A two-layer improved invasive weed optimization algorithm for optimal operation of cascade reservoirs

Guo-hua Fang, Cheng-jun Wu, Tao Liao, Xian-feng Huang and Bo Qu

ABSTRACT

This paper proposes a two-layer improved invasive weed optimization (TIIWO) algorithm to overcome the disadvantages of the low quality of its initial population and the low optimization performance of IWO. The TIIWO algorithm includes dynamic corridor constraints (in its outer layer) and iterative reciprocating optimization (in its inner layer). The convergence of the TIIWO algorithm is achieved by minimizing the Schaffer function, which is characterized by its strong oscillatory behavior.

In addition, the sensitivity of the main TIIWO parameters is analyzed using two methods, namely the revised Morris scheme and the Sobol index method. For experimental assessment, the TIIWO algorithm is firstly applied to a single reservoir. We investigate how the algorithm convergence is affected by four algorithm variants and parameter values. Then, the TIIWO algorithm is used to solve the problem of the optimal operation of cascade reservoirs. The results show that the TIIWO algorithm quickly and efficiently reaches the optimal operation of cascade reservoirs. In addition, this algorithm exhibits superior performance for high-dimensional, nonlinear and multi-constraint problems.

Key words | algorithm, convergence analysis, invasive weed optimization, reservoir optimal operation, sensitivity analysis

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INTRODUCTION

Reservoir optimal operation is a high-dimensional, non-linear and multi-constraint problem. Solutions to this problem are of great significance since they help alleviate water resource shortage and increase water usage efficiency. Also, the optimal operation of reservoirs for power generation is an extremely effective measure to fulfill the commitments of the Paris Agreement, adjust the energy structure, produce clean and renewable energy, and reduce greenhouse gas emissions (Bodansky *et al.* 2016).

Classical and intelligent optimization techniques have been proposed for achieving optimal reservoir operation (Ji *et al.* 2013). Classical optimization methods include those of large-scale system analysis (Tian & Xie 1998), linear programming (LP) (Needham *et al.* 2000), and non-linear programming (NLP) (Peng & Buras 2000). A prominent method of classical optimization is the dynamic programming (DP) algorithm, which was applied by Little in 1955 to optimize reservoir operation (Little 1955). Subsequently, improved DP algorithms were extensively applied in the optimization of reservoir operation. Those algorithms include the discrete differential dynamic programming (DDDP) (Heidari *et al.* 1971), dynamic programming with successive approximation (DPSA) (Recep *et al.* 2006) and progressive optimality algorithm (POA) (Howson & Sancho 1975). However, classical optimization methods for reservoir operation suffer from low efficiency and can only converge to local rather than global minima. Moreover, the utility of these methods diminishes with the increase in the number of state variables, as these methods become prone to the curse of dimensionality (Guo *et al.* 2010).

With the rapid development of computer technology, intelligent optimization algorithms have been developed to

overcome the shortcomings of classical optimization methods in solving various reservoir operation problems. Some of the widely used intelligent algorithms are particle swarm optimization (PSO) (Kennedy & Eberhart 2002), genetic algorithms (GA) (Chen & Chang 2007), and ant colony algorithm (ACO) (Moeini & Afshar 2009). Although these intelligent algorithms have high rates of convergence, they still can get trapped in local optima. So, it is necessary to explore new intelligent algorithms or improve existing algorithms for the optimization of reservoir operation.

The invasive weed optimization (IWO) algorithm is a new population-based numerical heuristic search algorithm (Mehrabian & Lucas 2006). This algorithm is inspired by the reproduction process of weeds in nature. In recent years, the IWO algorithm has been applied in many fields due to its simplicity and good performance. These fields include design of antenna arrays (Roy *et al.* 2011), large-scale economic problems (Barisal & Prusty 2015), digital terrain model extraction problems (Bigdeli *et al.* 2018), and robot motion planning problems (Panda *et al.* 2018). Unfortunately, there are only few studies on the application of the IWO algorithm in water resource management. Asgari *et al.* (2015) were the first to apply the IWO algorithm to water supply operation in reservoirs. They compared the results of the IWO algorithm with those obtained by the LP, NLP and GA algorithms, and concluded that the IWO algorithm efficiently optimizes the reservoir water supply operation. Later, the IWO algorithm was applied to reservoir hydropower stations by Azizipour *et al.* (2016). The results of the IWO algorithm were compared with those of the PSO and GA algorithms. The comparison indicated that IWO is more effective in solving large-scale problems.

Invasive weed optimization has been applied in many fields, and can be used in global and local optimization. However, depending on the IWO variance selection method, the IWO algorithm might still easily get stuck in a local optimum while solving large multi-constraint optimization problems (Manoharan *et al.* 2017). To overcome this problem, this paper proposes a two-layer improved invasive weed optimization (TIIWO) algorithm. The TIIWO algorithm includes dynamic corridor constraints (in the outer layer) and iterative reciprocating optimization (in the inner layer). The Schaffer function with strong oscillations is used to analyze the convergence of the TIIWO algorithm. The sensitivity of the main TIIWO parameters is analyzed using two sensitivity analysis methods, namely the revised Morris scheme and the Sobol index method. Based on the single-reservoir optimal operation model, we also analyze the influence of the TIIWO parameter values and implementation variants on the optimization results. Based on the TIIWO results for single-reservoir optimal operation, the application of TIIWO in cascade reservoir joint optimal operation is studied.

The remainder of this paper is organized as follows. The next section outlines the cascade reservoir optimal operation model firstly, and then introduces the two-layer improved invasive weed optimization (TIIWO) algorithm, explores the convergence of the TIIWO thirdly, utilizes the TIIWO algorithm to optimize the reservoir operation model fourthly. Subsequently, TIIWO sensitivity and optimal parameter set are analyzed. Case studies are presented next, followed by is the presentation and discussion of results, and conclusion of the paper.

CASCADE RESERVOIR OPTIMAL OPERATION METHOD

In cascade reservoir systems, each reservoir may have specific tasks and storage capacity. Also, the water demand of each system unit should be met. Based on these considerations, the power generation and the flood control benefit are generally formulated as single-objective or multi-objective functions. The control of such objective functions is realized by changing the cascade reservoir operation rules.

Cascade reservoir optimal operation model

In this paper, the mathematical optimization model of the cascade reservoir operation is based on the maximization of the generated power, which serves as the objective function, mathematically defined as

$$E_c = \sum_{i=1}^{Num} \sum_{t=1}^{T} k_i \cdot Q_{e,i,t} \cdot h_{i,t} \cdot \Delta t \tag{1}$$

where E_c is the power generated by the cascade reservoir hydroelectric plants (kW·h), Num is the number of cascade reservoirs in the system, T is the number of periods, k_i is the efficiency coefficient of the i-th hydroelectric plant, $Q_{e,i,t}$ and $h_{i,t}$ are the power generation flow (m³/s) and the effective head (m) of the i-th hydroelectric plant at period t, respectively, Δt is the number of hours at period t (h).

Subject to the following constraints

$$Q_{in,t}^i = Q_{r,t}^{i-1} + Q_{itv,t}^{i\sim i-1} \quad t = 1, 2, \cdots, T \tag{2}$$

$$V_{t+1}^i = V_t^i + (Q_{in,t}^i - Q_{r,t}^i) \cdot \Delta t \quad t = 1, 2, \cdots, T \tag{3}$$

$$Q_{r,i,t}^{\min} \le Q_{r,t}^i \le Q_{r,i,t}^{\max} \quad t = 1, 2, \cdots, T \tag{4}$$

$$Z_{i,t}^{\min} \le Z_t^i \le Z_{i,t}^{\max} \quad t = 1, 2, \cdots, T+1 \tag{5}$$

$$N_{i,t}^{\min} \le N_t^i \le N_{i,t}^{\max} \quad t = 1, 2, \cdots, T \tag{6}$$

where $Q_{in,t}^i$ and $Q_{r,t}^i$ are, respectively, the inflow and water release of the i-th reservoir at period t (m³/s), $Q_{r,t}^{i-1}$ is the water release of the $(i-1)$-st reservoir at period t (m³/s), $Q_{itv,t}^{i\sim i-1}$ is the interval inflow between the i-th reservoir and the $(i-1)$-th reservoir (m³/s), V_{t+1}^i and V_t^i are, respectively, the water storage of the i-th reservoir at period $t+1$ and period t (m³), $Q_{r,i,t}^{min}$ and $Q_{r,i,t}^{max}$ are, respectively, the minimum and the maximum water release of the i-th reservoir at period t (m³/s), $Z_{i,t}^{min}$ and $Z_{i,t}^{max}$ (m) are, respectively, the minimum and the maximum water levels of the i-th reservoir at period t, $N_{i,t}^{min}$ and $N_{i,t}^{max}$ (MW) are, respectively, the minimum power output and the installed capacity of the i-th hydroelectric plant at period t.

Two-layer improved invasive weed optimization (TIIWO) algorithm

According to the rule of the s-shaped curve (Rogers 1962) for biological populations under environmental resistance, the IWO algorithm realizes evolution using an initial population, reproduction, spatial dispersal and competitive exclusion (Azizipour *et al.* 2016). The reproduction and spatial dispersal are calculated in Equations (7) and

(8) as

$$Seed(i) = \text{int}\left\{\frac{F(i) - F_{\min}}{F_{\max} - F_{\min}} \cdot (Seed_{\max} - Seed_{\min}) + Seed_{\min}\right\} \tag{7}$$

$$\sigma_{iter} = \sigma_{fin} + \left(\frac{iter_{\max} - iter}{iter_{\max}}\right)^w (\sigma_{ini} - \sigma_{fin}) \tag{8}$$

where $Seed(i)$ is the number of seeds reproduced by the i-th parent weed, $int(X)$ is the integer function expressing the integer part of the real number X (i.e. the largest integer smaller than X), $F(i)$ is the individual fitness value of the i-th parent weed, F_{max} and F_{min} are, respectively, the maximum and the minimum fitness values of the parent population, $Seed_{max}$ and $Seed_{mi}$ are the maximum and minimum number of seeds that can be reproduced by weed, respectively, σ_{iter} is the standard deviation of the current iteration, σ_{fin} and σ_{ini} are the final and initial standard deviation, respectively, $iter_{max}$ is the maximum number of iterations, $iter$ is the current iteration, and w is the predetermined nonlinear modulation index.

When the IWO algorithm is used to solve the reservoir optimal operation problem, the initial population is typically poor in quality and easily falls into a local optimum. Therefore, the TIIWO algorithm is proposed in this paper to find the optimal cascade reservoir operation model.

In order to increase the quality of the IWO initial population, we propose a method by which we make a step-by-step reduction of the dimensionality and the stochastic corridor of the initial range. By analyzing the reservoir inflow and water release constraints in each period, we make a step-by-step dynamic adjustment of the initial random corridor range in the IWO algorithm to improve the quality of the initial population (Outer Layer). Taking the first and second periods as example, these constraints can be represented as shown in Figure 1.

Figure 1 presents a schematic diagram of the dynamic corridor constraints. Here, *R1* and *R2* are, respectively, the theoretical water level ranges that can be initialized randomly at time 2 and time 3, *Z1, Z2* and *Z3, Z4* are, respectively, the maximum and minimum water levels corresponding to the minimum and maximum water release at time 2 and time 3, Z_t^{up} is the maximum water level of the
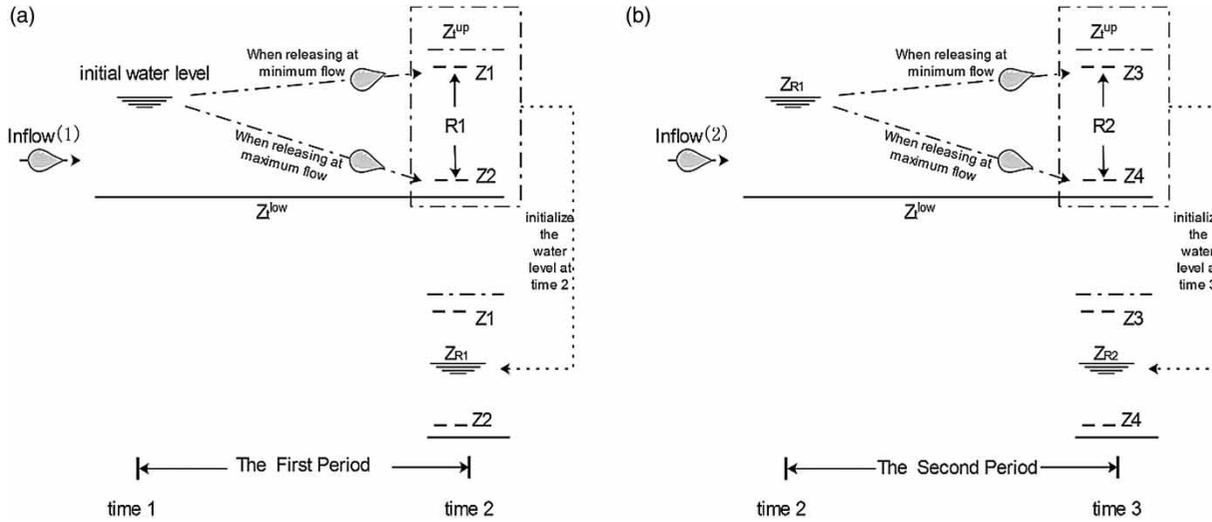
Figure 1 | Schematic diagram of the dynamic corridor constraints; (a) and (b) are the change process of corridor during the first and second periods, respectively.

reservoir under normal operation at period t (this is set to the flood control level in the flood season, and the normal water level in the non-flood season), Z_t^{low} is the dead-water level, Z_{R1} and Z_{R2} are, respectively, the water level after random initialization at time 2 and time 3.

Based on Figure 1, the formulas of the dynamic corridor constraints are given as

$$Z_{up}(t) = min\{Z_t^{up}, Z_1(t) = f[V_1(t)]\} \tag{9}$$

$$Z_{low}(t) = \max\{Z_t^{low}, Z_2(t) = f[V_2(t)]\} \tag{10}$$

$$V_1(t) = \hat{V}(t-1) + q(t) \times \Delta t - Q_1(t) \times \Delta t \tag{11}$$

$$V_2(t) = \hat{V}(t-1) + q(t) \times \Delta t - Q_2(t) \times \Delta t \tag{12}$$

$$\hat{Z}(t) = Rnd \times [Z_{up}(t) - Z_{low}(t)] + Z_{low}(t) \tag{13}$$

$$\hat{V}(t) = f^{-1}[\hat{Z}(t)] \tag{14}$$

where $Z_1(t)$ and $Z_2(t)$ are, respectively, the water levels of the reservoir at the end of period t under the conditions of $Q_1(t)$ and $Q_2(t)$, $V_1(t)$ and $V_2(t)$ are, respectively, the water storage values of the reservoir at the end of period t under the conditions of $Q_1(t)$ and $Q_2(t)$, $Q_1(t)$ and $Q_2(t)$ are, respectively, the minimum and maximum water release values of the reservoir at period t on the premise of ensuring the downstream water demand, $q(t)$ is the inflow at period t, $Z_{up}(t)$ and $Z_{low}(t)$ are, respectively, the upper and lower

bounds of the corridor water levels at the end of period t, $\hat{Z}(t)$ and $\hat{V}(t)$ are, respectively, the real vectors of the water level and water storage of the initial population at the end of period t, f is the water level of the reservoir as a function of the water storage, Rnd is a continuous random variable that follows a uniform distribution on the interval [0, 1], and $Z_1(0) = Z_2(0)$, $Z_1(T) = Z_2(T)$ are the starting and ending water levels, respectively.

To reduce the possibility of the IWO getting stuck in into local optima, Equation (8) is modified into a periodic cosine-based relation (Inner Layer), namely

$$\sigma_{iter} = \sigma_{fin} + \cos^2\left(\frac{iter}{iter_{max}} \cdot \frac{(2n+1)\pi}{2}\right)(\sigma_{ini} - \sigma_{fin}) \quad n = 1, 2, \cdots. \tag{15}$$

The standard IWO algorithm employing Equation (8) has a 'global-local' optimization mechanism. By comparison, the modified IWO algorithm employing Equation (15) is characterized by the repetitive 'global–local' behavior. This modified IWO algorithm produces iterative reciprocating optimization rather than the standard optimization. The modified algorithm should have better performance, since it breaks through the constraint of local optimization, and achieves global optimization more easily.

TIIWO convergence analysis

We examine the convergence of TIIWO by using the Schaffer function (shown as Equation (16)). This function is a two-dimensional complex function with numerous minimum points. Its minimum value of 0 is obtained at (0, 0). The function has a strong oscillatory behavior, and it is difficult to find its global optimal value. The TIIWO is used to find the minima of the Schaffer function.

$$\min f(x_1, x_2) = 0.5 + \frac{\left(sin\sqrt{x_1^2 + x_2^2}\right)^2 - 0.5}{\left(1 + 0.001(x_1^2 + x_2^2)\right)^2}, \quad (16)$$
$$x_1, x_2 \in [-200, 200]$$

The TIIWO parameter values are as follows: the initial population (represented by M_{ini}) is 30, the maximum population (represented by M_{fin}) is 50, $Seed_{max} = 5$, $Seed_{min} = 2$, $iter_{max} = 100$, $\sigma_{ini} = 10$ and $\sigma_{fin} = 0.0001$, and the parameter n in Equation (15) is 1. The optimization results are shown in Figure 2.

This figure shows that, in the early stage of the optimization process, the algorithm can quickly converge to a value close to the optimal value. In the middle and late optimization stages, although the algorithm converges to a certain local optimal solution repeatedly in different iteration periods, it can escape the local optima and gradually reach the global optimum in the subsequent iterations based on Equation (15).

TIIWO-based optimization of the reservoir operation model

According to the established mathematical model of the cascade reservoir operation and the TIIWO algorithm, the optimal reservoir operation model can be obtained as follows.

Step 1, **Initialize a population:** Each TIIWO parameter is set to a specific initial value. Each weed in the population represents a reservoir scheduling process line. The water levels at the beginning and end of each period constitute the feature vector of each weed. The weed positions in the initial population are randomly initialized with dynamic corridor constraints. The fitness of each weed in the population is evaluated with the maximum power generation as the objective function.
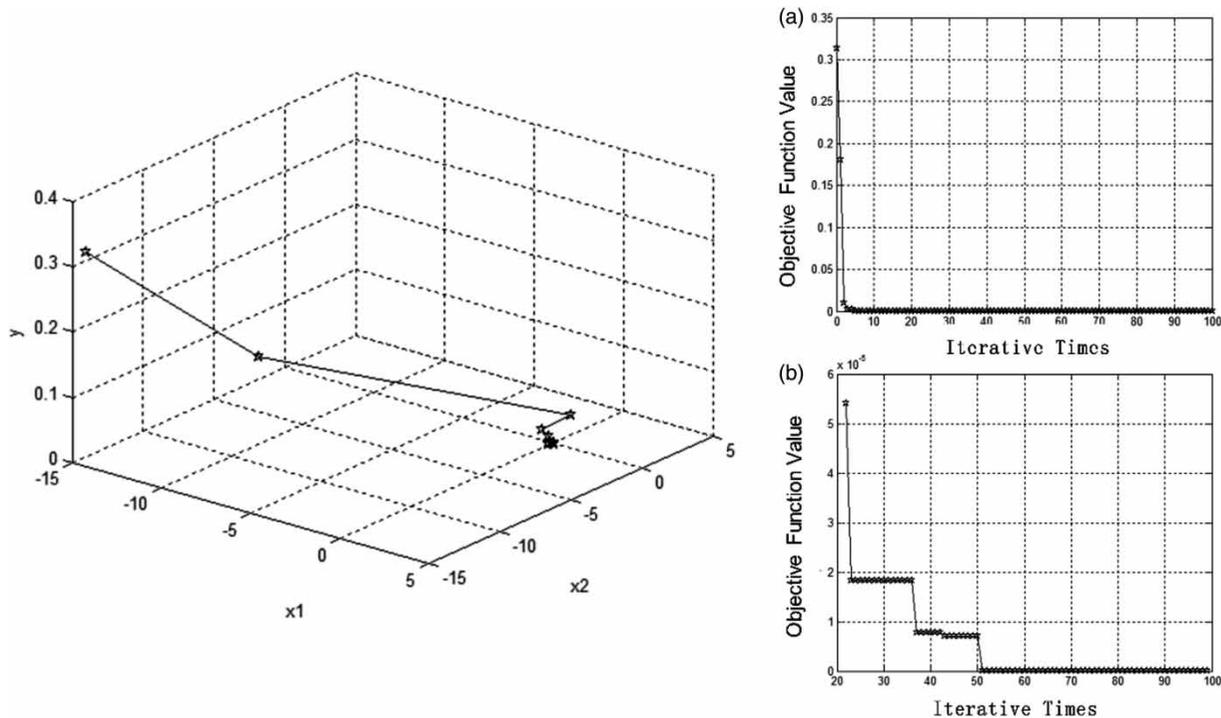

Figure 2 │ Three-dimensional diagram of the Schaffer function optimization process: (a) the overall change of the objective function value over the iterations 1–100; (b) the local change of the objective function value over the iterations 21–100.

Step 2, Reproduction: The maximum and minimum fitness values of the parent population are compared and determined. The number of seeds reproduced by each parent weed is calculated according to Equation (7) and the fitness value of the parent weed.

Step 3, Spatial dispersal: The standard deviation of the current iteration σ_{iter} is calculated according to Equation (15). Seeds are randomly distributed around the parent value according to a Gaussian distribution. The seed positions are given by

$$X_{i,s} = X_i + N(0, \sigma_{iter}^2) \tag{17}$$

where X_i is the position of the *i*-th parent weed, $X_{i,s}$ is the position of the *s*-th seed reproduced by the *i*-th parent weed, and $N(0, _{iter}^2)$ is a normal distribution with a zero mean and a standard deviation of σ_{iter}.

Suppose ξ represents the corresponding Gaussian random variable in an iteration, that is, $\xi = N(0, _{iter}^2)$. Then, ξ can be taken as a Gaussian scalar or a Gaussian diagonal matrix, respectively, representing two different variants of the TIIWO algorithm. If ξ is a Gaussian scalar, each dimension of the seeds will use the same random variables

in the process of spatial dispersal. This is an isotropic realization of the TIIWO algorithm. Under this isotropy condition, the TIIWO algorithm implementation includes the cases of Gaussian scalars based on iterations (denoted by I in Figure 3), Gaussian scalars based on parent weeds (denoted by II in Figure 3) and Gaussian scalars based on a single seed (denoted by III in Figure 3). If ξ is Gaussian diagonal matrix (a case denoted by IV in Figure 3), that is, $\xi = diag\{\xi_1, \xi_2, \cdots, \xi_D\}$ (D is the dimension, $D = T$), then the seeds use independent random variables in each dimension, leading to an anisotropic TIIWO realization. In theory, anisotropy can increase the population diversity and lead to better convergence. The pseudo-codes of the Gaussian scalar and Gaussian diagonal matrix TIIWO variants are shown in Figure 3.

Step 4, Competitive exclusion: When the population reaches or exceeds M_{fin} after reproduction, weeds should be ordered by the individual fitness values from the largest to the smallest. The M_{fin} weeds with the largest fitness values shall be retained for subsequent evolution. The remaining individuals with smaller fitness values are eliminated.

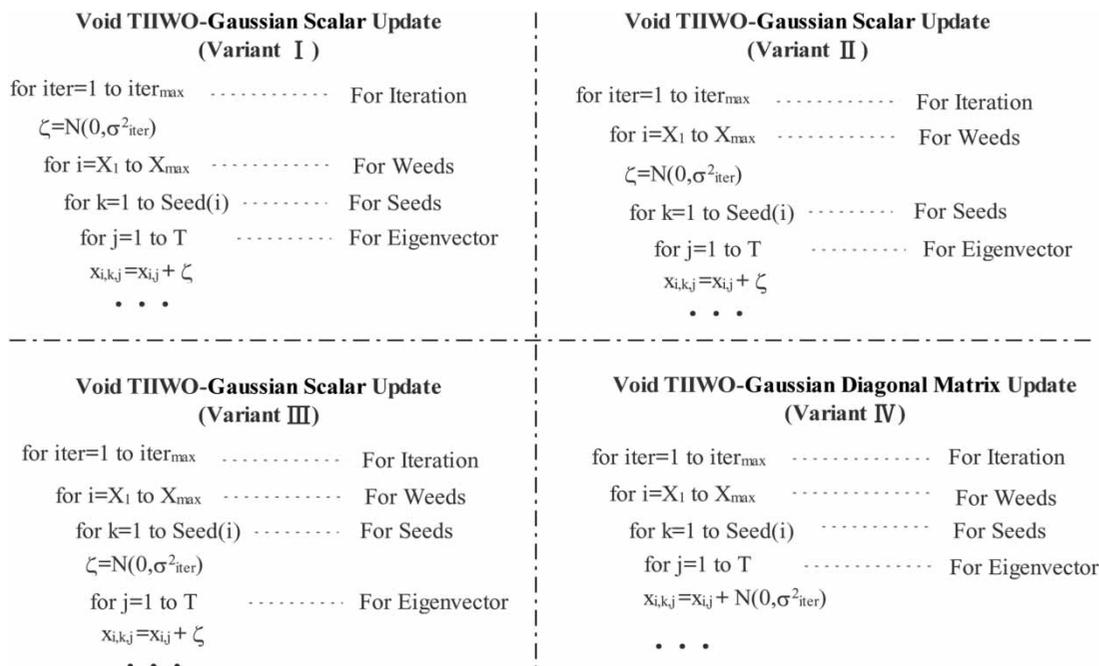**Step 5, Program termination:** Judge whether the current iteration number reaches the maximum iteration

Figure 3 │ The pseudo-codes of the Gaussian scalar and Gaussian diagonal matrix variants of the TIIWO algorithm.

number. If iter $\geq$ iter$_{max}$, terminate the iterative procedure and output the optimal result. Otherwise, return to Step 2 and continue the iterative evolution.

TIIWO SENSITIVITY ANALYSIS AND OPTIMAL PARAMETER SET

TIIWO sensitivity analysis

In order to assess the sensitivity of each TIIWO parameter and provide reference parameter values in practical applications, this paper uses the modified Morris method (Bailey & Ahmadi 2014) and the Sobol method (Baroni et al. 2018) to perform, respectively, local and global sensitivity analyses of the TIIWO parameters.

For global sensitivity analysis of the TIIWO parameters with the Sobol method, 100 samples are randomly generated, the total effect index (S_T) is taken as the main basis, and the first-order effect index (S) is used as a reference. When using the modified Morris local sensitivity analysis method, the nominal values of the TIIWO parameters, refer to other relevant literatures (Mehrabian & Lucas 2006; Naidu & Ojha 2018), are set as follows: $M_{ini} = 30$, $M_{fin} = 80$, $Seed_{max} = 8$, $Seed_{min} = 4$, $\sigma_{ini} = 10$ and $\sigma_{fin} = 0.001$, the greatest range, refer to (Yuan et al. 2019), is 30%, and the fixed step size is 5%, $iter_{max} = 100$.

In order to reduce the error caused by the change of the independent variables of the Schaffer function, the TIIWO algorithm is used to calculate each parameter value 30 times, and the average value of the resulting 30 objective function values is taken as the optimized objective function value. The modified Morris method and the Sobol method were run three times, respectively, and the results are shown in Table 1.

In the modified Morris method, the greater the absolute value of each parameter, the higher the sensitivity. In the Sobol method, the greater the calculation result of each parameter, the higher the parameter sensitivity. As shown in Table 1, according to the three calculation results and its average of absolute values of the modified Morris method, each TIIWO parameter exhibits some appreciable amount of sensitivity, and the parameters are sorted from large to small in order of sensitivity: $\sigma_{fin} > \sigma_{ini} > M_{ini} > Seed_{max} > M_{fin} > Seed_{min}$. According to the three-time calculation results and its average results of the Sobol method, the sensitivity of each parameter is shown as $\sigma_{fin} > \sigma_{ini} > M_{ini} > Seed_{max} > Seed_{min} > M_{fin}$.

By comparing and analyzing the results of the modified Morris and Sobol methods, the conclusions drawn from the two sensitivity analysis methods are basically the same. This observation provides a certain theoretical basis for the TIIWO parameter values in the reservoir optimal operation problem. Specifically speaking, in analyzing the effect of

Table 1 │ Sensitivity analysis results of the modified Morris and Sobol methods

Number of runs	Sensitivity analysis method		M_{ini}	M_{fin}	$Seed_{max}$	$Seed_{min}$	σ_{ini}	σ_{fin}
①	Modified Morris		−3.02	−1.75	−2.71	0.31	−2.71	−3.07
②			1.72	0.49	−0.29	−2.74	2.05	4.69
③			−2.16	−2.24	−2.98	−1.19	−2.98	−2.63
Average of absolute values			2.30	1.49	1.99	1.41	2.58	3.46
①	Sobol	S	0.15	0.03	0.17	0.04	0.25	0.58
		S_T	0.60	0.57	0.92	0.42	1.05	2.52
②		S	0.02	0.02	0.09	−0.06	0.04	0.17
		S_T	0.65	0.58	0.52	0.57	0.79	0.68
③		S	0.05	0.02	0.01	0.01	0.07	0.26
		S_T	0.90	0.46	0.45	0.72	1.97	1.22
Average		S	0.07	0.02	0.09	0.00	0.12	0.34
		S_T	0.72	0.54	0.63	0.57	1.27	1.47

parameter setting in TIIWO on the efficiency of the reservoir optimal operation model, the parameters with high sensitivity are transformed by a large margin, and the parameters with low sensitivity are transformed by a small margin. And then the best parameter set of TIIWO in reservoir optimal operation application is determined according to the solution efficiency (including calculation result and time cost).

TIIWO optimal parameter set for reservoir operation

We consider here a case study of a single-reservoir operation with hydropower utilization (Huang 2001). Its characteristic parameters are shown in Table 2.

For the reservoir operation model, the generated power is used as the objective function (to be maximized).

Based on the aforementioned TIIWO algorithmic steps for optimizing the reservoir operation model, this single-reservoir example is solved separately for each TIIWO variant. The simulations are run in a Visual Basic 6.0 programming platform on an Intel(R) Xeon(R) machine with a E5620 CPU @2.40 GHz, RAM of 4.00GB, and a 64-bit operating system.

Table 2 │ Characteristic parameters of the single reservoir

Name	Value	Name	Value
Normal water level (m)	704	Flood control level (m)	695
Dead water level (m)	685	Guaranteed output (MW)	78
Installed capacity (MW)	300	Efficiency coefficient	8.5
Flood season	6–8		

Note: (m) in this paper represents the elevation above sea level.

According to the abovementioned sensitivity analysis of the TIIWO parameters, in order to get the best TIIWO parameter values for optimal reservoir operation, the operation model is obtained respectively by transforming the key TIIWO parameters. The value of the parameter n in Equation (15) is 1 and $iter_{max,} = 200$. The values of the remaining parameters constitute eight kinds of parameter sets and are numbered from a to h respectively in Table 3.

For four different TIIWO variants and eight parameter settings, we repeated the calculations 30 times. The mean value, variance and running time of each calculated power generation result are shown in Table 4, where the time is the total time of the program running 30 times. The maximum operating results in each case are shown in Figure 4.

Table 4 shows the following. (1) From the columns of the average power generation, compared with the TIIWO variants II, III and IV, the power generation calculated by the variant I is lower, that is, the results based on the parent Gaussian scalar, the single-seed Gaussian scalar, and the Gaussian diagonal matrix are better than those results based on the iterations of the Gaussian scalar. (2) The variances of III and IV are generally smaller than those of I and II, that is, the operation results of III and IV are more stable than I and II, and the TIIWO variants III and IV can generally converge to a better solution. (3) The program running times increase from I to IV. Meanwhile, most program running times of I are under 1 s, while the running times of IV exceed 1 s and the highest time is 58 s. The reason for this is that in I, ξ (i.e. Gaussian random variable) calculates $iter_{max}$ times, while II is ΣX_i times of I, III is $\Sigma Seed(i)$ times of II, and IV is T times of

Table 3 │ Comparison of the key TIIWO parameters

Parameters	Parameter set a	b	c	d	e	f	g	h
M_{ini}	30	50	30	30	30	30	30	30
M_{fin}	100	200	100	100	100	100	100	100
$Seed_{max}$	5	5	10	5	5	10	10	5
$Seed_{min}$	2	2	5	2	2	5	5	2
σ_{ini}	2	2	2	5	10	5	10	10
σ_{fin}	0.001	0.001	0.001	0.001	0.01	0.01	0.001	0.001

Table 4 │ Operating results for different TIIWO algorithmic variants

Parameter set	I E_ave(10⁸kw·h)	Variance	Time(s)	II E_ave(10⁸kw·h)	Variance	Time(s)
a	14.87	0.0887	11.18	15.42	0.0315	47.02
b	15.08	0.1107	34.20	15.50	0.0061	187.19
c	14.90	0.0930	14.63	15.42	0.0292	149.01
d	15.21	0.1718	10.80	15.49	0.0132	42.14
e	15.28	0.1226	10.44	15.48	0.0129	24.18
f	15.27	0.0729	19.36	15.48	0.0206	105.74
g	15.19	0.1343	22.95	15.46	0.0214	89.00
h	14.69	0.0714	8.34	15.26	0.0639	82.93

| Parameter set	III E_ave(10⁸kw·h)	Variance	Time(s)	IV E_ave(10⁸kw·h)	Variance	Time(s)
a	15.41	0.0329	67.04	15.49	0.0094	325.42
b	15.53	0.0001	292.48	15.49	0.0224	1411.41
c	15.49	0.0131	217.53	15.50	0.0118	921.19
d	15.54	0.0001	49.80	15.29	0.0084	95.63
e	15.53	0.0024	23.99	15.25	0.0078	25.32
f	15.54	0.0001	210.37	15.43	0.0046	367.96
g	15.54	0.0000	187.48	15.33	0.0027	191.09
h	15.38	0.0414	102.33	15.48	0.0156	1,726.90

Note: I E_ave, II E_ave, III E_ave, IV E_ave columns express values in units of 10^8 kw·h.
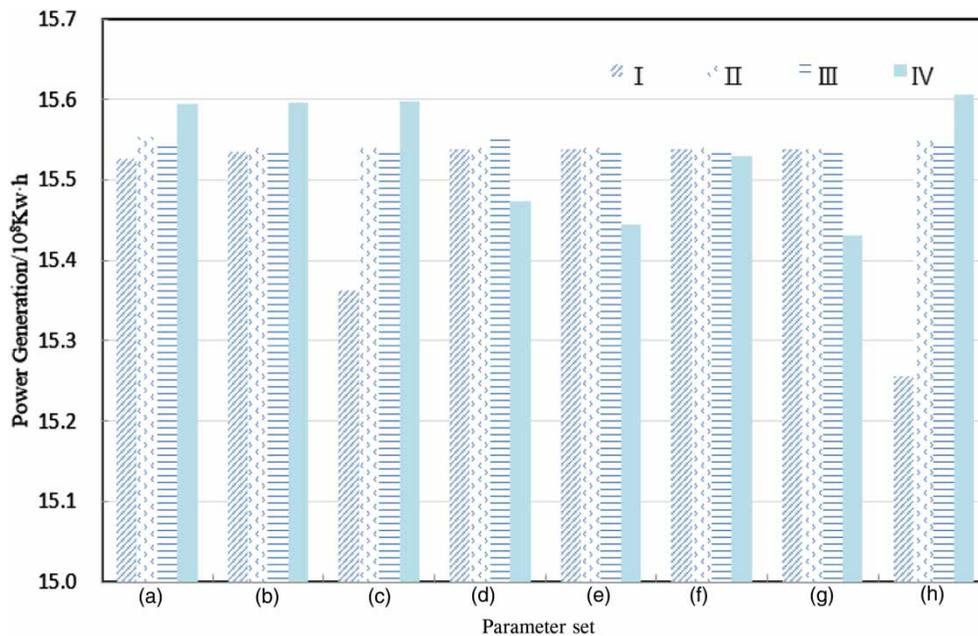
Figure 4 │ The maximum operating results for each parameter set and each TIIWO algorithmic variant.

Table 5 | Characteristic parameters of the cascade reservoirs of the WuJiang river basin

Name	Hong Jia Du	Dong Feng	Suo Feng Ying	Wu Jiang Du
Normal water level (m)	1,140	970	837	760
Flood control level (m)	1,138	970	837	760
Dead water level (m)	1,076	936	822	720
Guaranteed output (MW)	159.1	100	166.9	254
Installed capacity (MW)	600	695	600	1,250
Efficiency coefficient	8.4	8.35	8.4	8.17
Annual electricity production (10^8kw·h)	15.6	23.21	20.11	41.4

III. Here, ΣX_i and $\Sigma Seed(i)$ are the total number of weeds and seeds, respectively. (4) According to the operating results of the *a* and *b* parameter selections, with the increase of the initial population and the maximum population, the results of power generation increase slightly, but the program running times increase significantly. That is, increasing the population simply is not conducive to the operation of the algorithm. (5) According to the operating results of the *a* and *c* parameter selections, with the increase of the seed population, the results of power generation have no significant differences. Meanwhile, the running time of the program is greatly affected and the solution efficiency of the algorithm is reduced seriously. That is, simply increasing the number of reproduced seeds will reduce computational efficiency. (6) According to the operating results of *a*, *d*, *e* and *h*, and results of *f* and *g*, the operating results of the variants I, II and III increase with the increase of the initial standard deviation value and the decrease of the final standard deviation value. The operating results of the variant IV show the opposite.

Analyzing the results of Figure 4, we note that the operating results of the variants II and III have no significant differences, that is, parameter selections have small influence on the power generation produced for the variants II and III. The operating results of I with different parameter selections are quite different and the variant I doesn't converge easily to the global optimal solution. The operating results of IV with different parameter selections also show some differences, but if the parameter selection is appropriate (like parameter set h), the variant IV converges more easily to the

global optimal solution. Although parameter set h with variant IV takes a long time to run, the variance of the 30 calculation results is small, and the average value is large. In addition, compared with other parameter sets, parameter set h can converge to the maximum power generation. Therefore, parameter set h with variant IV will be applied to the cascade reservoir operation problem in this paper.

CASE STUDIES

As the dimension of single reservoir is lower than that of cascade reservoirs, the general intelligent algorithm can find an excellent solution. It is not significant to compare the application of TIIWO and IWO in a single reservoir. Therefore, the following is a comparative analysis of the efficiency of TIIWO and IWO in cascade reservoir optimal operation.

We analyze the operation of a cascade reservoir in the Wu Jiang river basin, located in the Guizhou province, China. The Wu Jiang river is a tributary of the Yangtze river, with a basin area of 87,900 km². We consider here four cascade reservoirs in the upper reaches of the Wu Jiang river. These reservoirs are Hong Jia Du, Dong Feng, Suo Feng Ying and Wu Jiang Du. The TIIWO algorithm was used to optimize the joint operation model of the four cascade reservoirs based on the runoff data of the Wu Jiang river basin from 1954 to 1993.

The Hong Jia Du and the Suo Feng Ying reservoirs represent, respectively, a carry-over storage and a daily storage, while the other two are incomplete annual regulation reservoirs. The flood season for each reservoir is from June to September every year. The characteristic parameters of each reservoir are shown in Table 5.

The starting water levels of the Hong Jia Du, Dong Feng, Suo Feng Ying and Wu Jiang Du reservoirs are set at 1,084 m, 960 m, 829.5 m, and 750 m, respectively. Meanwhile, for each reservoir, the starting and ending water levels are the same. The key parameters of TIIWO are set as parameter set h and variant IV is chosen here. In Equation (15), the parameter $n = 3$. The termination criteria is either $iter_{max} = 200$ or abs$\{[Ec(t + 1) - Ec(t)]/\ Ec(t)\} <$ 0.001. The program is run with the aforementioned computer settings.
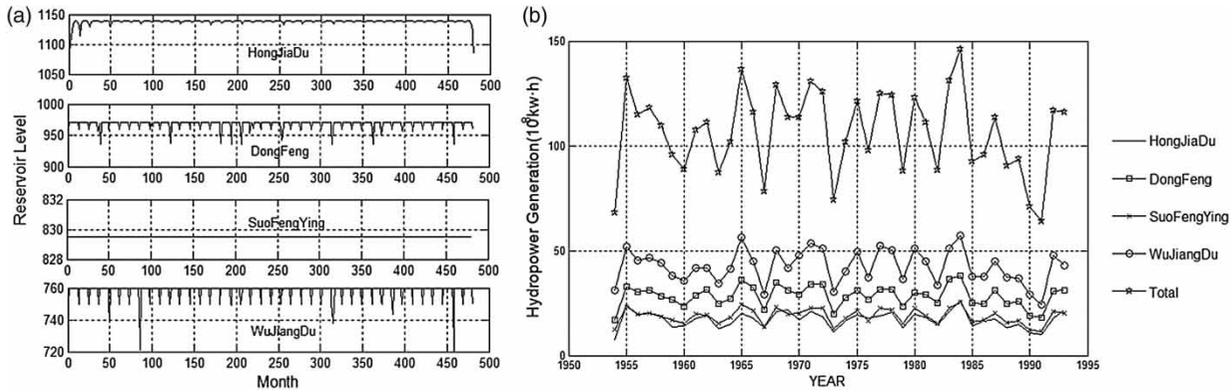
Figure 5 │ Simulation results of cascade reservoir optimal operation: (a) monthly water level changes of the cascade reservoirs; (b) annual power generation of the cascade reservoirs.

In order to verify the feasibility and reliability of the TIIWO algorithm in obtaining the optimal joint operation of the cascade reservoirs, the standard IWO algorithm is used to simulate the optimal operation of the cascade reservoir of the WuJiang river basin. The IWO parameter w of Equation (8) is 3. Other parameters and termination criteria are the same as those used with the TIIWO algorithm.

RESULTS AND DISCUSSION

The simulation running time for the cascade reservoir operation is 66.19 s. For the optimal joint operation model, the monthly water level changes and the annual power generation of the cascade reservoirs are shown in Figure 5.

The annual average generating capacity of each reservoir has been calculated and shown in Table 5 based on the joint optimal operating results of the cascade reservoirs. The IWO running time is 82.26 s.

Table 6 shows that the annual average generating capacities of the cascade reservoir calculated by IWO are less than those calculated by TIIWO and conventional operation. This indicates that IWO has been stuck into

local optima and failed to obtain global optimal solutions. Although the annual average generating capacities of Suo Feng Ying obtained by TIIWO is 6.96% lower than those of the conventional operation, the annual average power generation of Hong Jia Du, Dong Feng and Wu Jiang Du reservoirs is respectively 9.81%, 22.19%, and 2.49% higher than the conventional operation results of the corresponding reservoirs. Meanwhile, the total annual average power generation of the cascade reservoir calculated by TIIWO is 6.28% higher than that of the conventional operation. This shows that TIIWO has a good capability in optimizing the joint operation of cascade reservoirs. Indeed, the TIIWO algorithm is more reliable than the IWO algorithm in solving high-dimensional complex problems. Furthermore, the TIIWO algorithm has faster convergence compared to the standard IWO algorithm according to the running times of the two algorithms.

CONCLUSIONS

The standard IWO algorithm has the drawbacks of the low initial population quality and inferior optimization

Table 6 │ Annual average generating capacity of the cascade reservoirs (10^8 kw·h)

Name	Hong Jia Du	Dong Feng	Suo Feng Ying	Wu Jiang Du	Total generation
TIIWO	17.13	28.36	18.71	42.43	106.62
IWO	15.84	20.31	15.94	35.70	87.79
Conventional operation	15.60	23.21	20.11	41.40	100.32

capability. To alleviate these problems, a modified IWO algorithm, named TIIWO, has been proposed in this paper. Dynamic corridor constraints and iterative reciprocating optimization are the two key IWO improvements that led to TIIWO. After analyzing the convergence and parameter sensitivity of the TIIWO algorithm, this paper applies the TIIWO algorithm to both single-reservoir operation and cascade reservoir operation, discusses four different variants of the TIIWO algorithm, and draws the following conclusions.

When solving the optimization problem, the TIIWO algorithm avoids the problem of getting stuck in local optima and reaches a better solution than IWO.

The initial population, maximum population, initial standard deviation and final standard deviation of the TIIWO algorithm are highly sensitive. Besides, the values of these four parameters have a significant impact on the convergence performance and efficiency of the TIIWO algorithm. And a general recommendation of parameter set for reservoir optimal operation has been proposed.

The TIIWO variants based on a single-seed Gaussian scalar and a Gaussian diagonal matrix are better than the variants based on Gaussian scalar and a parent weed Gaussian scalar in terms of converging to the global optimal solution. However, the solution speed of the algorithm variants show opposite behavior.

The TIIWO algorithm can optimize the joint operation model of cascade reservoirs quickly and efficiently. Moreover, the TIIWO algorithm has good optimization performance when solving high-dimensional, nonlinear and multi-constraint problems.

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COMPETING FINANCIAL INTERESTS

The authors declare no competing financial interests.

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