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Application of the IGWO Algorithm for Flood Control in Reservoir Groups in Optimal Operation

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Abstract: The operation of reservoir flood control operation is a multifaceted engineering issue characterized by complexity, several stages, nonlinearity, and many dimensions. It involves various intricate constraints and interrelated decision variables. Traditional algorithms tend to be slow and prone to local optima when solving optimization problems for flood control in reservoir groups. In recent years, with the introduction of various optimization technologies, more intelligent algorithms have been applied to optimize reservoir flood control scheduling problems in recent years. However, this remains a challenging task for large-scale reservoir group optimization scheduling problems. This work utilizes an Improved Grey Wolf Optimisation algorithm (IGWO) that incorporates Levy fly and random walk techniques for more effective optimization and scheduling of reservoir groups. Taking the Xiaolangdi Reservoir, Sanmenxia Reservoir, Luhun Reservoir, and Guxian Reservoir in Yellow River's middle and lower reaches as examples, a flood control dispatch system composed of

four series and parallel reservoirs and a downstream control point at Huayuankou is studied as an example. We have established a flood control optimization scheduling model based on the Huayuankou control object, which maximizes the reduction of peak flow, and compared and analyzed the optimization results of the Improved Grey Wolf Algorithm (IGWO), Grey Wolf Algorithm (GWO), and Particle Swarm Optimization Algorithm (PSO). The results show that the Improved Grey Wolf Optimization algorithm achieves the best performance in calculating the maximum peak flow rate at Huayukou, with a peak flow rate of 18,681.1 m3/s and a peak reduction rate of 50.68%. This research offers novel perspectives and methodologies for addressing the optimization scheduling of reservoir clusters in flood control operations.

Keywords: GWO algorithm, IGWO algorithm, reservoir flood control operation, joint operation of reservoir group.

1. Introduction

Floods are one of the most devastating and recurrent natural calamities, presenting a substantial peril to human existence, assets, and the ecosystem (Wei Ding et al. 2023). Affected by climate change, the proportion of natural disasters caused by floods has increased to around 40%, making flood disasters more frequent and seriously affecting human life and property (Anderson 2014). To mitigate the losses caused by floods, numerous engineering and non-engineering measures have been taken to eliminate flood hazards. Among them, reservoir flood control regulation, which is a non-engineering measure integrated with reservoirs, plays a crucial role in flood management. It helps reduce peak flows, control floods, store floodwaters during flood seasons, and minimize flood disasters (Momtahen et al. 2007; Su et al. 2022).

When individual reservoirs within a basin operate independently, they lack coordination and cannot fully exert their flood control functions (Zha et al. 2020), but joint optimization of reservoir group flood control operation considers the entire group. It safeguards each reservoir and the downstream control point and changes upstream water flow using reservoir holding capacity. The basin's flood control features are maximized by this strategy (Hao Wang et al. 2019). Joint optimization operation of reservoir groups can also improve water storage scheduling, rationally allocate and use water resources in the basin, increase reservoir regulating capacity, and protect the ecological environment and people's lives and property. In practice, depending on different scheduling objectives, a joint operation of reservoirs can be categorized into flood control joint operation, hydropower and benefits joint operation, ecological joint operation, emergency joint operation, and more (Jin Chen et al. 2008).

Determining reservoir flood control operation rules, which determine the release volumes

during different periods of the flood season, is a multi-objective decision problem. Flood control focuses on upstream and downstream basin, reservoir, and catchment safety. Thus, reservoir flood control operation rules have strong limitations, many stages, nonlinearity, and high dimensionality (Wei Ding et al. 2023; Hsu et al. 2007; Zhu et al. 2020). Currently, the commonly used methods for solving flood control optimization models include traditional and intelligent optimization algorithms (Needham Jason et al. 2000; Cheng et al. 2008). Traditional optimization algorithms such as linear programming (Senlin Chen et al. 2017; Needham Jason et al. 2000; Zetai et al. 2022), nonlinear programming (Unver et al. 1990), and dynamic programming (Yakowitz 1982; Zhao et al. 2017; Cervellera et al. 2006) have been utilized. However, research has shown that as the operating cycle prolongs, the number of reservoirs increases, and the time step size increases, these methods exhibit a decrease in convergence speed and face the problem of the "curse of dimensionality" (Diao et al. 2021; Shimin Li et al. 2020a). Researchers have continuously explored optimization algorithms to address these issues and made significant breakthroughs. Multiple heuristic algorithms have been widely used to solve reservoir group optimization scheduling models and have achieved good results. (Hossain et al. 2013). Genetic algorithms (Ahmad et al. 2014) and particle swarm optimization algorithms (Hai-tao Chen et al. 2020; Yaoyao He et al. 2014) represent such methods, effectively solving water resource system planning problems. There are also emerging algorithms. For example, Wang et al. proposed the CoEISM (Cooperative Co-evolutionary Artificial Immune System) algorithm (Xiaolin Wang et al. 2010) for reservoir scheduling rule extraction. He et al. proposed the Improved Sparrow Search Algorithm (ISSA) (Ji et al. 2022), which combines Cauchy mutation and inverse learning strategy for joint scheduling of the Sanmenxia and Xiaolangdi reservoirs in the Yellow River main stem. Mohsen et al. introduced an improved atomic search optimization algorithm (IASO) (Moslemzadeh et al. 2023) to improve the solution results of the objective function in multi-reservoir systems, enhancing the accuracy of the obtained solutions. Wang et al. proposed a Cauchy mutation-based Yin-Yang Firefly Algorithm (YYFA) (Wen-chuan Wang et al. 2020) that uses the Good Nodes Strategy (GNS) to determine the initial positions of fireflies, ensuring the spatial representativeness of the firefly population. Chen et al. combined the Yin-Yang Firefly Algorithm with the ε-constraint method (Hai-tao Chen et al. 2021) to establish a flood forecasting model for reservoir groups. He et al. developed a Hybrid Slime Mold Algorithm with Stochastic Inverse Learning (HSMAAOA) (Ji He et al. 2023), which has also been applied in reservoir flood control scheduling. Intelligent optimization algorithms tackle the issues of slow convergence and the "curse of dimensionality" in reservoir flood control operations. However, they often exhibit a strong random nature and are susceptible to falling into local optima, leading to unstable results.

The Grey Wolf Optimizer (GWO) is an optimization technique based on population proposed

by Mirjalili et al. in 2014 (Mirjalili et al. 2014). This algorithm achieves optimization by simulating the social level and hunting behavior of gray wolves, and simulating behaviors such as tracking, surrounding, chasing, and attacking prey. The GWO algorithm has the advantages of simplicity, few adjustable parameters, and strong global search capability. It effectively avoids the "curse of dimensionality" (Zhang et al. 2019). Since its introduction, the GWO algorithm has gained significant attention from researchers due to its excellent optimization performance. Regarding function optimization, relevant research has shown that the GWO algorithm has better solving accuracy and faster convergence compared to the widely used particle swarm optimization algorithm. Therefore, the GWO algorithm has found extensive use in diverse domains like power systems, automatic control, work scheduling, machine learning, and path planning (Yiman Li et al. 2022). Despite its widespread application, the GWO algorithm has some issues, such as susceptibility to local optima, high randomness, and low solution accuracy. To address these challenges, Li Yang proposed a modified GWO algorithm based on random walk and Levy flight strategies (Yiman Li et al. 2022). Building upon the standard GWO algorithm, this method takes the lead in analyzing the effect of attenuation factors on the effectiveness of algorithm optimization. It proposes a segmented adjustable attenuation factor to balance the algorithm's global and local search capabilities. By selecting different parameters for different optimization functions, higher precision optimization can be achieved, reducing the algorithm's randomness. Additionally, this modification ensures that the algorithm retains a certain global optimization capability in the middle and later stages of optimization, avoiding premature convergence to local optima. Moreover, during the optimization process, the leader wolves' positions are updated using a probability-based selection of either Levy flight or random walk strategies, thereby enhancing the algorithm's global and local optimization capabilities. By taking this action, the search space can be expanded, population diversity can be increased, and the likelihood of escaping local maxima is increased. As a novel technique, the Improved Grey Wolf Optimizer (IGWO) algorithm has not yet been applied to reservoir group flood control operations. In this study, we employ the IGWO algorithm to solve such problems.

This article is the first to apply the Improved Grey Wolf algorithm (IGWO), which combines random walk and Levy flight strategy, to solve the optimization scheduling problem of reservoir group flood control. We selected Huayuankou in the middle and lower reaches of the Yellow River as the control object and studied four series and parallel reservoir systems on the river section above Huayuankou. At the same time, a comparison was made between the unimproved Grey Wolf algorithm and the representative Particle Swarm Optimization algorithm, and the results showed that the improved Grey Wolf algorithm could achieve better results. The algorithm proposed in this article provides a new idea and solution for improving the efficiency of reservoir group optimization

scheduling.

The article's structure: Chapter 2 elaborates on the constraints and objective functions of the reservoir joint flood control optimization operation model. Chapter 3 introduces the Grey Wolf optimization algorithm and the Grey Wolf algorithm that integrates improvement strategies, and performance testing of the algorithm. Chapter 4 first constructs an optimization scheduling model combining algorithms in the research area, analyzes the interval floods between reservoir objects under joint scheduling, and then solves the model and uses other algorithms to compare and analyze the effectiveness. Chapter 5 summarizes the research results and conclusions.

2. Reservoir group joint flood control operation model

According to the characteristics and elements of the reservoir flood control scheduling system, reservoir flood control scheduling needs to be considered from the following three aspects. Firstly, it is necessary to reduce the ratio of reservoir capacity to maximum flood control capacity to the lowest possible value. Secondly, once the flood control operation is completed, the water volume of the reservoir should be as close as possible to its maximum capacity. Finally, the peak flow after flood regulation should be maintained at the lowest level. The objective of implementing flood control operations for reservoir groups is to guarantee the security of reservoirs attain optimal flood control standards and ensure the safety of downstream protected entities. The former requires the reservoir to maintain a moderate upstream water level to ensure its safety, minimize losses caused by upstream floods, and maintain greater flood interception capacity; The latter requires ensuring the safety of the downstream flood control point, that is, the flow rate of the reservoir should not be too high, and can be achieved by keeping the water level a moderately constant level. At present, the flood control optimization operation of reservoir groups usually follows two principles: maximizing flood control benefits and minimizing peak flow of reservoirs (Yang Li et al. 2020b).

2.1 objective function

The flood prevention system mainly comprises reservoirs, flood embankments, flood control areas, diversion areas, and downstream control objects. If it is a large watershed, it is also necessary to consider flood storage and detention areas. This article does not consider any detention areas, diversion areas, etc., but mainly focuses on the operating conditions of the reservoir and the safety of downstream control objects. Taking typical flood events as an example, by solving the reservoir flood control optimization scheduling model, the peak flow of downstream control objects is minimized. The schematic diagram of the flood control scheduling for a multi-reservoir system is depicted in Figure 1.

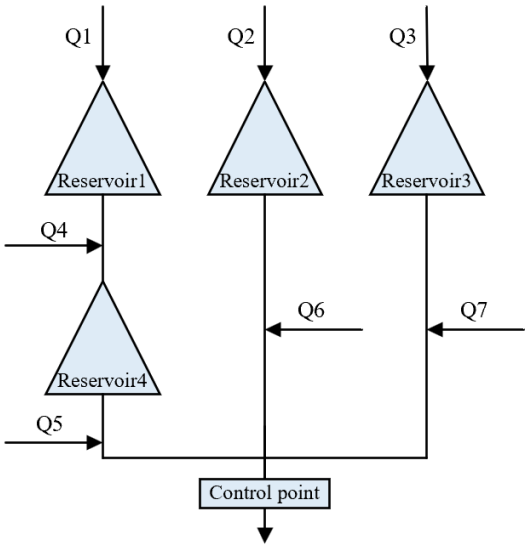

Figure 1 Schematic diagram of reservoir group flood control system

According to the requirements of maximum peak reduction at the downstream control point, the objective function is as follows:

$$ob = Max(Q_1(t) + Q_2(t) + Q_3(t) + Q_4(t)) \tag{1}$$

Where: $Q_1(t)$ 、 $Q_2(t)$ 、 $Q_3(t)$ and $Q_4(t)$ are the discharge process from reservoir 1,2,3and4 to the downstream control point, respectively. ob is the peak flow of downstream control points

2.2 constraint condition

(1) Water balance constraint

$$V_t^i = V_{t-1}^i + (\frac{Q_t^i + Q_{t+1}^i}{2} - \frac{q_t^i + q_{t+1}^i}{2})\Delta t \tag{2}$$

Where: V_t^i is the storage capacity of the ith reservoir in the t period; V_{t-1}^i is the storage capacity of the ith reservoir in the t-1 period. Q_t^i and Q_{t+1}^i are the average inflow of the ith reservoir in the t period and the t+1 period respectively; q_t^i and q_{t+1}^i are the average discharge of the ith reservoir in the t period and the t+1 period respectively, i =1,2,3,4.

(2) Downstream discharge constraint

$$0 \le q_i \le q_{\max,i} \tag{3}$$

Where: $q_{\max,i}$ is the maximum discharge of ith reservoir, q_i is the discharge of ith reservoir.

(3) Reservoir water level constraints

$$Z_{\min}^i \le Z_t^i \le Z_{\max}^i \tag{4}$$

Where: $Z_{\min}^i$ is the flood limit water level and $Z_{\max}^i$ is the flood control high water level of the i-th reservoir; Z_t^i is the initial water level of the i-th reservoir at time t.

(4) Initial water level constraint

$$Z_0 = Z_{\min,i} \tag{5}$$

Where: Z_0 and $Z_{\min,i}$ represent the initial water level at the beginning of the scheduling period for the

ith reservoir and the minimum permissible water level during flood operation in the ith reservoir respectively.

(5) Terminal water level constraint

$$Z_{end} = Z_{\min,i} \tag{6}$$

Where: Z_{end} and $Z_{\min,i}$ are the water level at the end of the ith reservoir's operation period and the lowest allowable water level during the ith reservoir's flood control operation.

(6) Maximum safe discharge constraint

$$q^i_{\square t} \le Q^i_{\max} \tag{7}$$

Where: $Q^i_{\max}$ is the maximum allowable discharge of the ith reservoir to ensure the safety of the downstream river.

(7) Nonnegative constraint: the above variables are nonnegative values

3. Grey wolf optimization algorithm

3.1 Grey wolf optimization algorithm (GWO)

The hunting behavior of the grey wolf inspires the grey wolf optimization algorithm. It achieves the purpose of optimization by simulating the wolf pack's social level and the leader's behavior. It has the characteristics of a simple principle, few parameters that can be adjusted, and strong global search capability. The characteristics of the Gray Wolf algorithm can be described from three aspects.

a) Social hierarchy

The gray wolf belongs to the canine family of social animals and is at the top of the food chain. Gray wolves strictly abide by a hierarchical relationship, as shown in Figure 2 below. Figure 2 depicts the hierarchy within the gray wolf group. The first level is the leader of the whole wolf group with management ability, which is called A ; The wolf in the second layer is called B ; assists in management; When the whole pack is missing A , B will take over A ; The wolf in the third layer is called C , obeyed A and B , can command the wolves on the fourth floor; The lowest wolf is called D , be responsible for balancing the internal relations of the group and completing A 、 B 、 C the task assigned by the wolf.

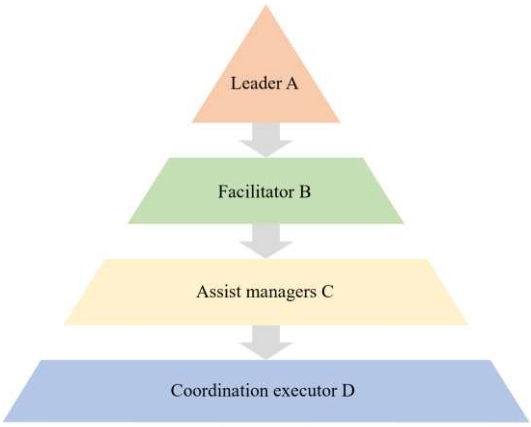

Figure 2 Grey Wolf Level Map

b) Surround prey

A 、 B and C Lead the wolves to surround, hunt and attack the prey. Determine the distance between the gray wolf and the prey through formula (8). The gray wolf group gradually approaches and surrounds the prey through formula (9):

$$d = | cx_p(t) - x(t) | \tag{8}$$

$$x(t+1) = x_p(t) - ad \tag{9}$$

Where: t is the current iteration number; $x_p(t)$ is the position of the prey, $x(t)$ is the position of the t-generation gray wolf; a and c are coefficient vectors. The specific formulas of a and c are as follows:

$$a = 2fr_1 - f \tag{10}$$

$$c = 2r_2 \tag{11}$$

Where: r_1 and r_2 is the random vector at [0,1]; f is the attenuation factor, which decreases in a linear from 2 to 0 as the number of iterations increases, $f = 2 - 2(t / max)$ and max is the maximum number of iterations.

c) hunting

When the wolves complete the encirclement of their prey, the wolves A lead B and C guide wolves to shrink the enclosure of prey to achieve the purpose of predation. The mathematical description of the individual position of the wolf pack update is as follows:

$$\begin{cases} d_A = c_1 x_A - x(t) \\ d_B = c_2 x_B - x(t) \\ d_C = c_3 x_C - x(t) \end{cases} \tag{12}$$

$$\begin{cases} x_1 = x_A - a_1 d_A \\ x_2 = x_B - a_2 d_B \\ x_3 = x_C - a_3 d_C \end{cases} \tag{13}$$

Where:gray wolf individual to A 、 B and C the locations are d_A、d_B、d_C ; x_A、x_B、x_C respectively

means wolf A 、 B and C location of; x_1 、 x_2 、 x_3 means wolf ω to wolf A 、 B and C forward direction and step size. In this iteration cycle, the final position of the gray wolf is:

$$x_{t+1} = (x_1 + x_2 + x_3) / 3 \tag{14}$$

The attack behavior of the gray wolf pack (wolf in Figure 3) is mainly based on A is realized by decreasing. When $|a|<1$, gray wolves attack prey (prey in Figure 3), corresponding to local search, as shown in Figure 3 (a); When $|a|>1$, the gray wolf disperses to conduct a global search, as shown in Figure 3 (b).

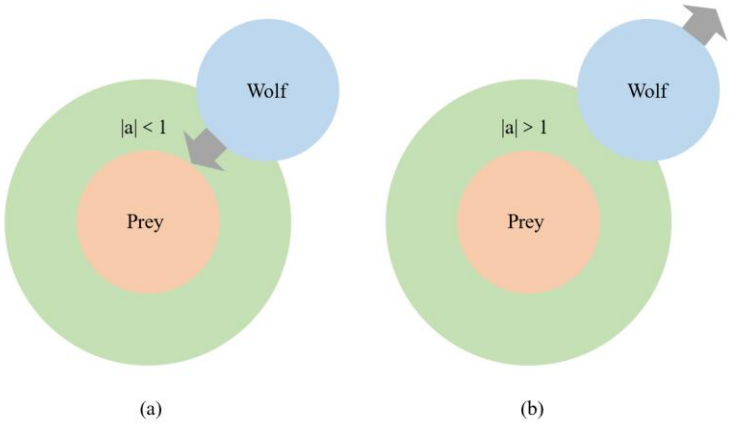

Figure 3 Siege and hunt for prey

The steps of the GWO algorithm are mainly divided into: the first step is to randomly initialize the grey wolf population, the second step is to lead the grey wolf to determine the position of the prey, calculate the distance between other grey wolves and the leading grey wolf, update the position, and achieve encirclement and hunting behavior of the prey. The third step is to calculate the fitness of the grey wolf and update the leading grey wolf.

3.2 Improved grey wolf optimization algorithm (IGWO)

Although the Grey Wolf algorithm has the characteristics of simple model and relatively few parameters, its convergence speed is slow, algorithm accuracy is not high, and it is easy to fall into local optimal solutions. This paper uses the improved strategy proposed by Li Yang to make up for the shortcomings of the algorithm (Yang Li et al. 2020b).

3.2.1 Piecewise adjustable attenuation factor

In the GWO algorithm, vector coefficients play a crucial role in directly determining the behavior of gray wolves. When $|a|>1$, the gray wolf starts to search for prey for global optimization; When $|a|<1$, the gray wolf starts to capture prey and conduct local optimization. In the early optimization stage, gray wolf individuals should be widely distributed in the whole search space; At the later optimization stage, the gray wolf individual converges to the global optimal value by using the search information. The attenuation factor α affects the coefficient vector a and then affects the balance between the algorithm's global and local optimization ability. When f >1, the

gray wolf will conduct a search and hunting, and according to equation (10), it can be calculated that the gray wolf will take $1-1/f$ probability of search motion and $1/f$ probability of hunting. When f <1, gray wolves only hunt. In the standard GWO, the proportion of iterations between the exploration and development stages is 50%: 50%. But for different optimization problems, the fixed proportion of iteration times is difficult to adapt to the actual search situation. Therefore, a piecewise adjustable attenuation factor is proposed in this paper:

$$f = \begin{cases} 2 - \frac{1}{\eta}\frac{1}{max}, \frac{t}{max} < \eta \\ \frac{1}{1-\eta}(1 - \frac{t}{max}), \frac{t}{max} > \eta \end{cases} \tag{15}$$

The gray wolf search and hunting movement is called the exploration stage, and the gray wolf-only hunting movement is called the development stage. Where: η is the iteration proportion of the exploration stage, when $\eta = 0.5$, the attenuation factor is consistent with that of the standard GWO algorithm. Generally, the effect is the best when the exploration iteration proportion is taken as 1, compared with the GWO algorithm, the IGWO algorithm uses the attenuation factor to increase the number of global search iterations and accelerate the early attenuation speed of the attenuation factor, which is the balance of convergence speed and convergence accuracy and ensure that the algorithm also has a certain degree of global optimization ability in the later stage of optimization iteration.

The coefficient vector represents the random weight of the influence of gray wolf position on prey, which affects the difficulty of the gray wolf population approaching prey and thus affects the algorithm's global exploration ability. In this article, the strategy of modifying control parameters proposed in reference (Mittal et al. 2016) is used to balance global exploration capabilities with local development capabilities. The specific expression is as follows:

$$c = 2r_3 - f \tag{16}$$

Where: r_3 is a random vector between [0.5,1.5].

3.2.2 Random walk and Levy flight strategy

In order to improve the performance of the algorithm in multiple aspects, this article combines random walk strategy and the Levy flight strategy (Ruicheng Ding et al. 2022) to achieve local and global optimization of the algorithm. Levy flight strategy (Yang Li et al. 2020b) enables gray wolf individuals to be widely distributed within the search range, which helps improve global optimization capabilities; The random walking strategy enables gray to optimize and search in relatively concentrated areas, improving the algorithm's local optimization ability.

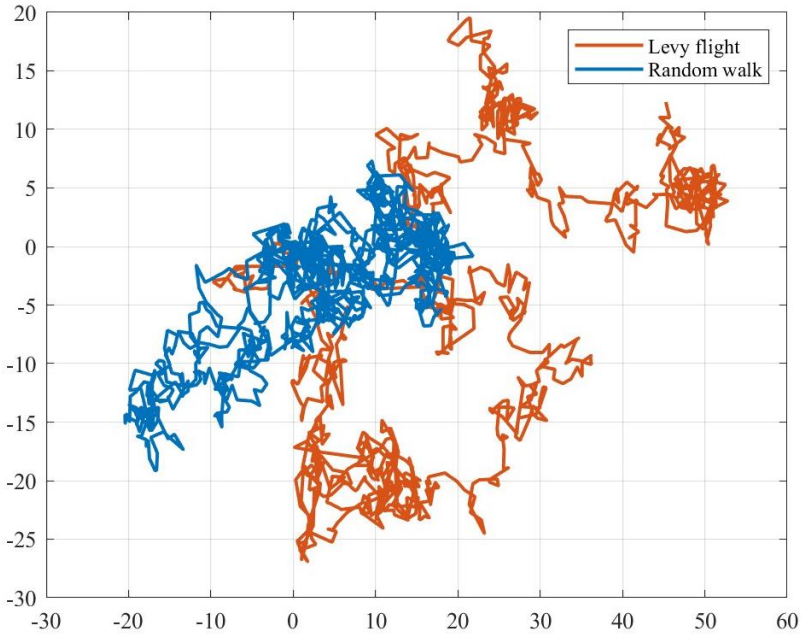

Figure 4 Comparison of simulation between random walk and Levy flight

Simulation experiments were conducted on the random walking strategy and the Levy flight strategy, respectively. The simulation steps are all 1000. The simulation results are shown in Figure 4. From the graph, it can be concluded that the random walk strategy has advantages in local optimization because its search range is relatively concentrated; Levy fligtht has advantages in local optimization because unique walking style, the search range is wider.

Levy flight (Xie et al. 2010) is a walking mode that alternates between short-distance search and occasional long-distance walking, which gives Levy flight excellent global search capabilities. The formula for updating the position of Levy flight strategy is as follows:

$$x_i^{'}(t) = x_i(t) + l \oplus levy(\lambda) \tag{17}$$

Where: $x_i^{'}$ represents the ith solution of generation t; x_i is the current optimal solution , $\oplus$ indicates point-to-point multiplication; l represents the weight of the control step, $l = 0.01(x_i(t) - x_b)$; $Levy(\lambda)$ indicates a path that obeys the Levy distribution, and satisfies: $Levy \sim u = t^{-\lambda}, 1 \le \lambda \le 3$. This article uses the Mantegna algorithm to imitate the Levy distribution The following is the step size calculating formula:

$$s = \frac{u}{|v|^{\frac{1}{r}}} \tag{18}$$

Where: and follows a normal distribution, and r is usually taken as 1.5.

The random walk generates new solutions by using mixed mutation and crossover, which can increase population diversity, to some extent prevent the attraction of regional mechanisms, and then strengthen the local search capability of the algorithm. Its application to the GWO algorithm can speed up finding the optimal solution. The formula for updating the position of the random walk strategy is as follows:

$$x_i^{'}(t) = x_i(t) + \varepsilon(x_j(t) - x_k(t)) \tag{19}$$

Where: $x_i(t)$ and $x_k(t)$ are two random solutions in generation t; ε is the scaling factor, $\varepsilon \sim U(0,1)$.

Although Levy flight and random walking both have the ability to update positions and enhance local and global optimization capabilities, there is no guarantee that the new solution will have better adaptability. Therefore, a greedy mechanism is introduced to optimize the solution.

$$x_i(t) = \begin{cases} x_i(t), fit(x_i^{'}(t)) < fit(x_i(t)) \\ x_i^{'}(t), fit(x_i^{'}(t)) > fit(x_i(t)) \end{cases} \tag{20}$$

Although Levy flight or random walk can optimize the calculation process for the position of gray wolves, if the position of each gray wolf in each iteration cycle is adjusted, the optimization time will be increased. Therefore, this paper only adjusts the position of the gray wolf in the leadership, and the gray wolf in the leadership will play a guiding role in updating the position of other gray wolves, thus having an indirect impact.

3.3 Function test

In order to verify the effectiveness of the Improved Grey Wolf algorithm, it was compared with standard Grey Wolf algorithms and classic Particle Swarm Optimization algorithms. Six functions in the cec2005 test set are selected for testing. Table 1 lists the relevant information on the standard test functions. F_1, F_2 and F_3 are unimodal functions used to test the local development ability of the algorithm; F_4, F_5 and F_6 are multimodal functions used to test the balance of exploration and development ability of the algorithm. To uphold the precision of the research findings, the sample size for all algorithms is established at 30, the dimension is set to 30, and the maximum number of iterations is set to 1000. These three algorithms independently perform operations, and each algorithm undergoes 25 iterations.In the PSO algorithm, the learning factors C_1 and C_2 are set to 2, and the linear attenuation weight is used, $\omega_{\min} = 0.2, \omega_{,\max} = 0.2$. Attenuation factor φ in IGWO algorithm takes 0.75 (Yang Li et al. 2020b).

Table 1 Test Function Related Information

Test function	Search Space
$f_1(x) = \sum_{i=1}^{n} x_i^2$	$[-100,100]^{30}$
$f_2(x) = \sum_{i=1}^{n} \lvert x_i \rvert + \prod_{i=1}^{n} \lvert x_i \rvert$	$[-10,10]^{30}$
$f_3(x) = \sum_{i=1}^{n} (\sum_{j-1}^{i} x_j)^2$	$[-100,100]^{30}$

$$f_4(x) = -20\exp(0.2\sqrt{\frac{1}{n}\sum_{i=1}^{n}x_i^2}) - \exp(\frac{1}{n}\sum_{i=1}^{n}\cos(2\pi x_i)) + 20 + e \qquad [-32,32]^{30}$$

$$f_5 = \frac{1}{4000}\sum_{i=1}^{n}x_i^2 - \prod_{i=1}^{n}\cos(\frac{x_i}{\sqrt{i}}) + 1 \qquad [-600,600]^{30}$$

$$f_6 = \frac{\pi}{n}\left\{10\sin^2(\pi y_1) + \sum_{i=1}^{n-1}(y_i-1)^2\left[1+10\sin^2(\pi y_{i+1})\right] + (y_n-1)^2\right\} + \sum_{i=1}^{n}u(x_i,10,100,4) \qquad [-50,50]^{30}$$

$$y_i = 1 + \frac{x_i+1}{4}, u(x_i,a,k,m) = \begin{cases} k(x_i-a)^m, x_i > a, x_i > a \\ 0, -a < x_i < a \\ k(-x_i-a)^m, x_i < -a \end{cases}$$

3.4 Comparison of solution accuracy

Usually, the mean and standardized deviation are used as validation indicators for algorithm testing. The mean value is close to the theoretical minimum value, and the smaller the standardized deviation, the better the performance. Table 2 displays the test results.

Table 2 Test Function 25 Test Results

Function	Evaluation Indicators	IGWO	GWO	PSO
F_1	Average Value	**8.30E-94**	3.90E-59	1.79E-04
	Standard Deviation	**0.00E+00**	7.30E-59	8.83E-04
F_2	Average Value	**1.42E-55**	7.63E-35	2.40E+00
	Standard Deviation	**0.00E+00**	9.34E-35	4.36E+00
F_3	Average Value	**4.47E-27**	5.82E-15	1.81E+03
	Standard Deviation	**0.00E+00**	2.28E-14	2.39E+03
F_4	Average Value	**7.55E-15**	1.61E-14	3.68E-01
	Standard Deviation	**0.00E+00**	3.24E-15	6.78E-01
F_5	Average Value	**0.00E+00**	2.34E-03	1.55E-02
	Standard Deviation	**0.00E+00**	7.46E-03	1.57E-02
F_6	Average Value	1.01E-01	3.55E-02	**5.39E-02**
	Standard Deviation	**0.00E+00**	2.03E-02	1.24E-01

Among the six test functions, F_1, F_2 and F_3 is a unimodal function and F_4, F_5 and F_6 is a multimodal function. For these six functions, the standard deviation obtained by the IGWO algorithm is 0, while the Particle Swarm Optimization algorithm has low accuracy and significant errors. The test results show that the improved Grey Wolf algorithm performs better than other algorithms.

To further illustrate the advantages of the Improved Grey Wolf algorithm, Figure 5 shows the iterative convergence curves of six test functions using three algorithms. To maintain the fairness of the results, set the population to 30 and the maximum number of iterations to 1000.

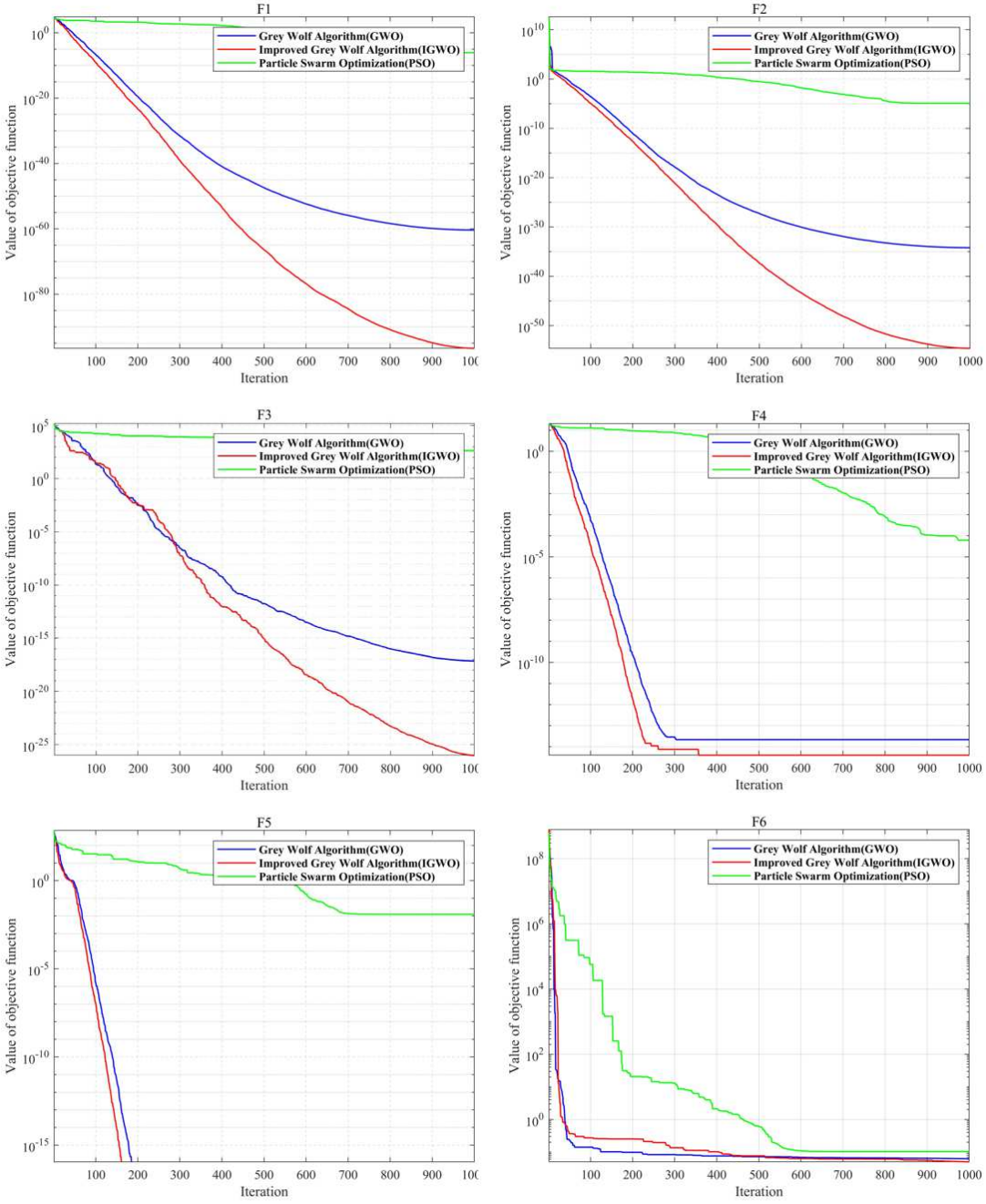

Figure 5 Optimization convergence curves of three algorithms for six test functions

The optimization convergence curve shows that the algorithm in this research has a somewhat faster convergence rate than the other two algorithms. For unimodal functions F_1 ~ F_3, the IGWO algorithm has better accuracy and faster convergence speed; For multimodal functions F_4 ~ F_4, the IGWO algorithm can converge to good results in a very short number of iterations. Because the algorithm adjusts the number of iterations in the exploration stage, it further proves that the Levi

flight and random walk strategies introduced in this paper not only improve the accuracy of algorithm optimization but also accelerate the convergence speed.

4. Modeling analysis

4.1 Solution steps for flood control optimization scheduling model

This study is the first to use the Improved Grey Wolf Algorithm (IGWO) to solve the optimization scheduling model for joint flood control scheduling of four reservoirs: Sanmenxia, Xiaolangdi, Luhun, and Guxian. A logistic chaotic map is added during population initialization to increase the diversity of the initial population. Figure 6 displays the model's precise steps:

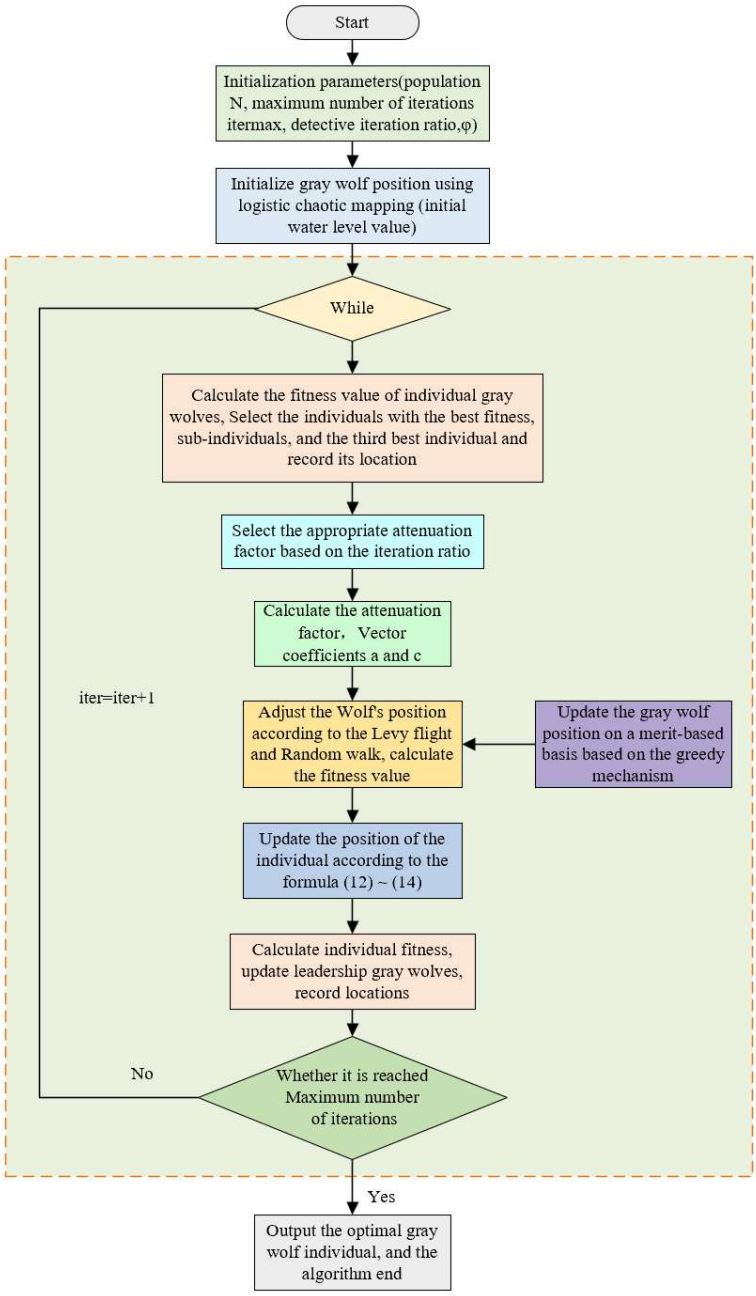

Figure 6 Model Steps

Step 1: Initialize parameters. For example, population size N, maximum iteration count iteration, and exploration iteration ratio φ; Initialize the water level value (i.e., initialize the position of the grey wolf population), the decision variable of the model is the initial water level of the reservoir, with 79 adjustment periods for Sanmenxia and Xiaolangdi reservoirs, 157 adjustment periods for Luhun and Guxian reservoirs, and a vector dimension of 472;

Step 2: Calculate the initial fitness value of gray wolf. Calculate the discharge flow of each reservoir at different times under constraint conditions by adjusting the reservoir, select the individual with the highest fitness value, the suboptimal individual, and the third optimal individual, and record the location of the individual.

Step 3: Calculate the attenuation factor according to formula (15);

Step 4: Calculate the values of parameters A and C according to formulas (10) and (16);

Step 5: Update the position of the gray wolf according to formulas (17) and (19), and select a position with better fitness based on the greedy mechanism of formula (13);

Step 6: Update the position of individual gray wolves in the leadership according to formulas (12), (13), and (14);

Step 7: Determine whether the algorithm meets the termination condition. If it does, output the optimal gray wolf individual, and the algorithm ends; Otherwise, repeat steps 2 to 6;

Step 8: Program ends and outputs the best result.

4.2 Flood control operation mode in the study area

The Yellow River is a large river located in the northern region of China, originating from the Bayan Kara Mountains on the Qinghai Tibet Plateau. It flows through nine provinces and eventually flows into the Bohai Sea in Kenli County, Shandong Province. The Yellow River Basin has a total area of 795000 km^2 and a main stream length of 5464 km, making it the main birthplace of Chinese civilization. This article selects the section from Sanmenxia Reservoir to Huayuankou in the middle and lower reaches of the Yellow River as the research area. A flood control optimization operation model for a group of reservoirs consisting of four series and parallel reservoirs, namely Sanmenxia, Xiaolangdi, Luhun, and Guxian, was established with Huayuankou as the control object. The main goal is to reduce the peak flow of downstream control objects and improve the effectiveness of flood control measures. The watershed water system map of the study area is shown in Figure 7:

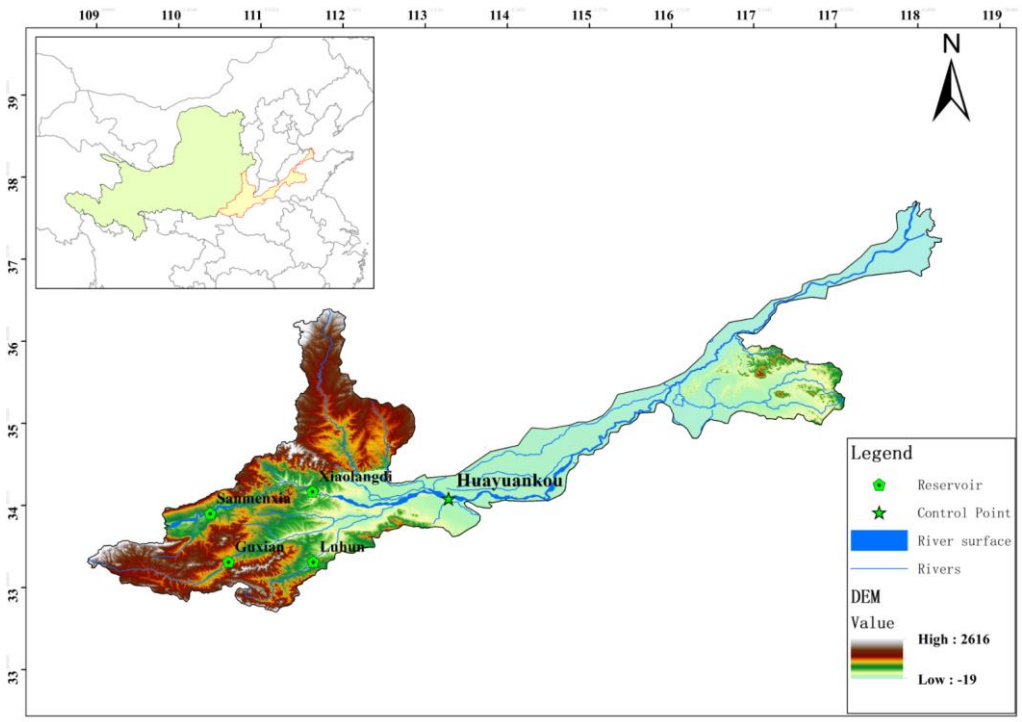

Figure 7 Location of reservoirs

The Sanmenxia Reservoir is the first large-scale water conservancy hub project on the Yellow River and the most important component of the Yellow River control project system. The reservoir focuses on flood management, while also considering power generation and irrigation. The control basin area of the reservoir is 688400 km^2. The reservoir possesses a cumulative storage capacity of 16.2 billion cubic meters. Xiaolangdi is 130 kilometers away from Sanmenxia Reservoir and 115 km downstream from Huayuankou in Zhengzhou. It is the only controlled project below Sanmenxia, the main stream of the Yellow River, that can achieve a large storage capacity. The controlled watershed area is 694000 km^2, with a cumulative storage capacity of 12.65 billion cubic meters. The Luhun Reservoir is located on the Yi River, a secondary tributary of the Yellow River, 67 km away from Luoyang City. It controls a drainage area of 3492 square kilometers, accounting for 57.9% of the total area of the Yi River basin. The total storage capacity of the reservoir is 1.32 billion cubic meters. The reservoir is mainly designed for flood control, irrigation and urban water supply. Guxian Reservoir is located in the upper reaches of the Luo River, a tributary of the Yellow River. The reservoir has a storage capacity of 1.175 billion cubic meters and a controlled basin area of 5370 km^2. This area accounts for 41.8% of the entire Luohe River basin area. The Sanmenxia and Xiaolangdi reservoirs form a hydraulic series connection relationship in the watershed, and together with the Luhun and Guxian reservoirs, they form a parallel relationship. Table 3 below shows the basic characteristic parameters of the four reservoirs:

Table 3 Characteristic parameters of each reservoir

Reservoir	Flood control limit water level (m)	Flood control high water level (m)	Flood control storage capacity (10^8m^3)	Total storage capacity (10^8m^3)
Sanmenxia	305	335	59.79	162
Xiaolangdi	230	275	40.5	126.5
Luhun	317	323	2.13	13.2
Guxian	527.3	548	4.82	11.75

4.3 Flood control operation model interval flood analysis

The flood control object of the research area is the downstream Huayuankou, which controls all floods within the research area. The main sources of floods include reservoir discharge and river channel evolution. The flood evolution process and control point flood composition of the reservoir are depicted in Figure 8.

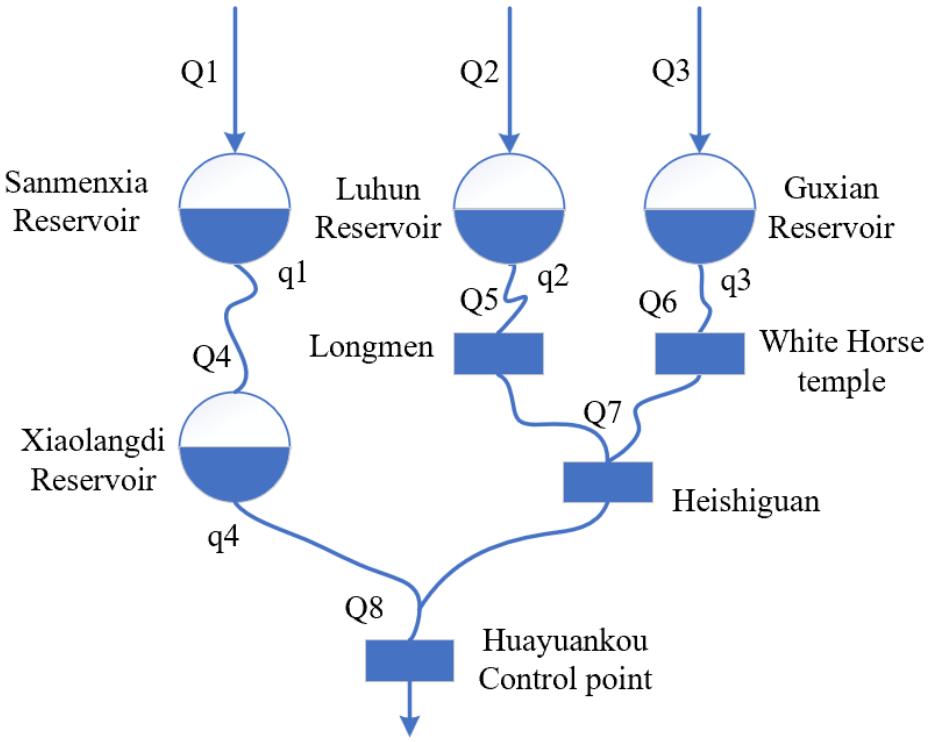

Figure 8 Flood composition at Huayuankou control point

Set Q_1、Q_2 and Q_3 as upstream floods of Sanmenxia reservoir, Luhun reservoir, and Guxian reservoir respectively. Q_4、Q_5、Q_6 and Q_7 represent the floods from Sanmenxia to Xiaolangdi, Luhun to White Hourse Temple, Guxian to Longmen, Longmen, and White Hourse Temple to Heishiguan, respectively, q_1、q_2、q_3 and q_4 are the discharge of Sanmenxia of Luhun, Guxian , and Xiaolangdi respectively. The discharge flood of each reservoir and the section flood evolution to Huayuankou jointly constitute the flooding process at Huayuankou.

Flood routing is the process of converting the inflow flood process of a river section or reservoir into an outflow flood process based on the storage and discharge relationship. Commonly used

calculation methods include fluid mechanics and hydrology. Due to the large study area and limited terrain data in this article, it is difficult to model fluid dynamics. Therefore, the commonly used hydrological method - the Muskingen method (Akram 1978) was chosen. The basic principle is to ignore the inertia term and simplify the dynamic equation into a savings equation, developing the entire river section calculation to the continuous calculation of different river sections. The calculation formula is as follows (21)~(24):

$$W = KQ'[xI + (1-X)Q] \tag{21}$$

$$\frac{1}{2}(I_1 - I_2)\Delta t - \frac{1}{2}(O_1 - O_2)\Delta t = W_2 - W_1 \tag{22}$$

$$O_2 = C_0 I_2 + C_1 I_1 + C_2 Q_1 \tag{23}$$

$$C_0 = \frac{\frac{1}{2}\Delta t - Kx}{\frac{1}{2}\Delta t + K - Kx};\ C_1 = \frac{\frac{1}{2}\Delta t + Kx}{\frac{1}{2}\Delta t + K - Kx};\ C_2 = \frac{-\frac{1}{2}\Delta t + K - Kx}{\frac{1}{2}\Delta t + K - Kx};\ C_0 + C_1 + C_2 = 1 \tag{24}$$

Where: W is the river storage capacity; Q' is the indicative storage flow rate; Δt is the calculation period long; K is the storage coefficient of the tank; x is the flow specific gravity factor. O_1、O_2 are the discharge of the downstream section at the start and finish of the computation cycle respectively I_1、I_2 are the inflow of the upstream section at the start and finish of the computation cycle respectively. Muskingum method is greatly influenced by parameters, and the uncertainty increases due to the lack of measured data; Due to the different river characteristics, the K and x parameter values of different research river sections are also different. The parameters of the river sections involved in this paper are shown in Table 4:

Table 4 Relevant parameters of the Muskingum method

Interval	Time of Flood Propagation	Number of River Sections	X	K	△t
Sanmenxia-Xiaolangdi	8	2	0.2	3.875	4
Xiaolangdi-Huayuankou	12	3	0.3	4.567	4
Luhun-Longmen	6	3	0.4	1.823	2
Longmen-Huangzhuang	2	1	0.3	2.25	2
Huangzhuang-Antan	2	1	0.3	2.182	2
Guxian-Changshui	2	1	0.5	2	2
Changshui-Yiyang	6	3	0.35	2	2
Yiyang-Baimasi	6	3	0.3	1.54	2
Baimasi-Xinzhai	2	1	0.35	2.61	2
Antan、Xinzhai-Heishiguan	2	1	0.3	3.22	2
Heishiguan-Huayuankou	8	2	0.4	4.61	4

5. Results and discussion

This article selects the real data of the 1985 Yellow River main stream's once in a thousand

year flood as the input data support for the model, with a flood duration of 312 hours. Based on the hydrological information gathered, the calculation period for the main stream is determined to be 4 hours, and the calculation period for the tributaries is 2 hours. Select the downstream Huayuankou as the control object, establish the maximum peak regulation criterion, and solve the optimization scheduling problem of the reservoir group. Using the IGWO algorithm for solution, and comparing the GWO algorithm and PSO algorithm for solution. In order to maintain the fairness of this method, the basic parameters of the algorithm are set to the same value, set the population to 100 and the maximum number of iterations to 1000. In addition, the attenuation factor of the IGWO algorithm is set to 0.75. Figures 9 to 12 describe the adjustment process of Sanmenxia, Xiaolangdi, Luhun, and Guxian solved by using the IGWO algorithm. The relevant calculation results are shown in Table 5. After implementing reservoir regulation measures, the peak flow of flood has significantly decreased. The peak shaving rates of Xiaolangdi, Luhun, and Guxian reservoirs are relatively high, at 62.86%, 55.54%, and 60.47%, respectively. The peak shaving rate of Sanmenxia Reservoir is very low, achieving a peak shaving rate of 20.76%.

Table 5 Results of reservoir joint operation

Reservoir	Initial regulating water level (m)	Final water level (m)	Maximum inflow (m^3/s)	Maximum outbound flow (m^3/s)	Peak clipping rate
Sanmenxia	307	307	12638	10014.86	20.76%
Xiaolangdi	230	244.29	29113.17	10811.76	62.86%
Luhun	317	317	4900	2178.32	55.54%
Guxian	527.3	527.3	10120	4000	60.47%

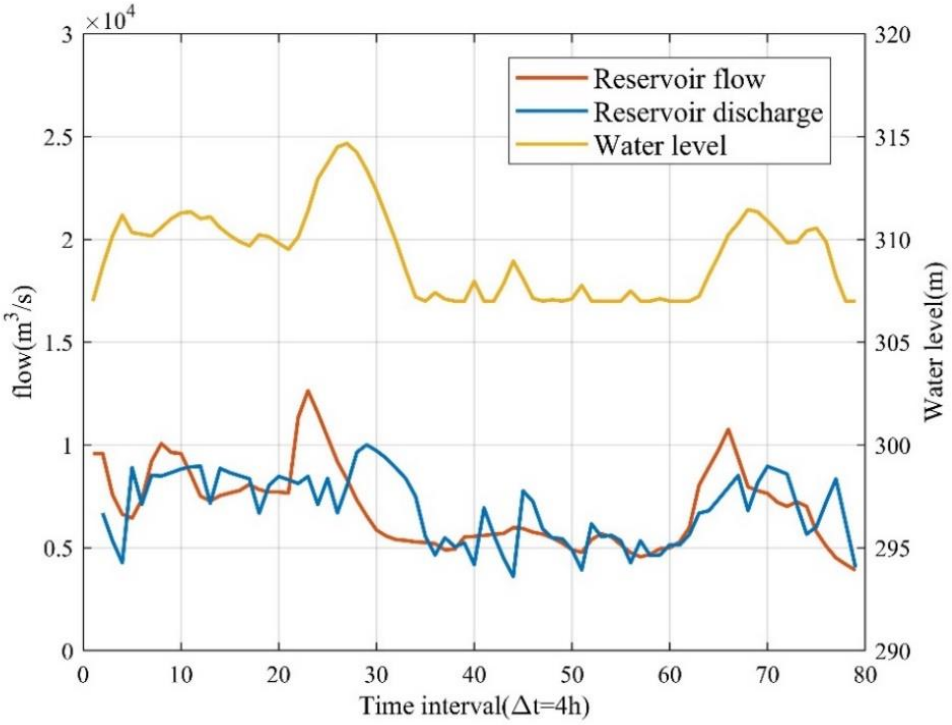

Figure 9 Sanmenxia Reservoir Operation Results

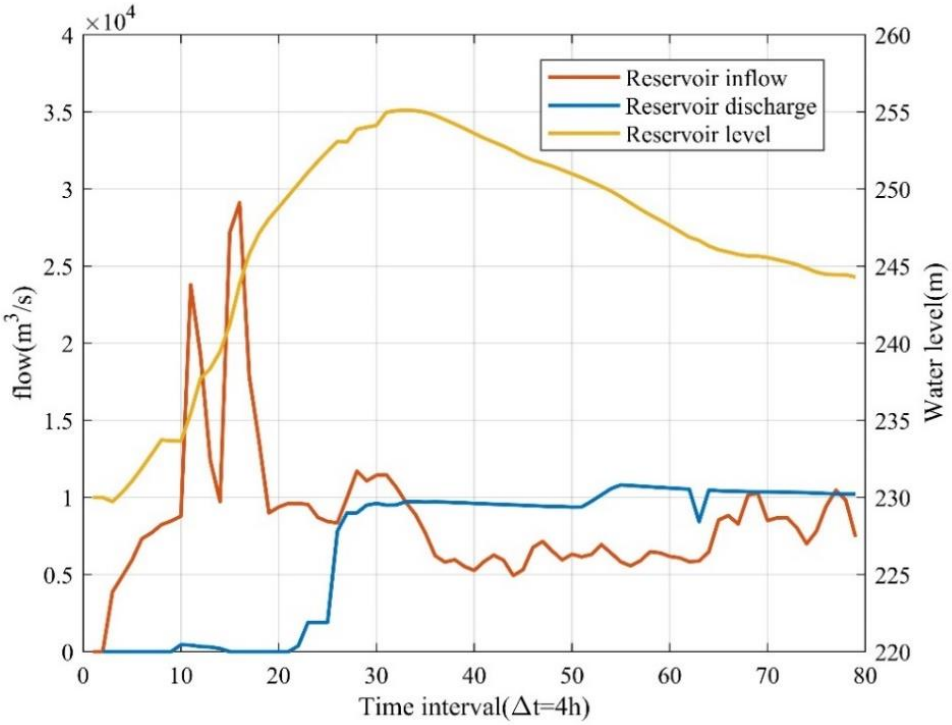

Figure 10 Xiaolangdi Reservoir Operation Results

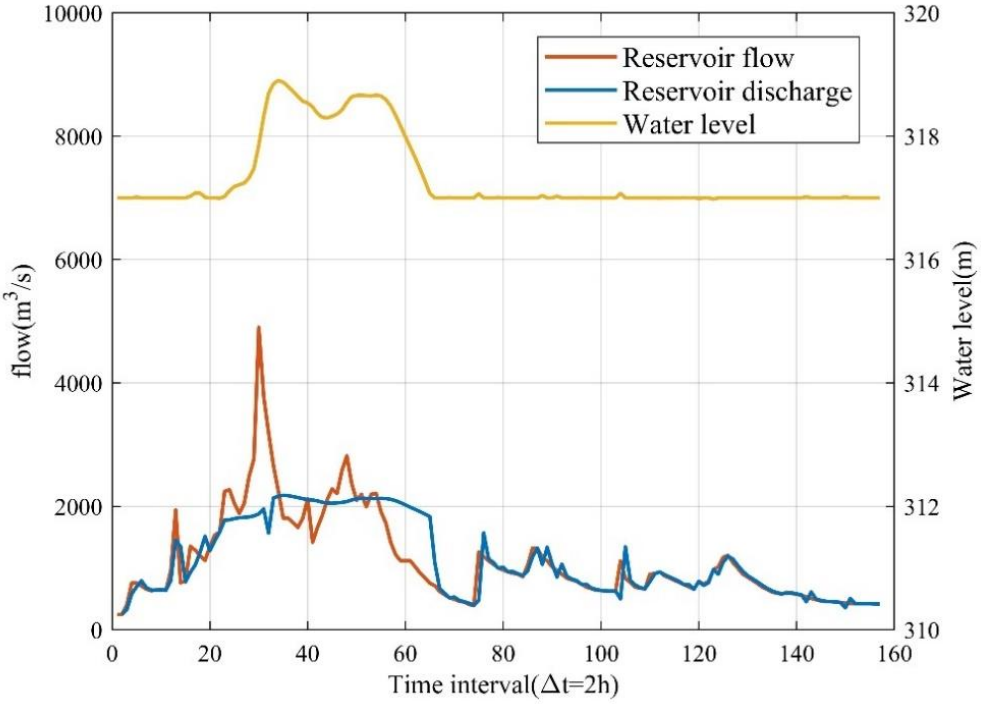

Figure 11 Luhun Reservoir Operation Results

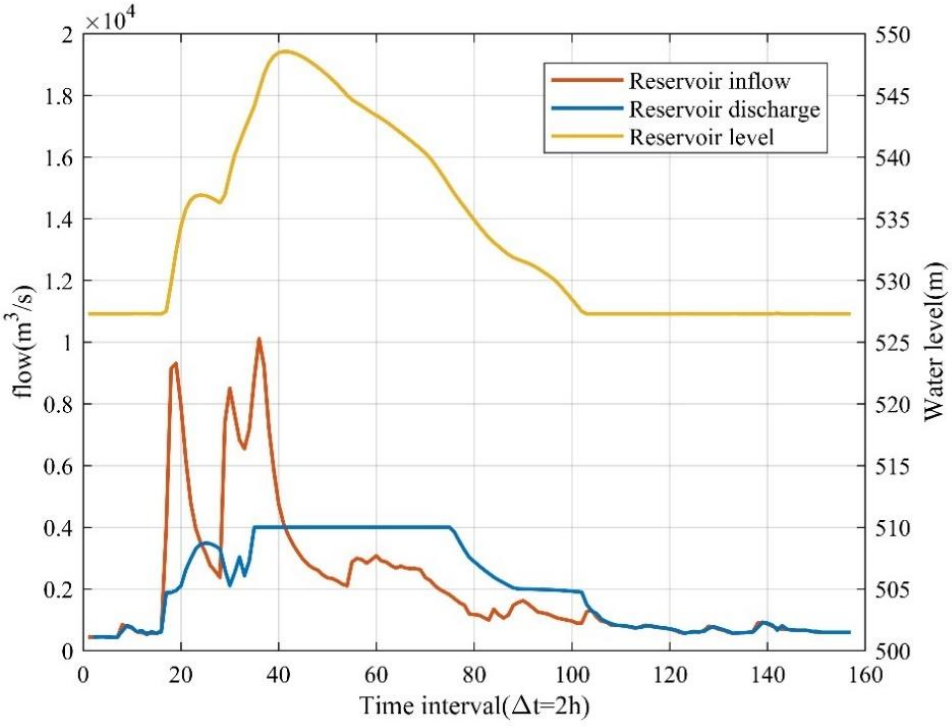

Figure 12 Guxian Reservoir Operation Results

Sanmenxia is connected in series with Xiaolangdi, and the discharge flow of Sanmenxia and the interval flood from Sanmenxia to Xiaolangdi jointly constitute the inflow flow of Xiaolangd. Therefore, it will constitute a large flow and high flood peak of the Xiaolangdi Reservoir, posing a

threat to the safety of downstream rivers. From the figure, Results indicate that combining the improved Grey Wolf Algorithm (IGWO) with the operation plan can effectively reduce the peak flow. In the initial stage of operation, the flow of the three reservoirs, Xiaolangdi, Guxian, and Luhun, is relatively small, mainly to avoid overlapping peak flow with interval peak flood, to accomplish the staggered peak effect of Huayuankou control point. In theory, without considering water storage, the final water level of the reservoir should be restored to the initial water level before flood regulation. However, since the optimization objective of this article is to reduce the water output of the reservoir, the final water level of the regulation result will not return to the initial regulating water level. In addition, this is also related to the degree of flooding and inundation in the beach area that needs to be considered in the actual scheduling process.

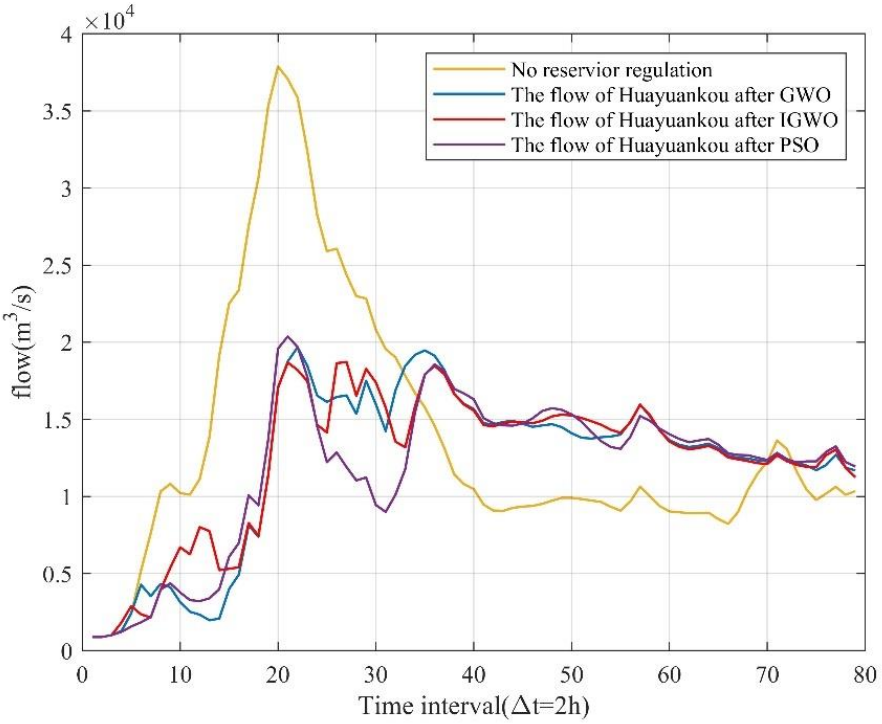

Figure 13 Flood process at Huayuankou section

From Figure 13, it can be seen that for the once-in-a-millennium flood in 1985, all three algorithms achieved their optimization goals to some extent. The peak flow at the Huayuankou control point did not exceed 22000, but the optimization effect of the IGWO algorithm was the most obvious. Among them, the blue line represents the control point flow without reservoir regulation, and the IGWO algorithm and GWO algorithm combined with reservoir regulation have achieved peak shifting effect. After reservoir regulation, the peak flow of Huayuankou has experienced double peaks, and the flood process has basically stabilized, which is beneficial for the flood control safety of the downstream river. The peak shaving effects of the three algorithms are shown in Table 6 below. The IGWO, GWO, and PSO algorithms were used to optimize solution. The maximum

peak flow rates at the Huayuankou control point were 18681.5, 19198.5, and 20375.5m^3/s, respectively, which met the flood control requirements of Huayuankou. Among them, the IGWO algorithm has the highest peak shaving rate, reaching 50.68%. The peak shaving efficiency of GWO algorithm and PSO algorithm is 48.02% and 50.68%, respectively, indicating that IGWO algorithm is better than the other two algorithms for reservoirs' cooperative flood control scheduling. Table 6 Peak shaving effect of each algorithm

Table 6 Peak shaving effects of various algorithms

Algorithm	Peak Discharge (m^3/s)	Peak flood reduction rate
No reservoir regulation	37881.1	/
PSO	20375.5	46.21%
GWO	19689.6	48.02%
IGWO	18681.5	50.68%

6. conclusion

This article takes the four series and parallel connection reservoir systems in the middle and lower reaches of the Yellow River as the research object, and selects Huayuankou as the downstream control object. Based on the maximum peak shaving criterion, a joint operation model for Sanmenxia, Xiaolangdi, Luhun, and Guxian reservoirs was established. The IGWO algorithm, which combines random walk and Levy flight, was first applied to reservoir combined flood control optimization scheduling problem, and the solution results of GWO algorithm and PSO algorithm were compared and analyzed under the same conditions. The main conclusions are as follows:

(1) This article applies the IGWO algorithm to the optimal operation of flood control in reservoir groups for the first time. This algorithm has fast convergence speed and convenient parameter adjustment, which can effectively avoid the problem of "dimensionality disaster" and expand the application space of the algorithm; Using the IGWO, GWO, and PSO algorithms to solve and compare the optimal operation of four reservoirs for joint flood control. The results show that the IGWO algorithm is more effective than the GWO algorithm and traditional PSO algorithm in solving reservoir joint optimization scheduling problems.

(2) Without reservoir regulation, the maximum peak flow at Huayuankou reaches 37881.1m^3/s, exceeding the flood control requirements of the control point Huayuankou (22000m3/s). After constructing a flood control dispatch system optimized by fusion algorithms, the calculation shows that the peak flow of Huayuankou has been reduced to 18681.1m3/s, and the peak regulation rate has reached 50.68%, explain that the proposed solution in this article can effectively ensure the safety of the control points at the Huayuankou. This approach also protects downstream control points and the reservoir against a once-in-a-millennium flood. This proves the model's validity and applicability, offering novel reservoir scheduling solutions.

Author Contributions: Hai-tao Chen. were responsible for the original concept and writing the

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Ethics Approval All authors kept the 'Ethical Responsibilities of Authors'.

Consent to Participate All authors gave explicit consent to participate in this work.

Consent to Publish All authors gave explicit consent to publish this manuscript.

Conflict of Interest The authors declare that they have no confict of interest

Availability of Data and Materials All authors made sure that all data and materials support our published

claims and comply with field standards.

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