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An Optimal Model and Application of Hydraulic Structure Regulation to Improve Water Quality in Plain River Networks

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Abstract: The proper dispatching of hydraulic structures in water diversion projects is a desirable way to maximize project benefits. This study aims to provide a reliable, optimal scheduling model for hydraulic engineering to improve the regional water environment. We proposed an improved gravitational search algorithm (IPSOGSA) based on multi-strategy hybrid technology to solve this practical problem. The opposition-based learning strategy, elite mutation strategy, local search strategy, and co-evolution strategies were employed to balance the exploration and exploitation of the algorithm through the adaptive evolution of the elite group. Compared with several other algorithms, the preponderance of the proposed algorithm in single-objective optimization problems was demonstrated. We combined the water quality mechanism model, an artificial neural network (ANN), and the proposed algorithm to establish the optimal scheduling model for hydraulic structures. The backpropagation neural network (IGSA-BPNN) trained by the improved algorithm has a high accuracy, with a coefficient of determination (R^2) over 0.95. Compared to the two traditional algorithms, the IGSA-BPNN model was, respectively, improved by 1.5% and 0.9% on R^2 in the train dataset, and 1.1% and 1.5% in the test dataset. The optimal scheduling model for hydraulic structures led to a reduction of 46~69% in total power consumption while achieving the water quality objectives. With the lowest cost scheme in practice, the proposed intelligent scheduling model is recommended for water diversion projects in plain river networks.

Keywords: optimal scheduling model; gravitational search algorithm; multi-strategy hybrid technology; artificial neural network

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1. Introduction

Water environmental pollution in plain river networks is a common problem in coastal areas. In recent years, a variety of comprehensive measures have been implemented to improve the regional water environment, including engineering measures and non-engineering measures. As an effective auxiliary control measure, water diversion projects have been widely used in foreign countries in the past [1–4]. They are also an important measure for water environment treatment in China, which can rapidly improve water quality and increase the fluidity of water bodies [5,6].

However, existing studies on the optimal dispatching of hydraulic structures mainly focus on flood control projects [7–10], hydroelectric projects [11–13], water distribution systems [14], reservoir operation decisions [15], and multi-objective water transfer projects [16]. Water diversion projects for improving water quality mainly adopt an empirical method or an exhaustive method [17,18] to determine a feasible water diversion scheme, which is difficult to obtain better environmental and economic benefits from. An artificial neural network coupled with a hybrid genetic algorithm is applied to solve the problem of optimal scheduling for small-scale water diversion projects [19]. Because the performance of traditional artificial neural networks based on gradient descent is often not as expected, it cannot be directly used to replace the water quality mechanism model of the complex plain river network. Therefore, the hydrodynamic-controlling optimal model cannot solve the problem of optimal scheduling for large-scale water diversion projects.

Nowadays, machine learning algorithms have been widely applied in many research fields, including the chemical engineering, civil engineering, agriculture and forestry science, and environmental fields. Feedforward Neural Networks are the best-known artificial neural network. The backpropagation algorithm is a classic algorithm for training Feedforward Neural Networks. The disadvantage of the backpropagation algorithm is that the global optimization ability is poor and it is easy to fall into local extreme values. In recent years, intelligent optimization algorithms have been used to train neural networks to avoid parameters falling into local extrema [20–24]. The typical optimization strategies can be broadly categorized into the following three types: one is to find the appropriate network structure for the ANN in a specific problem; the second is to apply intelligent optimization algorithms to determine the optimal learning rate, momentum factor, and other parameters for the ANN; and the third focuses on finding the optimal combination of network connection weights and node biases to minimize the error of the ANN.

In recent decades, intelligent optimization algorithms have been promptly developed and have become an effective means to solve the optimization problems in the fields of science and engineering [25–29]. Different from other optimization algorithms based on group behavior, the gravitational search algorithm (GSA) is an intelligent heuristic evolutionary algorithm in accordance with Newton's gravitation theorem. Compared to some proverbial swarm algorithms, such as the traditional genetic algorithm (GA) and particle swarm optimization algorithm (PSO), the GSA has clear advantages in both its search convergence speed and optimization accuracy [30,31]. However, the traditional GSA also has problems, such as the algorithm easily falling into local optimal solutions and individuals being prone to premature maturity [32,33]. The opposition-based gravitational search algorithm applies opposite numbers to the population initialization and exploration process to improve the convergence rate of the GSA [34]. In addition, several studies combined the GSA with other algorithms [35]. Since the traditional GSA is a memoryless heuristic optimization algorithm, there is a possibility to deviate from the optimum trajectory. Efforts have been made to improve the algorithm by using historical optimal solutions. A memory-based version of the GSA changes the force of every two individuals by using the global optimal solution of the population from the former iteration when calculating the individual positions [36]. In 2017, a modified gravitational search algorithm was proposed in which the position of each agent was regenerated in accordance with the crossover search tactic to extract favorable feedback from the optimum location obtained until now with a certain probability [37]. The PSOGSA is a hybrid algorithm that integrates with the advantages of PSO and the GSA, and has a better capability in avoiding local minima and convergence speeds. Compared with the GSA, the hybrid algorithm enhances the abilities of exploitation and makes the algorithm powerful enough to acquire the overall best solution of the extensive optimization problems [38]. To control oscillations and avoid the divergence of the PSOGSA, the fuzzy logic algorithm was applied to adjust the velocity in the search space [39]. In addition, the performance of the PSOGSA has also been enhanced in numerous studies by optimizing the related parameters [40], adopting the hybrid strategy [41], the mutation strategy [42], or the chaos strategy [43] to improve the structural defects of the GSA. Although efforts have been made to ameliorate the competence of the gravitational search algorithm, how to quickly obtain optimal solutions while maintaining high-quality capabilities remains a challenging task.

The combination of machine learning algorithms and artificial intelligence with existing science and technology in various fields to realize engineering digitization is a current scientific research hotspot. Intelligent scheduling is conducive to realizing the maximization of the economic and environmental benefits of water environment management projects. Therefore, it is necessary to establish an optimal scheduling model to provide optimal scheduling strategies for water diversion projects. In this paper, an improved gravitational search algorithm was applied to optimize the backpropagation neural network to replace the complex water quality mechanism model and solve the optimal scheduling problem of hydraulic structures in water diversion engineering to obtain the optimal scheduling scheme. Based on the rational allocation of water resources to optimize the economic and social development of the basin, an optimal scheduling model of water diversion projects was developed, which is composed of a water quality mechanism model, an artificial neural network, and the improved gravitational search algorithm. Through the rational joint management of sluices and pumps, this study minimizes the economic cost of water diversion projects and provides technical support and a theoretical basis for water environment management in plain river network areas.

2. Methods

2.1. Traditional Gravitational Search Algorithm

The traditional GSA is a heuristic evolutionary algorithm without memory that follows the law of universal gravitation and masses interaction force [28]. Every search individual has four characteristics: a position vector, inertial mass, active gravitation, and passive gravitation. Each position vector corresponds to a set of feasible solutions to the optimization problem, and the individual performance is evaluated based on their inertial mass. Due to the gravitational force, one agent actively attracts others and moves towards the heavier agent, thus affecting the direction and speed of the next iteration. Assuming that the dimension of the optimization problems is D and the search group consists of K individuals, the position and velocity of the j-th individual are described as follows:

$$X_j = \left(x_j^1, x_j^2, \cdots, x_j^D\right), \quad j = 1, 2, \cdots, K \tag{1}$$

$$x_j^d \in \left[low^d, up^d\right], \qquad d = 1, 2, \cdots, D \tag{2}$$

$$V_j = \left(v_j^1, v_j^2, \cdots, v_j^D\right), \quad j = 1, 2, \cdots, K \tag{3}$$

The closer the agent is to the optimum solution of the optimization problem, the greater the inertial mass (M), which is strongly associated with the fitness obtained at the current position of the agent. In accordance with the law of universal gravitation, the gravitational force (F_{ij}^d) defines the force of agent i acting on agent j at the t-th iteration. Therefore, the total force (F_j^d) and acceleration (a_j^d) on the d-th dimension of agent j are expressed as follows [44]:

$$F_j^d(t) = \sum_{i \in k_{best},\ i \neq j}^{K} rand_i \times F_{ij}^d(t) \tag{4}$$

$$F_{ij}^d(t) = G(t) \frac{M_i(t) M_j(t)}{\left\| X_i(t), X_j(t) \right\|_2} \left(x_i^d(t) - x_j^d(t)\right) \tag{5}$$

$$a_j^d(t) = \frac{F_j^d(t)}{M_j(t)} \tag{6}$$

$$m_j(t) = \frac{f_j(t) - f_{bad}(t)}{f_{best}(t) - f_{bad}(t)} \tag{7}$$

$$M_j(t) = \frac{m_j(t)}{\sum_{i=1}^{N} m_i(t)} \tag{8}$$

where k_{best} is a group of individuals with high fitness value in the population, which is correlated with time; $G(t)$ is the gravitational constant at time t; $M_j(t)$ is the inertial mass of particle j at time t; f_j, f_{bad}, and f_{best} are the fitness of agent j, the worst agent, and the best agent at the t-th iteration.

In the GSA, the search strategy is depicted as follows:

$$v_j^d(t+1) = rand_j \times v_j^d(t) + a_j^d(t) \tag{9}$$

$$x_j^d(t+1) = x_j^d(t) + \mathrm{v}_j^d(t+1) \tag{10}$$

where $rand_j$ is random value within the interval [0, 1].

2.2. Proposed Algorithm: IPSOGSA

An improved gravitational search algorithm (IPSOGSA) based on PSO and the GSA is proposed in this study by introducing opposition-based learning, the elitist agent mutation strategy, the Simulated Annealing Algorithm, a local search strategy, and co-evolution strategies. Firstly, we employed opposition-based learning for population initialization to alleviate the shortage of random initial populations. Then, to avoid trapping in local extrema during the search procedure, the Cauchy mutation operator was introduced into elite agents with a certain probability according to the population aggregation degree, and the Metropolis criterion based on the Simulated Annealing Algorithm was applied to determine whether elite agents should accept mutation updating. Finally, a local search strategy and co-evolution strategies were utilized to speed up the convergence velocity of the GSA. Details of the above functions are provided as follows:

2.2.1. Opposition-Based Learning

As a population-based optimization algorithm, the search process of the GSA is mainly divided into two aspects in a similar way: the random initialization of the population and updating the next generation based on Newton's gravitation theorem. Random initial populations tend to result in a slow convergence velocity and unstable solution accuracy. Hence, in the present work, the reverse vectors of all initial populations were calculated based on opposition-based learning [45], and the first K individuals were finally obtained as the initial populations by sorting the fitness values.

$$X' = up + low - X \tag{11}$$

2.2.2. Elite Mutation Strategy

As the iterations goes on, the convergence of particles leads to a decrease in population diversity, and it is easy to become trapped in local optimal solutions when disposing of multi-peak problems. Elite particle mutation could help particles to jump out of the current extreme value to explore other solution spaces.

$$S(t) = \frac{1}{\left(1 + \sqrt{\frac{1}{K}\sum_{j=1}^{K}\left(fit_j(t) - f_{avg}(t)\right)^2}\right)} \tag{12}$$

$$f_{avg}(t) = \frac{1}{K}\sum_{j=1}^{K} fit_j(t) \tag{13}$$

where $S(t)$ is the aggregation degree of population at the t-th iteration.

If the mutation rate (m) is greater than the random value, the Cauchy mutation operator is introduced to the elite agent. Then, the agent will be updated when $fit(\overline{x_j}) > fit(x_j)$ (e.g., minimum problem). Otherwise, based on the individual location update strategy of the Metropolis criterion in the Simulated Annealing Algorithm, if $fit(\overline{x_j}) < fit(x_j)$, the agent will only be updated with a certain probability.

$$m = \begin{cases} 0 \quad , & S(t) \le m_{min} \\ S(t)\frac{m_{max}}{1-m_{min}}, & S(t) > m_{min} \end{cases} \tag{14}$$

$$\overline{x_j} = x_j + c \times (up - low) \times Cauchy(\theta, \gamma) \tag{15}$$

$$T_{t+1} = T_t \times rate \tag{16}$$

$$\text{When } fit(\overline{x_j}) < fit(x_j),\ X_j = \begin{cases} \overline{x_j}\ , & rand \le e^{-(\frac{fit_{\overline{x_j}} - fit_{x_j}}{T_t})} \\ x_j\ , & rand > e^{-(\frac{fit_{\overline{x_j}} - fit_{x_j}}{T_t})} \end{cases} \tag{17}$$

where m_{max} and m_{min} are the maxima and minima of the mutation rate; c is a contraction constant between the interval [0, 1]; θ and γ are 0 and 1; and T_t is the temperature at the t-th iteration.

2.2.3. Local Search Strategy

The opposition-based learning strategy and elite strategy are applied to strengthen the population's exploration ability to avoid the decline of the local search ability after Cauchy mutation. A new set of solution vectors are generated by applying the opposition-based learning strategy to the agents with the top 40% fitness values. Then, the elitist strategy works on the agents with the top 20% fitness values in the new set and original population to produce new agents. After sorting the fitness of all agents, agents with poor performance are obsoleted to generate a new search population.

$$Q = R_{jbest} \times rand(-0.5,\ 0.5)/D \tag{18}$$

$$X_{jnew} = X_j \times Q \tag{19}$$

where R_{jbest} is the Euclidean distance between the j-th individual and the optimal individual.

2.2.4. Co-Evolution Strategies

Based on the evolutionary algorithm, the population in co-evolution strategies is divided into two groups: an elite subpopulation, which is implemented by an ego update, and a common subpopulation, which is implemented by a mutual compulsory update and a cooperation update [46]. Elite individuals with high fitness values lead the population evolution in the process of co-evolution, which speeds up the convergence of the algorithm by passing on good attributes to the offspring.

(1) Ego update

The initial population is divided into the elite subpopulation ($PopE = M$) and the common subpopulation ($PopC = K - M$) in accordance with the fitness value. In addition, the elite subpopulation should always satisfy the relationship of fitness(x_m) $\ge$ fitness(x_n), $1 \le m < n \le M$. The ego update strategy for the elite subpopulation is to generate two new individuals from two elitists through two opposite coupling patterns when the probability (Re) is greater than a random value. Then, the optimal value between the two temporary individuals ($E_{m,n}$) and the current worst individual is retained.

$$E_{m,n,d} = \begin{cases} x_{m,d} \pm rand \times (x_{m,d} - x_{n,d}), & rand < Re \\ x_{m,d} & , rand \ge Re \end{cases} \tag{20}$$

$$1 \le m < M,\ m < n \le M,\ 1 \le d \le D$$

where $E_{m,n,d}$ is the d-th dimension of the new individual, $E_{m,n}$.

(2) Compulsory update and cooperation update

The gravitational measurement value (GM) describes the relationship of two groups of subpopulations. According to the GM, the compulsory update is applied to the common individual corresponding to the minimum GM of any elite individuals, while other common individuals are applied the cooperation update. Each common individual is mandatorily updated and cooperation-updated as follows:

$$C_j^m = \begin{cases} x_{max'} & rand < Rc \\ x_{rand'} & rand \ge Rc \end{cases} \tag{21}$$

$$1 \leq max' \leq M, 1 \leq rand' \leq M, 1 \leq j \leq K - M$$

$$Ni_1 = x_{i,d} + rand \times \left(x_{i,d} - c_{j,d}\right) \quad (22)$$

$$Ni_2 = x_{i,d} - rand \times \left(x_{i,d} - c_{j,d}\right) \quad (23)$$

$$C_j^p = \begin{cases} Ni_1, & fitness(Ni_1) > fitness(Ni_2) \\ Ni_2, & fitness(Ni_1) < fitness(Ni_2) \end{cases} \quad (24)$$

$$1 \leq i \leq M, 1 \leq j \leq K - M, 1 \leq d \leq D$$

where C_j^m is the replacement of the individual C_j after mandatorily updating; x_{max} is the elitist individual that has the furthest distance to j; x_{rand} is a random elitist individual; Rc is a probability constant, the same as the Re; and C_j^p is the replacement of individual C_j after the cooperation update strategy.

2.2.5. Location Update Strategy

After each iteration, the agent-moving strategy considers the guide of individual memory and social information, which alleviate the shortcoming of the GSA that easily loses the optimal trajectory during the optimization process by enhancing the information-sharing ability.

$$\mathrm{v}_j^d(t+1) = rand_1 \times \mathrm{v}_j^d(t) + w_1 \times a_j^d + w_2 \times rand_2 \times \left(p_j^d - x_j^d\right) + w_3 \times rand_3 \times \left(p_g^d - x_j^d\right) \quad (25)$$

$$x_j^d(t+1) = x_j^d(t) + \mathrm{v}_j^d(t+1) \quad (26)$$

where w_1, w_2, and w_3 represent the degree of influence of "gravity", "memory", and "society" on the agent search speed, respectively; p_j^d is the historical optimum position of agent j until the t-th iteration; and p_g^d is the global optimum position of the population until the t-th iteration.

2.2.6. The Procedure of IPSOGSA

Opposition-based learning is first employed to improve random initial agents (Equation (11)), and the fitness of all agents is then calculated by using the objective function, and the optimal solution should be updated until the current iteration. After that, the convergence and mutation rate are defined as Equations (12)–(14), and whether the particles should be mutated and updated is determined (Equations (15)–(17)). In order to enable the algorithm to effectively deal with complicated optimization problems, the local search strategy and co-evolution strategies are incorporated (Equations (11), (18)–(24)). In each iteration, the gravitational mass, gravitational constant, resultant force, and acceleration of agents are calculated using Equations (4)–(8). Finally, the positions of agents are updated using Equations (25) and (26). The IPSOGSA will continue to search until the end of the iteration. The sequential steps of the IPSOGSA are depicted in Figure 1.

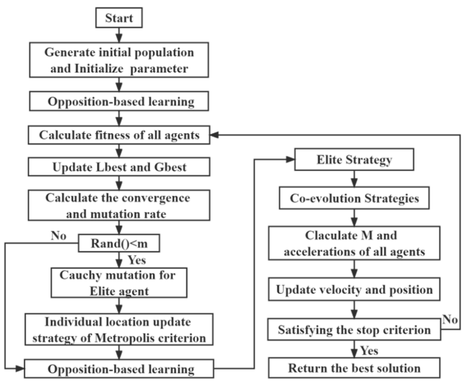

Figure 1. Implementation process of IPSOGSA.

2.3. Experiment Results and Discussion

Thirteen classical benchmark functions were applied to examine the feasibility and effectiveness of the algorithm, which are presented in Tables S1 and S2 (in Supplementary Materials) along with their dimension, range of search space, and optimal value of function [47]. The unimodal benchmark functions that have a unique minimum value in the search space are helpful for testing the exploitation and convergence of the algorithm. The multimodal benchmark functions have several local extreme points that are close to each other in the entire search range, which easily causes the algorithm to become trapped in the local minimum. The multimodal benchmark functions are applied to examine the exploration ability of the algorithm and verify whether the algorithm can effectually search the global optimum. The initial values of related parameters are presented in Table 1. The population size is 50. The max iteration was 1000 and the operation of the algorithm was repeated until the stopping criteria were met. The experiment results are presented in Tables S5 and S6 (in Supplementary Materials) in accordance with 30 independent runs.

Table 1. Parameters for GSA, PSOGSA, and IPSOGSA.

Algorithm	G_0	α	m_{min}	m_{max}	T_0	$rate$	T_{end}
GSA	100	20	-	-	-	-	-
PSOGSA	100	20	-	-	-	-	-
IPSOGSA	100	20	0.1	0.2	1000	0.96	0.01

In addition, two types of complex functions, IEEE CEC 2015 and CEC 2017, were applied to further evaluate the performance of the algorithm. Both test sets contain different numbers of unimodal functions, simple multimodal functions, hybrid functions, and composition functions (Tables S3 and S4 in Supplementary Materials), since these four types functions contain a single peak or multiple local extremes that are often applied to evaluate the ability of an algorithm to balance exploration and exploitation. The dimension of the IEEE test functions is 30. The population size is 150. The algorithm iteration terminating criterion is when the iteration reaches maximum = 6000. Each algorithm was run 51 times independently, and the experimental results are shown in Tables S8 and S9 (in Supplementary Materials).

With the objective of finding the minimum value, the capability of the algorithm was appraised from two aspects, the mean value and standard deviation, and was compared with the GSA and PSOGSA. Moreover, the boxplot graphs are applied to depict the quality of the optimal solutions on traditional benchmark test functions. Each box includes a median value, abnormal value, and the 25th and 75th percentiles of the 30 independent run results. All the optimal results are expressed in bold style with red color. The entire simulations were performed using MATLAB® version R2019b.

2.3.1. Classical Benchmark Functions Set

(1) Comparison with unimodal benchmark functions test set

The IPSOGSA showed the best performance on the mean value of six functions ($f_1(x)$–$f_5(x)$, $f_7(x)$), as illustrated in Table S5 (in Supplementary Materials). Especially for functions $f_1(x)$–$f_4(x)$, the IPSOGSA could acquire the theoretical optimal solution, 0, in three different dimensions. For function f_6 (Dim = 30/50), the mean value with the highest precision was obtained by the PSOGSA, while the IPSOGSA showed an improved performance compared to other two algorithms when dealing with the high-dimensional (Dim = 100) problem of function f_6, where the result differed by at least four orders of magnitude. On the other hand, their final ranks point out the superiority of the IPSOGSA over the GSA and PSOGSA, especially high-dimensional problems. the IPSOGSA provided 90% of the best mean values of the unimodal benchmark functions on three different dimensions, followed by the PSOGSA (10%) and the GSA (0%). These results imply that the GSA and PSOGSA suffered from premature convergence.

According to the convergence curve, the IPSOGSA always converges first to the optimal solution of the unimodal benchmark functions (Figure S1 in Supplementary Material). In addition, the IPSOGSA provided 95% of the best standard deviations on seven test functions over 30 independent runs. Since the standard deviation of the IPSOGSA in $f_1(x)$–$f_4(x)$ is 0, the other three representative results are selected to be exhibited in boxplots, and from left to right, the data distributions of the three algorithms from low-dimensional to high-dimensional are shown. The box-and-whisker diagrams illustrate that the proposed algorithm possesses the shortest distance and lowest altitude in Figure 2, while the GSA and PSOGSA have more discrete data distribution as the dimension increases. For the seven benchmark functions with dimensions 30/50/100, the IPSOGSA not only converged to the global optimal solutions, but also had stronger stability. These results indicate that the proposed algorithm is more competitive and reliable for solving unimodal benchmark functions.

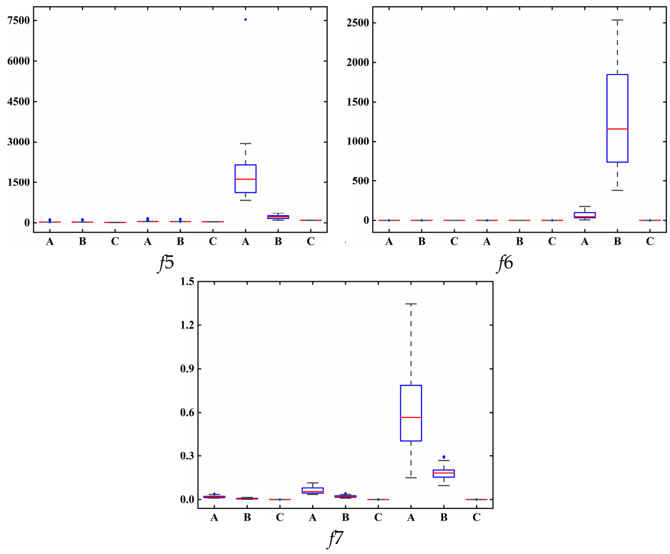

Figure 2. Boxplot graphs of optimal solutions on unimodal benchmark functions (Dim = 30/50/100, A: GSA, B: PSOGSA, C: IPSOGSA).

(2) Comparison with multimodal benchmark functions test set

The results in Table S6 (in Supplementary Materials) indicate that the IPSOGSA presented the best performance on the average results of five multimodal benchmark functions ($f_8(x)$–$f_{12}(x)$). For the multimodal benchmark functions $f_9(x)$ and $f_{11}(x)$ with dimensions 30/50/100, the IPSOGSA could also find the theoretical optimal solution of 0. For function $f_{13}(x)$, the IPSOGSA performed worse than the PSOGSA for low-dimensional problems (Dim = 30). However, with the increase in the function dimension, the advantages of the proposed algorithm appear more prominent. The IPSOGSA obtained the best mean value compared with the other two algorithms in the high dimension of function $f_{13}(x)$ (Dim = 100). In addition, the final overall ranking indicated that the IPSOGSA outperformed the GSA and PSOGSA in solving the global solution of multimodal benchmark functions in three different dimensions. The IPSOGSA obtained 89% of the best results on the mean and standard deviation of the multimodal benchmark functions. The PSOGSA was only superior to the IPSOGSA in two (11%) of the test results, while the GSA had the worst performance. According to the convergence curve, the IPSOGSA can obtain optimal results with fastest convergence velocity (Figure S2 in Supplementary Materials). The optimal results of f_8, f_{12}, and f_{13} are exhibited in boxplots (Figure 3). The box-and-whisker diagrams indicate that the IPSOGSA had a more concentrated distribution of optimal results over 30 independent runs and still performed well in high-dimensional problems. For the multimodal benchmark functions, the proposed algorithm had a higher probability of finding high-quality solutions compared to other algorithms. Evidently, the hybrid optimization scheme enhanced the exploration competence of the algorithm and prevented precocious convergence.

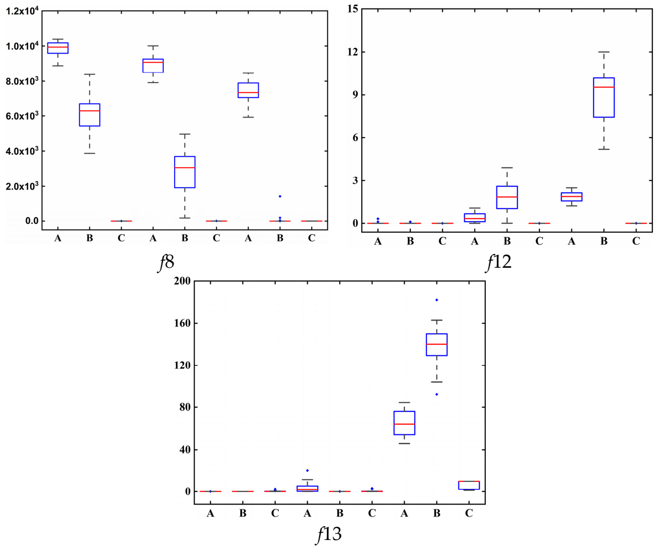

Figure 3. Boxplot graphs of optimal solutions on multimodal benchmark functions (Dim = 30/50/100, A: GSA, B: PSOGSA, C: IPSOGSA).

The above test was to assess the solution's quality and the convergence rate of three algorithms. To further evaluate the superiority of the IPSOGSA, the Wilcoxon signed-rank test with a significance level of α = 5% was applied to present the discrepancy between the three algorithms, where win (w), tie (t), and lose (l), respectively, indicate that the proposed algorithm is significantly superior, equal, and inferior to other algorithms. These statistical results of Table 2 demonstrate the superior performance of the IPSOGSA over the other algorithms. In addition, the performance of the IPSOGSA in high dimensional space shows that the improved strategy is effective and promising.

Table 2. Results of Wilcoxon signed-rank test on classical benchmark functions.

Dimension	IPSOGSA vs.	w (+)	t (=)	l (−)
30	GSA	12	0	1
	PSOGSA	11	1	1
50	GSA	12	0	1
	PSOGSA	11	0	2
100	GSA	13	0	0
	PSOGSA	13	0	0

(3) Comparison with the state-of-the-art variants

In order to measure the superiority of the proposed algorithm, we compared it with the state-of-the-art variants and novel meta-heuristic algorithm. All conclusions in this section are based on the mean results in the relevant papers (Table S7 in Supplementary Materials). For thirteen benchmark functions with 30, 50, and 100 variables, the IPSOGSA outperformed the HGSA (2021) on 7 (equal in 4 functions), 13, and 13 functions, respectively [11]. In addition, the IPSOGSA was far superior to the COGSA (2023) on f_1–f_5 and f_8–f_{12} with 30 variables [48]. Compared to a novel metaheuristic algorithm, the IPSOGSA outperformed the Chimp Optimization Algorithm (2020) on 10 high-dimensional (Dim = 100) traditional benchmark functions [49]. These findings suggest that the proposed algorithm possesses a strong exploration ability and is effective for high-dimensional (Dim = 100) traditional benchmark functions as well. The improved algorithm (IPSOGSA) significantly enhances the performance of the traditional gravitational search algorithm and demonstrates competitiveness in solving single-objective optimization problems.

2.3.2. Modern Benchmark Functions Set

(1) Comparison with CEC 2015 and CEC 2017 test sets

The CEC 2015 test set contains 2 unimodal functions, 3 simple multimodal functions, 3 hybrid functions, and 7 composition functions. The IPSOGSA and the GSA achieved best mean value on 10 and 4 functions, respectively, while the PSOGSA only performed best on F15 (Table S8 in Supplementary Materials). In addition, the IPSOGSA, respectively, outperformed the GSA and the PSOGSA on 10 and 12 test functions based on the analysis results of the Wilcoxon test and w/t/l.

According to the summary results of Table S9 (in Supplementary Materials), the IPSOGSA performed best on both the mean and standard deviation of 24 functions compared to the other two algorithms. The PSOGSA and GSA possessed better means only on 1 (F28) and 2 (F11, F28) functions than the IPSOGSA, respectively. Although the GSA slightly outperformed the IPSOGSA in standard deviations on 5 functions (F4, F7, F10, F11, F13), the latter was in the lead on the other 25 functions, with the largest gap being 10 orders of magnitude. The p-value results of the Wilcoxon test indicate the significant difference between the IPSOGSA and the two other algorithms. Over all, the IPSOGSA outperformed the other two algorithms on the mean results of 3 unimodal functions, 7 simple multimodal functions, 9 hybrid functions, and 9 composition functions. These results suggest that the proposed algorithm improves the global search ability and exploitation ability of the agent.

(2) Comparison with the state-of-the-art variants

Since the IPSOGSA is a new variant of a GSA and PSO, we compared it with up-to-date GSA and PSO variants and a novel meta-heuristic algorithm to further evaluate the performance of the proposed algorithm. All results on the CEC 2017 test set were directly obtained from relevant papers and summarized in light of the average results. Table S10 (in Supplementary Materials) orders the algorithms in terms of the final optimized mean results. The IPSOGSA outperformed all competitors on unimodal functions (F1–F3), which suggests that the proposed algorithm possesses a strong exploitation ability. According to the mean values on CEC 2017, the IPSOGSA was superior to GPSG [41], SSC [50], ESA [51], and HFPSO [52] on 18 (equal in 2 functions), 29, 21, and 30 benchmark functions, respectively. The above comparative algorithms are well-performing algorithms proposed in the last five years. For instance, the experimental results of GPSG [41] on the CEC 2017 test set outperform CSA [53], GWO [29], BSA [54], SCA [55], and PSOG [56]. These comparison results demonstrate that the improved strategies in this study are effective and reduce the possibility of algorithms falling into local extremes.

Both classical the benchmark function set and the modern benchmark function set include simple and complex functions, which are consistently applied to assess an algorithm's performance in balancing exploration and exploitation capabilities. Based on the above experimental results, it is further confirmed that the proposed algorithm enhances the global search and exploitation capabilities of the traditional gravitational search algorithm. Therefore, the proposed algorithm possesses significant potential in addressing complex optimization problems and can be employed for optimizing the performance of artificial neural networks, as well as joint scheduling issues in hydraulic structures.

3. Optimal Scheduling Model of Hydraulic Structures

3.1. Mathematical Problem Formulation

Hydraulic structure regulation (sluices and pumps) to effectively improve water quality is a multi-objective problem, including economic goals and water quality goals. In this study, water quality objectives are transformed into constraints for multi-objective decision making. We applied the improved gravitational search algorithm to minimize the economic cost and maximize the environmental benefits of water diversion projects.

3.1.1. Economic Objective

The economic goal of the optimal scheduling model can be depicted as follows:

$$Minimize\ \ EC = \sum_{i=1}^{P} U_C \gamma \frac{h_p Q_i t_i}{\eta} \tag{27}$$

where EC is the economic cost; P is the number of pumps; U_C is the unit cost; γ is the water weight; h_p is the pump head; Q_i is the flow of the i-th pump; t_i is the run time of the i-th pump; and η is the efficiency of the pump.

3.1.2. Water Quality Constraints

Water quality objectives should meet the following constraints:

$$q_j \leq q_j^s \tag{28}$$

where q_j is the concentration of the j-th pollutant; q_j^s is the upper concentration limit of the j-th pollutant.

3.1.3. Hydraulic Constraints

Hydraulic structures should meet the following constraints:

$$0 \leq Q_i \leq Q_i^{limit} \tag{29}$$

$$0 \leq t_i \leq t_i^{limit} \tag{30}$$

where Q_i^{limit} is the upper limit of flow; t_i^{limit} is the upper limit of the run time.

3.2. Water Quality Prediction Model

The intelligent scheduling model of water diversion projects includes a water environment model and an optimization model. Firstly, a process-based mechanism model was applied to simulate the change in hydrodynamic and water quality in complex basins. The application of intelligent optimization algorithms to solve dispatching problems usually involves multiple searches in the decision space to obtain the optimal solution. Water quality mechanism models coupled with optimization algorithms have the problem of complex interface processing or time-consuming multiple calls. Hence, we applied a BPNN instead of a water quality mechanism model to predict the improvement in water quality via different dispatching schemes, which is the state variable in the water quality objective function evaluation of the optimization dispatching model. Since it is easy to fall into the local extreme value during the training of the BPNN, we applied the proposed algorithm to optimize the connection weight and threshold of the BPNN. In addition, the proposed algorithm was used to solve the optimal scheduling problem of water conservancy equipment in water diversion projects.

4. Practical Application

4.1. Case Study

Jiaxing City is a plain river network area in eastern China. This plain river network is located between 30°21′ N and 31°2′ N latitude and 120°18′ E and 121°16′ E longitude. The study area covers a total area of more than 130 km^2, with 256 rivers and 52 hydraulic structures for flood control. Jiaxing City suffers from poor water quality in its rivers, owing to the stagnant water flow caused by flood control structures. Long-term practice has proved that water diversion through these structures can significantly improve the water quality of the river network. In order to maximize the economic benefit and environmental benefit, this study applied the improved gravitational search algorithm to solve the optimization problem of the joint management of sluices and pumps in water diversion projects. In this study, the IPSOGSA was applied as the optimizer. One is to optimize the weights and thresholds of the BPNN. The other is to solve the optimal dispatching problem of water diversion projects (Figure 4).

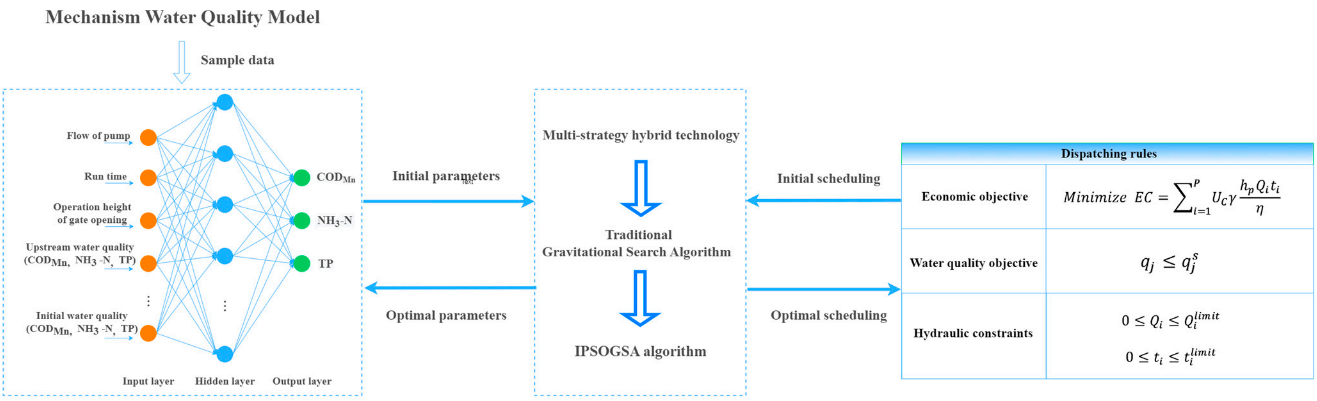

Figure 4. The framework of the optimal model.

4.2. Backpropagation Neural Network

The BPNN is a multi-layer feedforward network trained in accordance with the error backpropagation algorithm. Aimed at the problem that the BPNN can easily fall into local optima, the GA is commonly used to optimize the weights and thresholds to improve the accuracy of the BPNN. In this study, we compared the performance of the IPSOGSA, GA, and GSA to establish the optimal parameters of the BPNN. The sample data are derived from 1000 scheduling schemes simulated by the water quality mechanism model, with an accuracy of 86.7% established using the MIKE software (version 2016). The water quality prediction indicators are the chemical oxygen demand (COD_{Mn}), ammonia nitrogen (NH_3-N), and total phosphorus (TP). The sample data of three models were consistent, which was divided into a training set (900) and a test set (100). The network structure was 13-12-3. The initial interval of weights and thresholds was [−3, 3]. The max iteration was 10 and the population size was 40.

The impact of different algorithms on the performance of the BPNN was evaluated by using Equations (31) and (32). The root-mean-squared error (RMSE) and determination coefficient (R^2) of the predicted results were taken as evaluation indices to reflect the fitting degree of the BPNN in practical engineering applications. The smaller RMSE and larger R^2 mean that the model has a higher fitting degree, accuracy, and prediction ability.

$$\mathrm{RMSE}(r,\hat{r}) = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(r_i - \hat{r})^2} \tag{31}$$

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(r_i - \hat{r}_i)^2}{\sum_{i=1}^{n}(r_i - \bar{r})^2} \tag{32}$$

where r_i is the true value; $\bar{r}$ is the mean value; and $\hat{r}$ is the forecasting value.

The evaluation results of three different algorithms are shown in Table 3. All the optimal results are expressed in bold style. The IGSA-BPNN model obtained the smallest RMSE and the largest R^2 in both the training set and the test set. It is noteworthy that the R^2 values of the IGSA-BPNN model are all more than 0.95. Compared with the GA and GSA, the IGSA-BPNN model, respectively, achieved an average improvement of 1.5% and 0.9% in R^2 on the training set, and 1.1% and 1.5% on the test set. The IGSA-BPNN model led to a reduction of 18.6% and 13.1% in RMSE in the training set, and 13.3% and 19.7% in the test set. In addition, the IGSA-BPNN model does not suffer from overfitting or underfitting problems. These findings verified that the IGSA-BPNN model is the best model for water quality prediction.

Table 3. Evaluation results of three neural network models.

Phase	Indicators	GA		GSA		IGSA	
		RMSE	R^2	RMSE	R^2	RMSE	R^2
Training phase	COD_{Mn}	0.591	0.961	0.582	0.962	**0.472**	**0.975**
	NH_3-N	0.075	0.969	0.073	0.971	**0.058**	**0.981**
	TP	0.023	0.933	0.020	0.946	**0.020**	**0.950**
Test phase	COD_{Mn}	0.496	0.971	0.572	0.962	**0.463**	**0.975**
	NH_3-N	0.080	0.966	0.087	0.960	**0.066**	**0.976**
	TP	0.019	0.950	0.019	0.954	**0.016**	**0.967**

4.3. Optimal Operation Scheduling of Water Diversion Project

The water diversion project diverts water from the southwest and drains from the northeast. According to government requirements, water quality should meet the Class III environmental quality standards for surface water of China (Table S11 in Supplementary Materials). This study focused on a provincial control cross-section located in the northeast direction to determine the optimal joint management of hydraulic structures. To give evidence of the applicability and efficiency of the proposed algorithm, we compared it to traditional algorithms on different scenarios. The IGSA-BPNN model was used to replace the MIKE 11 model to predict the effect of water quality improvement on diversion schemes.

The maximum flow rates of pump 1 (P1), pump 2 (P2), and pump 3 (P3) are 72 m^3/s, 60 m^3/s, and 36 m^3/s, respectively (Figure 5). The maximum operation time of the pumps is 180 h. The operation height of the gate was [0.3, 1.5] (unit: meters). Five scenarios are depicted in Table 4. The initial target water quality in scenario 1 and scenario 2 is the same, and the upstream water quality in scenario 2 is better than that in scenario 1. The upstream water quality of scenario 2 and scenario 3 is the same, and the initial target water quality in scenario 3 is better than that in scenario 2. The target water quality in scenario 4 meets the Class III environmental quality standards for surface water. The target water quality in scenario 5 is better than the upstream water quality.

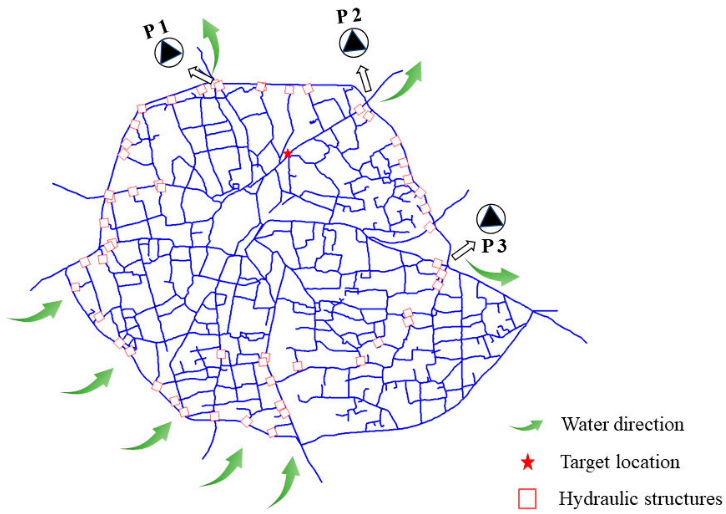

Figure 5. Schematic diagram of river network.

Under the condition of a consistent h_p and η of the pump, the economic cost of a water diversion project mainly depends on the water flow rate and the operation time. In scenarios 4 and 5, when the target water quality meets Class III of the environmental quality standards or is better than the upstream water quality, there is no scheduling required. In the other three scenarios, the proposed algorithm obtained the operation scheme with the minimum economic cost when the river water quality of Jiaxing city met the national standard. From scenario 1 to scenario 3, the operating cost of the optimal scheduling scheme gradually decreased, which indicates that the better the upstream water quality and the initial water quality, the less the demand for the scheduling of hydraulic structures. From the optimal scheme obtained by the IPSOGSA in Table 5, it can be concluded that the water quality of the provincial control section is mainly affected by the operation time and flow rate of pump 2, which is consistent with the actual situation. While in scenario 3, the optimal solution obtained by the GSA chooses to run pump 3 for a long time, which leads to an increase in the operating cost. Compared with the optimal plan of the GSA, the IPSOGSA reduces the economic cost by 69%, 66%, and 46% in scenarios 1 to 3, respectively. These results show that the proposed model provided the optimal operation schemes with the lowest cost of hydraulic structures to achieve the water quality objectives in water diversion projects.

Table 4. Scenario list.

Scenario Number	Description: Water Quality (mg/L)
S1	Upstream: COD_{Mn}:5; NH_3-N:0.75; TP:0.15 Initial: COD_{Mn}:15; NH_3-N:2.0; TP:0.4
S2	Upstream: COD_{Mn}:4; NH_3-N:0.5; TP:0.1 Initial: COD_{Mn}:15; NH_3-N:2.0; TP:0.4
S3	Upstream: COD_{Mn}:4; NH_3-N:0.5; TP:0.1 Initial: COD_{Mn}:10; NH_3-N:1.5; TP:0.3
S4	Upstream: COD_{Mn}:4; NH_3-N:0.5; TP:0.1 Initial: COD_{Mn}:6; NH_3-N:1.0; TP:0.2
S5	Upstream: COD_{Mn}:6; NH_3-N:1.3; TP:0.25 Initial: COD_{Mn}:6; NH_3-N:1.2; TP:0.25

Table 5. The optimal dispatching program of two algorithms on five scenarios.

Scenario Number	Algorithm	Height of Gate (m)	Flow (m^3/s)			Run Time (h)			Economic Cost ($\sum_{i=1}^{P} Q_i t_i$)
			P1	P2	P3	P1	P2	P3	
S1	GSA	1.4	0	36	24	0	170	34	2.50×10^7
	IPSOGSA	1.4	12	12	24	5	173	1	7.78×10^6
S2	GSA	0.7	72	12	12	45	177	53	2.16×10^7
	IPSOGSA	1.4	12	12	0	3	167	0	7.34×10^6
S3	GSA	1.2	12	0	12	104	0	145	1.08×10^7
	IPSOGSA	1.2	0	12	12	0	132	4	5.88×10^6
S4	No scheduling required								
S5	No scheduling required								

5. Conclusions

This paper proposed an improved gravitational search algorithm based on a multi-strategy hybrid optimization technique. The comparison experiments of the GSA, PSO, and IPSOGSA on traditional benchmark test functions and a modern benchmark test set established the superiority of the presented algorithm. We applied the improved algorithm to solve the problem of the optimal joint management of hydraulic structures in water diversion projects. The focus of this paper is to provide desirable environmental benefits while minimizing economic costs. In order to reduce the computational cost caused by the repeated invocation of water quality mechanism models in the optimization process, an artificial neural network was applied to replace the complex water quality mechanism model to predict the improvement degree of water quality under different scheduling schemes. Then, we integrated this algorithm with a backpropagation neural network to create an intelligent optimal scheduling model. Compared to other algorithms, the BPNN optimized by the IPSOGSA obtained smaller RMSE and higher R^2 values. The optimal scheduling model provided the optimal and feasible operation scheme under various scenarios for the multi-objective regulation problem of the Jiaxing water diversion project. These results show that the established intelligent scheduling model has good reliability and application prospects. The intelligent scheduling model can be applied to assist decision-makers in selecting the most efficient operation plan. This method can be extended to similar areas and used to develop operation strategies of water diversion projects for regional water quality improvement.

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