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Optimal Allocation of Water Resources in Canal Systems Based on the Improved Grey Wolf Algorithm

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Abstract: Xinjiang is located in the arid region of northwestern China, and agriculture accounts for an absolute share of total water use. Resource-based, engineering, structural, and managed water shortages coexist. Therefore, it is of great significance to vigorously develop water conservation technology and improve the efficiency of water transmission and distribution in canal systems. This research aims at addressing the problems of difficult manual regulation and the overall optimization of the final canal system, low-water-resource utilization efficiency, and management efficiency. Taking the branch-double two-stage canal system of Dongfeng branch canal in Mangxiang, Jinghe irrigation district, as a case study, and the rotation irrigation group and irrigation duration as decision variables, canal distribution is modeled with the goal of minimizing seepage losses. The improved grey wolf algorithm combined with particle swarm optimization is used for the first time and compared with the traditional grey wolf algorithm, genetic particle swarm optimization fusion algorithm, and northern goshawk algorithm. The results show that (1) on the basis of meeting the water discharge capacity and water demand requirements of the canal system, the diversion time of the water distribution scheme obtained by using the improved grey wolf algorithm is shortened from 11 d to 8.91 d compared with the traditional empirical water distribution scheme. (2) The improved grey wolf algorithm converges to the optimal value within 10 generations compared to the remaining methods, and the total water leakage is reduced from 16.15×10^4 m^3 to 11.75×10^4 m^3. (3) The number of gate adjustments is reduced, and the canal gates are opened and closed at the same time within each rotational irrigation group. The grey wolf algorithm improved by its combination with particle swarm has stronger optimization ability and convergence, which can better meet the requirements of efficient water resource allocation in irrigation canal systems, as well as a high application value.

Keywords: irrigation district; canal system; optimized water distribution; grey wolf algorithm; improved particle swarm optimization algorithm; northern goshawk algorithm

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1. Introduction

As the foundation of China's national economy, the development of agriculture has always been highly valued. To ensure the stable production of grain, China has been committed to the development of irrigated agriculture, which uses more water than other industries. Especially for Xinjiang, which is located in the arid inland area of Northwest China, the utilization efficiency of irrigation water resources has seriously affected the development of agriculture; therefore, the efficient utilization of agricultural water resources has become an important guarantee for the sustainable development of agriculture. By the end of 2021, the area of water-saving irrigation for crops in Xinjiang had reached 296.55×10^4 km^2, accounting for 56.57% of its total area of cultivated land, making Xinjiang the province with the largest area of water-saving irrigation in China [1]. With the implementation of continuous support projects and water-saving reconstruction projects in irrigation districts, the hardware facilities of water transmission and distribution and water supply regulation systems in most irrigation districts in Xinjiang have improved, and field-efficient water-saving irrigation technology is becoming increasingly mature and has achieved improved results. The irrigation water utilization factor increased from 0.480 in 2012 to 0.575 in 2021 [2]. Although the effective utilization factor has improved, about 43% of water is still being wasted in the irrigation process. This means that the irrigation water allocation mode relying on manual experience is not adapted to the short irrigation cycle and high rigidity of water demand flow under water-saving irrigation. Moreover, inefficiencies in irrigation water use are prominent. Therefore, in Xinjiang, which lacks water resources, a rational and efficient water distribution scheme has been adopted to shorten the duration of water distribution and effectively improve irrigation efficiency and water resource utilization, which not only helps to improve agricultural productivity but also to save water resources and achieve sustainable development.

Most traditional irrigation canal systems consist of "dry-branch-bucket-agricultural" multilevel channels, and traditional water distribution methods may cause more water leakage loss, ineffective water abandonment, frequent gate adjustment, local irrigation leakage, and other phenomena. In response to this phenomenon, scholars often address this problem by constructing and solving the optimal water distribution model of the canal system. The optimal water distribution of canal systems began to develop in an all-round way from the earliest simple deterministic logical decision to the introduction of nonlinear technology [3], and now to the efficient utilization of water resources considering uncertain conditions [4,5]. Early decision making mostly adopted linear integer programming models such as 0–1 integer programming, dynamic programming, and large-scale system hierarchical programming. For example, Suryavanshi et al. [6] determined the 0–1 linear programming water distribution model based on the assumption that the upper channel is composed of a group of flow pipes with equal flow and that the flow in the flow pipes is equal to the flow of the lower channel to reduce channel leakage loss and engineering investment. Based on previous studies, Reddy et al. [7] and Anwar et al. [8] introduced the water distribution demand of each subordinate channel during the predetermined distribution time of the user. The problem of crop yield reduction caused by the difference between the timing of water distribution in the lower channels during the rotation period and the timing of water distribution for the actual demand has been solved. However, with the deepening of the optimization problem and the complexity of the calculations required, research on the optimal allocation of water in canal systems has also begun to change from "single-objective" to "multi-objective", from "two-level channel" to "multilevel channel", from the ideal water distribution state of "equal flow in the lower channel" to "unequal flow in the lower channel", from only considering "static water transmission loss" to considering "dynamic water transmission loss" [9], from "no consideration of water quality conditions" to "treatment of water quality for irrigation" [10,11], and from only considering "single water source" to "multisource" joint scheduling [12,13].

At the same time, intelligent optimization algorithms, such as genetic algorithms [14], simulated annealing algorithms, retrospective optimization algorithms, and bull swarm optimization algorithms, have also been introduced into model solving [15]. Bonabeau and Dorigo et al. [16] first formally proposed the concept of group intelligence, which they emphasized is a process involving multiple individuals who can communicate directly or indirectly. These individuals exhibit complex and orderly swarm intelligence behavior through cooperation. Wardlaw et al. [17] compared the solution accuracy of the genetic algorithm and linear programming method through the optimal water distribution problem of subordinate channels and verified that the genetic algorithm has high accuracy, strong robustness, and global performance and can quickly solve the model. Pawde et al. [18] considered that the flow constraints of each lower channel were different in the actual water distribution process, established a model with the minimum number of gate adjustments as the optimization objective, and used the particle swarm optimization algorithm to determine the optimal rotation irrigation combination. Wang Qingjie et al. [19] adopted "large rotation irrigation and small continuous irrigation" in the water distribution mode and used improved particle swarm optimization (GA-PSO). The model results show that this method can effectively improve the water distribution efficiency. Tian Guilin et al. [20] used the bull swarm optimization (BSO) algorithm to solve the model, taking the minimum total loss of seepage as the objective, and the overwater time of each channel and the diversion flow rate of branch canals as the decision variables. The results were compared and analyzed with those of Bull's algorithm (BAS) and the particle swarm algorithm (PSO), which proved that the improved BSO algorithm is more suitable for the optimization of water resources of canal systems in irrigation areas. Although several optimization algorithms already exist in the research field of optimal water distribution in canal systems, the GA and PSO algorithms are more widely used. However, solving complex water allocation problems may also be affected by dimensionality catastrophe due to the constraints of multiple factors such as objective function, constraints, and decision variables. Complexity grows exponentially with the dimension of the state space [21]. A single optimization algorithm has limited applicability in computing. Therefore, how to integrate and improve the algorithms to achieve the optimal allocation of water resources in the canal system and increase the efficiency of water resource utilization still needs in-depth research.

The grey wolf optimization algorithm (GWO) is a new swarm intelligent zoo algorithm proposed by Seyed Ali Mirjalili et al. [22] in 2014. So far, the algorithm has been widely used in power grid engineering design, parameter optimization, path planning, dam section design, runoff prediction, water quality monitoring, and other fields [23,24]. The algorithm has the characteristics of few adjustment parameters, a simplified structure, easy program implementation, and high accuracy, and can achieve a balance between local and global searches. Compared to other algorithms, the grey wolf algorithm always looks for the three best solutions and then searches around the region for the best solution. However, there is little research on the adaptability of agricultural water management optimization. Therefore, the grey wolf algorithm was selected as the main optimization algorithm in this paper, using the Mangxiang Dongfeng branch canal and its subordinate canal in the Jinghe irrigation area as a case study. The goal was to minimize the amount of water lost through seepage during the conveyance of water through the canal system. The solution was performed using the IGWO, GWO, NGO, and GA-PSO algorithms, and the obtained water distribution times, rotational irrigation groupings, and seepage were compared. The aim was to find a water distribution scheme that has a short distribution time, the least amount of leakage, and the most water-efficient, time-saving, and labor-saving division of the rotational irrigation group. This study will provide a reference basis for the optimal management and allocation of water resources in irrigation areas.

2. Materials and Methods

2.1. Overview of the Study Area

In this study, the Jinghe irrigation district of Xinjiang Bortala Mongol Autonomous Prefecture was selected as the study area, and in particular, the Mangxiang Dongfeng branch canal and its subordinate bucket canals under the Jinghe East Main Canal of the Jinghe irrigation district were used as a case study. The Jinghe irrigation district covers an area of 46,700 hm^2 and has a typical temperate continental climate. In the spring, summer, and autumn, it relies mainly on runoff from the Jinghe River for irrigation, supplemented by rainfall in the summer, and in the winter, it relies mainly on groundwater for recharge. The average annual temperature in this irrigation area is 7.3 °C, the average annual evaporation reaches 1624.9 mm, the average annual precipitation is 91.4 mm, the intra-annual distribution of precipitation is not uniform, and the utilization rate is relatively low. Based on the measured data, the irrigation area management personnel calculated that the water use coefficient of the current canal system in the Jinghe irrigation area is 0.671, and the comprehensive irrigation water use coefficient is 0.586. For a schematic of the distribution of the Jinghe irrigation district and canals, please refer to Figure 1; the specific parameters of the branch canals are shown in Table 1. This study is based on the surface water irrigation data of the Jinghe irrigation district in late July 2022, with a rotation cycle of 11 d and a planned irrigation water volume of 549,100 m^3 in this round. The source of data for this study is the Mangxiang Water Management Station.

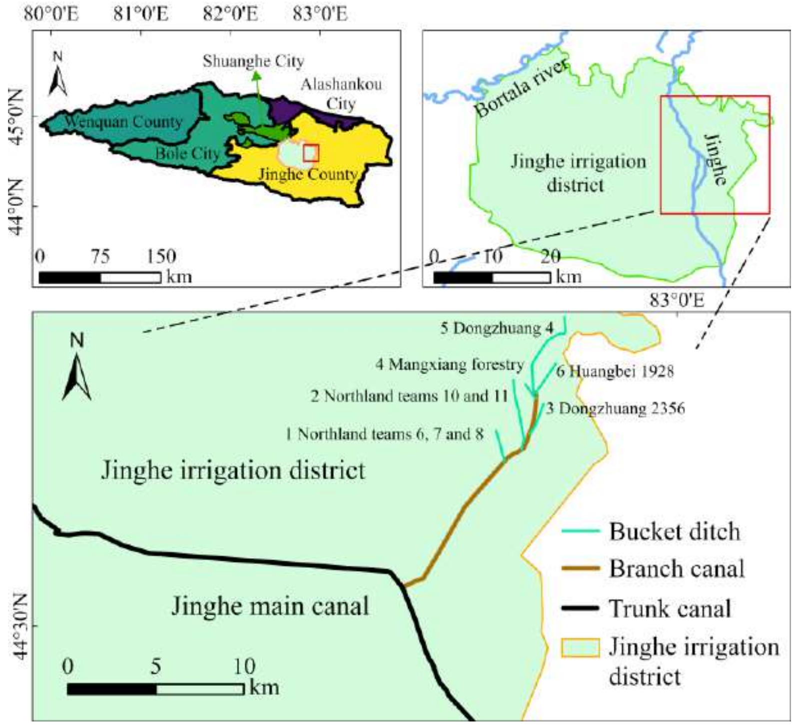


Figure 1. Schematic diagram of the drainage system of the Dongfeng branch canal in the Mangxiang and Jinghe irrigation areas.

Table 1. Basic parameter information for the lower channel of the Mangxiang Dongfeng branch canal.

Channel Number	Channel Name	Design Flow (m^3/s)	Length (km)	Irrigated Area (hm^2)	Water Demand (10^4 m^3)
1	Northland teams 6, 7, and 8	0.4	1.6	480.24	9.50
2	Northland teams 10 and 11	0.2	1.1	25.68	4.64
3	Dongzhuang 2356	0.5	4.8	578.96	19.07
4	Mangxiang forestry	0.3	1.3	146.74	5.76
5	Dongzhuang 4	0.3	1.4	20.01	9.72
6	Huangbei 1928	0.5	1.5	115.39	6.20

2.2. *Optimized Water Distribution Models and Research Methods for Canal Systems*

2.2.1. Optimized Water Distribution Model for Drainage Systems

In this study, the Dongfeng branch canal of Mangxiang in the Jinghe irrigation district and the lower level of bucket canals were taken as the focus, an optimization model of water distribution was constructed by minimizing the total amount of water lost through leakage of the canal system as the optimization objective, and the rotational grouping of the lower level of canals and the duration of water delivery as the decision variables.

(1) Objective function

$$Z = \mathrm{Min}\sum_{i=1}^{M}\left(\beta ALQ_s^{1-m}t_i^*/100+\sum_{j=1}^{N}\beta AL_j(q_j^*)^{1-m}t_i^*/100X_{ij}\right) \quad (1)$$

where Z is the total amount of water lost through seepage in the channel water transfer process (m^3); β is the reduction factor for the seepage loss of the channel lining; A is the soil permeability coefficient; L is the total length of the branch channel (km); Qs is the distribution flow of the branch canal (m^3/s); m is the soil permeability index; t_i^* is the length of time that the ith irrigation group has been irrigated (h); L_j is the length of the jth branch (km); q_j^* is the distribution flow of the jth branch canal; and X_{ij} indicates whether bucket j is organized in rotational irrigation group i.

(2) Constraints

Rotation period constraints: The total duration of diversion for each irrigation rotation group should not exceed the duration of the entire rotation cycle.

$$\sum_{i=1}^{M} t_i^* \le T \tag{2}$$

Water quantity constraint: The product of the channel distribution flow rate and the diversion duration should be equal, as much as possible, to the water demand of the controlled area of the canal system.

$$W_j = q_j^* t_i^* \tag{3}$$

Flow constraint: The sum of the lower channel flows within a rotating irrigation group is less than or equal to the upper channel distribution flow.

$$\sum_{j=1}^{N} q_j^* X_{ij} \le Q_s \tag{4}$$

Bucket channel overflow capacity: Each channel should meet the flow requirements without flushing or silting.

$$0.6\mathbf{q_j} \le \mathbf{q_j^*} \le 1.3\mathbf{q_j} \tag{5}$$

Subordinate canal gate constraints: Each branch canal can only be classified within a particular irrigation round group.

$$\sum_{i=1}^{N} X_{ij} = 1 \tag{6}$$

2.2.2. Model Solving Based on Multiple Algorithms

To ensure the reasonableness of the model parameters and the credibility of the solution results, the model parameters were optimized more comprehensively by solving with multiple algorithms, such as GWO, NGO, GA-PSO, and IGWO, to improve the accuracy and reliability of the solution results.

(1) Grey Wolf Optimization (GWO) Algorithm and Improvements

- Basic Grey Wolf Optimization Algorithm (GWO)

The GWO algorithm is a group intelligence optimization algorithm that originated from the simulation of the social hierarchies and group hunting behaviors of wild grey wolf populations. The population was categorized into 4 classes by simulating leadership: α, β, δ, and ω. Consider α as the optimal solution, β as the suboptimal solution, δ as the best solution, and ω as the candidate solution. The algorithm divides the hunting behavior into three steps: searching for prey, rounding up prey, and attacking prey.

- Searching for prey: The grey wolves are classified according to their adaptation values, and the grey wolf positions corresponding to the adaptation values from largest to smallest are recorded as X_α, X_β, and X_δ. Location updates are performed after determining the location of the prey.

$$\vec{\mathbf{D}} = |\vec{\mathbf{C}} \cdot \vec{\mathbf{X}}_p(t) - \vec{\mathbf{X}}(t)| \tag{7}$$

$$\vec{\mathrm{X}}(\mathrm{t}+1) = \vec{\mathrm{X}}_p(\mathrm{t}) - \vec{\mathrm{A}} \cdot \vec{\mathrm{D}} \tag{8}$$

where t is the current number of iterations of the algorithm, "·" is the dot product of vectors, "| |" is the absolute value of each component of the vector, $\vec{X}(\mathrm{t})$ is the current location of the grey wolf, $\vec{X}_p(\mathrm{t})$ is the prey's present position, $\vec{D}$ is the distance between the grey wolf and its prey, $\vec{X}(\mathrm{t}+1)$ is the updated location of the grey wolf, and $\vec{A}$ and $\vec{C}$ are vectors of coefficients calculated as follows:

$$\mathbf{a} = \mathbf{2} - \mathbf{t} \times (\mathbf{2}/\mathbf{maxIter}) \tag{9}$$

$$|\vec{\mathbf{A}}| = 2 \times \mathbf{a} \times \mathbf{r}_1 - \mathbf{a} \tag{10}$$

$$C = 2\mathrm{r}_2 \tag{11}$$

$$\mathrm{r}_1 = rand(0,1) \tag{12}$$

$$\mathrm{r}_2 = rand(0,1) \tag{13}$$

where a is a convergence factor that decreases linearly from 2 to 0 as the number of iterations t increases, and maxIter is the maximum number of iterations.

- Rounding up prey: During the iteration of grey wolves tracking their prey, the positions of the top three grey wolves obtained in the previous iteration are retained. In the next iteration, the grey wolf population estimates the position of its prey based on this positional information and adjusts its position accordingly, thus gradually approaching the prey. A schematic representation of the hunting process is shown in Figure 2. The positional update of individual grey wolves follows the following formulas:

$$\vec{\mathrm{D}}_\alpha = |\vec{\mathrm{C}}_1 \cdot \vec{\mathrm{X}}_\alpha(t) - \vec{\mathrm{X}}(t)|, \vec{\mathrm{X}}_1 = \vec{\mathrm{X}}_\alpha(t) - \vec{\mathrm{C}}_1 \cdot \vec{\mathrm{D}}_\alpha \tag{14}$$

$$\vec{\mathrm{D}}_\beta = |\vec{\mathrm{C}}_2 \cdot \vec{\mathrm{X}}_\beta(t) - \vec{\mathrm{X}}(t)|, \vec{\mathrm{X}}_2 = \vec{\mathrm{X}}_\beta(t) - \vec{\mathrm{C}}_1 \cdot \vec{\mathrm{D}}_\beta \tag{15}$$

$$\vec{D}_\delta = |\vec{C}_3 \cdot \vec{X}_\delta(t) - \vec{X}(t)|, \vec{X}_3 = \vec{X}_\delta(t) - \vec{C}_1 \cdot \vec{D}_\delta \tag{16}$$

$$\vec{\mathrm{X}}(t+1) = \frac{(\vec{x}_1 + \vec{x}_2 + \vec{x}_3)}{3} \tag{17}$$

where $\vec{D}_\alpha$, $\vec{D}_\beta$, and $\vec{D}_\delta$ denote the current distances of the candidate grey wolf from grey wolf α, grey wolf β, and grey wolf δ, respectively; $\vec{X}_\alpha$, $\vec{X}_\beta$, and $\vec{X}_\delta$ denote the locations of grey wolf α, grey wolf β, and grey wolf δ, respectively; and $\vec{X}_1$, $\vec{X}_2$, and $\vec{X}_3$ are the positions updated after perturbation for grey wolf α, grey wolf β, and grey wolf δ, respectively.

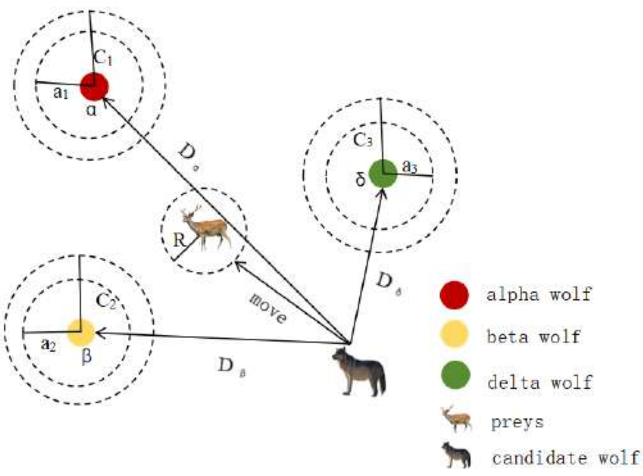


Figure 2. Schematic diagram of updating the position of each grey wolf via the grey wolf algorithm.

- Searching for prey to attack: By adjusting the value of $|\vec{A}|$ so that it is greater than 1 or less than -1, the grey wolf is kept at a certain distance from its prey, and thus searches for a more suitable prey. A schematic of the search method is shown in Figure 3.

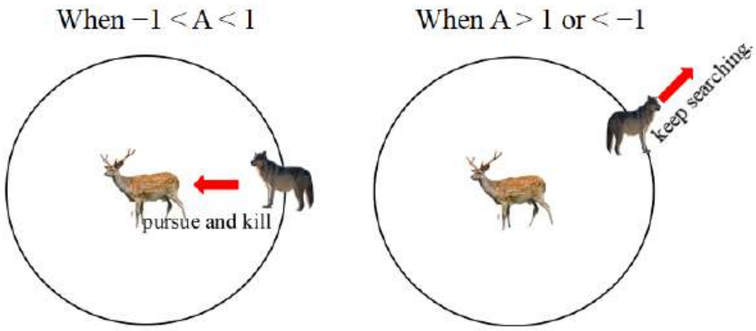


Figure 3. Schematic diagram of the grey wolf attack search method in the grey wolf algorithm.

- Improved Grey Wolf Optimization Algorithm (IGWO)

① Improvement through improved parameters

In population-based intelligent optimization methods, the usual convergence to the global expectation can be divided into two basic phases, the global search phase and the local search phase, so the balance between these two phases is particularly important for preventing the results from falling into the local optimum. In the GWO algorithm, the size of $|\vec{A}|$ determines whether the algorithm performs a global or local search, and from Equation (10), the parameter $|\vec{A}|$ is determined by the size of a. Therefore, in this study, we performed balancing by fine-tuning parameter a [25]. The whole search process of the GWO algorithm is nonlinear and complex, and the nonlinearity was reduced by adopting the logarithmic decay function for parameter a, which is calculated as follows:

$$a(t) = 2 - 2 \times \log(1 + (e-1) \times \frac{t}{\mathrm{maxIter}}) \quad (18)$$

With the maximum number of iterations set to 100, the variation curve of the convergence factor a is shown in Figure 4. It can be observed from the figure that the convergence factor after the nonlinear treatment decreases faster in the early stage, a feature that is conducive to improving the speed of global search, while in the later stage, the decrease gradually slows, which will help to carry out a more adequate local search.

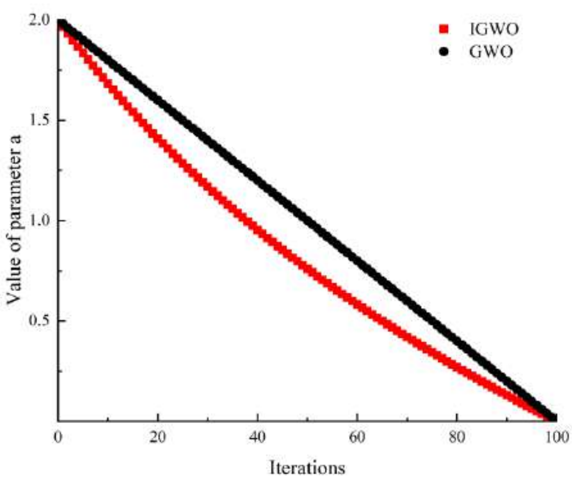


Figure 4. Values of a for the iterative process of IGWO and GWO.

② Improvement by introducing the particle swarm algorithm

The traditional grey wolf algorithm is a memoryless stochastic optimization algorithm based on population intelligence, inspired by the original particle swarm algorithm, which allows individuals to learn from both the globally optimal (grey wolf α) position and the best position in their personal history [26]. An improved position update rule is proposed:

$$X_{(t+1)} = \omega \times \frac{x_1 + x_2 + x_3 - 3 \times x_{(i,j)}}{3} + c_1 \cdot r_1 \cdot (X_{pbert} - X) + c_2 \cdot r_2 \cdot (X_1 - X) + X_{(i,j)} \tag{19}$$

where t denotes the current iteration; r_1 and r2 are random vectors in (0, 1); c_1 denotes the individual memory coefficient; c_2 denotes the group experience coefficient, where the PSO algorithm takes $c_1 = c_2 = 0.5$; and X_{pbest} denotes the individual historical best position, i.e., the position of grey wolf α. When dealing with real optimization problems, it is usually expected to first perform a global search so that the search space quickly converges to a certain region and then implement a local fine search to obtain a high-precision solution. Therefore, an adaptive adjustment strategy is proposed, where the value of ω decreases linearly as the iteration proceeds:

$$\omega = \omega_{\text{final}} + \frac{\text{maxlter} - \text{t}}{\text{maxlter}} \times (\omega_{\text{initial}} - \omega_{\text{final}}) \tag{20}$$

where ω initial = 0.9 and ω final = 0.4.

The flowchart of the algorithm is shown in Figure 5.

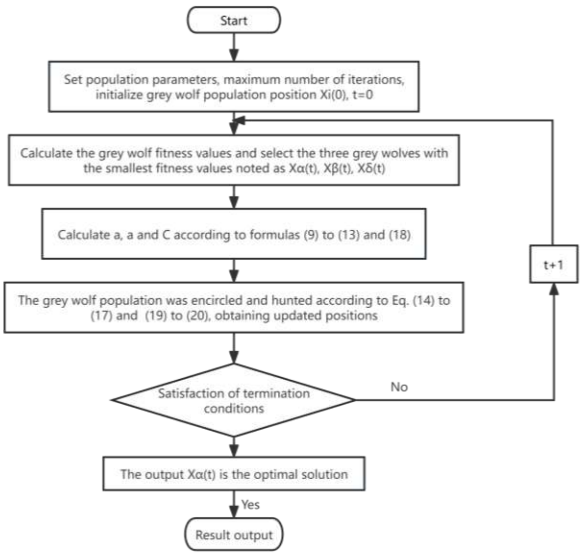


Figure 5. Flowchart of the grey wolf algorithm.

(2) Improved particle swarm algorithm (GA-PSO) and northern goshawk algorithm (NGO) optimization strategies

The particle swarm algorithm (PSO) was proposed by Kennedy and Eberhart in 1995 [27]. First, initial random positions and initial random velocities are assigned to all the particles in the space. Then, each particle is moved to find the known global optimal solution, the sharing is recorded, and the optimal solution is continued until all the particles are gathered together and the problem converges to obtain the global optimal solution. The PSO algorithm possesses fast convergence, has fewer parameter requirements, and is easy to execute, but it is also easily trapped in the local optimal solution; therefore, the incorporation of the simulated annealing algorithm and cross mutation in the genetic algorithm in the PSO algorithm is considered to improve it. The optimized PSO algorithm mainly consists of three core parts: improve, cross, and mutation.

The northern goshawk algorithm (NGO) is a new population intelligence optimization algorithm proposed by Dehghani M et al. in 2021 [28]. Northern goshawk hunting as a whole is divided into two phases. The first phase, prey identification and attack (the exploration phase), involves identifying the prey and quickly moving the northern goshawk toward the location where the prey is located. In the second phase, chase and escape (exploitation phase), the simulation of this behavior increases the ability to exploit local search in the algorithmic space due to the speed of the northern goshawk, which allows them to chase and ultimately capture their prey in almost any situation. The NGO algorithm has high convergence accuracy and good stability but still has the following limitations [29]: the initial solution is randomly uneven in the first period and may miss the potential optimal solution; and in the later period, the prey is chased too fast, which in turn leads to falling into a local optimum.

2.2.3. Algorithm Testing

In order to improve the efficiency of the irrigation district canal system water resource utilization and the water supply guarantee rate, it needs to be ensured that the canal system water resources are reasonably and accurately allocated. In this paper, the GWO algorithm is further improved by incorporating the PSO algorithm. The algorithm is also tested with data from Zhangye City, Black River [30], to prove the applicability of the improved grey wolf algorithm in canal water distribution. The Zhangye Xijun irrigation district Xidong trunk canal consists of 9 directly subordinate hopper canals, Xidong branch canals, and Maojiawan branch canals. The design flow rate is 2.5 m^3/s, the length is 10.23 km, the permeability coefficient of canal bed A is 3.4, the permeability index m is 0.5, the rotation period is 25 d, and the flow rate of the trunk canal is dominated by 1.78 m^3/s, based on the control area of the channel and the comprehensive irrigation quota to determine the amount of water required by the channel. The design parameters of the subordinate canals and the detailed parameters of the controlled irrigated area are shown in Table 2.

Table 2. Parameters of the Xidong main canal and subordinate channels.

Channel Number	Channel Name	Design Flow (m^3/s)	Lengths (km)	Irrigated Area (hm^2)	Water Demand (10^4 m^3)
0	Xidonggang canal	2.5	10.23	1259	151.08
1	Directly under Yidou canal	0.6	1.8	46	5.52
2	Directly under Erdou canal	1	4.2	146	17.52
3	Directly under Sandou canal	1	5.8	248	29.76
4	Directly under Sidou canal	0.6	1.25	65	7.8
5	Directly under Wudou canal	0.6	1.2	76	9.12
6	Directly under Liudou canal	0.5	0.88	55	6.6
7	Directly under Qidou canal	0.5	1.03	41	4.92
8	Directly under Badou canal	0.6	1.4	117	14.04
9	Directly under Jiudou canal	0.8	1.9	230	27.6
10	Xidong branch canal	1.5	6.17	233	27.96
11	Maojiawan branch canal	0.8	1.8	53	6.36

With the same data, the results were compared with those of Wang Qingjie [31], with the aim of prioritizing the satisfaction of the minimum possible water transmission seepage loss. The optimized water distribution duration of the grey wolf algorithm was reduced to 10.71 days, which is almost one day shorter compared to the 11.56 d of the improved particle swarm algorithm. The leakage loss is 30. 88 $\times$ 10^4 m^3, which is 5.67% lower compared to 32. 63 $\times$ 10^4 m^3 of the improved particle swarm algorithm. The water distribution results in Table 3 show that the improved grey wolf algorithm is well applied in the optimal water distribution model of the canal system.

Table 3. Comparison of leakage and diversion durations obtained using the improved PSO and GWO algorithms.

Algorithm Type	Loss through Seepage (10^4 m^3)	Total Duration of Water Diversion (h)
IGWO	30.88	256.99
GA-PSO	32.63	277.3

2.3. Determination of Parameters of Water Distribution Model Based on the Optimization of the Canal System in Jinghe Irrigation District

(1) Calculation of the number of rotational irrigation groups

Let the upper channel diversion flow be Qs. There are a total of N subordinate channels to which this channel belongs, the design diversion flow for each lower channel is qj, and by adopting an upward rounding strategy, the rotational irrigation group is:

$$M = ceil\frac{N}{Q_s/q_j} \tag{21}$$

(2) Calculation parameters of the water distribution model

The interrelationships and effects of parameters must be carefully considered when performing water distribution calculations for drainage systems. Therefore, based on *Irrigation and Drainage Engineering* [32] and *Agricultural Hydrology* [33], the following parameters are used in the canal distribution model equations: the drainage bed soil permeability coefficient (A) was 3.4, the permeability index (m) was 0.5, the anti-seepage measures discount coefficient (β) was 0.5, the minimum flow coefficient of the bucket ditch channel was 0.6, the coefficient of the increased flow rate was 1.3, and the Mangxiang Dongfeng branch drainage channel contained 6 bucket ditches. GWO, IGWO, NGO, and GA-PSO were used to solve the model, with the duration of the continuous diversion of water by each rotational irrigation group and the rotational irrigation formation of each subordinate branch canal as the decision variables and the total amount of water seepage as the optimization objective. To find the initial value for the calculation, we utilized feasible solutions within the domain of the definition of the model through population initialization. Feasible solutions for the decision variables were sought based on the wheeling period and flow constraints given in the model. The optimized final result was determined by iteratively updating and repeating the solution through the results of canal distribution flow and grouping, and eliminating the set of solutions that did not satisfy the constraints.

3. Results

The average flow rate of 0.73 m^3/s during the distribution of water from the Dongfeng branch canal in Mangxiang was used as the inlet flow rate of the branch canal, which means that Qs is 0.73. There are six lower bucket drains, i.e., N is 6. The average value of the design flow of the lower bucket channel is 0.36 m^3/s, i.e., qj is 0.36. According to formula (21), M = 3 is obtained. The GA-PSO, NGO, GWO, and IGWO algorithms are used to solve the channel water distribution model, and group irrigation result graphs are generated.

3.1. Algorithm Performance Analysis Based on Model Solution Results

The results indicate that when the inflow of the Dongfeng branch canal in Mangxiang is 0.73 m^3/s, the lower level canal can be divided into three rotational irrigation groups. The solution results of the four algorithms, NGO, IGWO, GA-PSO, and GWO, are shown in Table 4. As can be seen in Figure 6, the NGO algorithm converges faster than the rest of the algorithms at the starting time, but the improved grey wolf algorithm reaches the optimum in fewer than 10 generations, which makes it more suitable for this model compared to the other algorithms. Reducing the water distribution time from 11 d to 8.91 d in the manual water distribution round irrigation cycle, the leakage was 117,500 m^3, a reduction of 44,000 m^3. The improved grey wolf algorithm achieves relatively centralized and fast water distribution in terms of both distribution time and total leakage loss. The efficiency of water distribution is, therefore, improved and the solved rotational irrigation groupings are shown in Table 5. The flow rates of each channel after optimization are shown in Figure 7. The optimized flow rates are all between the increased flow rate and the minimum flow rate, meeting the requirement of not exceeding the flow rate. Compared with manual water distribution, the flow rate is closer to the design flow rate, ensuring the good operating conditions of the channel. The maximum amount of water distributed in the channel system is close to the water demand for irrigation crops, achieving on-demand water distribution to maximize the water utilization efficiency of the superior channel system. The conclusion indicates that adopting appropriate optimization methods can effectively regulate the timing and flow of channel water distribution, thereby significantly improving the efficiency of channel water resource utilization.

Table 4. Comparison of the solution results obtained using GA-PSO, NGO, GWO, and IGWO.

Algorithm Type	GA-PSO	NGO	GWO	IGWO
Iterations	33	50	33	9
Total leakage (m^3)	117,532.00	117,510.46	117,532.00	117,507.11
Total diversion time (d)	8.96	8.92	8.96	8.92

Table 5. Optimal rotation grouping and flow statistics.

No. of Rotation Irrigation Group	Rotation Irrigation Combination	Irrigation Duration (h)	Water Demand ($\times 10^4$ m^3)	Distribution Flow (m^3/s)
1	Dongzhuang 2356 Dongzhuang 4	112.98	19.07 9.72	0.47 0.24
2	Mangxiang Forestry Huangbei 1928	45.86	5.76 6.20	0.35 0.38
3	Northland teams 6, 7, and 8 Northland teams 10 and 11	55.15	9.50 4.64	0.48 0.23

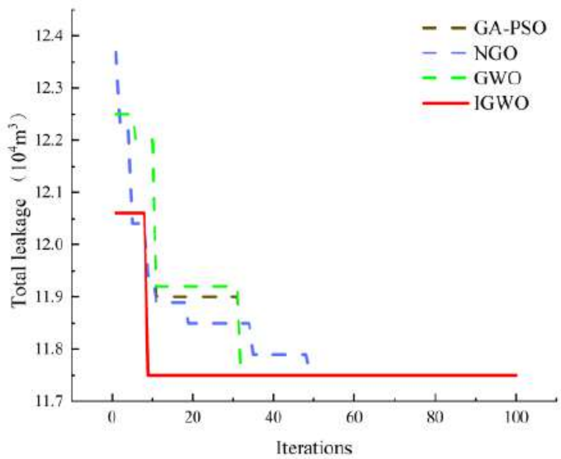


Figure 6. Adaptation graph.

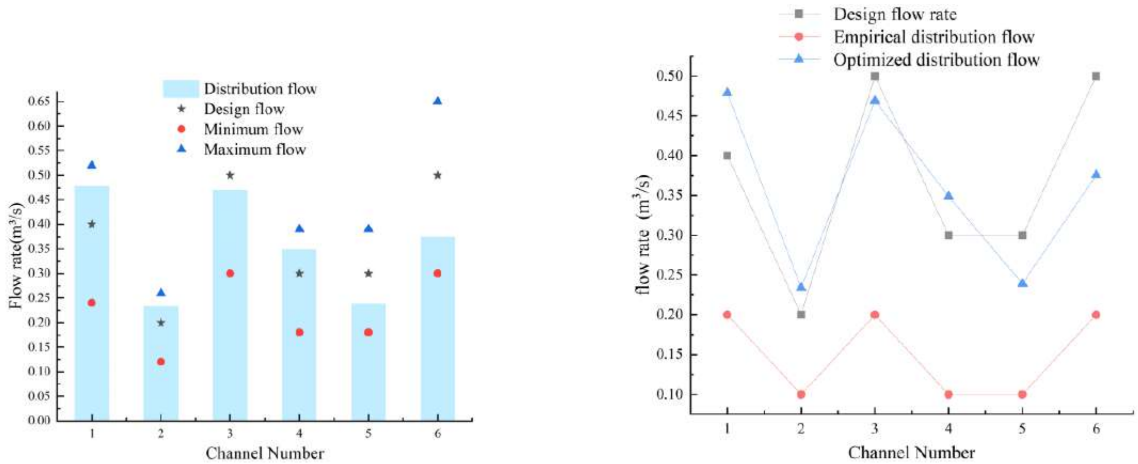


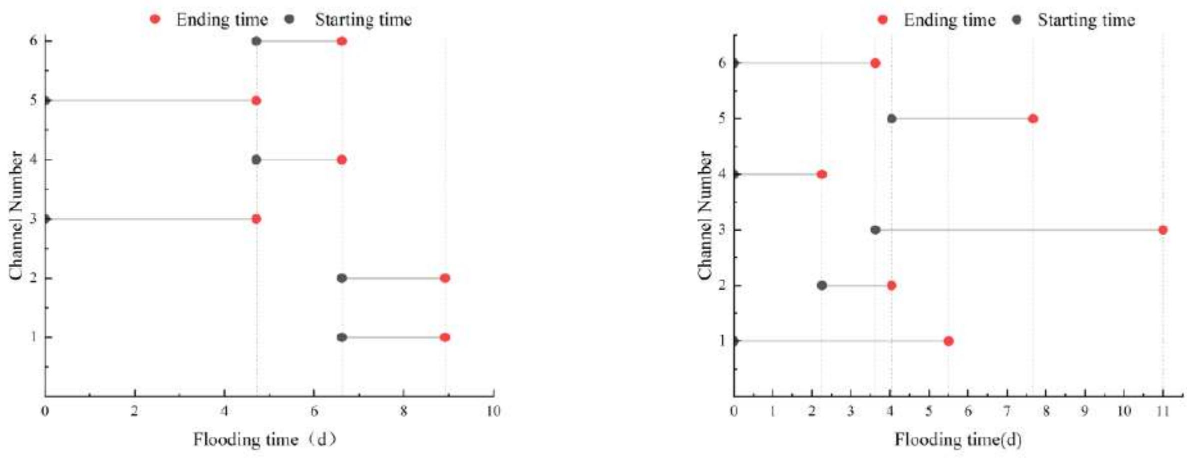
Figure 7. Comparison of distribution flows in subordinate channels of the Dongfeng branch canal. (**a**) Actual distribution flow in the channel. (**b**) Comparison of distribution flow rates.

3.2. Adaptability Analysis Based on Water Volume Changes

By jointly encoding the water distribution flow rate and the grouping of subordinate channels, a reasonable fitness function is designed to guide the optimization process to converge toward a very small feasible domain and improve algorithm efficiency and stability. At the same time, improving the convergence factor parameters and combining the particle swarm algorithm not only maintains the diversity of solutions, but also improves applicability by making the algorithm stable and easy to jump out of the local optimal solution during the calculation process. The water level of the Jinghe River in the research area varies seasonally, and the amount of water diverted from the canal head and the time of water diversion from various subchannels are limited. June to September is the summer and autumn irrigation period, and the water demand for crops is high. The IGWO algorithm uses upper channel flow stabilization with no fixed distribution time. If there are increases and decreases in the distribution process in the upper channel, a new distribution scheme can be obtained by simply adjusting the incoming flow from the upper channel at different times.

3.3. Rationality Analysis of the Algorithm Based on Management Efficiency

Due to the limitations of technology and hardware facilities in irrigation areas, current gate openings and closures still rely on personnel from irrigation area engineering management departments for control. Due to the large scale of the Jinghe irrigation area project and the numerous channel systems, zoning management is critical for improving the project's efficiency. According to the concentration of the water distribution time and the geographical distribution of the lower canal system, the implementation of zoning and a centralized and unified control of the canal can scientifically improve the management of the irrigation area for the construction canal system. In terms of manual experience, the opening and closing times of the irrigation gates are different, and the flow in the middle needs to be adjusted. According to Figure 8, the IGWO algorithm divides the lower canal system into three parts: No. 3 and 5, No. 4 and 6, and No. 1 and 2. At the same time, the flow in the water distribution process is stable without adjusting the gate, and the opening and closing times are unified. The zoning management based on the optimization algorithm can make each bucket gate in each round of irrigation group open and close at the same time, and the flow is stable without adjusting the flow in the middle, which is conducive to improving the overall management efficiency and reducing the workload of managers.



(a) (b)

Figure 8. Start and end of irrigation in lower channels. (**a**) Optimization method. (**b**) Empirical method.

4. Discussion

Under the traditional water distribution model, farmers submit an annual water demand application based on their experience, and the water management unit develops a yearly water distribution program, taking into account the amount of incoming water and historical water demand. This empirical water distribution model in the efficient water-saving irrigation district configuration method reveals an inefficient lack of science and backward thinking methods among the personnel in canal operation and management, resulting in the current irrigation management methods not being able to be adapted to the informatization and automation of the scheduling requirements. Therefore, with the implementation of digital irrigation district renovation projects in recent years, the scientific management of canal system water transmission and distribution is highly valued.

In this study, the same study conditions and different algorithms are used to solve the water distribution model in order to obtain the optimal water distribution scheme for the canal system. The results show that the IGWO algorithm can quickly solve the optimal water distribution scheme. This is consistent with the results of Zhang Yaqi's [34] study. Nong Xizhi et al. [35] and Tian Guilin et al. [36] showed that the meta-heuristic swarm intelligent optimization algorithm significantly improved the efficiency of canal water use in optimal canal water distribution. Liu Y et al. [37] showed that using the PSO algorithm significantly shortened the canal distribution time and was able to address the shortcomings of typical heuristics. Yu F et al. [38] showed that rational water distribution can effectively reduce the workload of managers, which is in line with the findings of this paper.

In this study, the Jinghe irrigation district is taken as a study case, and the IGWO algorithm is used to solve the model and achieve good results, which is of great reference value in the process of optimizing water distribution in the canal system. However, some issues were identified in the study that need to be further explored and researched. First, the model is constructed on the basis of two-stage channels, and subsequent studies can consider the optimal allocation of water resources in multi-stage canal systems. Secondly, only one irrigation of the crop was considered in this study. However, in the actual development of water distribution and scheduling programs, one should also take into account the amount of incoming water and diversion, the planting structure, the actual crop water demand, management staff arrangements, and other factors of change to achieve a shift from timed to real-time water distribution, and from a particular irrigation to optimized distribution over the entire crop life cycle. Finally, Internet of Things technology, machine learning, and other methods, combined with the optimization of the water distribution model, can be used to build an intelligent canal scheduling system in order to achieve the informatization, intelligence, scientification, and refinement of irrigation district management.

5. Conclusions

The optimal water distribution of canal systems is an important research direction for the rational and effective allocation of water resources in agricultural irrigation areas. The use of modern system optimization engineering technology to formulate a water distribution scheme can significantly shorten the traditional manual rotation irrigation grouping and water distribution flow determined by experience, which will reduce leakage loss in the water distribution process and effectively improve the utilization efficiency of water resources.

(1) In this paper, water distribution is modeled using rotational irrigation between groups and renewed irrigation within groups. With the objective of minimizing the total amount of seepage loss in canal system transmission, the improved grey wolf algorithm is applied to the optimal water distribution model of the irrigation canal system. The water distribution time is shortened from the planned 11 d to 8.91 d, and leakage is reduced from 16.15×10^4 m^3 to 11.75×10^4 m^3. Under the premise of ensuring that the actual distribution flow in the channel is within the range of the maximum and minimum flow, the scheme meets the objectives of a short distribution time, centralized water resource allocation, and low leakage.

(2) When compared to the GA-PSO, NGO, and traditional GWO algorithms, the IGWO algorithm shows its good optimization performance. The IGWO algorithm has few application constraints, fewer iterations, faster computation, stable solution, and a high degree of global optimization. At the same time, the model-solving algorithm can also adjust the basic data parameters according to the specific conditions of different irrigation canal systems in order to adapt to a variety of complex irrigation canal networks.

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