

Improved wind-driven optimization algorithm for the optimization of hydropower generation from a reservoir

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ABSTRACT

The improvement of reservoir operation optimization (ROO) can lead to comprehensive economic benefits as well as sustainable development of water resources. To achieve this goal, an algorithm named wind-driven optimization (WDO) is first employed for ROO in this paper. An improved WDO (IWDO) is developed by using a dynamic adaptive random mutation mechanism, which can avoid the algorithm stagnation at local optima. Moreover, an adaptive search space reduction (ASSR) strategy that aims at improving the search efficiency of all evolutionary algorithms is proposed. The application results of the Goupitan hydropower station show that IWDO is an effective and viable algorithm for ROO and is capable of obtaining greater power generation compared to the classic WDO. Moreover, it is shown that the ASSR strategy can improve the search efficiency and the quality of scheduling results when coupled with various optimization algorithms such as IWDO, WDO and particle swarm optimization.

Key words: constraint handling, reservoir operation optimization, search space reduction, wind-driven optimization

HIGHLIGHTS

- A new algorithm named wind-driven optimization algorithm (WDO) is first introduced to reservoir operation optimization.
- WDO is improved by two novel strategies.
- One of the strategies mentioned in point 2 is also suitable for other algorithms to improve the efficiency of algorithms.

1. INTRODUCTION

A major crisis of the 21st century is the huge water demand caused by the large population growth (Srinivasan *et al.* 2012; Kummu *et al.* 2016). The energy demand for human society is also continuously increasing with the rapid development of social economy (Barra *et al.* 2013). As a renewable and clean source of energy, water resources are one of the critical tools for dealing with the energy crisis (Mehta *et al.* 2012; Tayebian *et al.* 2016). Reservoir operation optimization (ROO) is employed for the regulation and management of water resources, and it can lead to comprehensive economic benefits. It is also of great significance for meeting water and energy demands in the future (Tayebian *et al.* 2016; Nair & Sasikumar 2019).

For the ROO problem, a proper optimization algorithm and even just a small improvement in it can greatly increase the efficiency of power generation (Tayebian *et al.* 2016). Various optimization algorithms have been developed and applied to the ROO problem (Afshar *et al.* 2007; Bashiri-Atrabi *et al.* 2015; Asgari *et al.* 2016; Bozorg-Haddad *et al.* 2016). The optimal algorithms commonly used in ROO can be classified into the classic and evolutionary algorithms (EAs). The classic algorithms include linear programming (LP) (Lee *et al.* 2008; Feng *et al.* 2018), nonlinear programming (NLP) (Chu & Yeh 1978; Arunkumar & Jothiprakash 2012) and dynamic programming (DP) (Zhang *et al.* 2013, 2015). LP is the simplest and most commonly used method in ROO. However, the linear form requirement of LP does not suit the nonlinear characteristics of ROO. Thus, the LP optimization results are usually problematic. NLP can solve the nonlinear problems but it has the limitation that the objective function and constraints must be differentiable and some approximations must be made to get the solution. This can lead to local optimum and poor convergence performance of NLP. DP is not affected by function discontinuity, nonlinearity and problem randomness. However, the computational cost of DP is greatly increased with the

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increase in the reservoir group scale, which leads to the so-called curse of dimensionality problem (Morgenstern & Bellman 1962). Discrete differential DP, DP successive approximations and progressive optimization algorithm are some of the modified DP algorithms which are developed to reduce its high computational cost (Opan 2011; Lu *et al.* 2013; Zhang *et al.* 2015). However, these improved algorithms suffer from the shortcoming of the initial trajectory impact on the final results (Feng *et al.* 2017; Changming *et al.* 2018). The EAs (Zitzler & Thiele 1998; Adeyemo & Stretch 2018), which benefit from the rapid development of computer technology, can satisfy the high-dimensional and nonlinear characteristics of ROO. Moreover, by using the constraint handling method, they can easily deal with the stringent constraint in ROO. EAs can obtain the Pareto-optimal solution, which means that within a reasonable calculation time there is no better solution in the search space and under all objectives. Due to the above advantages, EAs have been widely used in ROO in recent years. The most commonly used EAs are genetic algorithm (Chang *et al.* 2010; Akbari-Alashti *et al.* 2014), which simulates the natural gene and natural selection mechanism; cuckoo search algorithm (Ming *et al.* 2015; Meng *et al.* 2019), which simulates the brood parasitism of cuckoo; and particle swarm optimization (PSO) algorithm (Zhang *et al.* 2014; Niu *et al.* 2018), which simulates the foraging behavior of birds.

Whereas there is never the only best algorithm for a problem (Barra *et al.* 2013), and researchers have been trying to find a more efficient algorithm for ROO (Luo *et al.* 2014; Bashiri-Atrabi *et al.* 2015; Asgari *et al.* 2016; Bozorg-Haddad *et al.* 2017). In this paper, a novel algorithm, named wind-driven optimization (WDO), is introduced for ROO for the first time. Advantages such as clear concept, high efficiency, strong robustness and ease to implementation make WDO a widely used algorithm and some fields like scheduling residential loads of power grid (Javaid *et al.* 2017), segmentation and extraction of a carotid ultrasound image in medicine (Nagaraj *et al.* 2018) and the path planning of mobile robot (Pandey & Parhi 2017). Similar to other EAs, WDO still has the drawback of stagnating at local optima (Bao *et al.* 2015). To solve this issue, an improved WDO (IWDO) is proposed using the dynamic adaptive random mutation mechanism (RMM). Improving the algorithm efficiency and relieving the computation burden is another important problem when using EAs. The search space reduction (SSR) strategy of the decision variable through constraints transformation is usually employed to solve this problem (Li *et al.* 2015; Meng *et al.* 2019). However, the feasible region of SSR is computed before the start of EAs in these studies, which leads to a fixed feasible region for the strategies. In fact, the corresponding feasible space of the decision variable in each iteration is not always the same. An adaptive SSR (ASSR) strategy during the whole iteration process is introduced in this paper. ASSR narrows down the feasible region and improves the search efficiency. To summarize, the WDO algorithm is modified by a dynamic adaptive RMM, which reduces the chances of convergence to local optima and thus obtaining IWDO. Moreover, the ASSR strategy is used to improve the algorithm efficiency. The proposed algorithm and strategy for ROO are assessed by a case study.

2. METHODOLOGY

The flowchart as shown in Figure 1 contains the reservoir operation model and the introduced algorithm for ROO. It represents the following items:

1. Reservoir operation model with the objective function and various constraints (Section 2.1).
2. WDO and IWDO algorithms (Section 2.2).
3. ASSR for ROO in the whole process (Section 2.3).
4. Specific procedure of WDO for ROO (Section 2.4).

The above items will be explained in the corresponding section in detail. Table 1 is the list of parameters and abbreviations that have been used in this paper.

2.1. Reservoir operation model

2.1.1. Objective function

The goal of reservoir operation varies depending on the reservoir purpose. For instance, for a reservoir mainly used for power generation, the target is to yield the maximum power generation; for a reservoir mainly used for water supply, the target is to minimize the total water shortage; for a reservoir mainly used for ecology, the target is to minimize the deviation between the flow after operation and the natural flow. In this paper, we aim for the maximum power generation output. The objective

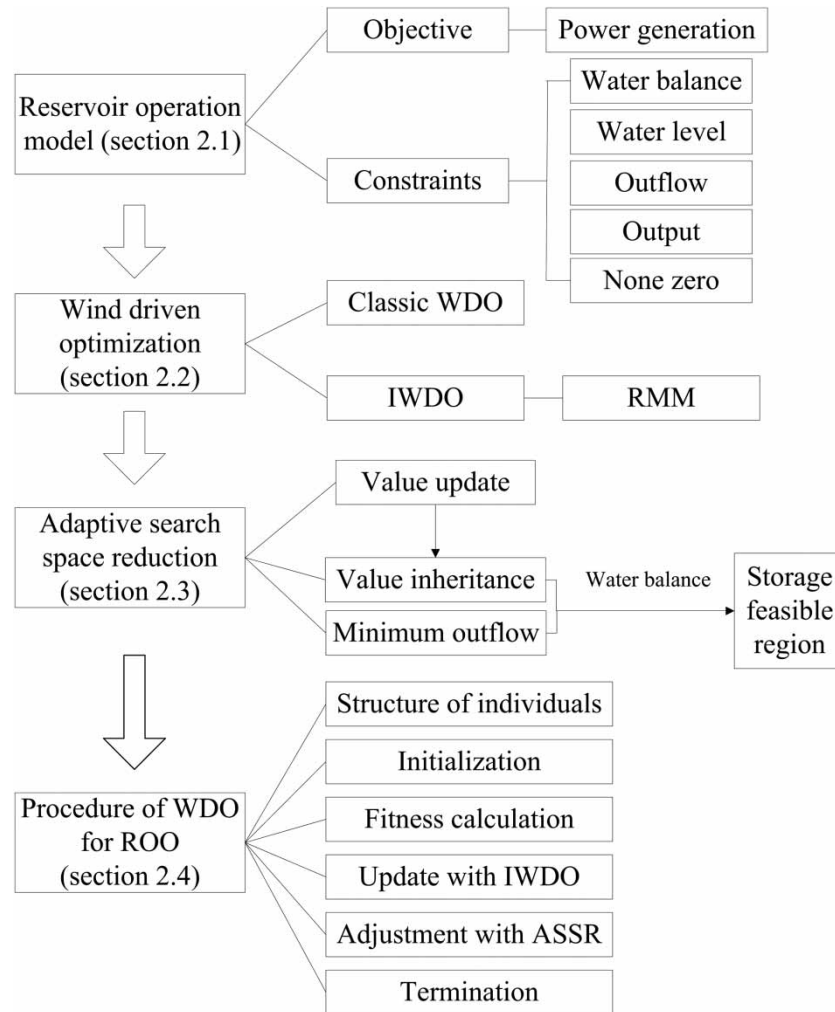


Figure 1 | Content of the methodology.

function in this case is defined as follows:

$$F = \begin{cases} \max \sum_{t=1}^T N_t \Delta t \\ N_t = A \cdot \leq out_t \cdot H_t \end{cases} \quad (1)$$

where F is the solution of objective function, N_t is the average output during the t -th period and Δt is the time interval. N_t is equal to the product of A (comprehensive output coefficient), out_t (outflow of the t -th period) and H_t (power generation head of the t -th period), where A equals the specific weight of water times the efficiency of the turbine.

2.1.2. Constraints

1. Water mass balance equation constraint

$$V_t = V_{t-1} + (in_t - out_t) \cdot \Delta t \quad (2)$$

2. Water-level constraint

$$Z_{t,min} \leq Z_t \leq Z_{t,max} \quad (3)$$

Table 1 | List of the abbreviations and variables

Abbreviation	Full name	Parameter	Description	Parameter	Description
ROO	Reservoir operation optimization	F	Objective function	T	Temperature
WDO	Wind-driven optimization	N	Output	g	Gravitational acceleration
IWDO	Improved wind-driven optimization	t	Dimension	α	Friction coefficient
ASSR	Adaptive search space reduction	Δt	Time interval	c	Constant value
RMM	Random mutation mechanism	A	Comprehensive output coefficient	m	Random number
PSO	Particle swarm optimization	out	Outflow	ε	Degree of speed disturbance
GHS	Goupitan hydropower station	H	Power generation head	Ω	Feasible region
SD	Standard deviation	V	Storage volume	δ	Random number
LP	Linear programming	in	Inflow	pop	Population number
NLP	Nonlinear programming	Z	Water level	F_f	Fitness function
DP	Dynamic programming	i	Air particle	j	Number of constraints
EAs	Evolutionary algorithms	u	Velocity	E_N	Power corresponding to the installed capacity
GA	Genetic algorithm	x	Position	k	Parameter which ensures the accuracy of the punish function
		P	Iteration number	C	Parameter of PSO
		R	Universal gas constant		

3. Outflow constraint

$$out_{t,min} \leq out_t \leq out_{t,max} \quad (4)$$

4. Generation output constraint

$$N_{t,min} \leq N_t \leq N_{t,max} \quad (5)$$

where V_t (i.e. terminal storage volume of the t -th period) is decided by V_{t-1} (initial storage volume of the t -th period), in_t (average inflow of the t -th period) and out_t . $Z_{t,min}$, $out_{t,min}$ and $N_{t,min}$ are the lower limits of Z_t (water level of the t -th period), out_t and N_t (output of the t -th period), respectively. $Z_{t,max}$, $out_{t,max}$ and $N_{t,max}$ are the upper limits of Z_t , out_t and N_t , respectively.

5. Nonzero constraint

All variables must be positive.

See Figure 2 to better understand the variables and the reservoir system. From Figure 2, we can see that when the outflow is greater than inflow, the water level, water storage and power generation head will decrease. If the outflow remains the same, as the decrease of power generation head, the power generation output will also decrease.

2.2. Wind-driven optimization

2.2.1. Classic WDO

WDO, a novel nature-inspired global optimization algorithm, was first proposed by Bayraktar in 2010 (Bayraktar *et al.* 2010). As an iterative heuristic global optimization method, it can deal with multi-dimensional and multi-modal problems, and it is

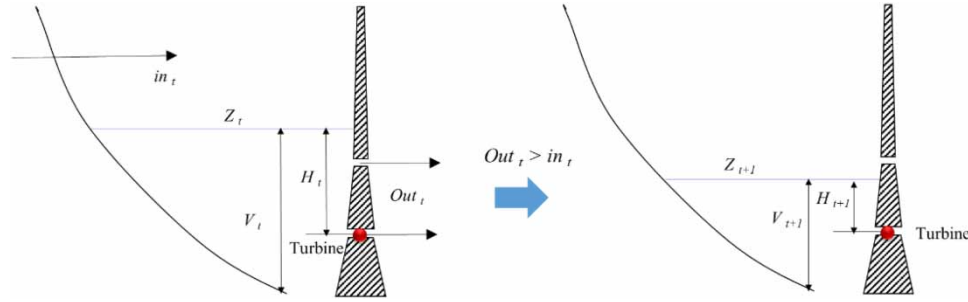


Figure 2 | Reservoir system.

suitable for both continuous and discrete problems. The inspiration of WDO is from the motion of wind, which is described by a Lagrangian model (Dickinson 1997); the physical equations based on Newton's second law of motion is used to describe the trajectory of air parcel, which is assumed to be dimensionless as well as weightless. Due to the stronger motion of horizontal particle compared to the vertical one, only the horizontal movement is taken into consideration. The atmosphere moves to reach the horizontal balance of the air pressure. Various forces affect this motion, but for the sake of simplification, only four forces are adopted in WDO. They are pressure gradient force, friction force, gravitational constant and the Coriolis effect. As a population-based algorithm similar to PSO (Boulesnane & Meshoul 2014), each air particle has its own velocity as the amount of displacement and position as the candidate solution (decision variable). All air particles form the population, and the pressure value (objective function) is used to evaluate the quality of candidate solution. The velocity and position of each dimension are updated iteratively in each iteration by the following equations:

$$u_{i,t}^{P+1} = (1 - \alpha)u_{i,t}^P - gx_{i,t}^P + \left[RT \left| \frac{1}{j} - 1 \right| (x_{t,opt}^P - x_{i,t}^P) \right] + \left(\frac{cu_{i,otherdim}^P}{j} \right) \quad (6)$$

$$x_{i,t}^{P+1} = x_{i,t}^P + u_{i,t}^{P+1} \Delta T \quad (7)$$

where subscript i represents the particle, subscript t represents the dimension and superscript P represents the iteration. u and x are the velocity and the position, respectively.

It is seen from Equation (6) that the velocity ($u_{i,t}^{P+1}$) of new generation is determined by four terms. The first term represents the friction effect on air particles, and it reflects the inheritance of the current velocity. The second term represents the effect of gravity which is related to self-cognition of air particles and speeds up the convergence speed. Gravity enables the air particles to approach the coordinate center in proportion to the constant g from the current position $x_{i,t}^P$, which is a reflection of enhancing the learning process. The third term is the 'detection' of the air particle position. Under the influence of the pressure gradient force, the air particle moves to the optimal pressure point (i.e. the global optimal position) and considers its past experience comprehensively to make the next decision. $x_{t,opt}^P$ is the Pareto-optima until generation P . j is the rank of the particles which is in ascending order by the pressure at a location. R is related to universal gas constant, and T is related to temperature. The fourth term provides the Coriolis effect on air particles, which enables the air particles to adjust their position properly in combination with the experience of their peers and, thus, to avoid the local optima. $u_{i,otherdim}^P$ is the air particle velocity of any dimension other than t .

Equation (7) shows that the position ($x_{i,t}^{P+1}$) of the new generation is equal to the current position plus the product of the new velocity and the unit time step (ΔT). For simplicity, $\Delta T = 1$.

Users set the iteration number, population, α , g , RT and c of the WDO algorithm. For details of the WDO algorithm, please refer to Bayraktar *et al.* (2013).

2.2.2. Improved WDO

As stated earlier in Section 2.2.1, the air particles constantly move to reach an equilibrium state. This means that once an external force acts on the air particles that are in equilibrium, they will move again. Inspired by this, a disturbance, named dynamic adaptive RMM to local optima, is used to overcome the premature convergence and obtain IWDO.

When the air particles search for the optimal solution in N -dimensional space and are trapped in local optima, we choose a random dimension t ($1 \leq t \leq N$) to be disturbed and introduce a random number m ($0 < m < 1$), which obeys the uniform distribution, to make a small disturbance in the speed of the t -th dimension using the following equation:

$$u_{i,t}^{P+1} = (2m - 1) \cdot \varepsilon \quad (8)$$

where ε , which represents the degree of speed disturbance, is a dynamic number changing with the number of iterations. As the number of iterations increases, the air particles are closer to the optimal solution. Thus, the disturbance should decrease with the increase of the number of iterations. In this paper, the value of ε is obtained by the following equation:

$$\varepsilon = \frac{1}{P^{0.25}} \quad (9)$$

In the next step, the position is updated according to Equation (7). The new position obtained after the random mutation is then compared with the previous optimal position. If the new position is better, it is used to replace the former optimal one. Otherwise, the previous optimal position is retained until the algorithm computation is over.

2.3. ASSR strategy

There are several constraints in various nonlinear optimization problems. While the so-called soft constraints can be violated, the violation of hard constraints results in invalid solutions (Chang *et al.* 2010). Due to the existence of the hard constraints in our problem, a large number of solutions are invalid, if they are not handled properly, the data redundancy will greatly reduce the algorithm's operational efficiency. To solve this issue, an ASSR strategy is employed in this study. For ROO, water storage at the end of each period is selected as the decision variable. We can see from Figure 1 that there is a one-to-one correspondence between the water storage and the water level; thus, the core idea of SSR is to obtain the feasible region of water level, which is to obtain the upper and lower limits of water level according to the water balance equation and considering various constraints in the solution process, and make sure that all the solutions generated during the iteration are within the feasible region (Barkat Ullah *et al.* 2008).

The approach for obtaining the feasible region is as follows:

1. *Update the value*: In each iteration, only the odd or even dimension water level is updated. In the P -th iteration, through updating the particle position at the end of period $t - 1$ and $t + 1$, $Z_{i,t-1}^P$ and $Z_{i,t+1}^P$ are generated ($2 \leq t \leq N - 1$).
2. *Value inheritance*: In generation $P + 1$, $Z_{i,t-1}^{P+1}$ equals to $Z_{i,t-1}^P$ and $Z_{i,t+1}^{P+1}$ equals to $Z_{i,t+1}^P$, and only $Z_{i,t}^{P+1}$ should be updated.
3. *Determine the feasible region*: Due to the fixed value of $Z_{i,t-1}^{P+1}$, $Z_{i,t+1}^{P+1}$, in_t and in_{t+1} , there must be a maximum and minimum value of $Z_{i,t}^{P+1}$ based on Equation (2):

$$Z_{i,t,\max}^{P+1} = Z_{i,t-1}^P + (in_t - out_{t,\min}) \cdot \Delta t \quad (10)$$

$$Z_{i,t,\min}^{P+1} = Z_{i,t+1}^P - (in_{t+1} - out_{t+1,\min}) \cdot \Delta t \quad (11)$$

The compressed feasible region Ω is obtained using Equations (10) and (11):

$$\Omega = \begin{cases} (Z_{i,t,\min}^{P+1}, Z_{i,t,\max}^{P+1}) & Z_{i,t,\min}^{P+1} < Z_{i,t,\max}^{P+1} \\ \frac{Z_{i,t,\min}^{P+1} + Z_{i,t,\max}^{P+1}}{2} & Z_{i,t,\min}^{P+1} \geq Z_{i,t,\max}^{P+1} \end{cases} \quad (12)$$

If the updated water-level value is not within the above feasible range, handle the value according to the following formula:

$$Z_t^{P+1} = \begin{cases} \frac{Z_{i,t,\min}^{P+1} + Z_{i,t,\max}^{P+1}}{2} & Z_{i,t,\min}^{P+1} > Z_{i,t,\max}^{P+1} \\ Z_{i,t,\max}^{P+1} & Z_{i,t}^{P+1} \geq Z_{i,t,\max}^{P+1} \\ Z_{i,t,\min}^{P+1} & Z_{i,t}^{P+1} \leq Z_{i,t,\min}^{P+1} \end{cases} \quad (13)$$

The values of $t - 1$ and $t + 1$ dimensions are computed in the next generation according to the above equations and cycle like this until the end of the iteration. The diagram of ASSR is shown in Figure 3. The particle position in black is inherited from the last generation, and only the red ones will be updated in the corresponding iteration.

2.4. IWDO combined with ASSR applied to the ROO problem

2.4.1. Structure of individuals

The reservoir water storage at different times t ($0 < t < N$) forms a set of vectors, which is represented by air particle i with N -dimensional search space in WDO. Set the population number pop and the iteration number. Each individual in the algorithm is represented as follows:

$$V_i^P = (V_{i,1}^P, V_{i,2}^P, \dots, V_{i,t}^P, \dots, V_{i,N}^P) \quad 0 < i < pop \quad (14)$$

2.4.2. Initialization

In the first iteration, individuals are randomly generated based on the following equation:

$$V_{i,t}^1 = V_{t,min} + \delta(V_{t,max} - V_{t,min}) \quad 0 < i < pop \quad (15)$$

where δ is a random number which ranges from 0 to 1 and follows a uniform distribution. To ensure the diversity of the initial population and the existence of a certain number of feasible solutions in the initial population, the following strategy is employed in this study: after the initial water storage is generated, calculate the outflow and output using Equation (2) and Equation (1), respectively. Ensure that the first quarter of individuals meets the minimum outflow constraint, and the last quarter of individuals meets the minimum output requirements, in addition to the minimum outflow constraint.

2.4.3. Fitness value calculation

To get the solution of WDO, water storage at the end of each period is selected as the decision variable, and the punish function, which is integrated into the fitness function, is used to deal with the constraints. The fitness function F_i of particle i in generation P is constructed as in Equation (16). Combined with the objective function, the fitness function can be expressed

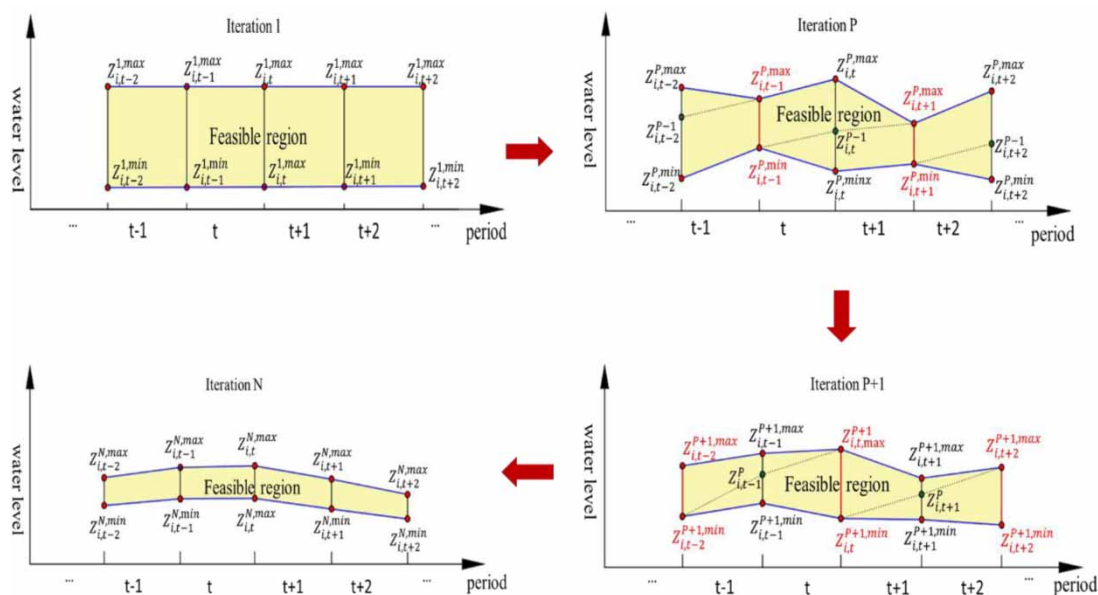


Figure 3 | Diagram of ASSR. Please refer to the online version of this paper to see this figure in color: <http://dx.doi.org/10.2166/hydro.2021.174>.

as Equation (17):

$$F_f = F \times \prod_{j=1}^J \sum_{t=1}^T f_{jt} \quad (16)$$

$$F_f = \sum_{t=1}^T \left(N_t \Delta t \times \prod_{j=1}^J f_{jt} \right) \quad (17)$$

where F is the objective function, and f_{jt} is the punish factor of the j -th constraint in the t -th period. The default value of f_{jt} is 1. It is noted that j refers to the number of constraints.

To integrate all the constraints into the fitness function, the following method is used. Since the water storage at the end of each period is selected as decision variable, the first step is to calculate the outflow using Equation (2). When the outflow is below zero, the nonzero punish factor is calculated using the following equation:

$$f_{1t} = -10E_N \quad (18)$$

where E_N refers to the power corresponding to the installed capacity.

If the outflow is greater than zero but less than the minimum outflow, the outflow punish factor is calculated using the following equation, which shows the outflow deviation from the minimum outflow:

$$f_{2t} = -\frac{out_{t,min}}{out_t} \quad (19)$$

Equation (1) indicates that the value of output is related to outflow. Thus, the second step is to calculate the output. The value of the output punish factor is calculated using the following equation when the output is less than the firm output:

$$f_{3t} = k \frac{N_{t,min}}{N_t} \quad (20)$$

where k is a parameter which ensures the accuracy of the punish function. The value of k is determined by the following equation:

$$k = \begin{cases} 1 & 0 < out_t < out_{t,min} \\ -1 & out_{t,min} < out_t \end{cases} \quad (21)$$

By using the method above, the violation of the constraints can be observed in the fitness function. A slight decrease will happen in the fitness function when there is a tiny degree of violation, while a notable decrease will happen when there is a high degree of violation. The mechanism for handling the constraints is represented in Figure 4.

2.4.4. Updating the population with IWDO

Equation (22) represents the IWDO algorithm applied to ROO. In this equation, the first term is the influence of the previous water level on the current water level. The second term denotes the water level approaching the highest water level (which can generate more electricity), and the third term represents the water level approaching the global optimal water level. The fourth term is the internal limitation of other periods on the current water level based on various constraints. This term shows that the final water level of the t -th period is related to the water surplus during period t and period $t + 1$. The speed update and the water-level update for ROO in IWDO are given by the following equations:

$$u_{i,t}^{P+1} = (1 - \alpha)u_{i,t}^P + g(V_{t,max} - V_{i,t}^P) + \left[RT \left(1 - \frac{1}{j} \right) (V_{t,opt}^P - V_{i,t}^P) \right] + \left(\frac{cu_{i,otherdim}^P}{j} \right) \quad (22)$$

$$V_{i,t}^{P+1} = V_{i,t}^P + u_{i,t}^{P+1} \quad (23)$$

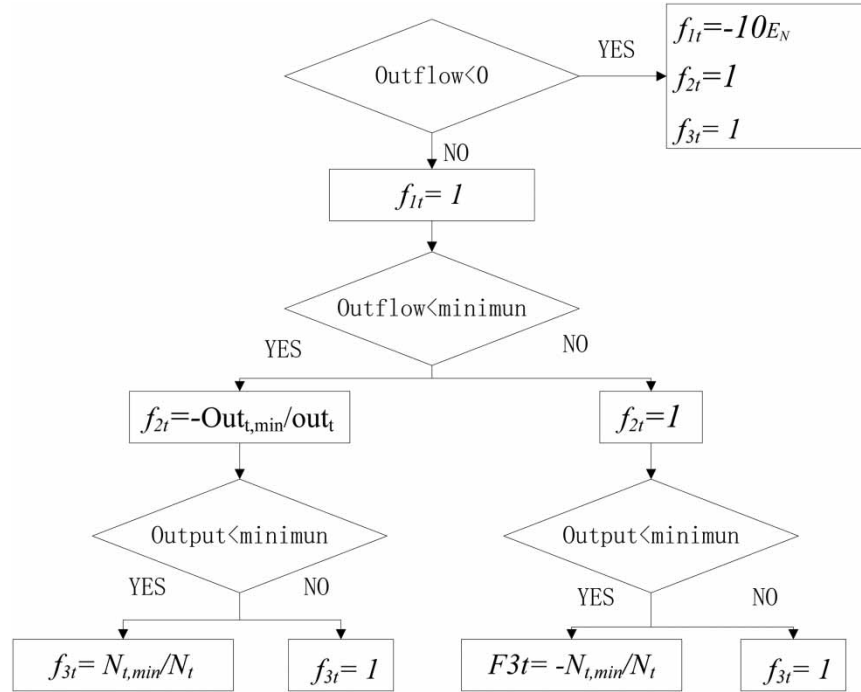


Figure 4 | Flowchart of constraints handling mechanism.

Next, the value of $u_{i,otherdim}^P$ is discussed. The fourth term in Equation (22) is a key factor that can dynamically adjust the direction of water-level movement depending on whether there is water surplus in the adjacent period. To meet the requirements, the value of c is set to $2j$. Thus, the fourth term will be simplified as $2u_{i,otherdim}^P$. Taking $K_{i,t}^{P+1}$ as an intermediate variable (defined in Equation (24)), $u_{i,otherdim}^P$ is dynamically defined using Equation (25):

$$K_{i,t}^{P+1} = (1 - \alpha)u_{i,t}^P + g(V_{t,max} + V_{i,t}^P) + \left[RT \left(1 - \frac{1}{j} \right) (V_{t,opt}^P - V_{i,t}^P) \right] \quad (24)$$

$$u_{i,otherdim}^P = \begin{cases} -K_{i,t}^{P+1} & \text{condition 1} \\ 0 & \text{condition 2} \end{cases} \quad (25)$$

Two conditions are explicated in the following. Condition 1: (1A) there is water surplus in the t -th period and not in the $(t + 1)$ -th period, when water level at the end of the t -th period in the next iteration should rise but the first three terms are negative values; or, (1B) there is water surplus in the $(t + 1)$ -th period and not in the t -th period, when water level at the end of the t -th period in the next iteration should decrease but the first three terms are positive values. Condition 2: any circumstances other than situation #1.

The fluctuation range and the value of water level are updated using Equations (22) and (23), respectively. The fitness value of V_i^P is calculated to find the Pareto solution, and RMM is used to avoid the premature solutions. The algorithm then goes to the next generation until the global optimal solution is obtained.

2.4.5. Solution adjustment based on ASSR

Update water storage by the ASSR method as described in Section 2.3.

2.4.6. Termination criteria

The IWDO algorithm is terminated after reaching the maximum number of iterations or termination conditions.

From the above introduction, the processing flow of the IWDO with the ASSR can be obtained. See Figure 5 for it. First, we set the parameters of the algorithm, and then the algorithm can initialize the individuals which is used in the first iteration.

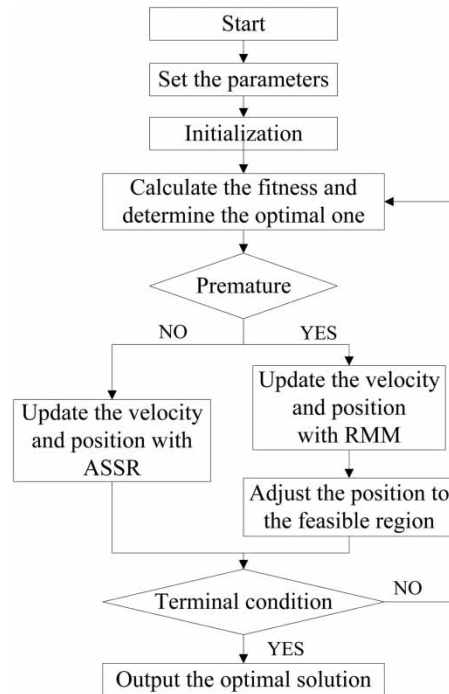


Figure 5 | Flowchart of iterative algorithms.

Then, the algorithm will calculate the fitness of each individual, and the one with the maximum fitness value will be chosen as the optimal one. Later, the algorithm will judge whether it is premature. If it is premature, RMM will be used to update the velocity and position of the local optima, and then adjust the new optima to the feasible region which is obtained through ASSR. If it is not premature, use the ASSR strategy to update the new generation. Up to now, the new generation is updated and the algorithm will terminate and output the optimal solution if it has reached the terminal condition. If the algorithm does not reach the terminal condition, it will be back to the new cycle.

3. CASE STUDY

3.1. Goupitan hydropower project

The Wujiang River, with a total length of 1,037 km and a drainage area of 87,920 km², is the largest tributary on the South Bank of the upper reaches of the Yangtze River. The Wujiang River originates from the Yunnan-Guizhou Plateau, flows through Hubei and Chongqing and finally joins the Yangtze River. The altitude of the basin is high in the southwest and low in the northeast, with rough topography and deep valley. Most of the area of the Wujiang River Basin belongs to the subtropical monsoon climate, with an average annual rainfall of 1,163 mm (Wenhui *et al.* 2015; Xiao *et al.* 2015).

The Goupitan hydropower station (GHS) is located in the middle reaches of the Wujiang River. Figure 6 shows the location of GHS. The purpose of GHS is mainly for power generation, followed by shipping and flood control. The GHS has an annual regulation capacity. It is the largest hydropower station in the Guizhou Province and the whole mainstream of the Wujiang River. The drainage area is 43,250 km², the total storage capacity is 6.454 billion m³, and the total installed capacity is 3,000 MW; the firm output is 600 MW and the minimum outflow is 300 m³/s. The operation period is from June to May of the following year, during which the flood period is from June to October. Twelve time intervals are set in months in a scheduling period for the operation. During the flood season, the flood control limit water level in June and July is 626 and 628 m in August. In other months, the upper limit of water level is 630 m. After the flood season, the incoming water gradually decreases, and thus, the water level should be kept at a high level to improve the power generation. However, in addition to the hydraulic head, the power generation is also related to the outflow. Therefore, ROO is employed to produce optimal results. The key parameters of GHS are given in Table 2.

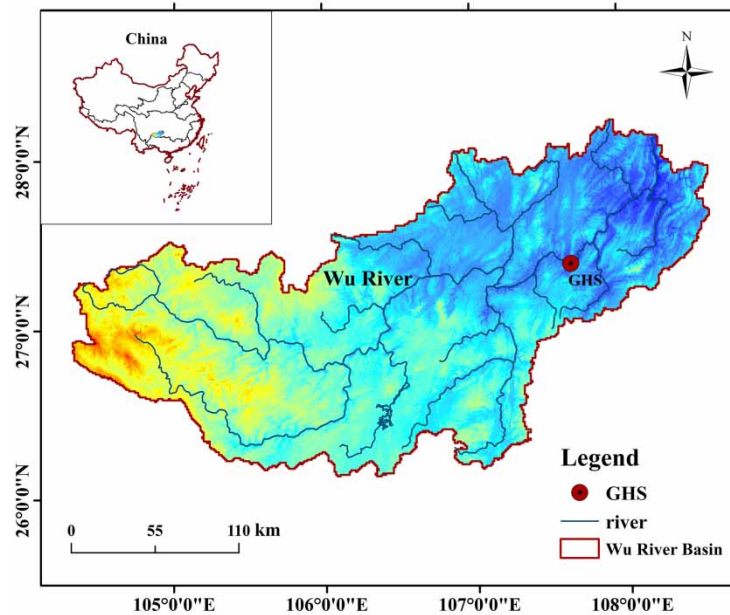


Figure 6 | Location of the GHS hydropower station.

Table 2 | Key parameters of GHS

Parameter	Value	Units
Total storage	64.54	10^8 m^3
Control area	43,250	km^2
Installed capacity	3,000	MW
Firm output	600	MW
Minimum outflow	300	m^3/s
Normal water level	630	m
Dead water level	590	m
Flood limited water level (Jun. and Jul.)	626	m
Flood limited water level (Aug.)	628	m
Power coefficient	8.5	

3.2. Parameter setting

In our case study, an optimal solution is obtained when parameters of the IWDO algorithm are chosen as $\alpha = 0.05$, $g = 0.5$, $RT = 0.1$, maximum iteration number = 500 and population size = 100. The performance of the WDO and IWDO algorithms with PSO is compared. When the parameters of PSO algorithm are $\omega = 0.729$, $C_1 = 2$ and $C_2 = 2$, it can obtain the best solution according to Mendes *et al.* (2004). The population size and iteration number of all algorithms are the same. It is noted that the same fitness function is used for all algorithms. The used parameters for each algorithm are in Table 3.

Table 3 | Parameters of PSO, WDO and IWDO

Algorithm	ω	C_1	C_2	α	g	RT
PSO	0.729	2	2			
WDO				0.05	0.5	0.1
IWDO				0.05	0.5	0.1

4. RESULTS AND DISCUSSION

4.1. Robustness of algorithms

Apply ASSR to WDO, PSO and IWDO to get ASSR-WDO, ASSR-PSO and ASSR-IWDO, respectively. Each algorithm for ROO is computed 10 times, and the standard deviation (SD) of power generation is used to analyze the robustness of algorithms. The best value, average value and SD of power generation are shown in Table 4, from which it can be found that the SDs of WDO and PSO are zero, indicating that the standard algorithms are in good robustness; the SD of IWDO is 0.01 and the SD of ASSR-IWDO is 0.001, indicating that RMM will cause some deviation but ASSR can reduce that.

4.2. Efficiency of IWDO

The efficiency of WDO and IWDO for the ROO problem can be assessed using the best scheduling results reported in Table 5. Results of PSO are also reported in this table as a reference for comparison. It can be seen that the results computed by all algorithms meet the hard constraints, indicating that they are all effective for ROO. Moreover, the total power generation obtained by IWDO is higher than WDO, which demonstrates the improvement caused by RMM. Moreover, it can be seen that the total power generation of WDO is higher than PSO. It is noted that the outflow and output of WDO in March are below the minimum value. See also February and March in the case of IWDO, and March and April in the case of PSO. Further research is required to overcome such shortcomings of the algorithms.

Table 4 | Power generation of different algorithms

Algorithm	Power generation (10 ⁸ kw-h)		
	Maximum	Average	SD
WDO	99.50	99.50	0
PSO	99.31	99.31	0
IWDO	99.57	99.55	0.01
ASSR-WDO	98.83	98.83	0
ASSR-PSO	98.70	98.70	0
ASSR-IWDO	99.22	99.21	0.001

Table 5 | ROO results of WDO, IWDO and PSO

Month	Outflow (m ³ /s)			Water level (m)			Output (MW)			Power (10 ⁸ kw-h)		
	WDO	IWDO	PSO	WDO	IWDO	PSO	WDO	IWDO	PSO	WDO	IWDO	PSO
6	1,505	1,505	1,505	626.24	626.24	626.24	2,365	2,365	2,365	17.03	17.03	17.03
7	1,670	1,670	1,670	626.24	626.24	626.24	2,653	2,653	2,653	19.10	19.10	19.10
8	1,108	1,063	1,063	627.03	628.12	628.12	1,790	1,724	1,724	12.89	12.42	12.42
9	842	772	772	627.20	630.00	630.00	1,374	1,275	1,275	9.89	9.18	9.18
10	563	678	678	630.00	630.00	630.00	934	1,129	1,129	6.73	8.13	8.13
11	428	428	428	630.00	630.00	630.00	719	719	719	5.18	5.18	5.18
12	301	359	364	629.20	627.79	627.67	507	601	609	3.65	4.33	4.39
1	363	369	416	625.63	623.67	621.85	603	609	683	4.34	4.39	4.92
2	369	294	381	620.48	620.84	616.00	600	478	606	4.32	3.44	4.36
3	195	272	299	620.95	618.65	612.87	316	436	466	2.28	3.14	3.35
4	375	380	293	620.22	617.73	615.00	601	602	454	4.33	4.34	3.27
5	862	791	712	620.00	620.00	620.00	1,355	1,237	1,109	9.76	8.91	7.98
Total										99.50	99.57	99.31

4.3. Efficiency of ASSR strategy

The optimal scheduling results of ASSR-WDO, ASSR-IWDO and ASSR-PSO are given in Table 6. It can be seen that all three algorithms combined with ASSR can fully satisfy all the constraints in every period, meaning that ASSR can ensure that the scheduling results of each algorithm are reasonable. As such, ASSR improves the solution quality. Figures 7–9 show the change of water level, discharge and output, respectively, and from which we can see that the water level in each period is higher than the dead level and lower than the max level, and the discharge and the output in each period are greater than the minimum value. The total power generation obtained by ASSR-WDO, ASSR-IWDO and ASSR-PSO is 9.88, 9.92 and 9.87 billion kw-h, respectively, proving that ASSR-IWDO can get the highest generation.

Figure 10 shows the convergence curve of the fitness value of all three algorithms. It can be seen that for ASSR-IWDO and IWDO, the initial fitness value is the same, but the final fitness value of ASSR-IWDO is much higher than that of IWDO. The number of iterations to reach the stable convergence in ASSR-IWDO is about 50% of that of IWDO, the same regularity of

Table 6 | ROO results of different algorithms

Month	Outflow (m ³ /s)			Water stage (m)			Output (MW)			Power (10 ⁸ kw-h)		
	ASSR-WDO	ASSR-IWDO	ASSR-PSO	ASSR-WDO	ASSR-IWDO	ASSR-PSO	ASSR-WDO	ASSR-IWDO	ASSR-PSO	ASSR-WDO	ASSR-IWDO	ASSR-PSO
6	1,588	1,505	1,590	623.91	626.24	623.83	2,470	2,364.94	2,473	17.78	17.03	17.80
7	1,588	1,670	1,588	626.24	626.24	626.18	2,514	2,653.19	2,513	18.10	19.10	18.10
8	1,063	1,063	1,062	628.12	628.12	628.07	1,724	1,724.43	1,723	12.42	12.42	12.41
9	772	772	773	630.00	630.00	629.93	1,275	1,275.10	1,276	9.18	9.18	9.19
10	678	678	677	630.00	630.00	629.94	1,129	1,128.99	1,128	8.13	8.13	8.12
11	428	428	430	630.00	630.00	629.89	719	719.08	723	5.18	5.18	5.20
12	376	358	389	627.38	627.81	626.95	628	600.05	649	4.52	4.32	4.67
1	376	364	377	622.85	623.88	622.21	618	600.62	618	4.45	4.32	4.45
2	386	374	377	616.84	618.26	616.48	616	601.82	601	4.43	4.33	4.33
3	397	386	407	610.30	612.12	609.60	613	600.39	626	4.41	4.32	4.51
4	407	396	447	608.45	610.65	606.38	613	603.78	667	4.42	4.35	4.80
5	524	587	464	620.00	620.00	620.00	806	907.69	712	5.81	6.54	5.13
Total										98.83	99.22	98.70

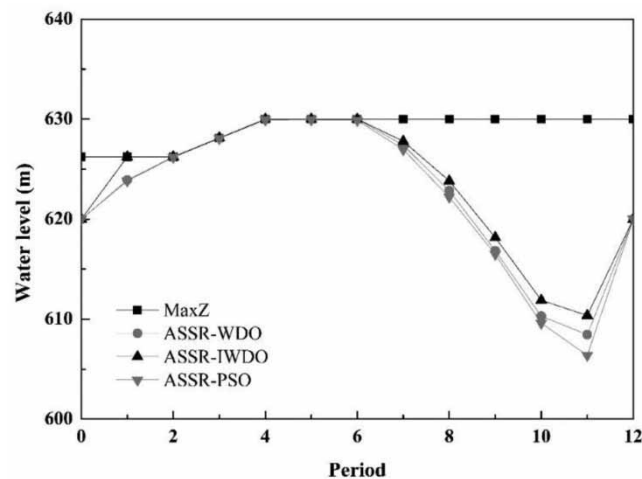


Figure 7 | Water level during the operation time of GHS.

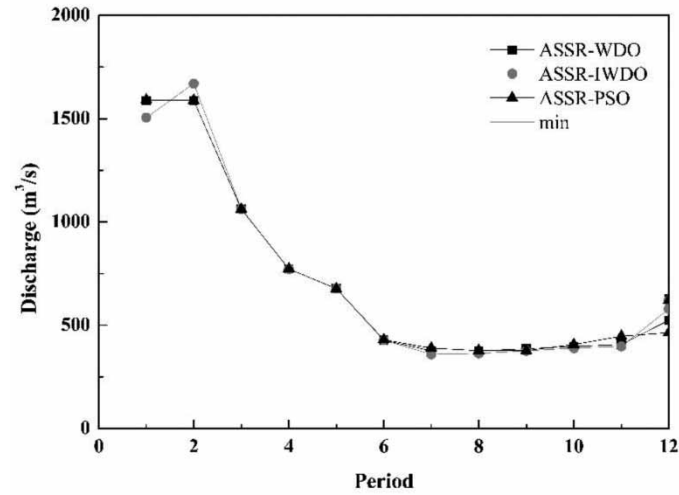


Figure 8 | Water discharge during the operation time of GHS.

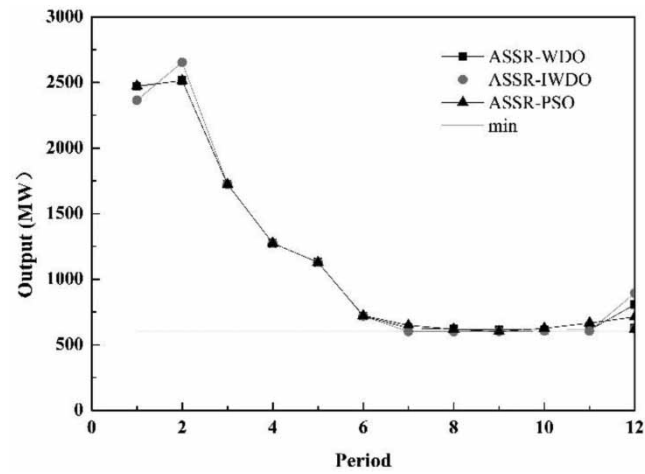


Figure 9 | Output during the operation time of GHS.

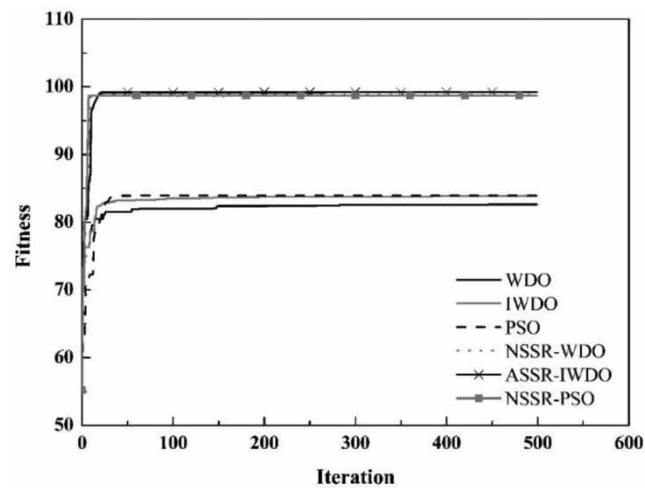


Figure 10 | Fitness convergence curve of different algorithms.

ASSR-WDO and WDO, which demonstrates that ASSR can improve the search efficiency. Moreover, a comparison of ASSR-PSO and PSO shows that ASSR can be successfully adopted for other algorithms.

5. CONCLUSION

In this study, WDO is first employed to ROO. An IWDO algorithm is further developed by using a dynamic adaptive RMM to avoid local optima. Furthermore, an ASSR strategy is proposed to improve the search efficiency of the algorithm. To generate a compressed feasible search region, ASSR only updates the value of odd or even dimension in each iteration, and it combines the water storage inherited from the previous iteration with the minimum outflow, and then making the use of the water balance equation to obtain the upper and lower limit of the water storage which is to be updated in the current iteration. Moreover, the efficiency of WDO and IWDO are evaluated in comparison to the PSO algorithm. The ASSR is also applied to the PSO algorithm to assess the performance of ASSR. Combined with ASSR, three algorithms are generated, including ASSR-WDO, ASSR-IWDO and ASSR-PSO. Using the GHS as the case study to evaluate the performance of the proposed algorithm, the following conclusions can be drawn:

1. IWDO is an effective algorithm for ROO. All three algorithms of WDO, IWDO and PSO meet the hard constraints. However, it is noted that in some months, the outflow and the output are below the lower limit.
2. In terms of efficiency, IWDO is superior to WDO, and WDO is superior to PSO. Comparing the obtained power generation shows that IWDO is capable of obtaining better solutions than WDO, and so is WDO than PSO.
3. ASSR can improve the search efficiency and search quality. The results of all algorithms combined with the ASSR strategy meet all the constraints. Moreover, ASSR-IWDO shows faster convergence and greater power generation compared to IWDO. The same result is presented when comparing ASSR-PSO with PSO. Thus, it is concluded that ASSR can be integrated into any optimization problem to enhance the search efficiency. The performance of ASSR-IWDO in solving the cascade ROO problem will be evaluated in a future study.

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DATA AVAILABILITY STATEMENT

All relevant data are included in the paper or its Supplementary Information.

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