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An Improved Slime Mold Algorithm and Its Application for Optimal Operation of Cascade Hydropower Stations

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ABSTRACT A recently modern stochastic optimization algorithm has been developed by observing the life of slime mold physarum polycephalum in nature. The algorithm is called the slime mold algorithm (SMA) with an excellent exploratory capacity and exploitation inclination. Still, slipping into optimal local is easy to happen and slowly converges speed while dealing with complicated problems. This article proposes a new process of improving SMA (namely ISMA) by adapting the weight coefficient and cooperating the reverse learning strategy in the expression of agents updating locations to enhance the algorithm's optimization performance. Many selected benchmark functions and the optimal operation of cascade reservoirs are applied to evaluate the performance of the proposed algorithm. Comparisons of the proposed approach's results with the various algorithms under the case situations show that the recommended solution produces better performance than the different competing algorithms.

INDEX TERMS Slime mold algorithm, optimal dispatching of cascade hydropower, reverse learning, dynamic weight.

I. INTRODUCTION

Artificial intelligence technology has become an essential tool for applying meaningful solutions to practical engineering problems in daily life [1]. The metaheuristic algorithms are a significant branch of rising artificial intelligence used in many fields in both industry and society applications [2]. Many artificial intelligence applications involved metaheuristic algorithms, e.g., in health care [3], financial evaluation [4], resource scheduling and management industries [5], and wireless sensor networks [6]. Several classifications of the metaheuristic algorithms can be considered the physical phenomena, human learning habits, evolution law in nature, animals' living habits, and swarms [7].

First, the metaheuristic algorithms inspired by nature's physical phenomena are like the Simulated annealing (SA) algorithm [8], Gravitational search algorithm (GSA) [9], Multi-verse optimizer (MVO) [10], [11], Sine-cosine algorithm (SCA) [12], Gradient-based optimizer (GBO) [13], Heap-based optimizer (HBO) [14], etc. Second, the algorithms based on human learning habits include the Tabu search (TS) algorithm [15], the Teaching and learning algorithm (TLBO) [16] that is the prominent representative of this kind of algorithm. Third, the type of algorithm inspired by the evolution law in nature consists of representative algorithms such as Genetic algorithm (GA) [17], and Differential evolutions (DE) algorithm [18]. Finally, the algorithms inspired by the living habits of animals and swarms in nature have Particle swarm optimization (PSO) algorithm [19], Bat algorithm (BA) [20], Gray wolf algorithm (GWO) [21], Whale optimization algorithm (WOA) [22], Cuckoo search algorithm (CS) [23], Slime mold algorithm (SMA) [24], Harris hawks optimization (HHO) [25] and Moth flame algorithm (MFO) [26]. Even though the metaheuristic algorithm has

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TABLE 1. The symbols used in the paper.

Symbols	Word shorted or meaning the symbols
SMA	Slime mold algorithm
ISMA	Improved slime mold algorithm
PSO	Particle swarm optimization
DE	Differential evolution algorithm
GWO	Grey wolf optimizer
MFO	Moth-flame optimization
IMFO	Improved moth flame optimization
PPSO	Parallel Particle swarm optimization
PMVO	Parallel Multi-Verse Optimizer
JDE	Adaptive differential evolution with optional external archive
u_b, l_b	u_b and l_b are the upper and lower limits of the search range
$r, rand, z$	r、$rand$ are random numbers between [0,1] , z is a constant
K_k	K_k is comprehensive output coefficient of reservoir k power station
$Q_{k,t}$	$Q_{k,t}$ is power generation flow of reservoir k in period t
$H_{k,t}$	$H_{k,t}$ is a generating head of a reservoir k in period t
Δt	A generating times delta
$V_{k,t}$	$V_{k,t}$ is the reservoir capacity of reservoir k in t period
$I_{k,t}$	$I_{k,t}$ is the inflow flow of reservoir k in period t
$O_{k,t}$	$O_{k,t}$ is the average outflow of reservoir k in period t.
$Z_{k,tmin}$, $Z_{k,tmax}$	$Z_{k,tmin}$, and $Z_{k,tmax}$ are the upper and lower limits of allowable water level of reservoir k in period t respectively.
$N_{k,tmin}$, $N_{k,tmax}$	$N_{k,tmin}$, and $N_{k,tmax}$ are the lower limit and upper limit of allowable power station output of reservoir k in t period
$Q_{k,tmin}$, $Q_{k,tmax}$	$Q_{k,tmin}$, and $Q_{k,tmax}$ are the minimum outflow flow and maximum inflow flow of the k^{th} reservoir in t period.
OBL	Opposition-based Learning
ω_{max}, ω_{min}	the maximum and minimum values of the weight coefficient
T_{max}	T_{max} is the maximum number of iterations
F	Scaling factor

been put forward for many years, it is also a research hotspot now [27], [28]. Table 1 lists the symbols, and shortened words are used in the document.

SMA algorithm [24] a recent metaheuristic algorithm as a stochastic approach of observing the slime mold algorithm of nature for global optimization with some advantages, e.g., with few parameters, robust, excellent capacitating exploratory, and inclination exploitation. SMA has a few parameters. The application would be easily implemented in programming languages; SMA has the robust, excellent potential exploratory capacity, and exploitation inclination when modifying the results would be better than the original one. SMA application for optimal operation of cascade reservoirs is still humble empty. Like other metaheuristic algorithms, the SMA algorithm has three aspects in processing optimization, such as exploration, exploitation, or, say, development, and transition between exploration and development [29], [30]. The exploration is to search for the parts that may have the optimal solution in the whole target area. Its purpose is to ensure that the region with the optimal solution is determined as far as possible. The development aspect determines the optimal solution in the feasible area defined by the exploration. The transition between the exploring and the exploiting parts is the switching key point for the algorithm's balance strategy search [31]. The processing slime mold observation can be divided into three phases: the close to food, the surrounding food, and then the getting food. A mathematical model is established to get the SMA algorithm through the status stages of the habit of slime mold simulation [24].

Moreover, the reservoir is one of the critical storages of surface water and the optimally working single or multi-reservoir network that is an integral feature of water supply management [32]. Cascade hydropower stations are productive in using water sources, water treatment delivery, and flood risk management [33]. Under changing climatic conditions, water sources may undergo dynamic shifts in spatial and temporal dimensions, which may cause numerous problems related to flood protection and water supply management and question the current optimum design of cascade hydropower stations [34]. The purpose of the optimal operation of cascade hydropower stations is to optimize the benefits of cascade hydropower stations by using effective operation methods on the premise of satisfying various constraints of cascade reservoirs [35]. The optimal reservoir operation, considered as a typical nonlinear optimization problem, can be figured out by using the optimization method according to the runoff data and the comprehensive utilization requirements to maximize the economic benefits of the reservoir in the operation cycle and improve the utilization efficiency of water energy resources [36].

The traditional reservoir operation methods [37], such as the dynamic programming algorithms [38], deal with a step-by-step optimization algorithm [39] that produces excellent results. However, the traditional methods would suffer from exploding the complicated computing time for the large scale of the optimal operation problems like cascade hydropower plants. The optimal operation of cascade hydropower stations is the NP-hard problem [40], as the multi-stage decision-making process and the uncertainty of runoffs [36], [41].

In recent years, with the rise of the metaheuristic algorithms [42], such as the mentioned swarm intelligence algorithms [19], [7], the optimal reservoir operation has entered a new stage of being dealt with by swarm intelligence algorithms [43]. Several works developed concerning the dealing with the optimal reservoir operation, e.g., Particle swarm optimization (PSO) algorithm for the optimal dispatch of cascade hydropower stations [44], Differential evolution (DE) algorithm for the optimal transform of cascade hydropower stations [45], Improved moth flame optimization (IMFO) algorithm for the cascade reservoirs operations [46], and Grey wolf optimizer (GWO) for the optimal operation of cascade reservoirs [47].

Although the swarm intelligence algorithms can provide a unique solution for cascade reservoir operation [43], [48], [49], it still also has disadvantages, e.g., falling optimal local, low optimization accuracy, and poor convergence performance [48], [50].

This article considers the first time solving the optimal operation of cascade hydropower stations based on the SMA and improved SMA metaheuristic algorithms to maximize hydropower stations' power generation in different stages for controlling the reservoirs' water quantity. A new, improved SMA algorithm (called ISMA) is introduced to enhance its performance based on hybridizing the original SMA algorithm, the adaptive inertia weight, and the reverse learning strategy to avoid the local optimum.

The highlighted contributions behind the proposed method are mentioned as follows.

- Suggesting an improved SMA algorithm (ISMA) based on hybridizing the original SMA algorithm, inertia weight parameter, and reverse learning strategy.
- Evaluating the suggested ISMA through testing with the CEC2013 test suite and comparing the results with the original algorithm and the other algorithms.
- Implementing the optimal operation of cascade hydropower stations by applying the ISMA to maximize hydropower stations' power generation in different stages for controlling the reservoirs' water quantity.

The remainder of the document is set out as follows. Section 2 presents the slime mold algorithm and the state of the cascade reservoir optimum operating model. Section 3 introduces the ISMA algorithm and evaluates the proposed algorithm over test functions. Section 4 implements the optimization cascade hydropower station by applying the ISMA algorithm. The summary of the paper is presented in Section 5 as a conclusion.

II. RELATED WORK

A. SLIME MOLD ALGORITHM (SMA)

The SMA algorithm is taken the simulation from the life of slime mold Physarum polycephalum that includes the nutritional stage, active stage, and dynamic stage of slime mold [24]. Developing a slime mold process is described as the processing of looking for food, surrounding food, and digesting food. After digesting the current food, slime mold extends through the front to form an unusual shape, creating an interconnected venous network in which the cytoplasm can flow. Every time the slime mold vein is close to the food source, a biological wave is generated inside the slime mold. After receiving the corresponding physical signals, the slime mold will increase the cytoplasmic flow through the vein. The quicker the cytoplasm flows, the thicker the vein becomes. Mucus may create a comparatively, superior optimized pathway to link food via this combination of positive feedback. Under such conditions, the slime mold will travel continuously to find fresh food while at the same time ingesting a variety of food. Changing the slime mold's contraction mode can change the slime mold's vein structure's morphology, which can be classified into three forms. First, as the contraction's strength varies from outside to inside, the coarse veins form around the radius. Second, anisotropy becomes apparent when the contraction mode is unstable. Third, the venous system shall no longer occur until the slime mold's contracting process is no longer spatiotemporal.

Slime mold chooses the right food supply automatically according to the food supplies' consistency and is similar to slime mold searching for the ideal solution. The mathematical description of the SMA algorithm is as follows according to the slime mold habit. According to food-generated knowledge, slime molds use cytoplasm flow in the vein to prevent the food from approaching. The mathematical description of coming food from slime mold is as follows.

$$X(t+1)=\begin{cases} X_c(t)+v_b\cdot(F\cdot X_A(t)-X_B(t)), & r<p \\ v_c\cdot X(t), & r>p \\ rand\cdot(u_b-l_b)+l_b, & r\ and<z \end{cases} \tag{1}$$

where X represents the position of slime mold, and X_c is the optimal value found, X_A and X_B is the two random individuals selected in the population, *rand* and r are the random numbers $\in [0, 1]$, z is a parameter, u_b and l_b are the upper and lower limits of the search range, F the mutation coefficient, v_b is a parameter in the range $[-a, a]$, v_c decreases linearly from 1 to 0, and p is a selector switch. The position of the searched individual can be updated according to the current best position X_c, and the fine adjustment of parameters v_b and F can change the position of the individual.

The oscillation frequency of slime mold is measured in the vicinity of food under varying food concentrations; the frequency helps the slime mold to enter the food faster while seeking high-quality foods. Around the same time, it prefers to step cautiously towards it for food that is of bad quality. Slime mold can be very close to high-quality food sources in this selection mechanism, enhancing slime mold efficiency to obtain high-quality food. Such a method is beneficial to the algorithm for the slime mold algorithm to converge more reliably to the optimum answer that is in (2), as shown at the bottom of the page, where r is a random number $\in [0, 1]$, *bestF* and *worstF* are the currently obtained optimal fitness and the worst fitness value respectively, and *index* is the sorted fitness values.

$$index = sort(\mathrm{S}) \tag{3}$$

Oscillates randomly value $v_b \in [-a, a]$ could approach to zero gradually. The oscillate value of $v_c \in [-1, 1]$, with the increase of iteration times, it would tend to zero. The synergistic effect of v_b and v_c are simulated the selective behavior of slime mold. A better source of food is found. Even after slime mold has found a better source of food, the slime mold can also extract certain organic compounds for exploration in other areas, seeking to find better food sources rather than placing all organic matter in one place.

Also, the state of slime mold is simulated the oscillation process of v_b to decide whether to approach food sources or to look for other food sources. During the period of the process of slime mold, detecting food faces difficulty because the slime mold may encounter various obstacles, such as light, dry environment, etc. These factors will limit the spread of slime mold so that slime mold can not usually move near to food sources. These disturbances can increase the ability of slime mold to escape from the local optimum. The value range of v_b is expressed as follows.

$$a = arctanh(1 - \frac{t}{Max\_ite}) \tag{4}$$

The expression of p is computed as follows.

$$p = tanh\left|S(i) - bestF\right| \tag{5}$$

where t is the current number of iterations and Max_ite is the maximum number of iterations.

B. STATE PROBLEM OF OPTIMAL OPERATION CASCADE HYDROPOWER STATIONS

The optimum operation of cascade hydroelectric power stations is typically split into three stages according to facility management and maintenance, which requires optimized output for the short, medium, and long term [41]. The optimal short-term operation of cascade hydropower stations is to discuss the optimal utilization rate of water resources and the optimal allocation of power load of reservoirs in a shorter period based on the distribution of long-term economical operation to period input [43]. The medium and long-term process of the reservoir group refers to the reservoir's long-term optimization rules to ensure the power system requirements and ensure the pool's safety under the premise of water inflow and complete tasks to obtain the maximum economic benefits. The goal of optimal operation of reservoir group power generation is to pursue the maximization of power generation benefits. Various objective functions of power generation dispatching of reservoir classes are constituted based on the generation benefits that have different definitions from multiple angles and application circumstances of cascade hydropower stations. The objective functions can be maximum power generation capability, maximum power generation gain, minimum water usage, full peak load power optimization, and combining the mentioned objective functions.

The reservoir category focuses not only on power generation but also on flood control, irrigation, water storage, and so forth in the actual cascade reservoir operation process. The model's primary function in this article is primarily power generation, without taking into account the effect and cross of other goals.

Improving the power station's operational gain also depends on generating electricity. Each cycle's generation flow can be reasonably regulated according to the reservoir's initial operating conditions and the inflow runoff under the constraints of water volume, quantity, and output of the hydropower station. It can be an optimization problem of maximizing the cascade hydropower stations' generating ability during the scheduling time. The original water level of each cycle is taken as the vector of optimization, and the cumulative power output is taken as the objective function of optimization. The objective function is mathematically

$$F\left(\mathrm{index\ (i)}\right) = \begin{cases} 1 + r \cdot \log\left(\dfrac{bestF - S\left(i\right)}{bestF - worstF} + 1\right), & if\ \ S(i) >= half\ \ rank(pop) \\ 1 - r \cdot \log\left(\dfrac{bestF - S\left(i\right)}{bestF - worstF} + 1\right), & otherwise \end{cases} \tag{2}$$

expressed as follows.

$$Cost = max \sum_{k=1}^{n} \sum_{t=1}^{T} K_k \cdot Q_{k,t} \cdot H_{k,t} \cdot \Delta t \tag{6}$$

where Δt, $H_{k,t}$, $Q_{k,t}$, and K_k are the length of period of operation time, the generating head of the reservoir, the power generation flow of reservoir k in period t, and the comprehensive output coefficient of reservoir k power station respectively; $Cost$ is objective function of the total power generation of cascade hydropower stations, n is the number of cascade reservoirs, T is the total number of operation periods.

Every problem of optimization requires corresponding constraints to ensure steady optimization process development. Several requirements of constraints for the objective function of the trial are described as follows. The waterfall reservoir power stations are situated within the same river or neighboring tributaries. Not only is there a series connection between upstream and downstream, but there is also a parallel connection. There are also machine production restrictions between hydropower stations alongside their capacity, water depth, and location. The reservoir category is typically composed of reservoirs with various regulating roles, and the restriction conditions usually are composed of water level, head, production, and other measures representing inequalities. The control mode is illustrated below with conditions of constraint for, e.g., the water balance, water level, output control of hydropower station, and reservoir discharge. The constraint for the water balance is expressed as follows.

$$V_{k,t+1} = V_{k,t} + \Delta t \cdot (I_{k,t} - O_{k,t}) \tag{7}$$

where $V_{k,t}$ is the initial reservoir capacity of the reservoir k in t period; $I_{k,t}$ is the inflow flow of reservoir k in period t; and $O_{k,t}$ is the average outflow of reservoir k in period t.

Water level constraints are expressed as follows.

$$Z_{k,tmin} \leq Z_{k,t} \leq Z_{k,tmax} \tag{8}$$

where $Z_{k,t}$ is the water level of reservoir k at the beginning of t period; $Z_{k,tmin}$, $Z_{k,tmax}$ are the upper and lower limits of allowable water level of reservoir k in period t respectively.

Under constraints of output hydropower station is expressed as follows.

$$N_{k,tmin} \leq N_{k,t} \leq N_{k,tmax} \tag{9}$$

where $N_{k,t}$ is the output of reservoir k at t section power station, $N_{k,tmin}$, $N_{k,tmax}$ are the lower limit and upper limit of allowable power station output of reservoir k in period t, and the two correspond to the guaranteed output of the k^{th} reservoir and the installed capacity of the k^{th} reservoir respectively. Under constraint conditions of reservoir discharge is given as follows.

$$Q_{k,tmin} \leq Q_{k,t} \leq Q_{k,tmax} \tag{10}$$

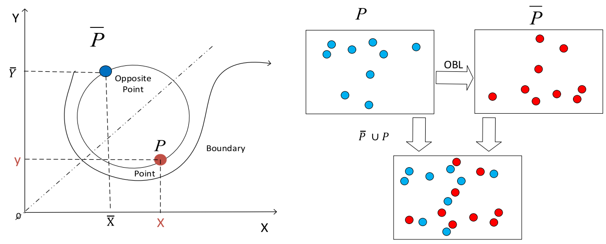
where $Q_{k,tmin}$, $Q_{k,tmax}$ are the minimum discharge and the maximum inflow flow of the k^{th} reservoir. The reservoir water level should not exceed the maximum discharge capacity related to the reservoir water level that discharged water. The difference of discharge between adjacent time periods should also be taken into account by:

$$\left|Q_{i,t+1} - Q_{i,t}\right| \leq \Delta Q_i \tag{11}$$

where ΔQ_i is an amount of permitted water discharge variation in the i^{th} reservoir water discharge between adjacent periods. A recursive based on dynamic programming for reservoir operation in handling with constraints of the reservoir k power station's comprehensive output coefficient is expressed as follows.

$$\begin{aligned} K_{k,t}(s_t) &= h_{k,t}(s_t, r_t) + K_{k,t}(s_{t+1}) \\ subject\ to: s_t + i_t &= r_i + s_{t+1} \end{aligned} \tag{12}$$

where $K_{k,t}(s_t)$ is the maximum cumulative utility from the current period t to total periods T; $h_{k,t}(s_t, r_t)$ is a single-period utility function according to the penalty method; s_t, r_i, and i_t are water storage, release, and inflow od the reservoir at period t, respectively.



a) An opposite-based point example b) The generated reverse solutions

FIGURE 1. A cooperating opposition-based learning (OBL) strategy.

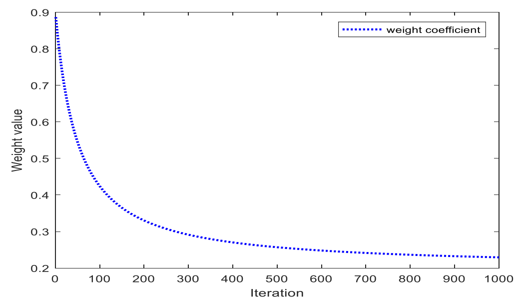


FIGURE 2. A chart of changes in inertia weight values.

III. IMPROVED SLIME MOLD ALGORITHM (ISMA)

This section presents a new process of improving the slime mold algorithm (namely ISMA). The algorithm's processing optimization is implemented by adapting the weight coefficient and cooperating the reverse learning strategy in the expression of the agent's updating positions to enhance the algorithm's optimization performance. The proposed algorithm's presentation is split into two subsections: improving SMA and evaluating the proposed algorithm's performance through testing with the benchmark functions. The description in detail of improving the algorithm is figured out as follows.

TABLE 2. The initial range, dimension, and name of the test benchmark functions.

Series	No.	Functions	*Max Gen.*	Range boundary Lb	Range boundary Ub	$f_i^* = f_i^*(x^*)$
Unimodal functions	1	Sphere Function	2000	-99	99	-1400
	2	Rotated High Conditioned Elliptic Function	2000	-99	99	-1300
	3	Rotated Bent Cigar Function	2000	-99	99	-1200
	4	Rotated Discus Function	2000	-99	99	-1100
	5	Different Powers Function	2000	-99	99	-1000
Basic Multimodal functions	6	Rotated Rosenbrock′s Function	2000	-99	99	-900
	7	Rotated Schaffers Function	2000	-99	99	-800
	8	Rotated Ackley′s Function	2000	-99	99	-700
	9	Rotated Weierstrass Function	2000	-99	99	-600
	10	Rotated Griewank′s Function	2000	-99	99	-500
	11	Rastrigin′ s Function	2000	-99	99	-400
	12	Rotated Rastrigin′s Function	2000	-99	99	-300
	13	Non-Continuous Rotated Rastrigin′s Function	2000	-99	99	-200
	14	Schwefel′ s Function	2000	-99	99	-100
	15	Rotated Schwefel′ s Function	2000	-99	99	100
	16	Rotated Katsuura Function	2000	-99	99	200
	17	Lunacek Bi_Rastrigin Function	2000	-99	99	300
	18	Rotated Lunacek Bi Rastrigin Function	2000	-99	99	400
	19	Expanded Griewank′s plus Rosenbrock's Function	2000	-99	99	500
	20	Expanded Scaffer′s F6 Function	2000	-99	99	600
Composition functions	21	Composition Function 1 (n=5,Rotated)	2000	-99	99	700
	22	Composition Function2 (n=3,Unrotated)	2000	-99	99	800
	23	Composition Function3 (n=3,Rotated)	2000	-99	99	900
	24	Composition Function 4(n = 3,Rotated)	2000	-99	99	1000
	25	Composition Function 5 (n = 3, Rotated)	2000	-99	99	1100
	26	Composition Function 6 (n = 5, Rotated)	2000	-99	99	1200
	27	Composition Function 7 (n=5,Rotated)	2000	-99	99	1300
	28	Composition Function 8 (n = 5, Rotated)	2000	-99	99	1400

A. IMPROVED SLIME MOLD ALGORITHM

A new process of the ISMA is figured out by cooperating opposition-based learning (OBL) strategy and adapting the weight coefficient for updating slime locations to improve the algorithm's optimization performance [51]. The mathematical concept of OBL proposed in 2005 [52] is the corresponding reverse solution in the solution space according to its evaluating the candidate solution. Because the inverse solution is in the opposite position of the solution space, the candidate position may be closer to the optimal global solution.

The reverse learning strategy is applied to generate new local solutions as selecting the better slime mold to participate in the subsequent iterative calculation for updating the optimal solution locations. In the search space, reverse individuals are generated by the current individuals and the best individual. Better individuals would be chosen from the two changing of the optimal current solutions and the global best to move forward to the promising area of searching optimizing target randomly in the community problem space.. The formula of opposition-based learning [52] is presented as follows.

$$X_{ij}^* = l_d - X_{ij} + u_d \tag{13}$$

where u_d and l_d are the minimum value and maximum value of j dimension. X_{ij} is the current solution of the i^{th} slime mold in the j dimension. X_{ij}^* is the reverse generated slime mold solution. The generated reverse solutions are used to compete with the current solutions as in the slime mold position to continue updating locations over the iterative course. The implementation of the reverse learning [52] strategy process can be expressed as follows.

$$X_{ij}^{next} = \begin{cases} X_{ij}^*, & f\left(X_{ij}^*\right) < f(X_{ij}) \\ X_{ij}, & otherwise \end{cases} \tag{14}$$

Here f is the fitness function (for the minimum problems), X_{ij} is the original slime mold locations, X_{ij}^* is the produced reverse slime mold locations, and X_{ij}^{next} is the selected slime mold to continue to participate in the optimization.

For further diverting agents and convergence ability of the algorithm, the inertia weight coefficient is an effective way to effectively increase the searching ability toward optimal solution [53]. Inspired by applying the inertia weight coefficient way, this article implements an improved SMA algorithm based on the inertia weight. The inertia weight coefficient can be changed in many ways, such as linear declining strategy and nonlinear attenuation [54]. The linear declining strategy can produce low diversity of the algorithm. So, a new inertia weight changing the design is proposed with nonlinear attenuation as expressed follows.

$$\omega = \omega_{min}\left(\frac{\omega_{max}}{\omega_{min}}\right)^{1/(1+\frac{10t}{T_{max}})} \tag{15}$$

where ω_{max} and ω_{min} are the maximum and minimum values of the weight coefficient, t is the number of iterations, and T_{max} is the maximum number of iterations. Figures 1 and 2 show the examples of the cooperating OBL strategy, and the inertia weight respectively.

Algorithm 1 Opposition-Based Learning (OBL) Strategy

Input1: *solution*, u_d and l_d

For (i=1 to *popsize*)
  For (j=1 to *dimension*)
    Generate opposite *solution** //Eq.(13)
  Next *j*
  Evaluate the fitness value of opposite *solution**
    If new opposite *solution** is better than the original *solution*, // Eq.(14)
    it is replaced with the new reverse solution
  End If
Next *i*

Output: $solution^{next}$

Changed inertia weight coefficient in the exponential form is determined by the population iteration times and T_{max}. It can be seen that a kind of inertia weight of the slime mold population in each generation is consistent, which can increase the diversity of the algorithm and maintains the stability of the algorithm.

Final, updating slime mold locations of the SMA are modified with the inertia weight coefficient as follows.

$$X(t+1) = \begin{cases} X_c(t) + \omega \cdot v_b \cdot (F \cdot X_A(t) - X_B(t)), & r < p \\ \omega \cdot v_c \cdot X(t), & r > p \\ rand \cdot (u_b - l_b) + l_b, & rand < z \end{cases} \tag{16}$$

The inertia weight is added to the formula of updating slime mold locations of the SMA algorithm that can be more conducive to the algorithm's development ability and exploration ability. For moreover, the pseudo-code of the improved SMA algorithm is shown in Algorithm 2.

Algorithm 2 Pseudo-Code of the ISMA

Initialization:

Set the parameters; search agent (*popsize*), Maximum number of iterations *maxiteration*

Iteration:

While $t < maxiteration$ **do**
  Use Eq. (15) to update ω the weight coefficient
  For $i = 1 : popsize$ **do**
  Reinitialize whether the optimization solution meets being within searching boundaries
  Calculate the fitness function for slime molds
  Generate a new solution according to Algorithm1
  Update the current best value and best solution
  Calculate F the mutation coefficient by Eq.(2)
  End for
  Calculate the updated fitness value
  For $i = 1$: popsize **do**
  Update pAv_bAv_c based on Eqs. (4) and (5)
  Update slime mold's positions Eq. (16)
  End for
  t=t+1
End while

Output: Global optimal solution and its optimal fitness value

B. EXPERIMENTAL RESULTS OF ISMA FOR TEST-SUITE OF CEC2013

In this section, the CEC2013 test suite[55] with twenty-eight real parameter single-objective optimization benchmark functions are used to verify the proposed algorithm of ISMA. The set of twenty eight benchmark functions in the experimental analysis can be divided into three groups of uni-modal, multi-modal, and composition functions, e.g., fa1-fa5 are uni-modal function group, fa6-fa20 are multi-modal function group, and fa21-fa28 are composition function group. Table 2 lists twenty-eight benchmark test functions of CEC 2013 with its function name, initial ranges, dimensions, and optimal targets. The objective function of testing these functions is to verify the minimum value of the error function through the feasibility of the optimization algorithms. Let $f_i^* = f_i^*(x^*)$ be corresponding to the optimal value of the testing function [56]. The testing results of the proposed improvement of the novel ISMA algorithm under 40D of the test suit are compared with several selected recent metaheuristic algorithms, e.g., SMA [24], PSO [19], Parallel PSO algorithm (PPSO) [57], MFO [26], DE [18], Adaptive differential evolution algorithm (JDE) [58], PMVO (Parallel MVO algorithm) [59] and GWO [22].

All tests are performed on Unix operating system on a Laptop with Inter (R) Core (TM) i7-7700-HQ CPU @ 2.80GH z, and all algorithms are implemented in the Unix version of the Matlab 2016b. Fitness error values that are larger than the "*eps*" values ($eps = 2.2204e - 016$) are known to be zeros[60]. In the experiment, 30 runs are performed for each test function, and the fitness value error has been reported

TABLE 3. Parameter setting of various algorithms.

Algorithms	Parameters setting
PSO	$Np = 100, c_1 = c_2 = 1.49455$, $V_{min} = -20$, $V_{max} = 20$, $w_{min} = 0.4$, $w_{max} = 0.9$
GWO	Np=100, $a = [2,0]$ $Maxiter = 2000$
SMA	Np=100, $z = 0.1$, $Maxiter = 2000$
MFO	Np=100, $b = 1, t = [-1,1], a \in [-1,-2], Maxiter = 2000$
DE	Np=100, $P_{cr} = 0.9$, $F = 0.8$
PMVO	Np=100, $G = 4, R = 20, 40, \ldots, Maxiter = 2000, w = 6, W_{min} = 0.2, W_{max} = 0.9$
ISMA	Np=100, $z = 0.1$, $Maxiter = 2000$,
PPSO	Np=100, $c_1 = c_2 = 1.49455$, $V_{min} = -20$, $V_{max} = 20$, $w_{min} = 0.4$, $w_{max} = 0.9$
JDE	Np=100, $\tau_1 = \tau_2 = 0.5$, $f_l = 0.4$, $f_u = 0.8$

TABLE 4. The obtained result of the PSO, MFO, and ISMA algorithms under CEC 2013 test suite.

40D	PSO			MFO			**ISMA**		
	BEST	MEAN	STD.	BEST	MEAN	STD.	BEST	MEAN	STD.
1	-1.26E+03	-4.86E+02	1.04E+03	1.07E+03	1.50E+04	6.45E+03	**-1.40E+03**	**-1.40E+03**	**3.76E-02**
2	1.43E+07	3.19E+07	1.44E+07	7.13E+06	1.22E+08	1.09E+08	**7.24E+05**	**2.67E+06**	**1.27E+06**
3	7.96E+09	5.27E+10	6.28E+10	3.12E+10	2.02E+12	9.97E+12	**6.48E+06**	**2.87E+08**	**4.80E+08**
4	2.44E+04	4.10E+04	9.12E+03	2.85E+04	1.09E+05	7.72E+04	**-5.99E+02**	**1.05E+03**	**1.28E+03**
5	-7.70E+02	-3.09E+02	5.05E+02	9.54E+02	4.02E+03	2.81E+03	**-1.00E+03**	**-1.00E+03**	**3.18E-02**
6	-7.73E+02	-6.72E+02	5.51E+01	-7.44E+02	3.00E+02	8.00E+02	**-8.35E+02**	**-8.27E+02**	**1.48E+01**
7	-7.08E+02	-6.14E+02	6.27E+01	-6.62E+02	-5.74E+02	9.33E+01	**-7.53E+02**	**-7.08E+02**	**1.93E+01**
8	**-6.79E+02**	**-6.79E+02**	1.31E-01	**-6.79E+02**	**-6.79E+02**	1.64E-01	**-6.79E+02**	**-6.79E+02**	**5.18E-02**
9	-5.60E+02	-5.54E+02	2.99E+01	-5.73E+02	-5.65E+02	4.76E+00	**-5.80E+02**	**-5.72E+02**	**3.94E+00**
10	-3.59E+02	-1.92E+02	1.30E+02	-5.13E+00	1.77E+03	9.17E+02	**-4.99E+02**	**-4.98E+02**	**5.47E-01**
11	-7.77E+01	4.19E+01	7.28E+01	-1.84E+02	1.88E-01	1.16E+02	**-3.65E+02**	**-3.36E+02**	**1.21E+01**
12	3.06E+00	1.66E+02	8.30E+01	6.86E+01	2.47E+02	1.09E+02	**-1.97E+02**	**-1.21E+02**	**4.37E+01**
13	1.65E+02	3.49E+02	9.41E+01	1.81E+02	4.04E+02	1.26E+02	**5.89E+00**	**7.07E+01**	**4.45E+01**
14	5.45E+03	6.67E+03	6.82E+02	3.32E+03	5.27E+03	1.09E+03	**9.82E+02**	**1.58E+03**	**4.03E+02**
15	5.42E+03	7.33E+03	8.34E+02	3.66E+03	6.02E+03	9.57E+02	**3.45E+03**	**4.39E+03**	**3.74E+02**
16	2.01E+02	2.02E+02	5.13E-01	**2.00E+02**	**2.01E+02**	2.96E-01	2.01E+02	**2.01E+02**	**2.67E-01**
17	6.91E+02	8.47E+02	9.92E+01	5.27E+02	1.06E+03	3.24E+02	**3.93E+02**	**4.30E+02**	**2.23E+01**
18	7.41E+02	9.06E+02	9.80E+01	7.36E+02	1.15E+03	3.03E+02	**5.84E+02**	**6.56E+02**	**4.19E+01**
19	5.39E+02	1.66E+03	2.94E+03	1.14E+03	1.27E+05	2.48E+05	**5.04E+02**	**5.07E+02**	**1.48E+00**
20	6.17E+02	6.18E+02	**4.36E-01**	**6.14E+02**	6.18E+02	9.15E-01	6.15E+02	**6.17E+02**	6.27E-01
21	1.28E+03	1.53E+03	**8.01E+01**	1.71E+03	2.89E+03	6.13E+02	**9.06E+02**	**1.32E+03**	1.88E+02
22	8.11E+03	1.06E+04	9.19E+02	4.50E+03	7.08E+03	1.31E+03	**2.57E+03**	**3.60E+03**	**4.53E+02**
23	9.11E+03	1.05E+04	**8.50E+02**	5.56E+03	7.73E+03	1.03E+03	**4.17E+03**	**5.98E+03**	8.83E+02
24	1.31E+03	1.34E+03	1.72E+01	1.29E+03	1.31E+03	1.04E+01	**1.27E+03**	**1.28E+03**	**6.56E+00**
25	1.46E+03	1.49E+03	1.87E+01	1.40E+03	1.43E+03	1.05E+01	**1.39E+03**	**1.41E+03**	**9.97E+00**
26	**1.40E+03**	1.59E+03	8.34E+01	**1.40E+03**	1.57E+03	6.03E+01	**1.40E+03**	**1.56E+03**	**3.22E+01**
27	2.66E+03	2.92E+03	1.35E+02	2.41E+03	2.61E+03	1.13E+02	**2.19E+03**	**2.33E+03**	**9.35E+01**
28	3.18E+03	5.87E+03	1.44E+03	3.85E+03	4.52E+03	5.42E+02	**1.80E+03**	**2.05E+03**	**8.37E+01**
W	22	24	23	24	24	25			
L	3	3	4	2	2	2			
D	3	1	1	2	2	1			

for each test, as the best (BEST), the mean (MEAN), and standard deviation (STD.) [61] of the fitness value error has been determined. X denotes the optimal solution achieved by an algorithm, and X represents an algorithm's proper optimal solution. The parameter settings of the algorithms are shown in Table 3. For the test functions, their dimension is set to 40. In order to ensure the fairness of the experiment, the basic conditions of all optimization algorithms are set uniformly. The collecting agents is uniformly set to 100, the solution range is $[-99, 99]$, and the number of iterations

TABLE 5. The obtained result of the SMA, DE, and ISMA algorithms under CEC 2013 test suite.

40D	SMA			DE			**ISMA**		
	BEST	MEAN	STD.	BEST	MEAN	STD.	BEST	MEAN	STD.
1	**-1.40E+03**	**-1.40E+03**	1.49E-01	**-1.40E+03**	**-1.40E+03**	1.75E+00	**-1.40E+03**	**-1.40E+03**	**3.76E-02**
2	1.40E+06	5.55E+06	5.18E+06	5.64E+06	1.43E+07	5.78E+06	**7.24E+05**	**2.67E+06**	**1.27E+06**
3	2.95E+07	5.26E+08	6.71E+08	3.78E+08	2.55E+09	3.97E+09	**6.48E+06**	**2.87E+08**	**4.80E+08**
4	-5.49E+02	1.69E+03	1.55E+03	-2.56E+02	1.88E+03	1.38E+03	**-5.99E+02**	**1.05E+03**	**1.28E+03**
5	**-1.00E+03**	-9.99E+02	1.17E-01	-9.97E+02	-9.95E+02	2.02E+00	**-1.00E+03**	**-1.00E+03**	**3.18E-02**
6	**-8.35E+02**	-8.27E+02	1.47E+01	**-8.35E+02**	**-8.33E+02**	**1.03E+00**	**-8.35E+02**	-8.27E+02	1.48E+01
7	-7.52E+02	**-7.10E+02**	2.31E+01	-7.47E+02	-7.00E+02	2.08E+01	**-7.53E+02**	-7.08E+02	**1.93E+01**
8	**-6.79E+02**	**-6.79E+02**	**4.23E-02**	**-6.79E+02**	**-6.79E+02**	6.18E-02	**-6.79E+02**	**-6.79E+02**	5.18E-02
9	-5.77E+02	-5.71E+02	**3.72E+00**	-5.75E+02	-5.56E+02	1.01E+01	**-5.80E+02**	**-5.72E+02**	3.94E+00
10	-4.97E+02	-4.95E+02	1.74E+00	-4.96E+02	-4.87E+02	1.16E+01	**-4.99E+02**	**-4.98E+02**	**5.47E-01**
11	-3.43E+02	-3.22E+02	1.26E+01	-2.16E+02	-1.49E+02	3.42E+01	**-3.65E+02**	**-3.36E+02**	**1.21E+01**
12	-1.68E+02	-1.02E+02	5.10E+01	2.44E+01	4.74E+01	**1.40E+01**	**-1.97E+02**	**-1.21E+02**	4.37E+01
13	**-4.82E+01**	**6.76E+01**	5.28E+01	1.21E+02	1.46E+02	**1.60E+01**	5.89E+00	7.07E+01	4.45E+01
14	1.42E+03	2.18E+03	4.25E+02	4.46E+03	6.73E+03	1.14E+03	**9.82E+02**	**1.58E+03**	**4.03E+02**
15	3.70E+03	4.86E+03	6.85E+02	9.77E+03	1.05E+04	8.41E+02	**3.45E+03**	**4.39E+03**	**3.74E+02**
16	**2.01E+02**	**2.01E+02**	4.17E-01	2.20E+02	2.03E+02	4.34E-01	**2.01E+02**	**2.01E+02**	**2.67E-01**
17	4.07E+02	4.62E+02	2.81E+01	5.96E+02	6.41E+02	3.39E+01	**3.93E+02**	**4.30E+02**	**2.23E+01**
18	**5.68E+02**	6.68E+02	5.31E+01	7.77E+02	7.96E+02	**1.30E+01**	5.84E+02	**6.56E+02**	4.19E+01
19	5.06E+02	5.09E+02	1.88E+00	5.24E+02	5.28E+02	1.52E+00	**5.04E+02**	**5.07E+02**	**1.48E+00**
20	6.16E+02	**6.17E+02**	5.23E-01	6.18E+02	6.18E+02	**1.58E-01**	**6.15E+02**	**6.17E+02**	6.27E-01
21	9.12E+02	1.34E+03	1.61E+02	9.91E+02	**1.05E+03**	**7.04E+01**	**9.06E+02**	1.32E+03	1.88E+02
22	2.72E+03	4.12E+03	6.43E+02	7.44E+03	8.26E+03	4.57E+02	**2.57E+03**	**3.60E+03**	**4.53E+02**
23	4.72E+03	6.50E+03	1.02E+03	9.93E+03	1.14E+04	**6.83E+02**	**4.17E+03**	**5.98E+03**	8.83E+02
24	**1.26E+03**	**1.28E+03**	1.03E+01	1.27E+03	1.32E+03	1.83E+01	1.27E+03	**1.28E+03**	**6.56E+00**
25	**1.38E+03**	1.41E+03	1.40E+01	**1.38E+03**	**1.40E+03**	1.11E+01	1.39E+03	1.41E+03	**9.97E+00**
26	1.55E+03	1.57E+03	**1.06E+01**	1.57E+03	1.60E+03	2.23E+01	**1.40E+03**	**1.56E+03**	3.22E+01
27	**2.13E+03**	2.36E+03	1.00E+02	2.33E+03	2.65E+03	1.97E+02	2.19E+03	**2.33E+03**	**9.35E+01**
28	2.00E+03	2.14E+03	1.44E+02	2.16E+03	2.25E+03	1.90E+02	**1.80E+03**	**2.05E+03**	**8.37E+01**
W	18	19	23	23	23	19			
L	5	2	5	1	3	9			
D	5	7	0	4	2	0			

is 2000. The obtained results of experiments of the proposed ISMA are compared with the other algorithms are presented in Tables 4 to 7 and Figures 3 and 4.

Tables 4 to 7 show the ISMA and the selected optimization algorithms test results for the twenty-eight test functions of the CEC2013. The tables' data consists of the obtained experimental results of the algorithms for the test functions in terms of BEST, MEAN, and STD that stand for the best, average, standard deviation, respectively. At the end of the tables, the statistical parameters, e.g., 'W,' 'L,' and 'D' are short for 'Win,' 'Lose,' or 'Draw' that used to metric pair comparison rate between the proposed ISMA and other algorithms respectively. If the proposed ISMA result is better than the compared pair algorithm, the 'W' will be added one; otherwise, if it's less than, the 'L' will be added one; otherwise, the 'D' will be added one. According to the analysis data in Table 4, the ISMA has several winners compared to the PSO, and MFO algorithms are 22 and 24 times in the 'BEST' column, respectively. However, the number of the loser ('L') and approximated equals ('D') of the ISMA algorithm in comparison with the PSO and MFO algorithms are 3, 2, and 3, 2, respectively. In the 'MEAN' and 'STD' columns, the ISMA algorithm has a number of the 'Win' are 24, 24 and 23, 25 times, but the number of the 'L' are 3, 2 and 4, 2, and the and 'D' are 1, 2, and 1, 1 in comparison with the PSO and MFO algorithms, respectively. It is seen that the performance of the ISMA is better than the PSO and MFO algorithms in Table 4. Doing the same observation method in Table 4 for Tables 5, 6 and 7, we can see that the number of the 'W's of the proposed ISMA algorithm are more than the number of the 'L's and equals 'D's in comparison with the algorithms of SMA, GWO, PMVO, and DE, respectively. It means that the proposed ISMA algorithm's performance for the test suite is better than that of PSO, MFO, SMA, GWO, PMVO, DE, PPSO, and JDE algorithms.

Figures 3 and 4 show the comparison of the proposed ISMA's convergence curves with several algorithms, e.g., the PMVO, SMA, PPSO, GWO, MFO, JDE, PSO, and DE for

TABLE 6. **The obtained result of the GWO, PMVO, and ISMA algorithms under CEC 2013 test suite.**

40D	GWO			PMVO			**ISMA**		
	BEST	MEAN	STD.	BEST	MEAN	STD.	BEST	MEAN	STD.
1	-3.17E+02	1.56E+03	1.88E+03	**-1.40E+03**	**-1.40E+03**	1.27E-01	**-1.40E+03**	**-1.40E+03**	**3.76E-02**
2	1.40E+07	5.10E+07	1.78E+07	3.72E+06	1.18E+07	3.93E+06	**7.24E+05**	**2.67E+06**	**1.27E+06**
3	6.12E+09	1.48E+10	5.00E+09	9.51E+06	**1.57E+08**	**1.83E+08**	**6.48E+06**	2.87E+08	4.80E+08
4	3.72E+04	5.10E+04	6.87E+03	6.00E+01	1.83E+03	1.40E+03	**-5.99E+02**	**1.05E+03**	**1.28E+03**
5	-7.98E+02	3.57E+02	1.04E+03	**-1.00E+03**	**-1.00E+03**	4.01E-02	**-1.00E+03**	**-1.00E+03**	**3.18E-02**
6	-7.69E+02	-6.64E+02	7.02E+01	**-8.35E+02**	-8.12E+02	2.65E+01	**-8.35E+02**	**-8.27E+02**	**1.48E+01**
7	**-7.67E+02**	**-7.40E+02**	**1.40E+01**	-7.50E+02	-7.16E+02	2.16E+01	-7.53E+02	-7.08E+02	1.93E+01
8	**-6.79E+02**	**-6.79E+02**	5.09E-02	**-6.79E+02**	**-6.79E+02**	**3.51E-02**	**-6.79E+02**	**-6.79E+02**	5.18E-02
9	-5.78E+02	-5.73E+02	3.59E+00	**-5.82E+02**	**-5.76E+02**	**2.97E+00**	-5.80E+02	-5.72E+02	3.94E+00
10	-3.32E+02	1.38E+02	3.57E+02	-4.98E+02	-4.96E+02	7.99E-01	**-4.99E+02**	**-4.98E+02**	**5.47E-01**
11	-3.22E+02	-2.03E+02	5.29E+01	-3.43E+02	-2.57E+02	4.04E+01	**-3.65E+02**	**-3.36E+02**	**1.21E+01**
12	-1.83E+02	-1.04E+02	5.26E+01	**-2.09E+02**	**-1.63E+02**	**3.08E+01**	-1.97E+02	-1.21E+02	4.37E+01
13	-4.45E+00	5.97E+01	5.26E+01	**-4.51E+01**	**3.50E+01**	**3.72E+01**	5.89E+00	7.07E+01	4.45E+01
14	2.93E+03	4.48E+03	9.66E+02	3.10E+03	5.14E+03	7.86E+02	**9.82E+02**	**1.58E+03**	**4.03E+02**
15	3.75E+03	5.23E+03	1.50E+03	3.67E+03	5.31E+03	8.04E+02	**3.45E+03**	**4.39E+03**	**3.74E+02**
16	2.02E+02	2.03E+02	3.57E-01	**2.00E+02**	**2.01E+02**	5.37E-01	2.01E+02	**2.01E+02**	**2.67E-01**
17	5.02E+02	5.88E+02	7.61E+01	4.85E+02	5.46E+02	3.47E+01	**3.93E+02**	**4.30E+02**	**2.23E+01**
18	6.21E+02	7.51E+02	8.22E+01	**5.77E+02**	6.69E+02	5.36E+01	5.84E+02	**6.56E+02**	**4.19E+01**
19	5.23E+02	2.20E+03	3.10E+03	5.10E+02	5.14E+02	3.43E+00	**5.04E+02**	**5.07E+02**	**1.48E+00**
20	6.16E+02	**6.17E+02**	5.63E-01	6.16E+02	6.18E+02	**5.20E-01**	**6.15E+02**	**6.17E+02**	6.27E-01
21	1.53E+03	2.39E+03	5.03E+02	9.10E+02	**1.12E+03**	1.98E+02	**9.06E+02**	1.32E+03	**1.88E+02**
22	5.07E+03	6.59E+03	1.14E+03	5.77E+03	7.44E+03	1.15E+03	**2.57E+03**	**3.60E+03**	**4.53E+02**
23	**3.89E+03**	7.43E+03	1.67E+03	5.40E+03	7.09E+03	9.78E+02	4.17E+03	**5.98E+03**	**8.83E+02**
24	**1.24E+03**	**1.27E+03**	1.06E+01	1.26E+03	1.28E+03	9.95E+00	1.27E+03	1.28E+03	**6.56E+00**
25	1.40E+03	1.42E+03	1.12E+01	**1.39E+03**	**1.41E+03**	1.01E+01	**1.39E+03**	**1.41E+03**	**9.97E+00**
26	**1.40E+03**	**1.53E+03**	6.63E+01	**1.40E+03**	1.55E+03	**2.98E+01**	**1.40E+03**	1.56E+03	3.22E+01
27	**2.12E+03**	**2.28E+03**	**7.84E+01**	2.13E+03	**2.28E+03**	8.17E+01	2.19E+03	2.33E+03	9.35E+01
28	2.60E+03	3.53E+03	4.46E+02	2.13E+03	2.28E+03	2.80E+02	**1.80E+03**	**2.05E+03**	**8.37E+01**
W	21	20	23	15	14	20			
L	5	6	5	7	8	8			
D	2	2	0	6	6	0			

several selected test functions. The results of the convergence graphs of the ISMA for test functions more several algorithms intuitively. It can be seen that in these competitions, the ISMA algorithm performs better convergence rates than other optimization algorithms. It reflects the ISMA performance is improved, which means that the ISMA has a more remarkable improvement in the convergence performance and the optimal values found than the original SMA algorithm.

IV. APPLIED ISMA TO CASCADE HYDROPOWER STATIONS' OPTIMAL OPERATION

In this section, the ISMA is applied to implement for dispatching optimal operation cascade reservoirs. A data collection of cascade reservoirs of the specific river basin in the Wujiang river basin [62] is used experimentally with the examination for managing the power grid. Initializing hydropower station as a collected data with three reservoirs of the Wujiang river basin is listed in Table 8. Wujiang river basin is one of the effects of large basins on hydropower bases in China [63]. Wujiang River is the seventh-largest tributary of the Yangtze River. It is extremely rich in hydropower resources and plays a vital role in China's hydropower generation.

The group of reservoirs has been formed in a sequence of three reservoirs with symbols of A, B, and C. Reservoir A is the first-level reservoir of the designated cascade reservoir system, the second-level pool is reservoir B, and the third-level reservoir is reservoir C. Figure 5 illustrates an example of a scenario of the schematic diagram system of the three reservoirs. The main significant task of the three pools is to generate electricity, and there is an interval inflow between the reservoirs.

In which I_i $(i = 1, 2, 3)$ and R_i $(i = 1, 2, 3)$ represent the interval inflow of the corresponding reservoir and the discharge of the corresponding reservoir, respectively. The three reservoirs consider power generation as their principal mission that the water supply for each pool is from the main river and other sources of supplemental water. The river represents

TABLE 7. The obtained result of the JADE, PPSO, and ISMA algorithms under CEC 2013 test suite.

40D	PPSO			JDE			**ISMA**		
	BEST	MEAN	STD.	BEST	MEAN	STD.	BEST	MEAN	STD.
1	**-1.40E+03**	-1.39E+03	4.66E+00	**-1.40E+03**	**-1.40E+03**	5.12E-01	**-1.40E+03**	**-1.40E+03**	**3.76E-02**
2	6.23E+06	1.38E+07	5.17E+06	**1.22E+04**	**5.01E+05**	**8.21E+05**	7.24E+05	2.67E+06	1.27E+06
3	5.17E+08	5.13E+09	3.34E+09	2.37E+07	1.49E+09	2.91E+09	**6.48E+06**	**2.87E+08**	**4.80E+08**
4	1.06E+04	1.98E+04	5.77E+03	**-1.10E+03**	**5.85E+02**	7.20E+03	-5.99E+02	1.05E+03	**1.28E+03**
5	-9.79E+02	-9.31E+02	1.95E+01	**-1.00E+03**	-9.83E+02	5.42E+01	**-1.00E+03**	**-1.00E+03**	**3.18E-02**
6	-8.34E+02	-7.78E+02	4.09E+01	**-8.35E+02**	-8.09E+02	4.59E+01	**-8.35E+02**	**-8.27E+02**	**1.48E+01**
7	-6.99E+02	-6.41E+02	3.87E+01	-7.40E+02	-6.66E+02	4.26E+01	**-7.53E+02**	**-7.08E+02**	**1.93E+01**
8	**-6.79E+02**	**-6.79E+02**	8.42E-02	**-6.79E+02**	**-6.79E+02**	1.12E-01	**-6.79E+02**	**-6.79E+02**	**5.18E-02**
9	-5.65E+02	-5.58E+02	3.99E+00	**-5.80E+02**	-5.70E+02	4.91E+00	**-5.80E+02**	**-5.72E+02**	**3.94E+00**
10	-4.80E+02	-4.44E+02	1.58E+01	**-5.00E+02**	-4.97E+02	1.08E+01	-4.99E+02	**-4.98E+02**	**5.47E-01**
11	-1.99E+02	-8.83E+01	6.30E+01	-3.14E+02	-2.09E+02	6.25E+01	**-3.65E+02**	**-3.36E+02**	**1.21E+01**
12	-6.93E+01	4.96E+01	8.48E+01	-1.86E+02	-8.29E+01	6.00E+01	**-1.97E+02**	**-1.21E+02**	**4.37E+01**
13	1.50E+02	2.68E+02	6.39E+01	8.26E+00	1.39E+02	6.94E+01	**5.89E+00**	**7.07E+01**	**4.45E+01**
14	3.76E+03	5.94E+03	7.97E+02	1.12E+03	2.41E+03	6.34E+02	**9.82E+02**	**1.58E+03**	**4.03E+02**
15	4.35E+03	6.87E+03	1.03E+03	**3.06E+03**	4.67E+03	8.02E+02	3.45E+03	**4.39E+03**	**3.74E+02**
16	2.01E+02	2.02E+02	4.72E-01	**2.00E+02**	**2.01E+02**	3.74E-01	2.01E+02	**2.01E+02**	**2.67E-01**
17	6.26E+02	7.69E+02	6.75E+01	4.68E+02	5.51E+02	6.52E+01	**3.93E+02**	**4.30E+02**	**2.23E+01**
18	7.27E+02	8.75E+02	7.54E+01	**5.68E+02**	6.75E+02	6.32E+01	5.84E+02	**6.56E+02**	**4.19E+01**
19	5.26E+02	5.40E+02	1.29E+01	5.10E+02	5.51E+02	2.33E+01	**5.04E+02**	**5.07E+02**	**1.48E+00**
20	6.17E+02	6.18E+02	3.99E-01	**6.15E+02**	**6.17E+02**	**7.38E-02**	**6.15E+02**	**6.17E+02**	6.27E-01
21	1.09E+03	1.41E+03	**6.01E+01**	**9.00E+02**	**1.26E+03**	2.08E+02	9.06E+02	1.32E+03	1.88E+02
22	5.86E+03	8.66E+03	1.23E+03	4.71E+03	6.07E+03	7.43E+02	**2.57E+03**	**3.60E+03**	**4.53E+02**
23	7.61E+03	9.35E+03	9.85E+02	5.16E+03	6.45E+03	9.68E+02	**4.17E+03**	**5.98E+03**	**8.83E+02**
24	1.32E+03	1.34E+03	1.33E+01	1.28E+03	1.30E+03	1.31E+01	**1.27E+03**	**1.28E+03**	**6.56E+00**
25	1.45E+03	1.48E+03	1.57E+01	1.41E+03	1.43E+03	1.15E+01	**1.39E+03**	**1.41E+03**	**9.97E+00**
26	**1.40E+03**	**1.45E+03**	9.26E+01	**1.40E+03**	1.57E+03	4.59E+01	**1.40E+03**	1.56E+03	**3.22E+01**
27	2.66E+03	2.88E+03	1.27E+02	2.32E+03	2.48E+03	1.06E+02	**2.19E+03**	**2.33E+03**	**9.35E+01**
28	2.29E+03	3.17E+03	1.26E+03	2.17E+03	2.79E+03	5.45E+02	**1.80E+03**	**2.05E+03**	**8.37E+01**
W	24	26	27	14	21	26			
L	0	1	1	7	3	2			
D	4	1	0	7	4	0			

TABLE 8. The parameters with the estimation metric data of the system of initializing hydropower station with three reservoirs.

Name / Parameter	A	B	C
Dead water level (m)	1076	936	822
Average water level (m)	1140	970	837
The storage capacity of the reservoir (Billion m^3)	44.97	8.64	1.68
Regulating storage capacity Billion m^3)	33.61	4.91	0.668
Regulation performance	Year	Incomplete year	Year
Installed capacity (MW)	600	695	600
Output coefficient	8.5	8.35	8.5

the main channel to the water supply. The supplementary water sources I_i flows into reservoirs A, B, and C. The pools of discharge water sources R_i flow into the forwarded main river.

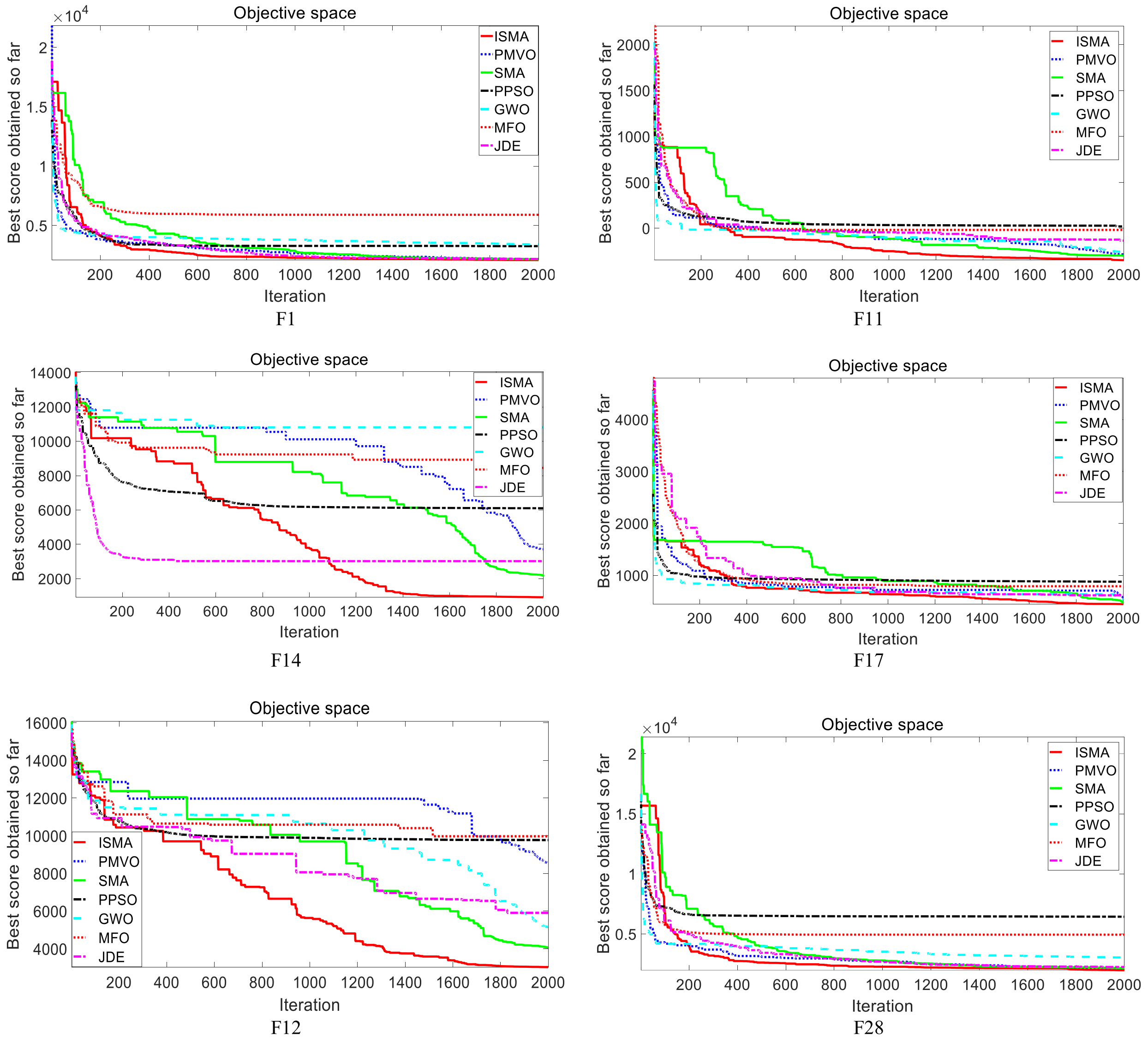


FIGURE 3. Convergence graphs of six selected test functions under different algorithms of the ISMA compare with the PMVO [59], SMA [24], PPSO [57] GWO [22], MFO [26] and JDE [58]algorithms.

Table 8 lists the parameters with the initializing hydropower station system's estimation metric data with three reservoirs.

The maximum value of the three reservoirs' total annual power generation is calculated as the objective of the solution to optimal operation. A selected system with three pools is monthly scheduling of 12 months as the time cycle starts from January and ends in December. That is 12 months as a scheduling cycle in Table 8. That is the specific parameters of the three selected reservoirs. The water level is taken as the optimization variable, and the total power generation of the three power stations is taken as the objective function of optimization. Figure 6 shows the flow chart of the proposed ISMA process for optimal operations of cascade hydropower stations. The operation of three reservoirs for the cascade hydropower stations is scheduled for the interval period, e.g., weekly, monthly, or quarterly. Monthly scheduling is one year, with 12 months used that the period started is in January of the year and ended is in December. The maximum value of the three reservoirs' total power generation in one year is the objective function for calculating the goal of optimization. The group reservoirs with several scenarios, e.g., the typical rainy years, specific average years, and typical dry years of calculation cases, are selected for implementation for testing the proposed scheme of optimal operation based on the applied ISMA. Eq. (6) is considered the objective function of optimization for taking the sum of the power generation of the hydropower stations that are figured out by optimizing the proposed scheme. Let X be the water level, with $X = [x_i^1, \ldots, x_i^{12}, x_i^1, \ldots, x_i^{12}, x_i^1, \ldots, x_i^{12}]$ as the optimized variable with subscript $i (i = 1, 2, n)$ is the *i-th* reservoirs, e.g., 1, 2, and 3 as a sequence of

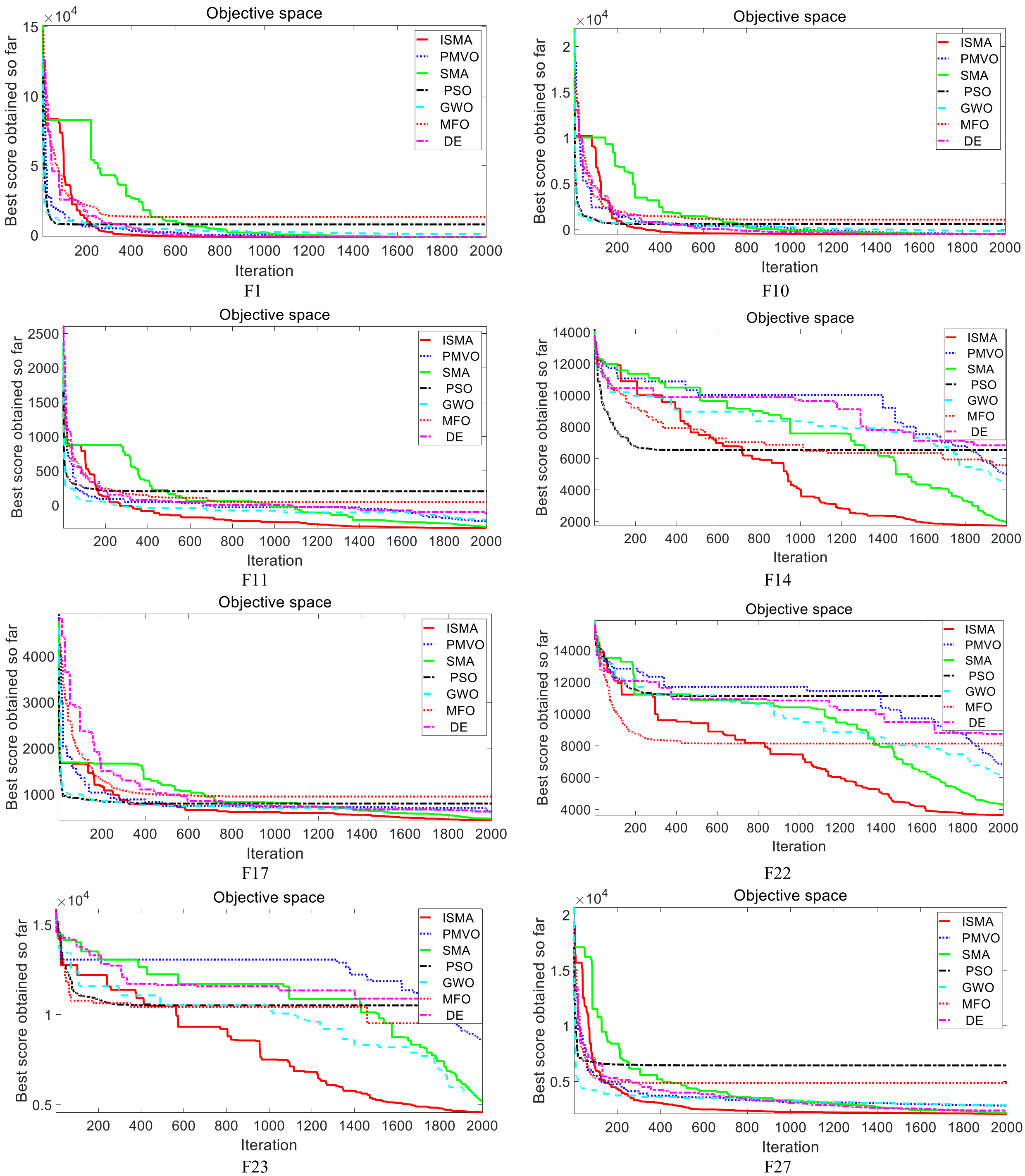


FIGURE 4. Convergence graphs of six selected test functions under different algorithms of the ISMA compare with the PMVO[59], SMA [24], PSO [19], GWO [22], MFO [26] and DE [18] algorithms.

mentioned A, B, and C reservoirs. Figure 6 shows the flow chart of the process of optimizing the hydropower stations by using the ISMA. The obtained results of the proposed scheme ISMA are compared with the other schemes, e.g., the PSO [44], IMFO [46], DE [45], GWO [47], and SMA [24] algorithms for the operation hydropower stations. Setting the experiment environment for the algorithms is such as the search agent is set to 100; the total number of iterations is 500; the number of runs for algorithm involved independently is set to 30. Table 9 records the ISMA's obtained statistical data compared with the other schemes, e.g., the PSO, MFO, DE, SMA, and GWO for the managing operation problem

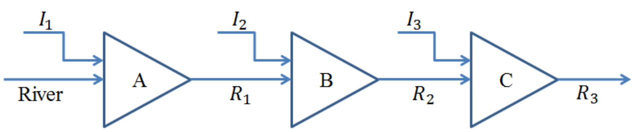


FIGURE 5. Schematic diagram of selected cascade reservoirs.

of the cascade hydropower stations. The obtained statistical data consist of the best value, worst value, average value, and standard deviation of the 30 runs results in different typical years. The scenario of varying water levels depends on the specific years that composed the rainy year, the average year, and the dry year.

Observed Table 9 shows that the obtained results data of the ISMA are increased amount of the average, the best, and standard deviation compared with the other schemes. The rate statistically recorded data results in compared pair between the ISMA and the different algorithm is calculated as the ISMA subtracted by comparative algorithms: PSO, IMFO, DE, GWO, and SMA for the average value and standard deviation, are 3.8124, 3.5201, 0.5987, 1.7241, and 0.9738 billion kW · h, 1.4698, 0.2715, 0.1620, 0.4036, 0.2617 billion kW · h, respectively in the operation of the wet year.

We do the same as the ISMA's subtracted calculations with comparative algorithms for the year of regular and dry operations in terms of the average values (*Mean*) and standard deviations (*Std.*). The calculation results of the average costs and standard deviations are 2.7467, 3.2505, 0.3212, 1.3604, and 0.5295 billion kW · h, and 1.0087, 0.3695, 0.0984, 0.2102, 0.072 billion kW · h, respectively in a regular year.

The figures for the dry year are 2.5125, 1.8756, 0.3763, 1.1327 and 0.509 billion kW · h, and 0.8661, 0.2209, 0.1003, 0.2125, 0.1662 billion kW · h, respectively.

In general, the comparison data analysis results of the ISMA with other schemes for the optimal operation of cascade hydropower stations shows that the ISMA scheme provides robustness and saves significantly better energy than the SMA, PSO, DE, GWO, and MFO algorithms.

Figures 7, 8, and 9 show the curves of the obtained optimum result chart of the power generation in the typical year (rainy, ordinary, and dry year) of the ISMA, PSO [44], SMA [24], DE [45], IFMO [46], and GWO [47] algorithms for the operation hydropower stations. It can be seen from the diagrams corresponding to several specific years that ISMA can obtain the largest generation of performance and maintain optimization ability in optimization.

Figures 10, 11, and 12 show the comparison of the rate of saving energy in the optimal operation of managing water

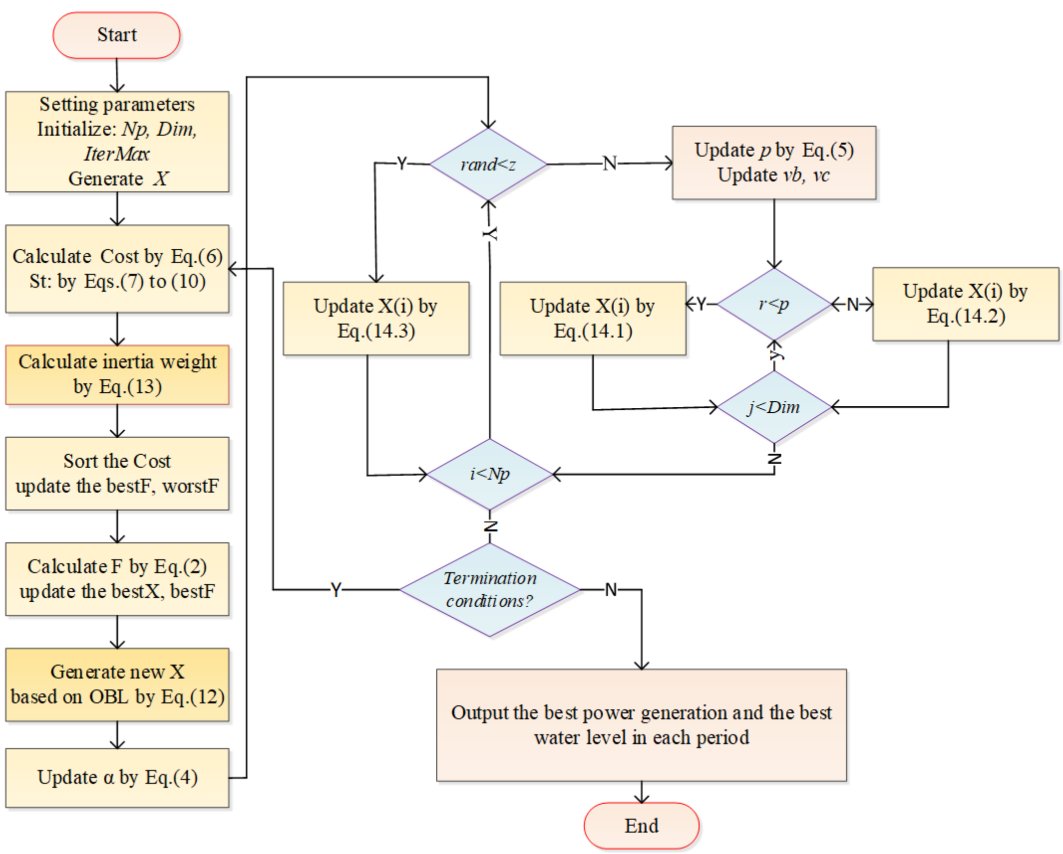


FIGURE 6. A flow-chart of the proposed ISMA for optimal operations of cascade hydropower stations.

TABLE 9. Joint scheduling results of three reservoirs in various typical years (10^8 KW·H).

Typical year	Algorithms	Best	Mean	Std
Rainy year	PSO	83.7537	81.4801	1.4904
	IMFO	82.3601	81.7724	0.2921
	DE	84.9501	84.6938	0.1826
	GWO	84.1359	83.5684	0.4242
	SMA	84.7351	84.3187	0.2823
	ISMA	**85.3273**	**85.2925**	**0.0206**
Normal year	PSO	69.5700	67.9521	1.0185
	IMFO	68.1487	67.4483	0.3793
	DE	70.5438	70.3776	0.1082
	GWO	69.7000	69.3384	0.2200
	SMA	70.4083	70.1693	0.0818
	ISMA	**70.7169**	**70.6988**	**0.0098**
Dry year	PSO	61.9037	60.3186	0.8758
	IMFO	61.3245	60.9555	0.2306
	DE	62.6509	62.4548	0.1100
	GWO	62.1294	61.6984	0.2222
	SMA	62.6753	62.3221	0.1759
	ISMA	**62.8377**	**62.8311**	**0.0097**

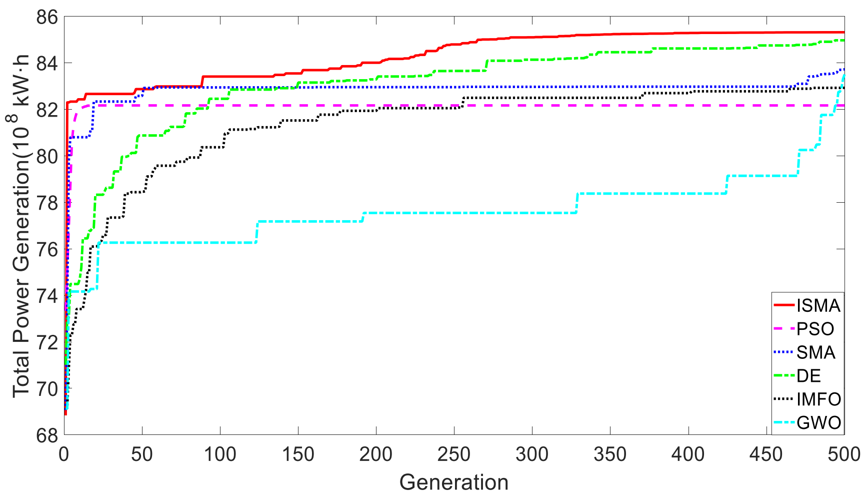


FIGURE 7. The curve of the obtained optimum result chart of the power generation in a rainy year of six schemes, e.g., the ISMA, PSO [44], SMA [24], DE [45], IFMO [46], and GWO [47] algorithms for the operation hydropower stations.

levels of the IMSA with the PSO, SMA, GWO, DE, and IFMO schemes for reservoirs over month periods in typical years of rainy, dry, or normal rain levels.

Implementing dispatching scheduling operation of managing water changes for cascade hydropower stations based on applying ISMA provides more conducive efficient operation. It saves more energy than the other methods, e.g., the PSO, GWO, DE, MFO schemes, in comparison under setting the same condition to guarantee water energy conservation while supplying the power generation.

Compared with the original SMA algorithm, the ISMA algorithm obtained water level position changes more smoothly. Moreover, as added more equations to the algorithm that causes the complexity time. However, for dealing

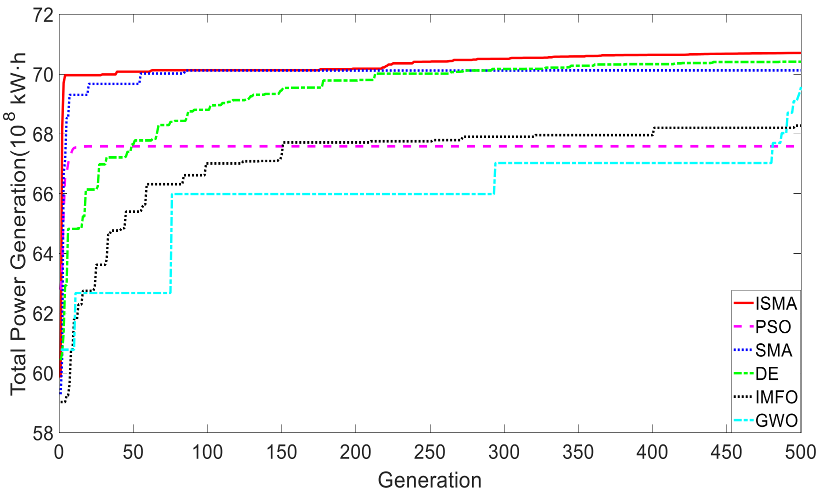


FIGURE 8. The curve of the obtained optimum result chart of the power generation in a normal year of six schemes,.g., the ISMA, PSO [44], SMA [24], DE [45], IFMO [46], and GWO [47] algorithms for the operation hydropower stations.

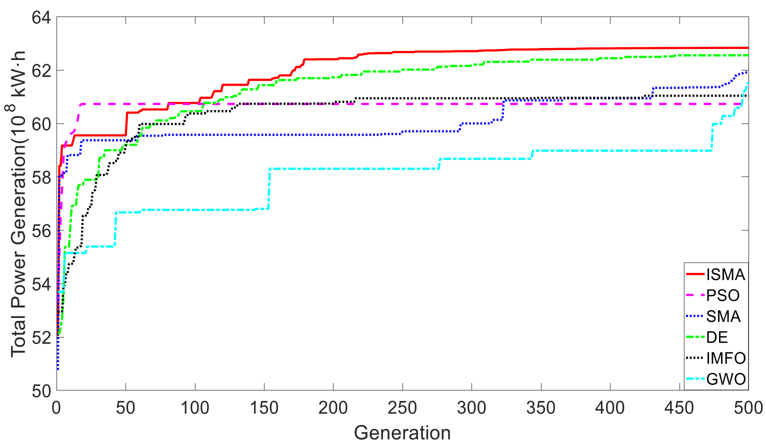


FIGURE 9. The curve of the obtained optimum result chart of the power generation in a dry year of six schemes, e.g.,.g., the ISMA, PSO [44], SMA [24], DE [45], IFMO [46], and GWO [47] algorithms for the operation hydropower stations.

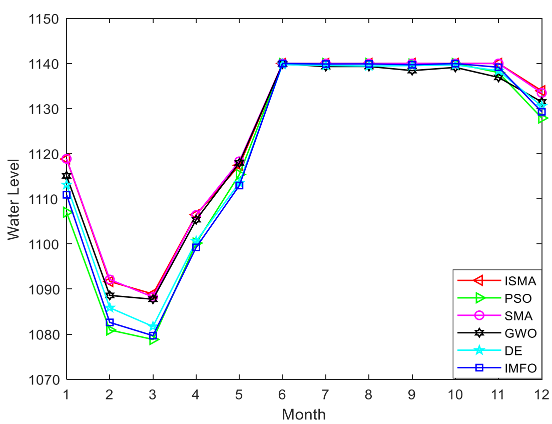


FIGURE 10. Comparison of the rate of saving energy in the optimal operation of managing water levels of the IMSA with the PSO, SMA, GWO, DE, and IFMO schemes for reservoirs over month periods in a rainy year.

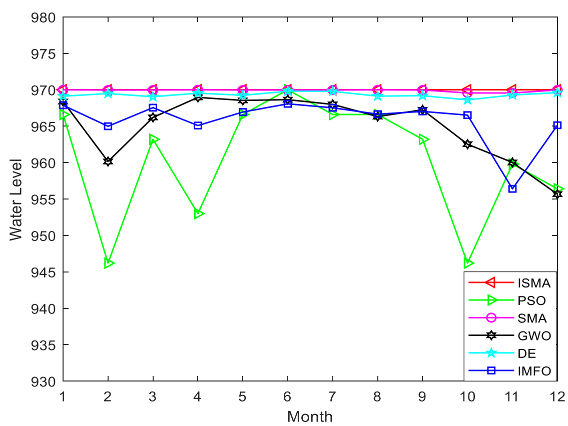


FIGURE 11. Comparison of the rate of saving energy in the optimal operation of managing water levels of the IMSA with the PSO, SMA, GWO, DE, and IFMO schemes for reservoirs over month periods in a normal year.

with a complicated problem, time complexity (time consumption) is not much bigger encountering effective than the original SMA algorithm.

From the obtained water level information maps of different typical years, its water levels change advantage can be controlled undeniable. The maintained water level at a higher

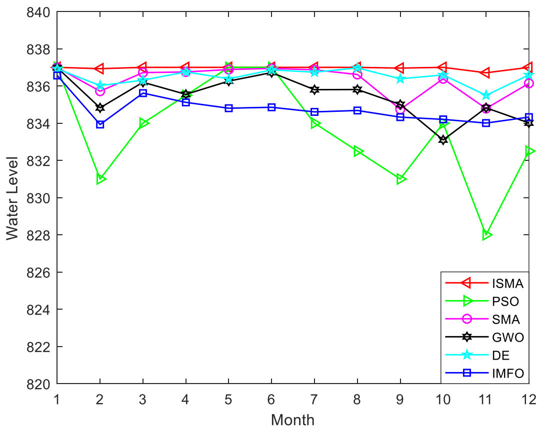


FIGURE 12. Comparison of the rate of saving energy in the optimal operation of managing water levels of the IMSA with the PSO, SMA, GWO, DE, and IFMO schemes for reservoirs over month periods in a normal year.

level ensures the storage of water energy while providing power generation, which is more conducive to dispatching work.

V. CONCLUSION

In this article, we proposed a new improvement of the slime mold algorithm (ISMA) for dealing with the optimal operation of cascade reservoirs. The proposed ISMA was implemented based on adapting the inertia weight coefficient and cooperating opposition-based learning (OBL) strategy for reverse agents, updating location expression. The adaptive weight strategy provides the location update mechanism of slime mold dynamically, adjusts according to the actual situation, and increases search converge performance of slime mold. And the reverse learning mechanism produces good slime mold to replace the low slime mold rate of fitness, so agents' potential is enhanced higher for escaping from local optimum. The proposed algorithm's performance evaluation was figured out by experimenting with testing many selected benchmark functions and cascade reservoirs' optimal operations. Comparisons of the proposed approach's results with the various algorithms under the same case situations show that the recommended solution produces better performance than the different competing algorithms. Compared with the other schemes for dispatching cascade hydropower stations, the applied ISMA algorithm performs the generation capacity of the optimal operation, and joint reservoirs are better than that of other optimization schemes. The experimental results of the experiments can verify the effectiveness and feasibility of the ISMA algorithm. We would apply the proposed IMSA for further solutions to dispatching load electricity power [64] and future work combinatorial problems [5] in future work.

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