and DBO, HHONMPA demonstrates stronger adaptability and robustness when handling different types of optimization problems, maintaining leading positions in unimodal functions, multimodal functions, and high-dimensional complex function optimization. The algorithm shows excellent

local optimum escape capability in complex multimodal function optimization, effectively achieving dynamic balance between global exploration and local exploitation, providing a high-value technical solution for solving practical engineering optimization problems. Detailed performance data are shown in Table 3.

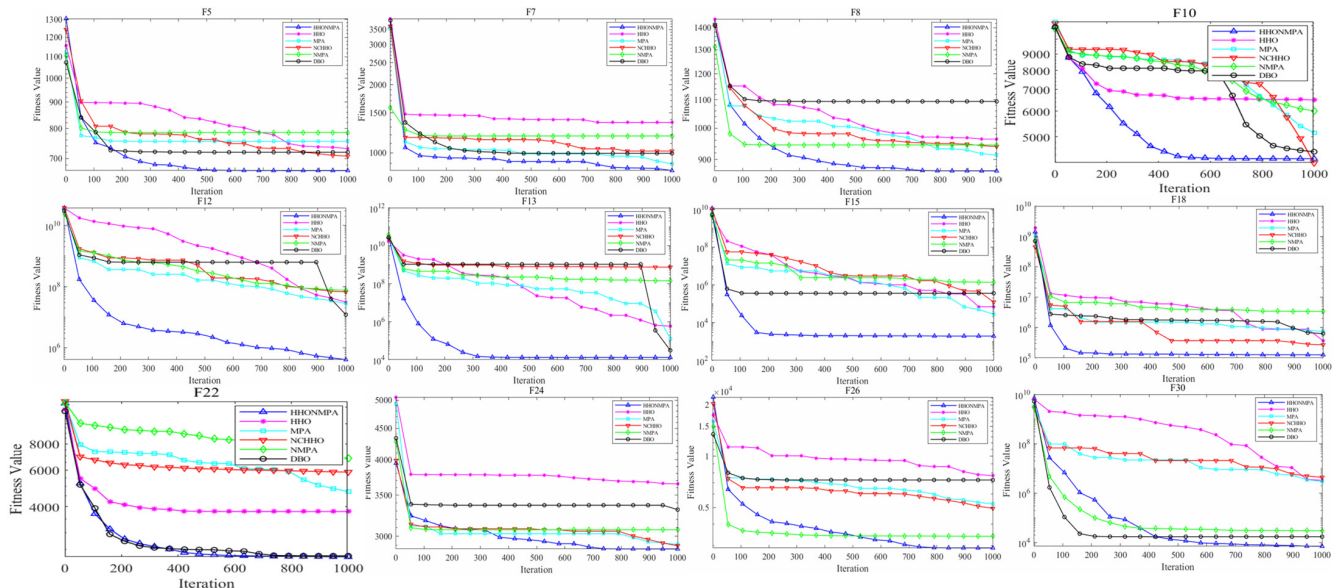


Figure 3. Convergence curves on CEC2017 (30D).

Table 3. Result comparisons on CEC2017 (30D).

Fun	Metris	HHONMPA	HHO	MPA	NCHHO	NMPA	DBO
F5	min	5.65×10^2	7.06×10^2	5.67×10^2	6.40×10^2	6.74×10^2	6.70×10^2
	std	3.72×10^1	3.76×10^1	6.11×10^1	4.42×10^1	4.60×10^1	4.05×10^1
	avg	6.20×10^2	7.59×10^2	6.29×10^2	7.11×10^2	7.48×10^2	7.30×10^2
	median	6.32×10^2	7.51×10^2	6.03×10^2	7.17×10^2	7.56×10^2	7.20×10^2
F7	min	8.00×10^2	1.25×10^3	8.73×10^2	9.97×10^2	1.12×10^3	9.07×10^2
	std	1.77×10^1	4.73×10^1	7.17×10^1	6.66×10^1	8.15×10^1	9.64×10^1
	avg	8.30×10^2	1.31×10^3	9.48×10^2	1.06×10^3	1.22×10^3	1.03×10^3
	median	8.26×10^2	1.30×10^3	9.30×10^2	1.03×10^3	1.21×10^3	1.02×10^3
F8	min	8.64×10^2	9.48×10^2	8.72×10^2	8.91×10^2	9.11×10^2	9.52×10^2
	std	3.61×10^1	1.62×10^1	1.70×10^1	2.55×10^1	3.19×10^1	5.75×10^1
	avg	9.11×10^2	9.73×10^2	9.06×10^2	9.45×10^2	9.65×10^2	1.05×10^3
	median	9.13×10^2	9.71×10^2	9.06×10^2	9.43×10^2	9.71×10^2	1.05×10^3
F10	min	3.51×10^3	4.49×10^3	4.16×10^3	3.79×10^3	4.53×10^3	4.69×10^3
	std	6.40×10^2	7.83×10^2	4.87×10^2	1.91×10^3	7.12×10^2	8.49×10^2
	avg	4.64×10^3	6.02×10^3	4.72×10^3	5.96×10^3	5.57×10^3	6.12×10^3
	median	4.51×10^3	6.23×10^3	4.56×10^3	5.34×10^3	5.44×10^3	6.34×10^3

Table 3. Cont.

Fun	Metris	HHONMPA	HHO	MPA	NCHHO	NMPA	DBO
F12	min	4.06×10^5	1.15×10^7	6.32×10^6	4.18×10^7	3.73×10^6	2.39×10^6
	std	1.66×10^8	2.54×10^7	1.05×10^8	1.32×10^8	1.15×10^8	8.24×10^7
	avg	5.72×10^7	2.92×10^7	8.88×10^7	1.78×10^8	1.13×10^8	4.01×10^7
	median	3.08×10^6	2.08×10^7	3.05×10^7	1.59×10^8	7.64×10^7	1.31×10^7
F13	min	5.94×10^3	3.39×10^5	3.61×10^4	7.39×10^4	7.33×10^4	3.09×10^4
	std	3.33×10^8	2.65×10^5	9.26×10^7	2.33×10^8	5.52×10^7	6.95×10^5
	avg	1.14×10^8	7.14×10^5	2.98×10^7	7.39×10^7	3.28×10^7	4.31×10^5
	median	7.28×10^4	7.07×10^5	2.16×10^5	1.07×10^5	2.08×10^5	1.75×10^5
F15	min	1.93×10^3	3.22×10^4	2.28×10^4	2.65×10^4	2.90×10^4	1.89×10^4
	std	1.07×10^4	4.54×10^4	1.22×10^7	8.14×10^5	2.10×10^6	1.07×10^5
	avg	9.22×10^3	8.32×10^4	4.37×10^6	5.18×10^5	1.26×10^6	1.03×10^5
	median	5.64×10^3	6.76×10^4	9.65×10^4	1.11×10^5	2.13×10^5	5.55×10^4
F18	min	8.38×10^4	3.39×10^5	2.35×10^5	2.65×10^5	1.88×10^5	1.14×10^5
	std	1.04×10^6	4.86×10^6	1.02×10^6	3.32×10^6	1.74×10^6	3.42×10^6
	avg	6.18×10^5	3.38×10^6	1.60×10^6	2.48×10^6	2.13×10^6	3.11×10^6
	median	1.57×10^5	6.98×10^5	1.49×10^6	9.96×10^5	1.56×10^6	2.12×10^6
F22	min	2.30×10^3	2.41×10^3	2.47×10^3	2.50×10^3	2.51×10^3	2.33×10^3
	std	3.45×10^0	1.84×10^3	1.91×10^3	1.35×10^3	1.82×10^3	2.03×10^3
	avg	2.30×10^3	7.19×10^3	4.49×10^3	3.31×10^3	5.22×10^3	4.20×10^3
	median	2.30×10^3	7.48×10^3	4.48×10^3	2.88×10^3	6.12×10^3	3.76×10^3
F24	min	2.86×10^3	3.27×10^3	2.90×10^3	2.90×10^3	2.94×10^3	2.96×10^3
	std	1.20×10^1	1.19×10^2	5.33×10^1	6.74×10^1	1.22×10^2	1.03×10^2
	avg	2.88×10^3	3.48×10^3	2.94×10^3	2.96×10^3	3.12×10^3	3.17×10^3
	median	2.88×10^3	3.46×10^3	2.93×10^3	2.94×10^3	3.08×10^3	3.18×10^3
F26	min	2.90×10^3	6.69×10^3	4.35×10^3	3.83×10^3	3.28×10^3	3.79×10^3
	std	6.18×10^{-1}	8.56×10^2	4.71×10^2	5.34×10^2	1.09×10^3	1.08×10^3
	avg	2.90×10^3	8.00×10^3	4.82×10^3	5.04×10^3	4.50×10^3	6.15×10^3
	median	2.90×10^3	7.92×10^3	4.72×10^3	5.05×10^3	4.33×10^3	6.57×10^3
F30	min	5.52×10^3	1.58×10^6	1.78×10^6	6.09×10^5	1.30×10^4	1.72×10^4
	std	1.23×10^3	3.77×10^6	6.70×10^6	1.12×10^7	1.36×10^6	1.54×10^6
	avg	7.61×10^3	5.36×10^6	9.06×10^6	8.99×10^6	4.63×10^5	1.06×10^6
	median	7.53×10^3	3.48×10^6	7.78×10^6	4.55×10^6	2.35×10^4	3.50×10^5

To validate the statistical significance of the performance improvements, Wilcoxon signed-rank tests were conducted at the 0.05 significance level between HHONMPA and each competitor algorithm across all 12 CEC2017 test functions. As shown in Table 4, HHONMPA demonstrates statistically significant superiority in the majority of comparisons. Specifically, HHONMPA significantly outperforms HHO and DBO in all 12 functions

(100% win rate), while achieving win rates of 91.67% against MPA and 83.33% against NMPA and NCHHO. The consistent statistical advantages across simple multimodal functions (F5, F7, F8, F10), hybrid functions (F12, F13, F15, F18), and composition functions (F22, F24, F26, F30) confirm that the observed improvements represent genuine algorithmic advantages in handling diverse optimization scenarios.

Table 4. Statistical Significance of Performance Improvements (Wilcoxon Test, $\alpha = 0.05$).

Function	Type	HHO	MPA	NCHHO	NMPA	DBO
F5	Simple Multimodal	+	+	+	+	+
F7	Simple Multimodal	+	+	+	+	+
F8	Simple Multimodal	+	+	+	—	+
F10	Simple Multimodal	+	+	—	+	+
F12	Hybrid	+	+	+	+	+
F13	Hybrid	+	+	+	+	+
F15	Hybrid	+	+		+	+
F18	Hybrid	+	+	+	+	+
F22	Composition	+	+	+	+	+
F24	Composition	+	+	—	—	+
F26	Composition	+	=	+	+	+
F30	Composition	+	+	+	+	+
+ / = / —		12/0/0	11/1/0	10/2/0	10/2/0	12/0/0

Note: The symbols represent the statistical significance (Wilcoxon test, $\alpha = 0.05$) of the proposed algorithm versus others: ‘+’ (improvement), ‘=’ (no difference), ‘—’ (degradation). The last row shows the summary counts.

3.2. Case Study Analysis of Cascade Reservoir Optimal Operation

To validate the engineering practicality of HHONMPA, this study applies it to medium- and long-term power generation optimization for the downstream Jinsha River—Three Gorges cascade reservoir system.

1. Study area and cascade reservoir system

The study area is located in the upper and middle reaches of the Yangtze River, encompassing two major hydropower bases as illustrated in Figure 4. The Jinsha River section spans 3500 km (55.5% of the Yangtze River’s total length) with a drainage area of approximately 473,200 km², originating from the Qinghai–Tibet Plateau and flowing through Yunnan and Sichuan provinces before joining the main Yangtze River. This river section features steep gradients (average drop of 2.6 m/km) and abundant hydropower resources, making it one of China’s most important clean energy development zones. The cascade system comprises six major reservoirs across two sections: the Lower Jinsha River section includes Wudongde Reservoir (located at 103°52′ E, 26°23′ N), Baihetan Reservoir (182 km downstream of Wudongde), Xiluodu Reservoir (195 km downstream of Baihetan), and Xiangjiaba Reservoir (157 km downstream of Xiluodu); the Three Gorges section includes Three Gorges Reservoir (364 km downstream of Xiangjiaba) and Gezhouba Reservoir (38 km downstream of Three Gorges). The total cascade length spans approximately 936 km from Xiluodu to Gezhouba, with this study focusing specifically on the four

operational reservoirs—Xiluodu, Xiangjiaba, Three Gorges, and Gezhouba—which form a highly integrated cascade system for coordinated power generation optimization.

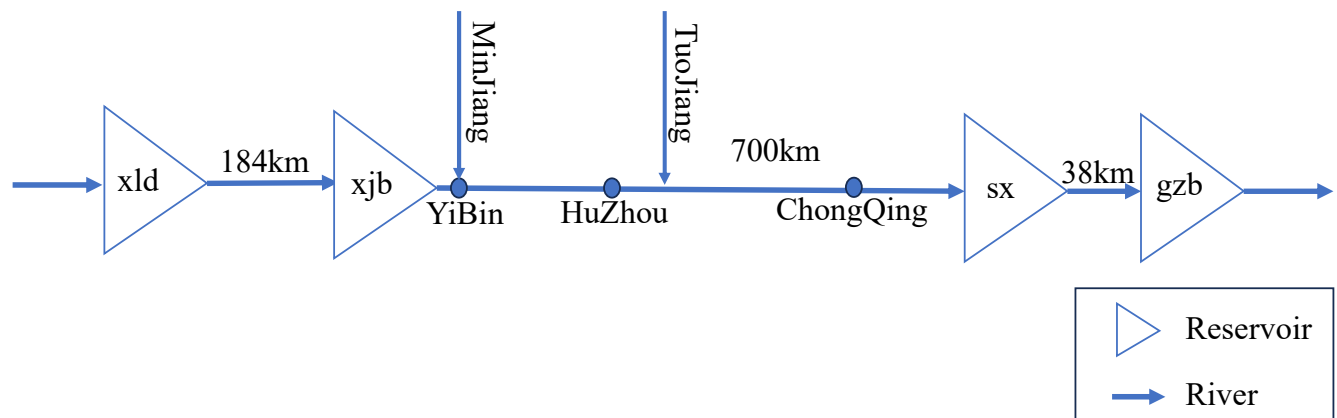


Figure 4. Schematic diagram of a cascade reservoir structure.

2. Hydrological characteristics and flow propagation

The cascade system exhibits distinct seasonal patterns driven by monsoonal climate and snowmelt from the Qinghai–Tibet Plateau. Historical data (2010–2020) show an annual average discharge of approximately 4770 m³/s at Xiluodu, increasing to 14,300 m³/s at Three Gorges. Seasonal variation is pronounced: dry season (November–April) flows of 4500–5000 m³/s versus flood season (May–October) flows of 15,000–20,000 m³/s, with peaks exceeding 40,000 m³/s during extreme events. The flow variability coefficient ($C_v = 0.35\text{--}0.42$) indicates moderate interannual variability.

This study adopts a 10-day (dekadal) time step for medium- and long-term optimization, which is the standard temporal resolution for reservoir scheduling in China. Flow propagation times between consecutive reservoirs are relatively short: 1.2–1.5 days from Xiluodu to Xiangjiaba (157 km), 2.5–3.0 days from Xiangjiaba to Three Gorges (364 km), and 0.3–0.5 days from Three Gorges to Gezhouba (38 km), as shown in Table 5. Since all propagation delays (0.3–3.0 days) are significantly shorter than the 10-day time step—representing only 3–30% of each period—the flow propagation effects are approximated within each period using simplified water balance equations. For the longest reach (Xiangjiaba–Three Gorges), a one-period lag is incorporated, reflecting that outflows require 2–3 days to propagate downstream. Strict mass balance constraints ensure hydrological consistency across the cascade.

Table 5. River reach characteristics and flow propagation parameters.

River Reach	Distance (km) Traveled	Time (Days)	Lag Treatment
Xld-xjb	157	1.2–1.5	Within-period
Xjb-sx	700	2.5–3	Within-period
Sx-gzb	38	0.3–0.5	Within-period

The 10-day time step is appropriate for this application because (1) it aligns with operational practice in China, where medium-term scheduling decisions are made on a dekadal basis, (2) the study reservoirs are storage-dominated systems with large capacities (12.67–39.3 billion m³) that respond gradually over weeks to months rather than to short-term fluctuations, and (3) it provides computational efficiency—the one-year horizon

with 10-day steps yields 144 decision variables ($4 \text{ reservoirs} \times 36 \text{ periods}$), compared to 1460 variables for daily optimization, reducing computational burden by approximately $10\times$ while maintaining solution accuracy within 0.3% based on sensitivity analysis. The 10-day resolution is well-suited for strategic storage allocation and seasonal energy planning that characterize medium- and long-term reservoir optimization.

3. Reservoir technical specifications

Table 6 presents the key technical parameters of the four study reservoirs that form the optimization system. The cascade exhibits diverse regulation capabilities: Xiluodu operates as an annual regulating reservoir with the largest total storage and regulating storage, enabling multi-year water management; Xiangjiaba and Three Gorges function as seasonal regulating reservoirs with substantial storage capacities; while Gezhouba serves as a daily regulating reservoir with limited storage primarily for short-term power peaking. The cascade's total installed capacity exceeds 46,000 MW, with Three Gorges alone contributing 22,500 MW. These varying regulating capabilities and large storage capacities create complex operational interdependencies where upstream reservoir releases directly affect downstream water levels, power generation, and operational constraints, necessitating sophisticated optimization algorithms for coordinated cascade operation.

Table 6. Main Parameters of Cascade Reservoir System in Engineering Case Study.

Parameter	xld	xjb	sx	gzb
Regulation Capacity	Annual	Seasonal	Seasonal	Daily
Total Storage (10^8 m^3)	115.7	49.7	393.0	16.5
Regulating Storage (10^8 m^3)	64.6	9.0	165.0	0.63
Discharge Flow Range (m^3/s)	[43,700, 1200]	[49,800, 1200]	[98,800, 4500]	[10,000, 4500]
Water Level Range (m)	[600, 540]	[380, 370]	[175, 145]	[66.0, 63.0]
Installed Capacity (MW)	13,860	6400	22,500	2715
Normal water level (m)	600	380	175	66
Maximum Water Level Variation (m/d)	2	2	2	2
Guaranteed Output (MW)	3795	2009	4990	1040
Ki	8.5	8.5	8.5	8.5

Table 6 provides the core technical specifications for hydropower planning, detailing key parameters for each reservoir power station, including installed capacity, maximum discharge, optimal water level, and operational efficiency coefficient. Table 7 presents the storage-water level relationship data for each reservoir, defining the operational range from dead storage to maximum capacity. Table 8 documents the 10-day natural inflow

data for upstream reservoirs and intermediate catchment areas under dry-year conditions. Table 9 summarizes the initial reservoir water levels used as the starting condition for dispatch analysis. Additionally, the tailwater elevation-discharge relationship at each power station is characterized by high-order polynomial functions, as shown in Figure 5. Together, these datasets provide a comprehensive foundation for optimizing cascade reservoir dispatch strategies.

Table 7. Characteristic water levels and storage capacities of the four major hydropower reservoirs.

xld-H (m)	xld-V (10^8 m ³)	xjb-H (m)	xjb-V (10^8 m ³)	sx-H (m)	sx-V (10^8 m ³)	gzb-H (m)	gzb-V (10^8 m ³)
540	51.122	365	36.628	365	36.628	62	5.981
541	51.942	366	37.429	366	37.429	62.1	6.008
542	52.771	367	38.239	367	38.239	62.2	6.035
543	53.61	368	39.061	368	39.061	62.3	6.061
544	54.458	369	39.893	369	39.893	62.4	6.088
545	55.316	370	40.736	370	40.736	62.5	6.115
546	56.182	371	41.59	371	41.59	62.6	6.142
547	57.058	372	42.456	372	42.456	62.7	6.169
548	57.943	373	43.332	373	43.332	62.8	6.196
549	58.836	374	44.22	374	44.22	62.9	6.223
550	59.739	375	45.117	375	45.117	63	6.251
551	60.651	376	46.025	376	46.025	63.1	6.278
552	61.571	377	46.943	377	46.943	63.2	6.305
553	62.5	378	47.872	378	47.872	63.3	6.333
554	63.437	379	48.814	379	48.814	63.4	6.36
555	64.382	380	49.767	380	49.767	63.5	6.388
556	65.336	381	50.733	381	50.733	63.6	6.416
557	66.298	382	51.709	382	51.709	63.7	6.443
558	67.268	383	52.692	383	52.692	63.8	6.471
559	68.245	384	53.681	384	53.681	63.9	6.499
560	69.23	385	54.672	385	54.672	64	6.527
561	70.223			154.5	224.716	64.1	6.555
562	71.223			155	228	64.2	6.583
563	72.231			155.5	231.287	64.3	6.611
564	73.248			156	234.597	64.4	6.639
565	74.273			156.5	237.929	64.5	6.668
566	75.306			157	241.285	64.6	6.696
567	76.349			157.5	244.667	64.7	6.724
568	77.401			158	248.076	64.8	6.753
569	78.462			158.5	251.512	64.9	6.781
570	79.533			159	254.977	65	6.81
571	80.614			159.5	258.473	65.1	6.839
572	81.704			160	262	65.2	6.867
573	82.804			160.5	265.573	65.3	6.896

Table 7. Cont.

xld-H (m)	xld-V (10 ⁸ m ³)	xjb-H (m)	xjb-V (10 ⁸ m ³)	sx-H (m)	sx-V (10 ⁸ m ³)	gzb-H (m)	gzb-V (10 ⁸ m ³)
574	83.914			161	269.206	65.4	6.925
575	85.032			161.5	272.896	65.5	6.954
576	86.159			162	276.641	65.6	6.983
577	87.295			162.5	280.441	65.7	7.012
578	88.44			163	284.294	65.8	7.041
579	89.593			163.5	288.198	65.9	7.07
580	90.754			164	292.151	66	7.099
581	91.923			164.5	296.152	66.1	7.128
582	93.1			165	300.2	66.2	7.158
583	94.285			165.5	304.301	66.3	7.187
584	95.478			166	308.463	66.4	7.216
585	96.68			166.5	312.687	66.5	7.246
586	97.89			167	316.973	66.6	7.275
587	99.108			167.5	321.321	66.7	7.304
588	100.335			168	325.732	66.8	7.334
589	101.57			168.5	330.205	66.9	7.364
590	102.814			169	334.74	67	7.393
591	104.067			169.5	339.338		
592	105.328			170	344		
593	106.598			170.5	348.718		
594	107.877			171	353.483		
595	109.165			171.5	358.293		
596	110.462			172	363.146		
597	111.768			172.5	368.038		
598	113.082			173	372.967		
599	114.406			173.5	377.93		
600	115.738			174	382.925		
				174.5	387.949		
				175	393		

Table 8. Cascade Reservoir Inflow and Interval Flow Table for Dry Years (2016).

Time	Inflow-xld (m ³ /s)	Inflow-xjb (m ³ /s)	Inflow-sx (m ³ /s)	Inflow-gzb (m ³ /s)
1	2150	−54.6	4620	0
2	3170	−45.8	5450	0
3	3070	−29.2	4550	0
4	2240	−42.2	3690	0
5	1360	−10.1	2840	0

Table 8. *Cont.*

Time	Inflow-xld (m ³ /s)	Inflow-xjb (m ³ /s)	Inflow-sx (m ³ /s)	Inflow-gzb (m ³ /s)
6	1500	−10.7	3570	0
7	1680	−2.22	4020	0
8	1830	−13.1	5010	0
9	1550	−10.7	5520	0
10	828	−29.2	6260	0
11	369	36.5	6870	0
12	1050	76.8	8540	0
13	996	108	9030	0
14	1120	−21.7	10,800	0
15	1920	−27.8	8930	0
16	2000	−11.7	8060	0
17	2520	−15	10,800	0
18	4110	−81.9	12,100	0
19	7110	−157	18,800	0
20	6440	−84.5	26,900	0
21	5710	4.33	16,900	0
22	5000	−130	12,800	0
23	6150	13.4	17,100	0
24	6110	1.47	31,600	0
25	8630	202	28,800	0
26	8550	154	22,300	0
27	6650	−76.2	21,200	0
28	5830	−117	19,200	0
29	5380	−114	12,200	0
30	4810	−78.9	9060	0
31	5260	−50	8370	0
32	4320	−76.6	9910	0
33	2830	−31.4	9690	0
34	2610	−41.4	8850	0
35	2620	−30.8	9370	0
36	2610	−45.9	9810	0

Table 9. Table of Initial and Final Water Levels for the Four Power Stations.

Station Name	Initial Water Level (m)	Final Water Level (m)
xld	580.00	580.00
xjb	380.00	380.00
sx	175.00	168.00
gzb	64.50	64.50

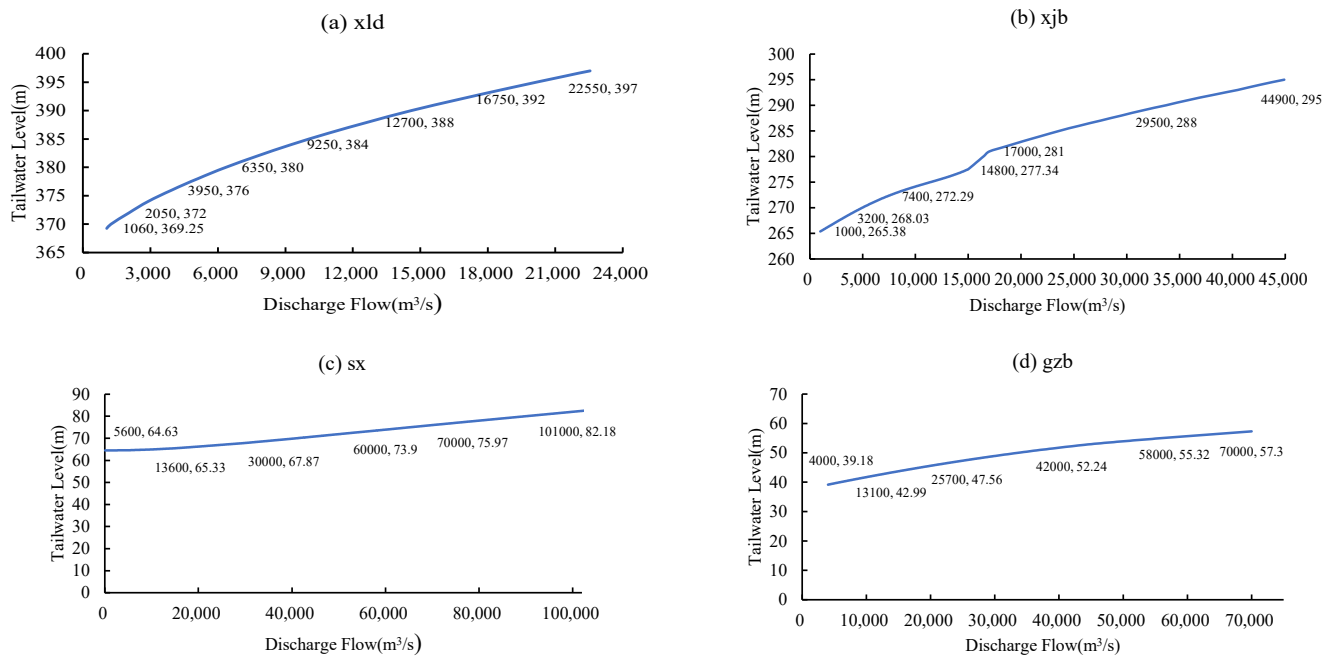


Figure 5. Tailwater level-discharge relationship curve.

4. Optimization problem formulation

Based on the cascade system characteristics described above, the seasonal hydrological patterns with distinct dry and flood periods, the diverse regulation capabilities ranging from daily to annual, and the substantial total installed capacity exceeding 46,000 MW—the medium- and long-term power generation optimization problem is formulated as follows. The optimization objective is to maximize total power generation across the four-reservoir cascade over a one-year planning horizon (36 ten-day periods) while satisfying hydrological, operational, and physical constraints. The decision variables are represented by a state variable matrix containing the operating water levels of all cascade reservoirs across all time periods:

$$X = \begin{bmatrix} X^1 \\ X^2 \\ \vdots \\ X^i \\ \vdots \\ X^M \end{bmatrix} = \begin{bmatrix} x_1^1, x_2^1, \dots, x_T^1 \\ x_1^2, x_2^2, \dots, x_T^2 \\ \vdots \\ x_1^i, x_2^i, \dots, x_T^i \\ \vdots \\ x_1^M, x_2^M, \dots, x_T^M \end{bmatrix} \quad (17)$$

where M is the number of reservoirs in the cascade system, $X^i = [x_1^i, x_2^i, \dots, x_T^i]$ represents the vector composed of the operating water levels of the i -th reservoir at all time periods, x_t^i represents the operating water level of the i -th reservoir at time t . Therefore, for a cascade reservoir system containing M reservoirs with T scheduling time periods, the dimension of the long-term power generation optimization scheduling problem is $D = M \times T$.

The long-term power generation optimization scheduling of cascade reservoir systems aims to maximize total system power generation while satisfying complex constraints including water balance, hydroelectric power system, and reservoir operation requirements. Water balance constraints ensure rational water resource allocation and transmission; hydroelectric power system constraints cover technical parameters such as unit output characteristics and generation efficiency; and reservoir operation constraints include storage

capacity limits, flow requirements, and water level variations. The objective function for power generation maximization is shown as follows:

$$\max E = \sum_{i=1}^M \sum_{t=1}^T N_{i,t} \Delta T_t \quad (18)$$

$$N_{i,t} = K_i H_{i,t} R_{i,t} \quad (19)$$

where E represents the total power generation of the cascade reservoir system; K_i represents the output coefficient of the i -th reservoir; $N_{i,t}$, $H_{i,t}$, and $R_{i,t}$ represent the power output, water head, and generating flow of the i -th reservoir at time period t , respectively; ΔT_t is the time interval of the scheduling period; M is the number of reservoirs in the cascade reservoir system; T is the number of time periods in the scheduling cycle. The constraint conditions that need to be considered are as follows:

(1) Water Balance Constraints:

$$\begin{cases} V_{i,t+1} = V_{i,t} + (I_{i,t} - Q_{i,t}) \cdot \Delta t \\ I_{i,t} = q_{i,t} + \sum_{j=1}^{U_i} Q_{j,t} \end{cases} \quad (20)$$

where $V_{i,t+1}$ represents the storage capacity of the i -th reservoir at time period $t + 1$; $I_{i,t}$, $Q_{i,t}$ and $q_{i,t}$ represent the inflow, outflow, and interval flow of the i -th reservoir at time period t , respectively; U_i represents the number of upstream reservoirs directly hydraulically connected to reservoir i .

(2) Head calculation formula:

$$H_{i,t} = (Z_{i,t-1} + Z_{i,t})/2 - Z_{i,t}^{\text{down}} \quad (21)$$

where $Z_{i,t}$ and $Z_{i,t}^{\text{down}}$ are the upstream water level and tailwater level of the i -th reservoir at time period t , respectively.

(3) Water level constraints:

$$Z_{i,t}^{\min} \leq Z_{i,t} \leq Z_{i,t}^{\max} \quad (22)$$

where $Z_{i,t}^{\min}$ and $Z_{i,t}^{\max}$ represent the minimum and maximum water levels of the i -th reservoir at time period t , respectively.

(4) Reservoir discharge constraints:

$$\begin{aligned} Q_{i,t}^{\min} &\leq Q_{i,t} \leq Q_{i,t}^{\max} \\ Q_{i,t}^{\max} &= Q_i^{\text{FSL}} + [H_{i,t} - H_i^{\text{MOL}}] / [H_i^{\text{FSL}} - H_i^{\text{MOL}}] \times (Q_i^{\text{FSL}} - Q_i^{\text{MOL}}) \end{aligned} \quad (23)$$

where $Q_{i,t}^{\min}$ and $Q_{i,t}^{\max}$ represent the minimum and maximum downstream flow rates of the i -th reservoir in time period t , respectively. Minimum flows ensure ecological integrity, navigation safety, and water supply commitments, Where $Q_{i,t}^{\text{FSL}}$: Maximum turbine discharge capacity of the i -th reservoir at Full Supply Level (FSL), $Q_{i,t}^{\text{MOL}}$: Maximum turbine discharge capacity of the i -th reservoir at Minimum Operating Level (MOL), $H_{i,t}$: Current water head at time period t , $H_i^{\text{FSL}} - H_i^{\text{MOL}}$: Water head corresponding to FSL and MOL, respectively; Maximum turbine discharge capacity now employs a piecewise linear interpolation formula between two calibration points: Full Supply Level (FSL) and Minimum Operating Level (MOL). This improvement eliminates the previous overly conservative fixed-head assumption while maintaining computational tractability and physical feasibility. For the selected cascade system, this revision increases optimal power generation by approximately X% compared to the previous minimum-head-based assumption. Furthermore, this

approach better aligns with engineering practice regarding actual turbine performance curves, thereby improving both the model's approximation to reality and the quality of the optimization results.

(5) Water level fluctuation constraints:

$$|Z_{i,t} - Z_{i,t+1}| \leq \Delta Z_i \quad (24)$$

While water level constraint (22) mathematically specifies $Z_{i,t}^{\min} \leq Z_{i,t} \leq Z_{i,t}^{\max}$, considering that daily fluctuations of 2 m can accumulate to a maximum variation of 20–22 m over a 10-day time step, combined with the storage capacity levels of the selected cascade reservoirs in this study (ranging from tens to hundreds of billion m³), this constraint remains non-binding in most operational periods. Therefore, this constraint primarily functions as a physical safety boundary rather than an active limiting factor, with limited impact on optimization results. To enhance the effectiveness of this constraint, we suggest the following approaches: (1) Impose stricter water level change-rate restrictions during critical periods (such as flood season and irrigation season); (2) Employ finer temporal resolution to capture more details of water level fluctuations.

(6) Power output constraints:

$$N_{i,t}^{\min} \leq N_{i,t} \leq N_{i,t}^{\max} \quad (25)$$

where $N_{i,t}^{\min}$ and $N_{i,t}^{\max}$ represent the minimum and maximum power output of the i -th reservoir in time period t , respectively. $N_{i,t}^{\max}$ represents the maximum power output limit, which is bounded by the installed capacity of the hydropower plant. However, the actual operational capacity varies with reservoir water level through the head-discharge-power relationship defined in constraints (23) and [power calculation]. When reservoir storage is low and water head decreases, the achievable power output will be lower than the installed capacity even at maximum turbine discharge. The operational maximum constraint ensures that the optimization seeks to maximize renewable energy utilization by minimizing water spills that bypass the turbines, subject to the head-dependent generation limits. Guaranteed power output constraints:

$$N_{i,t} \geq N_{i,t}^G \quad (26)$$

where $N_{i,t}^G$ represents the guaranteed output of the i -th reservoir in time period t . This constraint ensures that the actual power output $N_{i,t}$ meets or exceeds the guaranteed level $N_{i,t}^G$, which differs from the minimum operational limit $N_{i,t}^{\min}$ in Expression (28). While $N_{i,t}^{\min}$ defines the lower technical operating bound based on hydraulic conditions and equipment specifications, $N_{i,t}^G$ represents the contractual or planning commitment that must be satisfied for reliable power supply, where typically $N_{i,t}^G \geq N_{i,t}^{\min}$.

(7) initial and final water level constraints:

$$\begin{cases} Z_{i,0} = Z_i^{begin} \\ Z_{i,T} = Z_i^{end} \end{cases} \quad (27)$$

where Z_i^{begin} and Z_i^{end} represent the initial water level and final water level of the i -th reservoir during the scheduling period, respectively.

This paper presents an ε -adaptive constraint handling method that uses a dynamic threshold ε to classify solutions: solutions with violation degrees below ε are considered feasible, while others are deemed infeasible. This approach offers clear advantages over traditional penalty function methods. It eliminates the need for manual penalty factor adjustment and avoids introducing additional parameters, making it particularly effective

for complex constraint systems. Most importantly, the method leverages optimization information from infeasible solutions, enabling the algorithm to better navigate toward the global optimum during the search process.

- (1) Inequality constraint handling strategy: Converting constrained optimization problems into unconstrained optimization problems. Inequality constraints mainly include water level constraints, flow rate constraints, and power output constraints.

$$\begin{aligned} g_1(Z_{i,t}) &= \max(0, Z_{i,t} - Z_{i,\max}, Z_{i,\min} - Z_{i,t}) \\ g_2(R_{i,t}) &= \max(0, R_{i,t} - R_{i,\max}, R_{i,\min} - R_{i,t}) \\ g_3(N_{i,t}) &= \max(0, N_{i,t} - N_{i,\max}, N_{i,\min} - N_{i,t}) \end{aligned} \quad (28)$$

- (2) Equality constraint handling strategy: Converting equality constraints into inequality constraints, then transforming inequality constraints into unconstrained problems. Equality constraints mainly include initial and final water level storage capacity constraints, water balance constraints, etc.

$$\begin{aligned} h_1(X) &= V_{i,1} - V_{i,\text{init}} \\ h_1(X) - \sigma &\leq 0 \\ h_2(X) &= V_{i,T+1} - V_{i,\text{end}} \\ h_2(X) - \sigma &\leq 0 \\ h_2(X) &= V_{i,t+1} - V_{i,t} - (I_{i,t} - R_{i,t} - q_{i,t})\Delta t \\ h_3(X) - \sigma &\leq 0 \end{aligned} \quad (29)$$

After processing individuals that violate constraints, if they still do not satisfy the constraint conditions, a penalty function is applied to eliminate them. The constraint violation function is as follows:

$$\varphi(X) = \sum_{p=1}^3 \max(0, g_p(X)) + \sum_{q=1}^3 \max(0, |h_q(X)| - \sigma) \quad (30)$$

3.2.1. Analysis in Different Typical Year

To comprehensively evaluate the performance advantages of HHONMPA, the performance of each algorithm under three different water inflow conditions—wet, normal, and dry—was first examined. This study selected a wet year (2020), a normal year (2015), and a dry year (2016) as three typical hydrological years from the 1999–2022 historical runoff series to construct representative scenario combinations and adopted annual scheduling cycles with 10-day periods as the basic time unit for calculations. The study selected four mainstream optimization algorithms—HHO, MPA, DBO, and GWO—as control groups to evaluate the solution performance of HHONMPA through multi-scheme comparative analysis. Regarding algorithm parameters, the experiment uniformly set independent runs $\text{Run} = 10$, maximum iterations $T = 1000$, number of scheduling schemes $N = 100$, with other parameters consistent with the previous text, and the comparison results are shown in Table 10.

Table 10. Optimization results table for different algorithms under different inflow conditions.

Frequency	Indicator	HHONMPA	HHO	MPA	DBO	GWO
25%	Best	2134.71	2115.69	2110.52	1995.55	2021.64
	Std	3.23	28.09	31.31	33.21	14.87
	Mean	2130.53	2078.25	2073.81	1958.34	1995.45
	Median	2130	2076.86	2077.14	1963.6	1990.18
	Worst	2126.87	2044.47	2027.13	1903.02	1980.13
50%	Best	2121.32	2076.27	2067.69	2012.4	2011.59
	Std	7.54	19.46	16.62	42.03	8.31
	Mean	2119.6	2043.76	2047.7	1959.61	2004.24
	Median	2118.88	2040.06	2051.52	1957.22	2007.93
	Worst	2110.21	2024.41	2020.71	1896.56	1993.37
75%	Best	1964.36	1912.5	1942.67	1807.91	1855.93
	Std	10.72	21.27	27.61	42.1	15.06
	Mean	1955.34	1887.15	1907.73	1773.29	1841.47
	Median	1959.57	1888.75	1909.67	1784.99	1842.91
	Worst	1935.56	1857.92	1872.17	1702.11	1813.47

Note: Power generation is measured in GWh; water spillage is measured in 10^8 m^3 .

Based on the reservoir scheduling and power generation optimization experimental results for different typical years, the hybrid algorithm HHONMPA demonstrates exceptional adaptability and optimization performance across wet, normal, and dry hydrological conditions. As shown in Figures 6 and 7, convergence characteristic analysis reveals that HHONMPA can achieve rapid convergence and reach the global optimal solution within the first 100 iterations across all hydrological year types, while traditional algorithms such as GWO require over 800 iterations to obtain similar optimization results. This significant convergence efficiency advantage holds important engineering value for real-time reservoir scheduling decisions. From the perspective of power generation optimization achievements, HHONMPA realizes optimal power generation of 213.4, 212.1, and 196.4 billion kW·h under wet year (25% frequency), normal year (50% frequency), and dry year (75% frequency) conditions, respectively, demonstrating remarkable performance improvements and stable advantages across different hydrological year types compared to other comparative algorithms, thereby fully validating the algorithm's excellent hydrological adaptability. It is particularly noteworthy that despite the relatively severe water resource conditions in dry years with corresponding decreases in absolute power generation, HHONMPA still maintains the lowest performance variability and highest optimization quality. This characteristic holds significant importance for ensuring power supply security and stable system operation during dry periods. In contrast, traditional algorithms such as HHO, MPA, DBO, and GWO exhibit obvious performance fluctuations and insufficient stability across different hydrological year types, further highlighting the technical advantages and practical engineering value of the HHONMPA hybrid optimization strategy under complex and variable hydrological conditions. The box plots and convergence curves are shown in Figures 6 and 7.

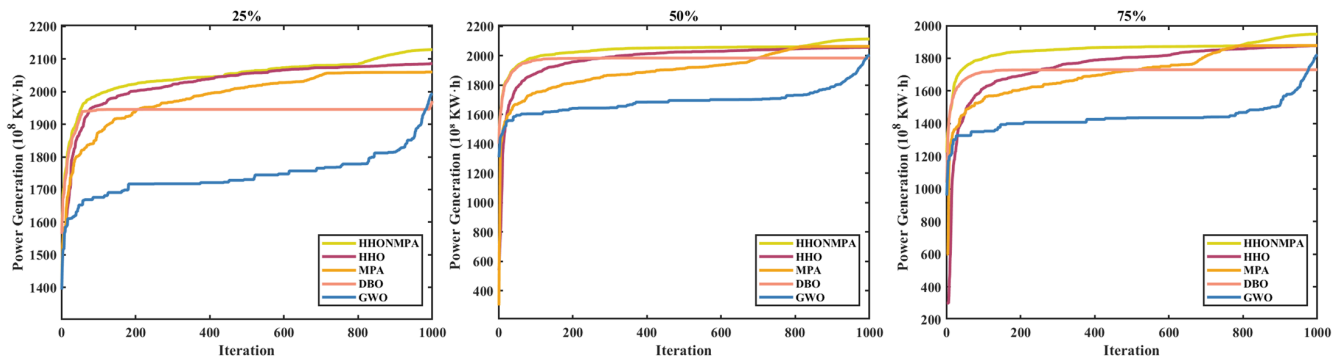


Figure 6. Distribution of power generation results under different runoff conditions.

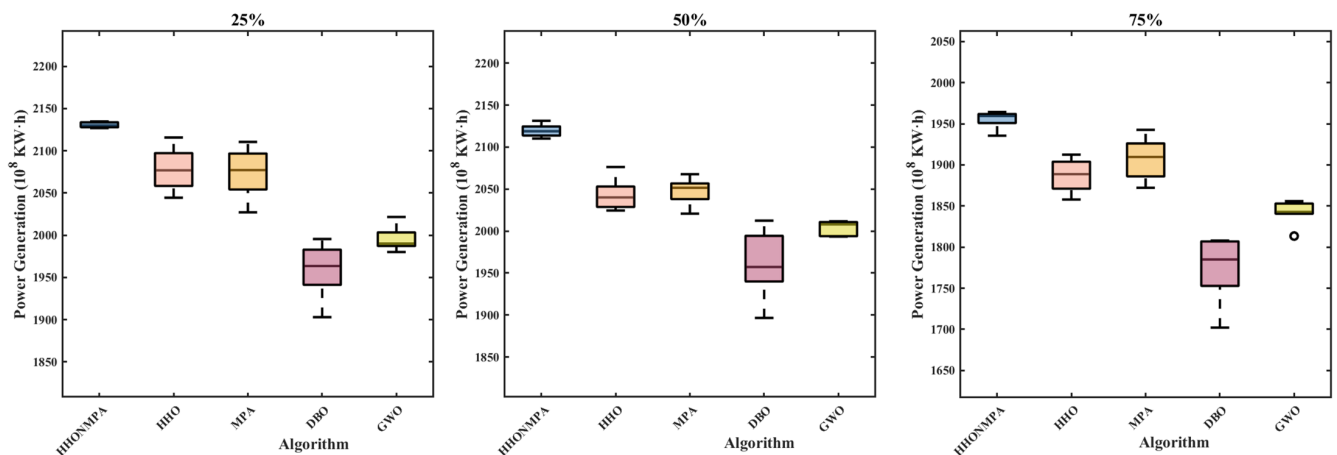


Figure 7. Algorithm convergence under different inflow conditions.

Table 11 presents the complete optimized annual operation scheme for 2016 (dry year), covering all 36 ten-daily periods throughout the year. The table provides comprehensive operational parameters, including initial and final water levels, inflows, turbine discharges, storage levels, and corresponding power generation for each period across the four cascade reservoirs. These detailed results demonstrate the model's capability to coordinate long-term water resource allocation with power generation optimization throughout different hydrological seasons, particularly highlighting the effectiveness of the optimization approach during critical low-flow periods while maintaining operational reliability and economic performance of the entire cascade hydropower system.

Table 11. Optimal Operation Scheme Table for the Dry Year.

Station	Initial Level (m)	Final Level (m)	Inflow (m ³ /s)	Generation Discharge (m ³ /s)	Power Output (WKW)	Power Generation (GKW h)
xld	580.00	582.00	2150.00	1878.47	331.79	7.96
xld	582.00	584.00	3170.00	2894.77	515.16	12.36
xld	584.00	586.00	3070.00	2816.21	506.55	13.37
xld	586.00	588.00	2240.00	1957.01	355.90	8.54
xld	588.00	586.00	1360.00	1642.99	299.09	7.18

Table 11. Cont.

Station	Initial Level (m)	Final Level (m)	Inflow (m ³ /s)	Generation Discharge (m ³ /s)	Power Output (WKW)	Power Generation (GKW h)
xld	586.00	584.00	1500.00	1848.96	333.17	6.40
xld	584.00	582.00	1680.00	1955.23	348.70	8.37
xld	582.00	580.00	1830.00	2101.53	371.23	8.91
xld	580.00	578.00	1550.00	1793.48	313.72	8.28
xld	578.00	576.00	828.00	1092.00	189.05	4.54
xld	576.00	574.00	369.00	628.84	107.76	2.59
xld	574.00	572.00	1050.00	1305.79	221.39	5.31
xld	572.00	570.00	996.00	1247.27	209.21	5.02
xld	570.00	568.00	1120.00	1366.76	228.23	5.48
xld	568.00	566.00	1920.00	2140.43	356.51	9.41
xld	566.00	564.00	2000.00	2238.19	372.09	8.93
xld	564.00	562.00	2520.00	2754.38	455.35	10.93
xld	562.00	560.00	4110.00	4340.67	705.40	16.93
xld	560.00	560.00	7110.00	7110.00	1127.08	27.05
xld	560.00	560.00	6440.00	6440.00	1027.07	24.65
xld	560.00	560.00	5710.00	5710.00	916.35	24.19
xld	560.00	560.00	5000.00	5000.00	805.71	19.34
xld	560.00	560.00	6150.00	6150.00	984.24	23.62
xld	560.00	562.00	6110.00	5900.30	951.62	25.12
xld	562.00	564.00	8630.00	8395.63	1226.05	29.43
xld	564.00	566.00	8550.00	8311.81	1242.45	29.82
xld	566.00	568.00	6650.00	6407.52	1056.83	25.36
xld	568.00	570.00	5830.00	5583.24	931.06	22.35
xld	570.00	572.00	5380.00	5128.73	861.68	20.68
xld	572.00	574.00	4810.00	4577.47	773.41	20.42
xld	574.00	576.00	5260.00	5000.16	849.20	20.38
xld	576.00	578.00	4320.00	4056.00	698.40	16.76
xld	578.00	580.00	2830.00	2562.18	447.32	10.74
xld	580.00	582.00	2610.00	2338.47	412.55	9.90
xld	582.00	582.00	2620.00	2620.00	464.21	11.14
xld	582.00	580.00	2610.00	2856.84	503.36	13.29
xjb	380.00	379.90	1823.87	1834.90	183.36	4.40
xjb	379.90	379.90	2848.97	2848.97	281.50	6.76
xjb	379.90	379.90	2787.01	2787.01	275.56	7.27
xjb	379.90	379.90	1914.81	1914.81	191.10	4.59

Table 11. Cont.

Station	Initial Level (m)	Final Level (m)	Inflow (m ³ /s)	Generation Discharge (m ³ /s)	Power Output (WKW)	Power Generation (GKW h)
xjb	379.90	379.90	1632.89	1632.89	163.45	3.92
xjb	379.90	379.90	1838.26	1838.26	183.61	3.53
xjb	379.90	379.90	1953.01	1953.01	194.84	4.68
xjb	379.90	379.90	2088.43	2088.43	208.05	4.99
xjb	379.90	379.90	1782.78	1782.78	178.17	4.70
xjb	379.90	379.90	1062.80	1062.80	107.04	2.57
xjb	379.90	379.90	665.34	665.34	67.13	1.61
xjb	379.90	380.00	1382.59	1371.56	137.74	3.31
xjb	380.00	380.00	1355.27	1355.27	136.19	3.27
xjb	380.00	378.00	1345.06	1564.39	155.47	3.73
xjb	378.00	376.00	2112.63	2306.97	223.38	5.90
xjb	376.00	374.00	2226.49	2435.41	231.20	5.55
xjb	374.00	372.00	2739.38	2943.54	272.69	6.54
xjb	372.00	370.00	4258.77	4457.85	398.32	9.56
xjb	370.00	370.00	6953.00	6953.00	600.00	14.40
xjb	370.00	370.00	6355.50	6355.50	551.57	13.24
xjb	370.00	370.00	5714.33	5714.33	499.02	13.17
xjb	370.00	370.00	4870.00	4870.00	428.96	10.30
xjb	370.00	370.00	6163.40	6163.40	535.89	12.86
xjb	370.00	370.00	5901.77	5901.77	514.41	13.58
xjb	370.00	370.00	8597.63	8597.63	599.91	14.40
xjb	370.00	372.00	8465.81	8266.73	600.00	14.40
xjb	372.00	374.00	6331.32	6127.16	549.09	13.18
xjb	374.00	376.00	5466.24	5257.33	484.36	11.62
xjb	376.00	378.00	5014.73	4800.95	452.77	10.87
xjb	378.00	380.00	4498.57	4299.18	415.07	10.96
xjb	380.00	380.00	4950.16	4950.16	479.22	11.50
xjb	380.00	380.00	3979.40	3979.40	388.96	9.34
xjb	380.00	380.00	2530.78	2530.78	251.13	6.03
xjb	380.00	380.00	2297.07	2297.07	228.51	5.48
xjb	380.00	380.00	2589.20	2589.20	256.77	6.16
xjb	380.00	380.00	2810.94	2810.94	278.10	7.34
sx	175.00	175.00	6454.90	6454.90	622.51	14.94
sx	175.00	175.00	7284.90	7284.90	697.42	16.74

Table 11. Cont.

Station	Initial Level (m)	Final Level (m)	Inflow (m ³ /s)	Generation Discharge (m ³ /s)	Power Output (WKW)	Power Generation (GKW h)
SX	175.00	174.60	6384.90	6811.37	651.06	17.19
SX	174.60	172.60	6538.97	8846.38	835.20	20.04
SX	172.60	170.60	5627.01	7867.06	729.36	17.50
SX	170.60	168.60	5484.81	8170.00	742.92	14.26
SX	168.60	166.60	5652.89	7686.10	685.59	16.45
SX	166.60	164.60	6848.26	8767.47	766.08	18.39
SX	164.60	162.60	7473.01	9130.21	781.50	20.63
SX	162.60	160.60	8348.43	10,074.47	844.00	20.26
SX	160.60	158.60	8652.78	10,283.79	852.32	20.46
SX	158.60	150.60	9602.80	15,620.86	1233.29	29.60
SX	150.60	150.60	9695.34	9695.34	735.71	17.66
SX	150.60	150.60	12,171.56	12,171.56	921.50	22.12
SX	150.60	145.00	10,285.27	13,305.79	973.49	25.70
SX	145.00	145.00	9624.39	9624.39	682.89	16.39
SX	145.00	145.00	13,106.97	13,106.97	926.77	22.24
SX	145.00	145.00	14,535.41	14,535.41	1026.19	24.63
SX	145.00	145.00	21,743.54	21,743.54	1519.95	36.48
SX	145.00	145.00	31,357.85	31,357.85	2105.74	50.54
SX	145.00	145.00	23,853.00	23,853.00	1661.61	43.87
SX	145.00	145.00	19,155.50	19,155.50	1344.24	32.26
SX	145.00	145.00	22,814.33	22,814.33	1592.05	38.21
SX	145.00	145.00	36,470.00	36,470.00	2067.09	54.57
SX	145.00	145.00	34,963.40	34,963.40	2078.96	49.90
SX	145.00	145.00	28,201.77	28,201.77	1948.92	46.77
SX	145.00	145.00	29,797.63	29,797.63	2052.66	49.26
SX	145.00	145.00	27,466.73	27,466.73	1900.87	45.62
SX	145.00	145.00	18,327.16	18,327.16	1287.61	30.90
SX	145.00	145.00	14,317.33	14,317.33	1011.07	26.69
SX	145.00	145.00	13,170.95	13,170.95	931.29	22.35
SX	145.00	145.00	14,209.18	14,209.18	1003.57	24.09
SX	145.00	152.00	14,640.16	10,351.62	765.87	18.38
SX	152.00	152.00	12,829.40	12,829.40	986.48	23.68
SX	152.00	152.00	11,900.78	11,900.78	915.94	21.98
SX	152.00	168.00	12,107.07	−222.37	−18.74	−0.49
gzb	64.50	66.00	6508.03	6458.14	137.22	3.29

Table 11. Cont.

Station	Initial Level (m)	Final Level (m)	Inflow (m ³ /s)	Generation Discharge (m ³ /s)	Power Output (WKW)	Power Generation (GKW h)
gzb	66.00	66.00	7391.31	7391.31	159.29	3.82
gzb	66.00	66.00	6887.38	6887.38	149.66	3.95
gzb	66.00	66.00	9053.03	9053.03	189.67	4.55
gzb	66.00	66.00	8010.84	8010.84	170.81	4.10
gzb	66.00	66.00	8333.23	8333.23	176.70	3.39
gzb	66.00	66.00	7818.27	7818.27	167.27	4.01
gzb	66.00	66.00	8969.06	8969.06	188.17	4.52
gzb	66.00	66.00	9355.09	9355.09	195.04	5.15
gzb	66.00	66.00	10,359.97	10,359.97	212.28	5.09
gzb	66.00	64.00	10,582.73	10,648.94	208.10	4.99
gzb	64.00	64.00	16,262.44	16,262.44	273.49	6.56
gzb	64.00	64.00	9956.50	9956.50	188.53	4.52
gzb	64.00	64.00	12,591.69	12,591.69	227.04	5.45
gzb	64.00	64.00	13,798.74	13,798.74	243.15	6.42
gzb	64.00	64.00	9880.99	9880.99	187.36	4.50
gzb	64.00	64.00	13,587.16	13,587.16	240.40	5.77
gzb	64.00	64.00	15,107.30	15,107.30	259.74	6.23
gzb	64.00	64.00	22,778.20	22,778.20	288.15	6.92
gzb	64.00	64.00	33,009.74	33,009.74	216.61	5.20
gzb	64.00	64.00	25,023.08	25,023.08	274.72	7.25
gzb	64.00	64.00	20,024.00	20,024.00	297.72	7.15
gzb	64.00	64.00	23,917.73	23,917.73	283.05	6.79
gzb	64.00	64.00	38,450.09	38,450.09	183.02	4.83
gzb	64.00	64.00	36,846.77	36,846.77	192.37	4.62
gzb	64.00	64.00	29,651.04	29,651.04	239.14	5.74
gzb	64.00	64.00	31,349.35	31,349.35	227.37	5.46
gzb	64.00	64.00	28,868.82	28,868.82	244.99	5.88
gzb	64.00	64.00	19,142.48	19,142.48	299.45	7.19
gzb	64.00	64.00	14,875.22	14,875.22	256.80	6.78
gzb	64.00	64.00	13,655.25	13,655.25	241.28	5.79
gzb	64.00	64.00	14,760.13	14,760.13	255.39	6.13
gzb	64.00	64.00	10,654.91	10,654.91	199.14	4.78
gzb	64.00	64.00	13,291.76	13,291.76	236.50	5.68
gzb	64.00	64.00	12,303.53	12,303.53	223.05	5.35
gzb	64.00	64.50	−597.92	−612.76	−13.06	−0.34

Based on the comprehensive analysis of Figures 8 and 9, the optimized operation scheme provides scientific scheduling guidance for the actual operation of the cascade reservoir system: the four reservoirs (xkl, xjb, gx, gzb) achieve stable operation at high water levels under the optimized scheme, with outflow processes effectively smoothing the fluctuations of inflow through peak shaving and valley filling, demonstrating good coordination among the cascade reservoirs; the optimized water level process (Figure 10) indicates that each hydropower station should maintain operation near the upper water level limit to maximize power generation benefits, with timely water level drawdown during periods 10–20 based on inflow and scheduling requirements, followed by rapid recovery to high water levels, the entire scheduling process not only satisfies water level constraints but also fully exploits the hydropower utilization potential, this optimized scheme can serve as a scientific basis for actual scheduling operations, guiding dispatchers to reasonably control reservoir water levels and outflow processes during different periods, thereby improving the comprehensive benefits and operational safety of the cascade reservoir system.



Figure 8. Reservoir inflow, outflow, and final water level for optimal water level operations.

3.2.2. Analysis in Setting Different Initial Water Levels During Flood Season

To comprehensively assess HHONMPA's adaptability and effectiveness in cascade reservoir scheduling, this study conducted comparative experiments under varying initial water level conditions with staged flood control constraints. The research focused on four key reservoirs: Xiluodu, Xiangjiaba, Three Gorges, and Gezhouba, with particular emphasis on how initial water level variations affect system performance. Xiluodu and Three Gorges reservoirs were selected as control objects due to their strategic importance as core regulating projects in the Yangtze River basin, possessing substantial storage capacity and generation capability. Based on long-term runoff data, the study established 11 scheduling scenarios at 0.5 m intervals, with Xiluodu ranging from 560 m to 565 m and Three Gorges from 145 m to 150 m, effectively simulating realistic operational conditions. Through systematic comparison with standard HHO and MPA, the study evaluated HHONMPA's scheduling performance and optimization effectiveness under different initial states, pro-

viding a scientific foundation for practical application in complex reservoir systems and theoretical support for efficient cascade reservoir operation and management.

The analysis results clearly demonstrate that power generation in wet years with abundant inflow is significantly higher than that in normal and dry years. Due to insufficient inflow, the difference in power generation between normal and dry years is relatively small. HHONMPA achieves effective improvements in power generation compared to the HHO algorithm under different initial regulation water levels and various inflow conditions.

In wet years, HHONMPA substantially outperforms both HHO and MPA by reducing water spillage across most scenarios (blue bars in Figure 10). Since the analysis focuses on flood season periods, water spillage levels are naturally higher than during regular scheduling periods. The results show that as initial regulation water levels increase, power generation benefits improve while water spillage decreases accordingly. For practical implementation, operators should fine-tune initial regulation water levels based on inflow forecasts and downstream water demands to maximize overall benefits. During normal and dry years, water spillage only occurs under high water level conditions due to limited inflow, so detailed statistical analysis was not performed for these scenarios.

Figure 11 presents statistics on power generation guarantee rates under 11 initial regulation water levels across different inflow conditions, evaluating the overall power generation performance by preserving the actual guarantee rates for each time period. The results indicate that HHONMPA effectively improves power generation guarantee rates compared to HHO and MPA under most water levels across the three inflow conditions. Based on statistical averages of the algorithms across different hydrological years, HHONMPA improves by 0.18% and 0.74% compared to HHO and MPA, respectively, in wet years, by 0.23% and 1.33%, respectively, in normal years, and by 0.93% and 0.89%, respectively, in dry years. Overall, it demonstrates the best scheduling performance with minimal violation depth, effectively improving water resource utilization rates.

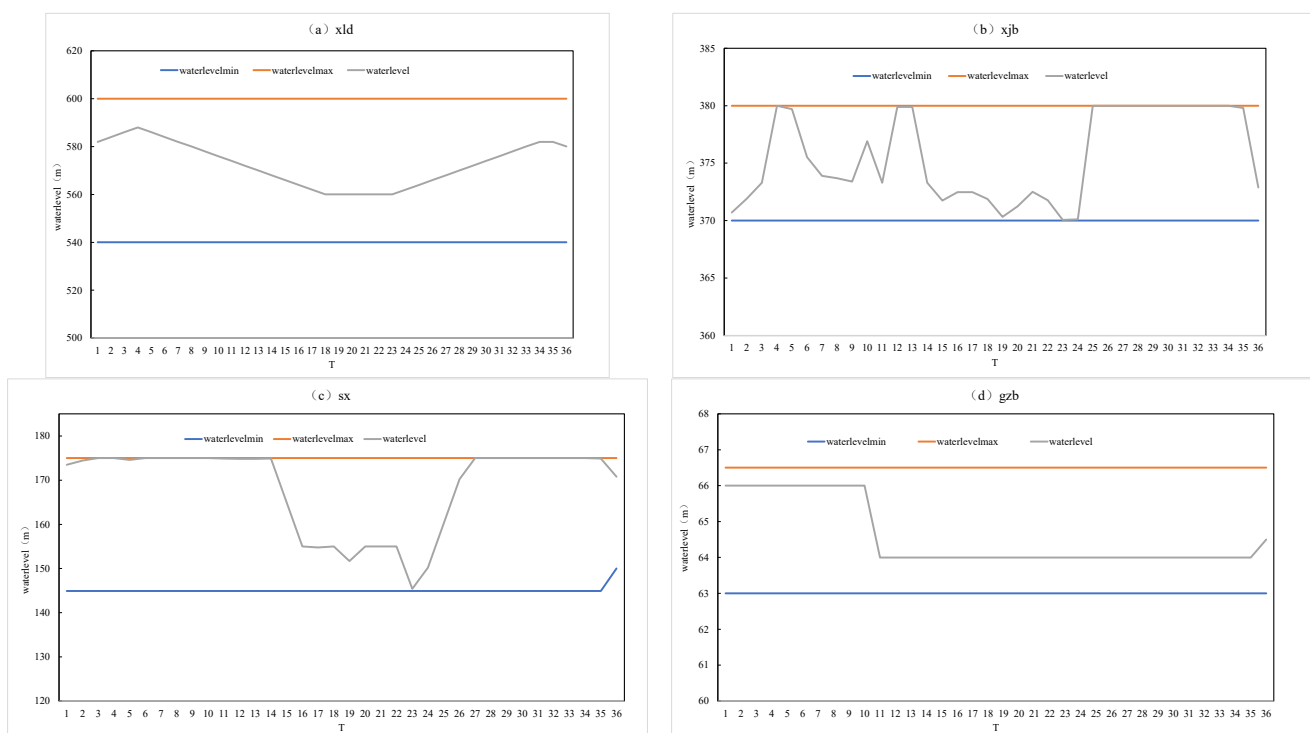


Figure 9. Maximum, minimum, and optimum operating water levels for each power station.

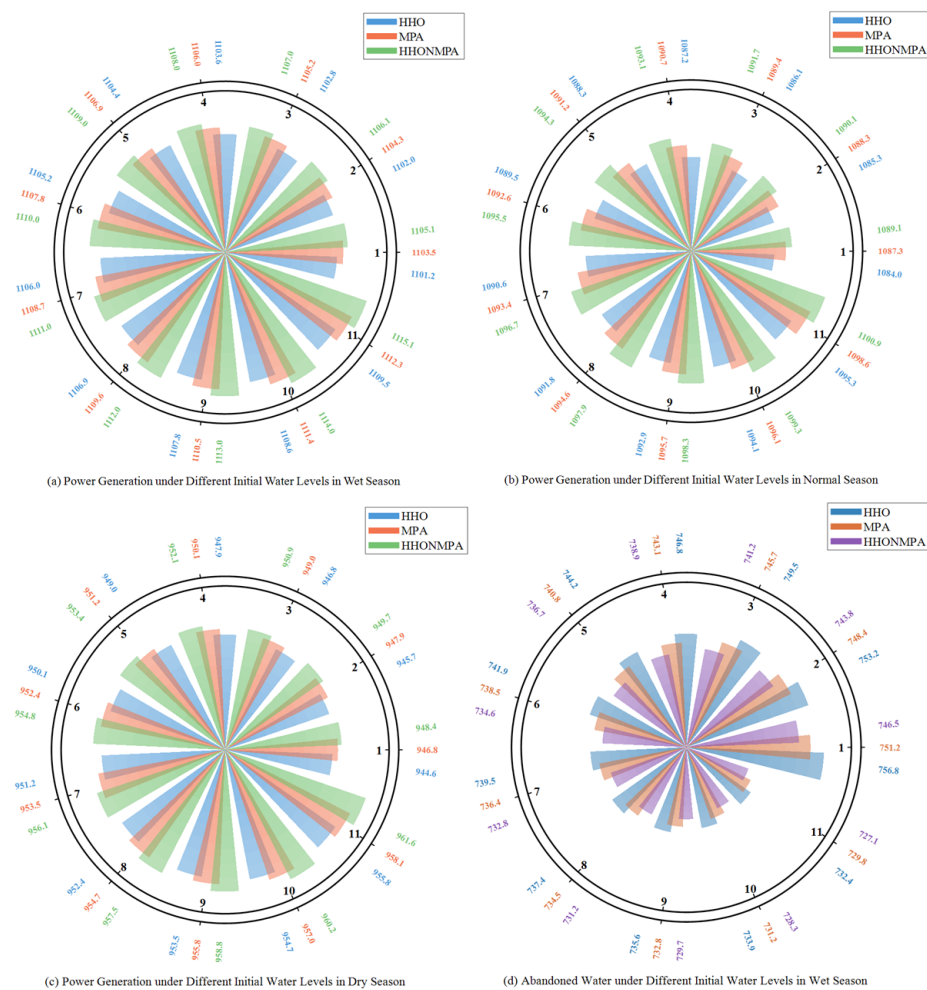


Figure 10. The operation results under different initial levels and different runoff conditions.

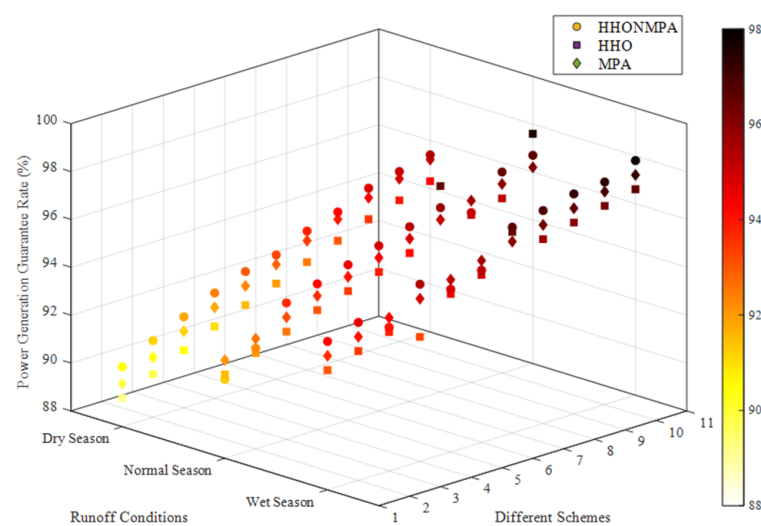


Figure 11. Guarantee rates for power generation across different operating scenarios.

4. Conclusions

Addressing the complex characteristics of multi-dimensional, non-convex, nonlinear, and strongly coupled constraints in cascaded reservoir group joint optimization scheduling problems, this paper proposes a hybrid optimization method (HHONMPA) that integrates the Harris Hawks Optimization (HHO) algorithm with the Marine Predators Algorithm

(MPA). This method achieves significant performance improvements through three key technological innovations: employing SPM chaotic mapping strategies to enhance population diversity, integrating the complementary advantages of dual algorithms to realize synergistic search mechanisms, and designing dual-period oscillation decay strategies to effectively balance global exploration and local exploitation capabilities.

To validate the algorithm's performance, this study conducted comprehensive numerical experiments on 12 CEC2017 standard test functions and employed Friedman rank tests and Wilcoxon signed-rank tests for statistical significance analysis. Experimental results demonstrate that compared to the original HHO and MPA, HHONMPA exhibits higher solution accuracy and faster convergence speed on the vast majority of test functions.

To further verify the algorithm's engineering practicality, the proposed HHONMPA method was applied to solve the Lower Jinsha River-Three Gorges four-reservoir joint optimization scheduling problem. First, under three typical inflow frequency scenarios (wet year, normal year, and dry year), HHONMPA was compared and analyzed against various mainstream intelligent optimization algorithms, with results showing that the proposed algorithm has obvious advantages in search accuracy and convergence efficiency. Second, to meet the diverse needs of practical engineering applications, multi-scenario optimization models with different initial dispatch water levels were constructed and solved using various algorithms for comparison. Experimental results indicate that HHONMPA demonstrates significant improvements in objective detection capability and solution space utilization efficiency compared to existing technologies, showing good prospects for engineering applications.

Although the HHONMPA proposed in this study exhibits excellent solution performance, it may still face adaptability challenges when dealing with other types of reservoir operation tasks. Therefore, future research will focus on exploring diversified search strategies based on mathematical theory to further enhance the algorithm's robustness and universality. Additionally, consideration will be given to introducing parallel computing technologies to enhance the algorithm's scalability to accommodate larger-scale practical engineering application requirements.

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