Computers and Mathematics with Applications 62 (2011) 2463–2471

Contents lists available at SciVerse ScienceDirect

Computers and Mathematics with Applications

journal homepage: www.elsevier.com/locate/camwa

Short-term scheduling of cascade reservoirs using an immune algorithm-based particle swarm optimization

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ARTICLE INFO

Article history:
Received 17 September 2009
Received in revised form 13 April 2011
Accepted 13 July 2011

Keywords:
Cascade reservoirs
Short-term operations
Immune algorithm-based particle swarm optimization

ABSTRACT

This paper presents a new approach for short-term hydropower scheduling of reservoirs using an immune algorithm-based particle swarm optimization (IA-PSO). IA-PSO is employed by coupling the immune information processing mechanism with the particle swarm optimization algorithm in order to achieve a better global solution with less computational effort. With the IA-PSO technique, the hydro-electrical optimization model of reservoirs is formulated as a high-dimensional, dynamic, nonlinear and stochastic global optimization problem of a multi-reservoir hydropower system. The purpose of the proposed methodology is to maximize total hydropower production. Here it is applied to a reservoir system on the Qingjiang River, in the Yangtze watershed, that consists of two reservoirs. The results are compared with the results obtained through conventional operation method, the dynamic programming and the standard PSO algorithm. From the comparative results, it is found that the IA-PSO approach provides the most globally optimum solution at a faster convergence speed.

1. Introduction

Hydroelectricity is a clean and renewable energy whose quantity depends on the volume of water flow and the amount of head created by the water reservoir. In cascade reservoirs, the reservoir water level of a downstream plant is influenced by the generation of the upstream plant. Therefore, hydropower scheduling is a complicated nonlinear dynamical optimization problem that includes nonlinear flows, nonlinear dynamical hydraulic heads and the interactional relationships of nonlinear input and output variables. The objective is to obtain the optimal utilization of the hydro resources available for maximum hydroelectric generation given a set of starting conditions and many complex constraints in the hydropower system.

To solve the problem of scheduling optimal hydropower, several hydropower optimization techniques have been developed. These techniques can be classified into two main categories: (1) Mathematical programming techniques, which are applied to quantitative information with well-structured algorithmic processes, such as Network Flow Optimization [1–4], linear programming [5,6], Stochastic Linear Programming [7], Nonlinear Programming [8,9] and Dynamic Programming [10,11] etc. (2) These heuristic programming techniques, which are employed with both quantitative and qualitative information in this paper, based on rules-of-thumb, personal experience or various analogies, such as genetic algorithms [12–14], artificial neural networks [15–17], particle swarm optimization [18,19] and an improved algorithm [20,21] and so on.

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0898-1221/$ – see front matter
doi:10.1016/j.camwa.2011.07.032

Mathematical programming techniques lead to suboptimal solutions with certain suppositions or simplifications, where as heuristic programming techniques can achieve global optimal solutions to problems [22]. Compared with other heuristic algorithms, the particle swarm optimization (PSO) algorithm is attractive because of its ease of implementation and low computational cost [18,19]. However, we should take into consideration the premature convergence, reduced individual diversity and enmeshed local extreme point along with the ongoing iterative process involved with PSO [23]. Several improved PSO have been proposed for solving these problems, such as incorporating PSO with new the stretching function [24], Gaussian mutation [25], sub-swarm [26] and so on. Incorporating these new methods cannot guarantee the stability of the algorithm within a global optimization solution nor can they accelerate the speed of convergence in the evening of evolution; therefore, a robust technique is needed to handle the scheduling of reservoirs in a hydropower system. As a result, an immune algorithm-based particle swarm optimization is presented by integrating a special concentration selection mechanism and an immune vaccination with PSO [20]. This method possesses a better ability to search the global optimum solution and accelerate the convergence speed more than the original PSO algorithm. Meanwhile, The IA-PSO approach has been successfully applied in load distribution among cascade hydropower stations, however, the results of the application of IA-PSO to the short-term scheduling of cascade hydropower plants have not yet been reported.

This paper develops an IA-PSO method for the short-term hydropower scheduling of cascade plants in order to obtain optimal hydropower generation on a global level. The efficiency and robustness of the proposed method is demonstrated via comparison of its applied PSO techniques performance in two cascade reservoirs located at the tributary of the upper Yangtze River basin.

2. Hydroelectric operation optimization model

The Hydroelectric operation optimization model can be generalized as follows.

2.1. Objective function

The aim of hydropower operations is to maximize total hydroelectric generation by making the best use of hydro resources over a certain scheduling duration. The Objective function can be equivalently expressed as

$$\begin{cases} F = \max \sum_{t=1}^{n} \sum_{i=1}^{m} N_{i,t} \Delta t \\ N_{i,t} = \eta H_{i,t} R_{i,t} \end{cases} \tag{1}$$

where F denotes hydropower generation of hydro units over a scheduling period n; m is the total number of cascaded hydropower plants under consideration; $N_{i,t}$ is the power corresponding to plant i during period t, which is the decision variable of the model; Δt is the short time interval; $H_{i,t}$ is the hydraulic head of plant i during period t; $R_{i,t}$ is the release passing turbines of the hydropower plant i during period t; η represents the power coefficient.

2.2. Constraints

- *Power constraints of stations*

The power constraints of stations are expressed as

$$N_{i,t\,\min} \le N_{i,t} \le N_{i,t\,\max} \quad i = 1, 2, \ldots, m;\ t = 1, 2, \ldots, n \tag{2}$$

where $N_{i,t\,\min}$ and $N_{i,t\,\max}$ are the upper limits and lower limits of power for plant i during period t respectively.

- *Reservoir continuity*

The reservoir continuity of mass can be described by the following finite difference formulas

$$\begin{cases} V_{i,t+1} = V_{i,t} + \eta(I_{i,t} - Q_{i,t}) \\ V_{i+1,t+1} = V_{i+1,t} + \eta(I_{t+1,t} - Q_{i+1,t}) \quad i = 1, 2, \ldots, m;\ t = 1, 2, \ldots, n \\ I_{i+1,t} = IQ_{i+1,t} + Q_{i,t-\tau_i} \end{cases} \tag{3}$$

where $V_{i,t}$ is the initial storage volume of reservoir i at the beginning of period t; $I_{i,t}$ is the inflow into reservoir i during period t; η is the conversion coefficient for unit; $IQ_{i+1,t}$ is the interzone inflow into reservoir $i+1$ during period t; $Q_{i,t}$ is the outflow from reservoir i during period t, which includes the power release and spillway release; τ_i is the flow routing time from reservoir i to downstream reservoir $i+1$.

- *Physical limitations*

Physical limitations on the water level of reservoirs are given by

$$L_{i,t\,\min} \le L_{i,t} \le L_{i,t\,\max} \quad i = 1, 2, \ldots, m;\ t = 1, 2, \ldots, n \tag{4}$$

where $L_{i,t\,\min}$ and $L_{i,t\,\max}$ are the minimum and maximum water level corresponding to reservoir i during period t.

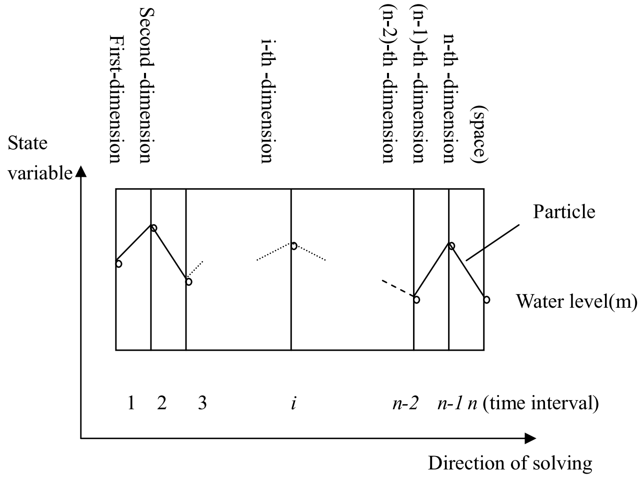

Fig. 1. Sketch map for particles of a hydropower plant.

The initial and final reservoir water level are given by

$$L_{i,0} = L_{i,\text{begin}} \qquad L_{i,n} = L_{i,\text{end}} \quad i = 1, 2, \ldots, m \tag{5}$$

where $L_{i,\text{begin}}$, $L_{i,\text{end}}$ are the initial and final water levels of reservoir i respectively.

The outflow limits are given by

$$Q_{i,t\,\min} \le Q_{i,t} \le Q_{i,t\,\max} \quad i = 1, 2, \ldots, m;\ t = 1, 2, \ldots, n \tag{6}$$

where $Q_{i,t\,\min}$ and $Q_{i,t\,\max}$ are the minimum and maximum outflow of reservoir i during period t.

3. IA-PSO algorithm for hydropower scheduling

Short-term optimal scheduling of cascade hydropower plants is a dynamic, multi-stage sequential decision-making process. Therefore, the key to the application of the PSO algorithm is to achieve a multi-stage continuous optimization. As the particle swarm gets the optimal solution through the multi-dimensional space flight, the time dimension of optimal scheduling will be assumed as the space dimension for the particle swarm. Assuming the total scheduling period is n for reservoirs, we can determine that n is the space dimension for the particle swarm. The optimal scheduling of the n period for reservoirs translates into the optimal location of the n-dimensional space for particles. Consequently, a multi-stage process of scheduling can be carried out by calculation in the space dimension order. The track of particles in the n-dimensional space (such as the water level of a reservoir) for any hydropower plant is equivalent to the trajectory used in dynamic programming (as shown in Fig. 1)

The immune algorithm-based particle swarm optimization (IA-PSO) was proposed by combining the immune information processing mechanism with an original particle swarm optimal algorithm, which with its special concentration selection mechanism and immune vaccination [20], improves the ability to seek a globally excellent result and increases convergence speed. Fig. 2 shows the flowchart of IA-PSO algorithm for hydropower scheduling. Compared with the PSO algorithm, the IA-PSO algorithm has three main parts. The part outside the dashed boxes A and B can run independently to control the iterative process of conventional optimization algorithms described by following Steps 1–2. Part A shows the immune memory and self-adjustment to realize the diversity of the population stated by following Steps 3–5. Part B carries out vaccination to improve the convergence of algorithm depicted by following Steps 6–7. The steps of the flowchart are as follows:

Step 1: Randomly generate N particles satisfying the constraints Eqs. (2)–(6), and initialize the position and velocity of these particles.

Step 2: Utilize the objective function Eq. (1) as a function of particle fitness. Calculate fitness of the particle for a position in the n-dimensional space. Adjust the speed of the particle according to the current fitness value and the gap among the individually best position (*pBest*) and the globally best position (*gBest*), and then adjust its position to form a new particle. The new velocity and position are respectively given by [20]:

$$v_{i,t}^{j}(k+1) = w \times v_{i,t}^{j}(k) + C_1 \times \text{Rand}() \times (x_{i,t}^{pbest} - x_{i,t}^{j}(k)) + C_2 \times \text{Rand}() \times (x_{i,t}^{gbest} - x_{i,t}^{j}(k)) \tag{7}$$

$$x_{i,t}^{j}(k+1) = x_{i,t}^{j}(k) + v_{i,t}^{j}(k+1) \quad i = 1, 2, \ldots, m;\ t = 1, 2, \ldots, n \tag{8}$$

where w is an inertial factor; C_1 and C_2 are learning factors; Rand() is a random number between 0 and 1; $x_{i,t}^{pbest}$ and $x_{i,t}^{gbest}$ are, respectively, the individually best position and the globally best position for plant i at time step t; $x_{i,t}^{j}(k)$ and $x_{i,t}^{j}(k+1)$ are

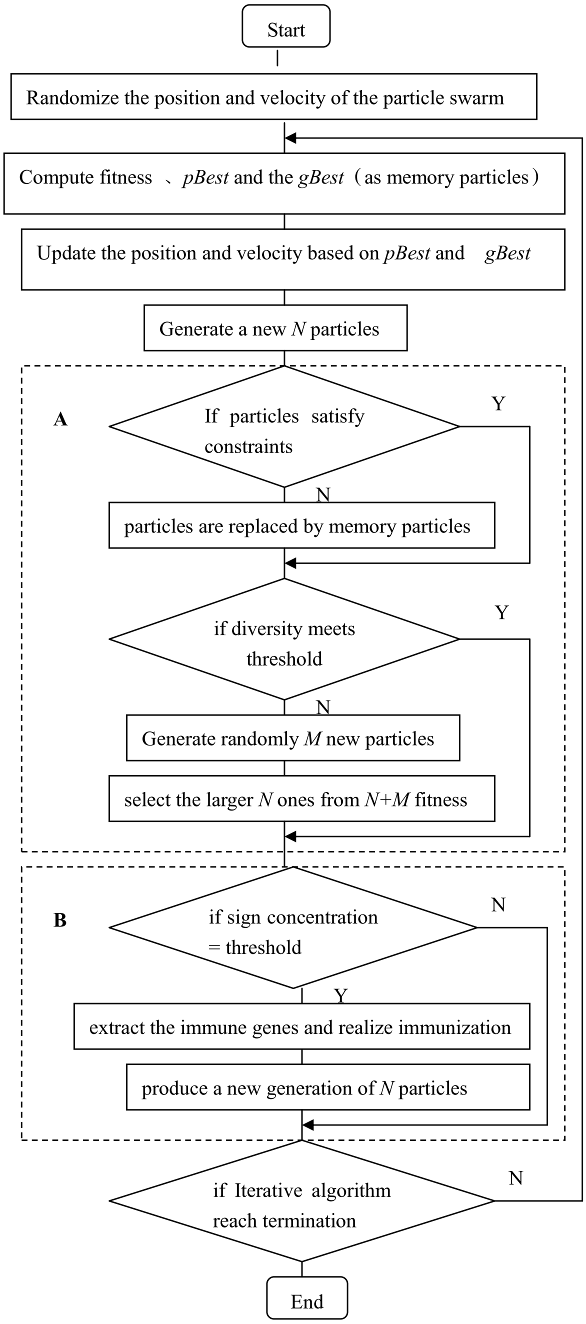

Fig. 2. Flowchart of IA-PSO algorithm.

respectively the k-th iteration and $(k+1)$-th iteration position of j-th particle for plant i at time step t; $v_{i,t}^{j}(k)$ and $v_{i,t}^{j}(k+1)$ are respectively the k-th iteration and $(k+1)$-th iteration velocity a of j-th particle for plant i at time step t.

Step 3: Check the new particles generated by Step 2. If a particle does not satisfy the constraints Eqs. (2)–(6), particles will be replaced by memory particles, namely, the globally best particles.

Step 4: Check whether the diversity of the population is greater than the threshold $\widetilde{\xi}$, if so, divert to Step 6; if not, go to Step 5 to implement immune regulation to prevent the algorithm of "precocious" phenomenon. The relative diversity of the population $\xi(k)$ is defined by the formula

$$\xi(k) = \frac{\mathrm{div}(k)}{\mathrm{div}(0)} \tag{9}$$

$$\mathrm{div}(k)=\sqrt{\frac{1}{Nmn}\sum_{j=1}^{N}\sum_{i=1}^{m}\sum_{t=1}^{n}\left[\frac{(x_{i,t}^{j}(k)-x_{i,t}^{gbest}(k))}{(b_{i,t}-a_{i,t})}\right]^{2}} \tag{10}$$

where $b_{i,t}$ and $a_{i,t}$ are respectively the upper limit and lower limit of the power corresponding to plant i during period t; $\mathrm{div}(0)$ and $\mathrm{div}(k)$ are respectively diversity of the population at initiation and k-th iteration.

Step 5: Generate randomly M new particles that meet the constraints Eqs. (2)–(6) again based on the N new particles and compute the probability of selection of particle j according to the consistency of particle j. Then the values for the probability of selection for $N+M$ particles are ordered decreasingly and the top N particles are selected as the next-generation of evolution. The probability of selection of particle j can be expressed as [20]:

$$P(X^j)=\frac{\frac{1}{D(X^j)}}{\sum_{j=1}^{N+M}\frac{1}{D(X^j)}}\quad j=1,2,\ldots,(N+M) \tag{11}$$

$$D(X^j)=\frac{1}{\sum_{J=1}^{N+M}|f(X^j)-f(X^J)|}\quad j=1,2,\ldots,(N+M) \tag{12}$$

where $D(X^j)$ is the consistency of particle j; $P(X^j)$ is the probability of selected particle j.

Step 6: Check whether the sign concentration of the particle is equal to the threshold concentration, and if so, extract the immune genes and realize immunization, and then produce a new generation of particles. The sign concentration can be respectively expressed as:

$$p_l(x_{i,t})=\frac{1}{N}\sum_{j=1}^{N}a_l \tag{13}$$

where a_l is integer 0 or 1, which can be determined by

$$a_l=\begin{cases}1 & g(x_{i,t}^{j})=\zeta_l\\ 0 & \text{elsewise}\end{cases} \tag{14}$$

where $g(x_{i,t}^{j})$ is a symbol and is given by

$$g(x_{i,t}^{j})=\begin{cases}\zeta_1 & N_{i,t\,\min}\le x_{i,t}^{j}<N_{i,t,1}\\ \zeta_2 & N_{i,t,1}\le x_{i,t}^{j}<N_{i,t,2}\\ \cdots & \cdots\\ \zeta_L & N_{i,t,L-1}\le x_{i,t}^{j}\le N_{i,t\,\max}\end{cases} \tag{15}$$

where $\zeta_l(l=1,2\ldots,L)$ is a symbol of power interval; $N_{i,t\,\min}$ and $N_{i,t\,\max}$ are respectively the minimum and maximal power of plant i; $N_{i,t,l}(l=1,2\ldots,L-1)$ is the l-th discrete power for plant i at time step t.

Step 7: Judge whether the Iterative algorithm has reached termination, if it has, then stop; repeat Steps 2–6 accordingly. In this paper we present a dual termination criterion that secure a certain number of iterations while reaching the given objective function error between current best fitness value and the previous best one.

4. Application

The methodology described previously is applied to the cascade reservoirs in the QingJiang River basin. The cascade reservoirs in this study comprise of the Geheyan reservoir and the Gaobazhou reservoir which are located on the downstream reaches of the Qingjiang River. The Qingjiang River winds its way from west to east with a total length of 425 km and has a watershed area of 17 000 km^2, joining the Yangtze River in the city of Zhicheng, Hubei province.

The Geheyan reservoir is primarily for hydropower generation, flood control and navigation. The Gaobazhou reservoir lies in the downstream of Geheyan reservoir with a 50 km distance and also plays an important role in hydropower generation and navigation. The two reservoirs were constructed in 1994 and 2000 respectively. The two hydropower plants corresponding to the two reservoirs belong to the Qingjiang Hydropower Corporation of Hubei Province. The main physical parameters of the reservoirs are given in Table 1.

The inflow into the cascade reservoirs is shown in Fig. 3. The time of stream routing from the Geheyan reservoir to the Gaobazhou reservoir is 2 h. The time step for the scheduling calculation is 1 h and the total number of time steps is 24 respectively, which means that the model is run for a day with hourly time steps with 48 decision variables.

To evaluate the performance of the proposed IA-PSO, the parameters used are set as follows: The total number of the particle swarm is 25, which are achieved by making some tries. It is also found from trial that the solution is led to local

Table 1
Main physical parameters of the two reservoirs.

Physical parameter	Geheyan reservoir	Gaobazhou reservoir
Reservoir storage capacity (10^8 m^3)	34	4.33
Normal water level (m)	200	80
Dead water level (m)	160	78
Hydropower generation capacity (10^4 kw)	120	25.2
Average annual generation (10^8 kwh)	30.4	8.98

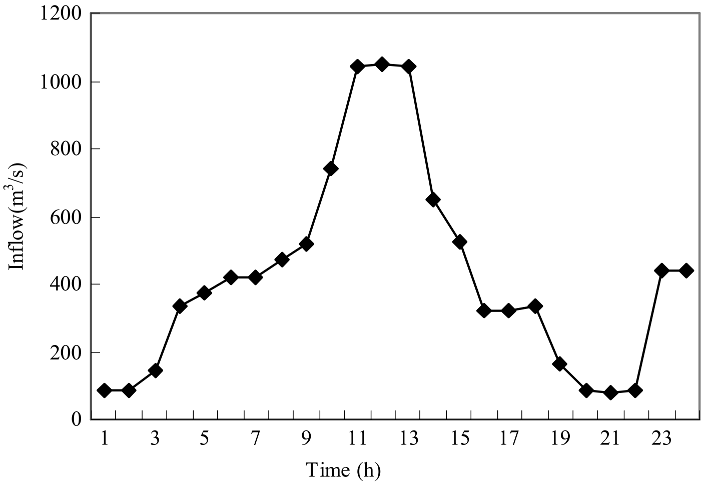

Fig. 3. Inflow hydrograph for cascading plants.

Table 2
The results of the operation with three methods: (1) the conventional operation method; (2) the dynamic programming; (3) the IA-PSO.

Hydropower plants	Generation with method (1) (mwh)	Generation with method (2) (mwh)	Generation with method (3) (mwh)	Hydropower rate increased compared between method (3) and (1) (%)	Hydropower rate increased compared between method (3) and (2) (%)
Geheyan plant	9310.66	9807.32	9810.53	5.369	0.033
Gaobazhou plant	3469.84	3586.97	3587.789	3.399	0.023
Total	12780.5	13394.29	13398.319	4.834	0.030

convergence with a total number less than 15 while the computing efficiency wasn't significantly improved with over a number of 25 particles. The learning factors are both 2.0 [27]. The threshold for diversity of the population is 0.4. Results show that the evolution of the population stabilized in the vicinity of this value and the diversity of the population need to strengthen through self-regulating. The threshold of concentration for immune extraction is 0.6.

The optimal hydropower generation for the Geheyan and Gaobazhou hydropower plant is obtained by using the algorithm described previously.

Table 2 gives the results of operation with the conventional operation method, dynamic programming and the IA-PSO method. They show that the hydropower generation of the cascade reservoirs change with three different methods. Cascade hydropower stations will enable 4.83% more electricity with the IA-PSO algorithm than the conventional operation. Furthermore, the IA-PSO increases 0.03% of the hydropower rate, so it is better than dynamic programming. Since the results of dynamic programming obtained depend strongly on discrete accuracy the IA-PSO has a higher precision in the optimization process. This means that compared to the known and accepted dynamic programming method, the IA-PSO is more accurate for the prediction of hydropower generation in cascade reservoirs. The results of the optimized operation are shown in Figs. 4–6. In the beginning of scheduling, the Geheyan plant releases flow as far as possible to generate more hydropower. The operations of the two reservoirs gradually go into stability when the storage water level of the Gaobazhou reservoir power station gradually reaches the maximum. The release and hydropower from the Geheyan reservoir will thus increase with the release accretion from the downstream dam. Therefore, the hydrographs of Figs. 4–6 will be in line with the operation rules for the short-term optimal scheduling.

Fig. 7 shows the relative diversity of the population and optimal individual fitness with the number of evolution for PSO and IA-PSO algorithms given the same initial conditions. The evolution of the two algorithms is almost the same because of good diversity of the population in the early evolution. But the optimal individual solution in the PSO algorithm appears to have a relatively early convergence with an advance in the evolutionary process due to a decline in population diversity. While the diversity of groups has been well maintained due to self-regulation of immune mechanisms, the IA-PSO algorithm

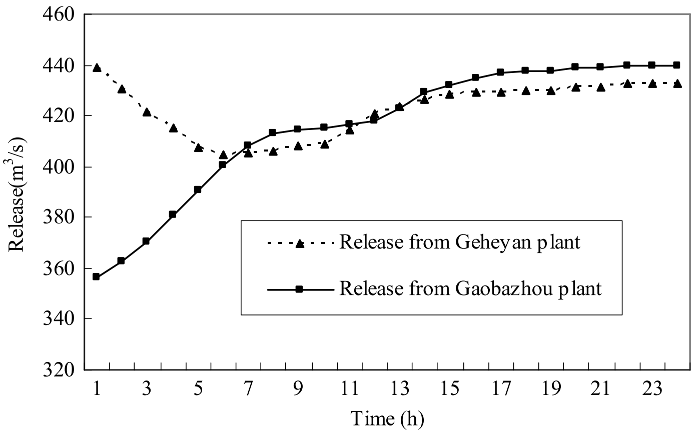

Fig. 4. Release hydrograph for cascading plants.

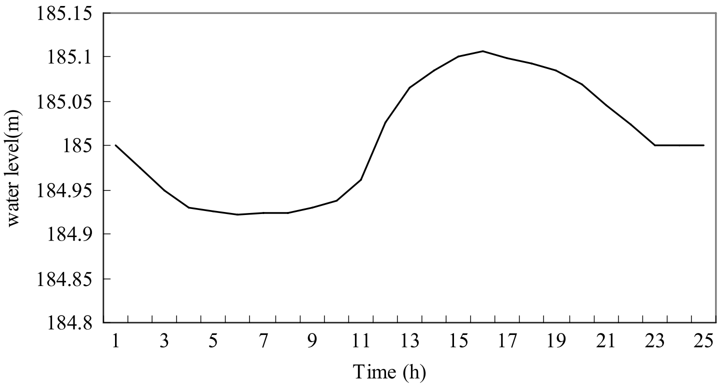

Fig. 5. Water level hydrograph of the Geheyan reservoir.

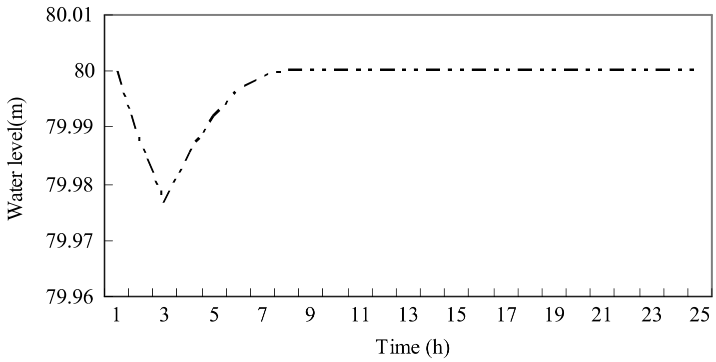

Fig. 6. Water level hydrograph of the Gaobazhou reservoir.

and the relative diversity are distributed over a certain threshold. The best individual solution, therefore, is the global optimization solution rather than present premature convergence. Results reflect that the IA-PSO algorithm surpasses the PSO algorithm in global optimization and in convergence speed.

5. Conclusions

The methodology of the immune algorithm-based particle swarm optimization has been presented in this paper as a solution to the problem of optimizing hydropower in cascade reservoirs, and its effectiveness has been tested by being applied to a reservoir system in the QingJiang River basin.

The conventional operation method and the dynamic programming method were applied to verify the feasibility and superiority of the IA-PSO. It can be concluded from this validation that the IA-PSO has good accuracy in the calculation of

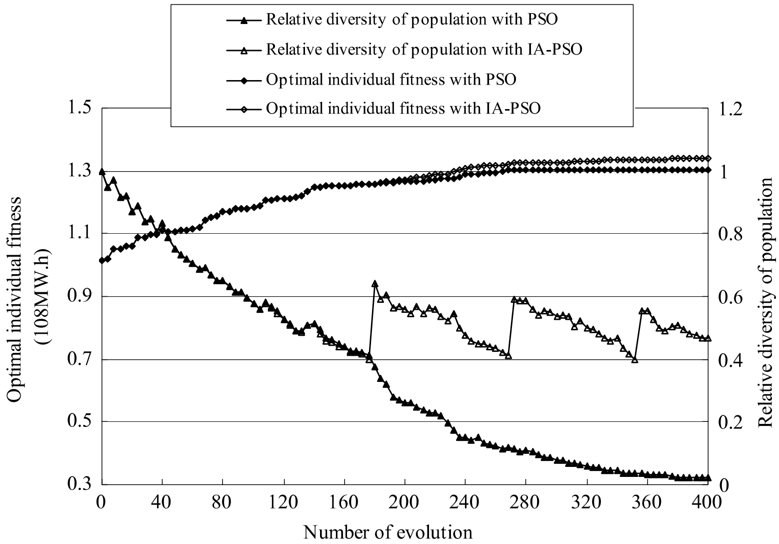

Fig. 7. Comparison of PSO and IA-PSO algorithm.

hydropower generation. The run time is almost the same for the three algorithms. A comparison of A comparison of run time shows that the PSO is somewhat faster than IA-PSO, while dynamic programming is slightly slower than the IA-PSO.

The selection mechanism of particle concentration combined with vaccination is adopted in this methodology to keep explicit diversity of population from a local maximum point and to speed up the convergence in order to search for a better global solution than PSO. The results show that the IA-PSO is able to find the most satisfactory operating policy for the reservoir system. Since this method is effective and efficient for two-cascade hydropower plants, it may be promising to apply it to optimal scheduling of multi-reservoir systems.

Acknowledgments

This paper was supported by the National Natural Science Foundation, China (Grant No. 50739003). The authors would like to thank the reviewers for their valuable comments and suggestions.

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