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Improved particle swarm optimization algorithm for multi-reservoir system operation

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Abstract: In this paper, a hybrid improved particle swarm optimization (IPSO) algorithm is proposed for the optimization of hydroelectric power scheduling in multi-reservoir systems. The conventional particle swarm optimization (PSO) algorithm is improved in two ways: (1) The linearly decreasing inertia weight coefficient (LDIWC) is replaced by a self-adaptive exponential inertia weight coefficient (SEIWC), which could make the PSO algorithm more balanceable and more effective in both global and local searches. (2) The crossover and mutation idea inspired by the genetic algorithm (GA) is imported into the particle updating method to enhance the diversity of populations. The potential ability of IPSO in nonlinear numerical function optimization was first tested with three classical benchmark functions. Then, a long-term multi-reservoir system operation model based on IPSO was designed and a case study was carried out in the Minjiang Basin in China, where there is a power system consisting of 26 hydroelectric power plants. The scheduling results of the IPSO algorithm were found to outperform PSO and to be comparable with the results of the dynamic programming successive approximation (DPSA) algorithm.
Key words: *particle swarm optimization; self-adaptive exponential inertia weight coefficient; multi-reservoir system operation; hydroelectric power generation; Minjiang Basin*

1 Introduction

Multi-reservoir system operation is one of the key issues among a variety of problems in water resources systems. From the viewpoint of power generation, reasonable multi-reservoir system operation strategy could not only maximize the utility of natural water resources, yielding a large amount of social and economic wealth, but also guarantee the stability and reliability of the power grid. Therefore, multi-reservoir system operation optimization is vital to all countries, especially ones in which hydroelectric power is the largest power source or is expected to make up a fairly large proportion, such as Brazil and China. Over the past sixty years, many mathematical techniques have been used to solve multi-reservoir system operation problems, including traditional methods such as linear programming, network flow

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optimization, nonlinear programming, and modern heuristic algorithms. Along with these methods, a large variety of optimization models, such as dynamic programming (DP) (Archibald et al. 1997; Faber and Stedinger 2001; Kumar and Baliarsingh 2003; Tejadaguibert et al. 1995), artificial neural networks (ANN) (Chaves and Chang 2008; Chaves and Kojiri 2007; Neelakantan and Pundarikanthan 2000), the genetic algorithm (GA) (Chen 2003; Jothiprakash and Shanthi 2006; Kim et al. 2006; Li and Wei 2008; Sharif and Wardlaw 2000), the ant colony optimization (ACO) algorithm (Jalali et al. 2006, 2007; Kumar and Reddy 2006), fuzzy programming (Russell and Campbell 1996), and the shuffled complex evolution (SCE) algorithm (Ngo et al. 2007), as well as hybrid models (Cai et al. 2001, 2004; Chandramouli and Raman 2001; Cheng et al. 2008; Chiu et al. 2007; Mousavi et al. 2004a, 2004b; Ponnambalam et al. 2003; Reis et al. 2005; Yuan et al. 2008), have been widely used. More extensive and detailed understanding of these applications can be found in Labadie (2004) and Yeh (1985). Although so many models have been applied to the optimization of multi-reservoir system operation, the gap has been widening between theoretical research and real-world implementation, as pointed out by researchers such as Labadie (2004). Because of the complexity of multi-reservoir systems, featuring stochastic, dynamic, multi-dimensional, and nonlinear characteristics, many handicaps are not avoidable in the practical implementation of multi-reservoir system operation, including the so-called curse of dimensionality, which results in failure of many optimization models such as fuzzy programming (Russell and Campbell 1996).

In recent years, the particle swarm optimization (PSO) algorithm (Kennedy and Eberhart 1995), a new heuristic search optimization technique, has drawn significant attention from researchers and has been widely applied to many optimization fields, including chemistry (Call et al. 2007), physics (Pastorino 2007; Robinson and Rahmat-Samii 2004), finance (Ko and Lin 2006), power systems (del Valle et al. 2008), architectonics (Rao and Anandakumar 2007), and material science (Lee et al. 2007), due to its efficacy in nonlinear system optimization. In the field of water resources, the PSO algorithm is also increasingly applied in parameter estimation for hydrological models (Gill et al. 2006), hydrological forecasting (Chau 2007; Hong 2008; Wu and Chau 2006), and water supply planning (Shourian et al. 2008). However, reports on the application of PSO to reservoir system operation are relatively few. Kumar and Reddy (2007) proposed an elitist-mutated particle swarm optimization (EMPSO) technique, applied it to a hypothetical multi-reservoir system and a realistic multipurpose reservoir, and concluded that EMPSO could yield better solutions compared with standard PSO and GA techniques. The EMPSO technique was also used to make an operational model of short-term reservoir operation for irrigation of multiple crops (Reddy and Kumar 2007a). Furthermore, Reddy and Kumar (2007b) presented an elitist-mutation multi-objective particle swarm optimization (EM-MOPSO) approach for generating Pareto-optimal solutions to reservoir operation problems. Shourian et al. (2008) integrated PSO with a generalized river basin network flow model, MODSIM, for the optimal operation of the upstream Sirvan River Basin in Iran. Although the number of applications in many fields increases rapidly, the conventional PSO algorithm suffers from the problems of prematurity, slow convergence in the later evolutionary stage, and a tendency to get trapped in local optima, which decrease its efficiency, especially in dealing with the optimization of complicated multi-reservoir systems.

In this paper, a new hybrid improved particle swarm optimization (IPSO) algorithm for multi-reservoir system operation is proposed, to overcome the internal drawbacks mentioned above in two ways. First, the conventional linearly decreasing inertia weight coefficient (LDIWC) is replaced by a self-adaptive exponential inertia weight coefficient (SEIWC), which could improve the balancing ability of the PSO algorithm in both global and local searches. Second, the crossover and mutation idea inspired by GA is imported into the particle updating method to enhance the diversity of populations. The potential ability of the IPSO algorithm in nonlinear numerical function optimization was first inspected through an optimization test with three classical benchmark functions, including a unimodal function and two multimodal functions, and the results are encouraging when compared with those of GA. A long-term multi-reservoir system operation model based on IPSO, using energy maximization with a specified guaranteed output as the objective function to be optimized, was designed, and a case study was carried out in the Minjiang Basin in Fujian Province, China.

2 Improved particle swarm optimization algorithm

2.1 Conventional particle swarm optimization algorithm

The PSO algorithm originally proposed by Kennedy and Eberhart (1995) was based on the social behavior of organisms such as birds flocking and fish schooling, coupled with swarm theory. Like many other evolutionary computation techniques, for example GA and ACO, the PSO algorithm begins by generating an initial population of random potential solutions and searches the solution space for optimal fitness according to its optimization mechanism, individual (particle) improvement, and population (swarm) evolution, through an iterative computation. Every particle has two attributes, position and velocity, marked as $\boldsymbol{X}$ and $\boldsymbol{U}$, respectively, and their updating relies on their own experience and the experience of neighboring particles, which represent the individual cognitive level and the social cognitive level, respectively. Assuming the solution space to be D-dimensional, the position of the ith particle of a swarm can be represented by a D-dimensional vector, $\boldsymbol{X}_i = \left(x_{i1}, x_{i2}, ..., x_{iD}\right)^{\mathrm{T}}$. For the previous t times of iteration, the best position for particle i is marked as $\boldsymbol{P}_i = \left(p_{i1}^t, p_{i2}^t, ..., p_{iD}^t\right)^{\mathrm{T}}$, and the best particle in the swarm, with the best global fitness value, is marked as $\boldsymbol{P}_{\mathrm{g}} = \left(p_{\mathrm{g}1}^t, p_{\mathrm{g}2}^t, ..., p_{\mathrm{g}D}^t\right)^{\mathrm{T}}$. Consequently, the new velocity and position of the ith particle is adjusted as follows:

$$v_{id}^{t+1} = \omega v_{id}^t + c_1 r_1 (p_{id}^t - x_{id}^t) + c_2 r_2 (p_{\mathrm{g}d}^t - x_{id}^t) \tag{1}$$

$$x_{id}^{t+1} = x_{id}^t + v_{id}^{t+1} \tag{2}$$

where $d = 1, 2, \cdots, D$; r_1 and r_2 are two random numbers uniformly distributed in $[0,1]$; c_1

and c_2 are two positive constants called the individual cognitive level and social cognitive level, respectively, both generally specified to be 2; and ω is the inertial weight coefficient, which controls the influence of the velocity of previous iterations on the current iteration.

2.2 Self-adaptive exponential inertia weight coefficient

It can be found that, in terms of Eq. (1), a large ω is beneficial to a global search and a small one is beneficial to a local search. Thus, parameter ω is significant to the balance between the global and local search ability of PSO. In general, a linearly decreasing inertia weight coefficient (LDIWC), proposed by Shi and Eberhart (1999), in which ω changes from $\omega_{\max}$ to $\omega_{\min}$ through a linear decrease procedure as represented in Eq. (3), is used in conventional PSO:

$$\omega(t) = \omega_{\max} - \frac{\omega_{\max} - \omega_{\min}}{T} t \tag{3}$$

where $\omega_{\max}$ and $\omega_{\min}$ are usually specified to be 0.9 and 0.4, respectively, and T is the total number of iterations. In order to overcome the disadvantages of the conventional PSO, including prematurity, slow convergence in the later evolutionary state, and liability to getting trapped in local optima (Shi and Eberhart 1999), a new self-adaptive exponential inertia weight coefficient (SEIWC) is proposed. It makes use of an exponential function as the basic trace and a proportional coefficient *k*, depending upon the fitness variation, to adjust ω. When $F_i(t)$ is defined as the fitness of the *i*th particle in the *t*th iteration, the fitness variation can be represented as follows:

$$\Delta F_i(t) = \left[F_i\left(t+1\right) - F_i\left(t\right) \right] \big/ F_i(t) \tag{4}$$

$$\omega_i(t) = (1+kb)\left[\left(\omega_{\max} - \omega_{\min} \right) \mathrm{e}^{at} \right] \tag{5}$$

where a is the curvature coefficient of the exponential function, which controls the relative position between the SEIWC trace and LDIWC trace; b is a proportional range coefficient; and k is a control coefficient that makes ω fitness-adaptive and is determined by a piecewise function as follows:

$$k = \begin{cases} 1 & \Delta F_i(t) \geq 0.1 \\ 0 & 0.03 < \Delta F_i(t) < 0.1 \\ -1 & \Delta F_i(t) \leq 0.03 \end{cases} \tag{6}$$

An appropriate parameter a (for example, 0.01) can lower the SEIWC trace below the LDIWC trace, as shown in Fig. 1. In the earlier stage ($t \leq T_0$), ω decreases faster by using SEIWC than by using LDIWC, and makes the velocity relatively lower, which could relieve the prematurity problem. In the later stage ($t > T_0$), by contrast, using SEIWC causes ω to decrease more slowly, which could in turn cause the particle to maintain a relatively higher velocity, and further enhance the diversity of populations, extend the scope of search space, and prevent the PSO algorithm from falling into local optima. Moreover, the flying velocity accelerates when the fitness value increases by more than 10%, and decelerates when the fitness variation is not so significant, such as to an extent of 3%.

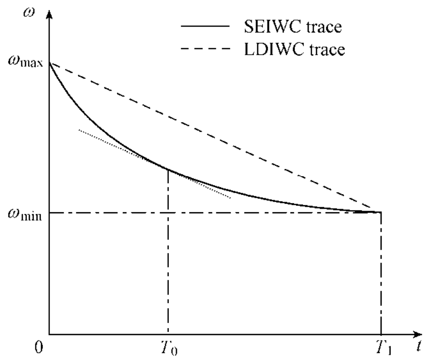


Fig. 1 Different traces of SEIWC and LDIWC

2.3 Crossover and mutation operation

GA could effectively improve the diversity of genes through the crossover and mutation operation with chromosomes, and this is a good analogy for the PSO algorithm. A certain amount of individuals from the population are selected for crossover, and the velocities $\boldsymbol{U}_i$ and $\boldsymbol{U}_j$ and positions $\boldsymbol{X}_i$ and $\boldsymbol{X}_j$ of two particles *i* and *j* are adjusted as follows:

$$\boldsymbol{U}_i' = \frac{\boldsymbol{U}_i + \boldsymbol{U}_j}{\left\|\boldsymbol{U}_i + \boldsymbol{U}_j\right\|}\left\|\boldsymbol{U}_i\right\| \tag{7}$$

$$\boldsymbol{U}_j' = \frac{\boldsymbol{U}_i + \boldsymbol{U}_j}{\left\|\boldsymbol{U}_i + \boldsymbol{U}_j\right\|}\left\|\boldsymbol{U}_j\right\| \tag{8}$$

$$\boldsymbol{X}_i' = p_1\boldsymbol{X}_i + \left(1 - p_1\right)\boldsymbol{X}_j \tag{9}$$

$$\boldsymbol{X}_j' = p_1\boldsymbol{X}_j + \left(1 - p_1\right)\boldsymbol{X}_i \tag{10}$$

where p_1 is the crossover probability. The PSO algorithm can be augmented with an additional mutation operator such as Gaussian mutation or Cauchy mutation, as described by Andrews (2006). In this study, the Gaussian mutation proposed by Higashi and Iba (2003) was used and a certain amount of individuals from the population were chosen for mutation operation according to p_2, defined as mutation probability. The position of particle *i*, $\boldsymbol{X}_i$, was updated as follows:

$$\boldsymbol{X}_i'' = \boldsymbol{X}_i\left[1 + G\left(\sigma\right)\right] \tag{11}$$

where σ is 0.1 times the length of the search space in one dimension, and $G\left(\sigma\right)$ is a random number drawn from a Gaussian distribution, with a standard deviation of σ.

2.4 IPSO testing by numerical function optimization

Three famous benchmark functions, the Rosenbrock, Rastrigin, and Griewank functions, (Andrews 2006), the first of which is a unimodal function while the latter two are multimodal, were employed to test the performance of IPSO and its potential ability in nonlinear numerical function optimization. The results were compared with those of PSO and GA. Parameters of IPSO were chosen as follows: $r_1, r_2 \in [0,1]$, $c_1 = c_2 = 2$, $\omega_{\max} = 0.9$, $\omega_{\min} = 0.4$, $a = 0.01$, $b = 0.2$, $p_1 = 0.4$, $p_2 = 0.2$, and $m = 20$ (m is the population size). The expression of the three selected functions can be found in Andrews (2006). All of these functions have the same global minimum, 0. In our experiment, the problem dimension was 10 and the variable value range was determined to be $(-10,10)$ for each function. A random experiment was carried out fifty times for each function, with a maximum epoch of 10 000 at each time. The statistical results are listed in Table 1. Because of the high number of dimensions and maximum epoch limit, none of these algorithms could converge to a high accuracy such as 10^{-5}. However, the results demonstrate that the PSO and GA algorithms are comparable and the IPSO algorithm is superior to them, especially in the mean fitness results of Rastrigin and Griewank. Consequently, the proposed IPSO algorithm is considered to be suitable for nonlinear numerical function optimization, particularly for multimodal functions.

Table 1 Comparison of IPSO, PSO, and GA for nonlinear numerical function optimization

Function	Minimum fitness			Maximum fitness			Mean fitness		
	IPSO	PSO	GA	IPSO	PSO	GA	IPSO	PSO	GA
Rosenbrock	2.965	3.306	3.320	16.590	19.404	18.455	4.450	6.281	6.151
Rastrigin	3.346	4.761	5.056	11.067	14.349	14.127	5.194	7.873	8.438
Griewank	0.086	0.115	0.119	1.326	2.155	1.873	0.121	0.824	0.987

2.5 IPSO for long-term multi-reservoir system operation

For the optimization of multi-reservoir system operation, the choices of objective functions depend on the purpose and operational period. As far as long-term operation for hydropower systems is concerned, energy maximization is the most popular one. In this study, energy maximization for one year, with a specified guaranteed output, which contains an additional constraint of minimum output of hydropower systems rather than the conventional energy maximization, was used as the objective function:

$$E = \max \sum_{j=1}^{n} \sum_{i=1}^{N} P_{i,j} \Delta\tau \tag{12}$$

where E is the total electricity generation; $\Delta\tau$ is the time step (months); n is the number of time steps during the operational period, and $n = T/\Delta\tau$; T is the length of the operational period (months); N is the number of hydroelectric power plants; and $P_{i,j}$ is the mean output of the ith power plant during the jth time step. This procedure was subjected to the following constraints:

Water balance equation of reservoirs:

$$V_{i,j+1} = V_{i,j} + \left(Q'_{i,j} - Q_{i,j} - S_{i,j}\right)\Delta\tau \tag{13}$$

Minimum output:

$$\sum_{i=1}^{N} P_{i,j} \geq P_j^{\min} \tag{14}$$

Reservoir storage volume:

$$V_{i,j}^{\min} \leq V_{i,j} \leq V_{i,j}^{\max} \tag{15}$$

Hydroelectric power plant output:

$$P_{i,j}^{\min} \leq P_{i,j} \leq P_{i,j}^{\max} \tag{16}$$

Discharge used for power generation:

$$Q_{i,j}^{\min} \leq Q_{i,j} \leq Q_{i,j}^{\max} \tag{17}$$

Reservoir-released discharge:

$$q_{i,j}^{\min} \leq Q_{i,j} + S_{i,j} \leq q_{i,j}^{\max} \tag{18}$$

where $P_j^{\min}$ is the minimum output of the system during the jth time step; $V_{i,j}$ is the initial storage volume of the ith reservoir during the jth time step; $Q'_{i,j}$, $Q_{i,j}$, $S_{i,j}$, and $q_{i,j}$ are the inflow, discharge for power generation, discharge from spillways or dam bodies, and reservoir-released discharge of the ith reservoir during the jth time step, respectively; and $V_{i,j}^{\min}$, $V_{i,j}^{\max}$, $P_{i,j}^{\min}$, $P_{i,j}^{\max}$, $Q_{i,j}^{\min}$, $Q_{i,j}^{\max}$, $q_{i,j}^{\min}$, and $q_{i,j}^{\max}$ are the maximum and minimum values of variables $V_{i,j}$, $P_{i,j}$, $Q_{i,j}$, and $q_{i,j}$.

The basic computational outline of IPSO-based long-term multi-reservoir system operation, using reservoir storage volume as a decision variable is designed as follows:

(1) The dimension of solution space $D = 12N$, the population size $m = 80$, the maximum evolutionary epoch is 3 000, and other related parameters are specified as mentioned above.

(2) Initially, the particle swarm is generated using a random procedure, and the iteration time t is set as 0.

(3) The output of each station and the total power generation (fitness) are calculated. Constraints from Eqs. (13) through (18) are checked; if they are not satisfied, penalty terms are employed to decrease the fitness, and different penalty coefficients are suggested for different constraints. The particle's optimal position $\boldsymbol{P}_i$ and the swarm's optimal position $\boldsymbol{P}_{\mathrm{g}}$ are calculated.

(4) The fitness variation ΔF_i and parameter k are computed, and $\omega_i(t)$ is recalculated.

(5) The velocity and position of particles are updated.

(6) The crossover and mutation operation are performed.

(7) If t reaches the maximum evolutionary epoch, the optimization computation ends, or it is looped back to step (3).

3 Case study

The cascade reservoir system of the Minjiang Basin was selected for a case study of the proposed IPSO algorithm. As the largest basin in Fujian Province, China, the Minjiang Basin covers a watershed area of 60 992 km^2 and comprises five rivers, the Shaxi, Jinxi, Futunxi, Youxi, and Gutianxi rivers. The cascade reservoir system consists of 26 hydroelectric power plants with a combined installed capacity of 3 250 MW. Five of these hydroelectric power plants, the Ansha, Chitan, Jiemian, Gutian I, and Shuikou stations, have reservoirs with seasonally or multi-yearly regulating capacity, while the others have daily regulating reservoirs, as shown in Fig. 2. Considering the requirement of a system-specified guaranteed output and slightly dry conditions of the Minjiang Basin in recent years, 60%-frequency mean annual discharges were used as representative inflows in this study, as shown in Table 2.

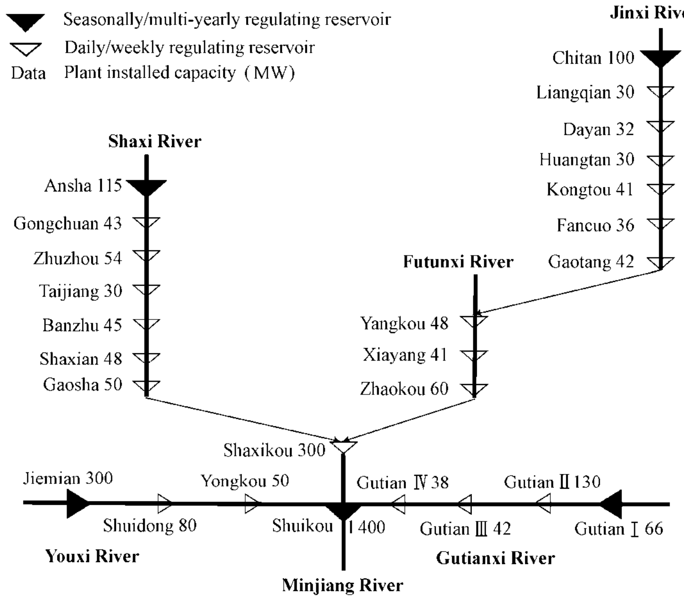


Fig. 2 Cascade reservoir system and installed capacity of different hydroelectric power plants of Minjiang Basin

Table 2 Inflows of reservoirs with seasonally or multi-yearly regulating capacity m^3/s

Month	Mean monthly inflow				
	Ansha	Chitan	Jiemian	Gutian I	Shuikou
1	40.9	46.9	11.7	14.9	205.8
2	58.1	68.3	15.5	20.8	284.9
3	114.2	121.0	19.5	31.0	450.1
4	196.1	196.0	31.6	46.5	747.0
5	279.0	274.4	55.4	67.5	1 002.0
6	351.5	322.6	64.2	88.8	1 236.4
7	148.3	142.0	31.4	38.5	558.1
8	114.9	100.0	28.5	39.5	456.2
9	89.7	78.1	24.9	33.1	352.3
10	67.5	71.1	16.7	18.8	269.0
11	50.2	50.6	14.1	15.1	211.2
12	43.3	44.2	12.6	13.8	182.6

Note: 60%-frequency mean annual discharges were taken as the inflows of reservoirs.

For the purpose of comparison with traditional non-linear programming (NLP) techniques, the IPSO algorithm, together with the PSO and DPSA algorithms, was applied to long-term multi-reservoir system operation in the Minjiang Basin, using energy maximization with a specified guaranteed output as an objective function to be optimized. In our modeling procedure, hydroelectric power plants that had a daily regulating reservoir were arranged to generate power subjected to a fixed headwater level because of their lack of regulating capacity. The guaranteed output of the system was specified to be 500 MW, and the results of annual electricity generation for each model are shown in Table 3.

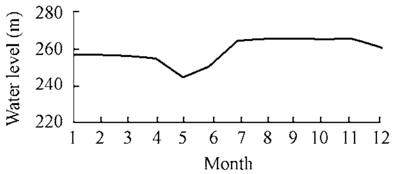
Table 3 shows that the proposed IPSO algorithm can produce 114.28×10^5 MW·h of electricity, which is 3.37×10^5 MW·h or 2.95% more than the 110.91×10^5 MW·h of electricity yielded by the PSO algorithm. Considering the pool purchase price (PPP) for hydropower in the current period in Fujian Province and its increasing tendency, electricity generated by IPSO will make additional profits of about 200 million yuan over those made by PSO per year for the Fujian Province Power Grid. The results based on IPSO are comparable to those of DPSA, a traditional classical method coupled with dynamic programming (DP) and the successive approximation (SA) algorithm (Bellman and Dreyfus 1962; Yeh 1985); that is, the respective results are almost consistent.

Table 3 Comparison of annual electricity generation from IPSO, PSO, and DPSA 10^5 MW·h

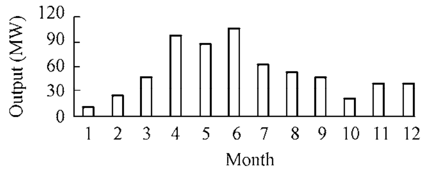
Hydroelectric power plant	Annual electricity generation		
	IPSO	PSO	DPSA
Ansha	4.49	4.16	4.52
Chitan	4.38	3.95	4.36
Jiemian	2.02	1.98	2.00
Gutian I	2.74	2.45	2.79
Shuikou	55.34	53.82	55.94
Others	45.31	44.55	44.90
Total	114.28	110.91	114.51

As pointed out in much of the literature, the computational efficiency of algorithms should be taken into account as a significant factor when dealing with the optimization of multi-reservoir system operation, and the computational efficiency of IPSO was also analyzed in this study. The average time consumption of the optimization computation based on IPSO was about 35 s. It was lower than the 44 s of the conventional PSO, indicating that the conventional PSO is actually improved by SEIWC and the crossover and Gaussian mutation operation. Generally, the optimization based on DPSA needs a lot of CPU time and tremendous memory to satisfy the complex computation process and huge variable storage requirement, and these requirements increase quickly with the stage variables and state variables, especially for large-scale multi-reservoir system operation. In our experiment, the DPSA algorithm took about 78 s to accomplish the optimization calculation, when the interval step of the reservoir storage volume was assumed to be 40×10^6 m^3. Both IPSO and PSO could save much computation time; the time consumption of IPSO is less than half that of DPSA. Therefore, the proposed IPSO algorithm performs better than PSO and DPSA, in terms of both optimization ability and computational efficiency.

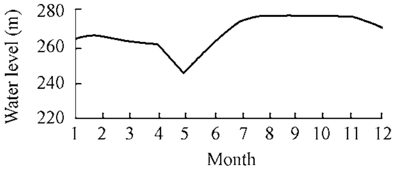
Fig. 3 provides the scheduling results of reservoir water level and hydroelectric power plant output of cascade reservoirs in the Minjiang Basin based on IPSO. During the dry period from October to April of the following year, reservoirs with better regulating abilities, such as the Jiemian Reservoir (multi-year regulation) and Gutian-I Reservoir (multi-year regulation), will operate according to the guaranteed output of the system as compensating power stations, while the seasonally regulating reservoirs like the Ansha, Chitan, and Shuikou reservoirs will operate at high reservoir water levels in order to take advantage of the water head. When the flood season, usually defined as May to September, is coming, the seasonally regulating reservoirs reduce the water level by enhancing their outputs in advance, in order to diminish the possibility of surplus water brought by the frequent rainstorms that are coming, and then raise the water level gradually to the normal water level by the end of the flood season. The whole schedule of the system is reasonable and operational.



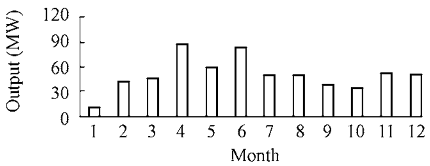
(a)Water level of Ansha Reservoir



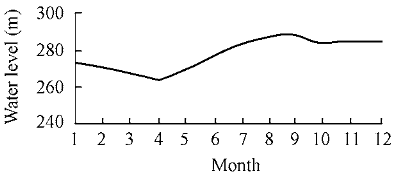
(b) Output of Ansha Plant



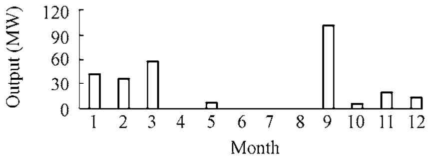
(c) Water level of Chitan Reservoir



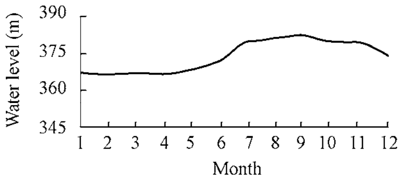
(d) Output of Chitan Plant



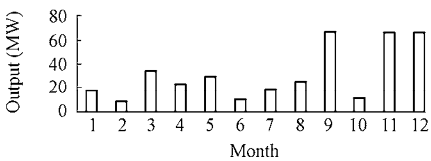
(e) Water level of Jiemian Reservoir



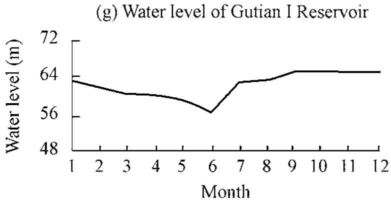
(f) Output of Jiemian Plant



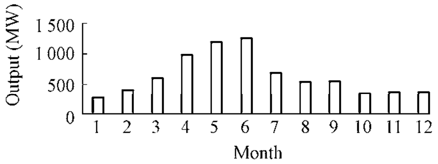
(g) Water level of Gutian I Reservoir



(h) Output of Gutian I Plant



(i) Water level of Shuikou Reservoir



(j) Output of Shuikou Plant

Fig. 3 Scheduling results of cascade reservoirs in Minjiang Basin based on IPSO

4 Conclusions

In this study, an IPSO algorithm is presented to deal with the optimization of hydroelectric power scheduling in multi-reservoir systems. In order to overcome the inherent drawbacks, such as prematurity, slow convergence, and liability to falling into local optima, the conventional PSO algorithm is improved in two ways. To begin with, SEIWC is adopted to render the algorithm capable of better balance ability in both global and local searches. Moreover, particles are handled with crossover and Gaussian mutation operation, which could enhance their diversity and prevent the algorithm from being trapped in local optima. The performance of IPSO in nonlinear numerical function optimization was investigated with a test of three classical benchmark functions, and the results are encouraging and promising in both computational efficiency and search ability when compared with PSO and GA. Then, the proposed IPSO was applied to the optimization of long-term multi-reservoir system operation, using energy maximization with a specified guaranteed output as the objective function to be optimized, and a case study was carried out in the Minjiang Basin in Fujian Province, China. The scheduling results of IPSO outperform those of the conventional PSO and are comparable with the results of the traditional DPSA algorithm. Therefore, the proposed IPSO can provide efficient and effective solutions with respect to the optimization of multi-reservoir system operation and is a good alternative to traditional NLP techniques, in terms of both optimization ability and computational efficiency.

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