A New Particle Swarm Optimization Algorithm to Hierarchy Multi-objective Optimization Problems and Its Application in Optimal Operation of Hydropower Stations

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Abstract—Some engineering optimization problems, such as multi-objective daily generation scheduling for the hydropower stations, the objective functions has obvious hierarchy and priority, simultaneously, the constraints is very complex. It is difficult to solve the operation problems by adopting traditional optimal technique. In this paper, a new particle swarm optimization algorithm solving hierarchy multi-objective optimization problems is proposed. The algorithm can handle the level multi-objective optimization problem effectively. By adopting the adaptive inertia weight algorithm (AWA) and mutative scale local search algorithm (MSLSA), the convergence performance of the algorithm is improved. Then, A multi-objective daily generation scheduling model for the hydropower stations is established, in which two objective functions including maximization of peak-energy capacity benefits and maximization of power generation are involved. Finally, Multi-objective daily generation scheduling problem of the Three Gorges cascade hydropower system during low-flow period is studied with proposed algorithm to obtain the maximum peak-energy capacity benefits, as well as power generation benefits of three gorges cascade stations.

Index Terms—multi-objective optimization, particle swarm optimization algorithm, daily generation scheduling

I. INTRODUCTION

The hydropower stations are important economic and kinetic energy unit in power system, which, on the one hand, can gain capacity benefits through peak load regulation, frequency modulation and undertaking spinning reserve capacity; and, on the other hand, can gain electricity quantity benefit by replacing the thermal power stations [1]. The traditional economic benefits of hydropower systems generally only consider the generation benefit, and rarely include dynamic benefits, such as peak-energy capacity benefits, spinning reserve capacity benefits, etc [2], which is disadvantageous to optimize energy structure and resource allocation, and economically dispatch and safely operate of grid. With the development of power market in our country, the capacity benefits of hydropower system have played a more and more important role. It's an important issue worthy of deep study to change the optimal scheduling model which includes capacity and electricity quantity benefits from the traditional scheduling model which objective function only is maximizing the power generation.

The objective functions of optimal operation for cascaded hydroelectric stations, such as minimizing the peak value of residual load process, minimizing the increasing trend of the peak and vale difference, uniforming residual load process as much as possible and maximizing the generation benefit of hydropower stations, have obvious precedence relationship, it is difficult to solve the operation problem by adopting traditional optimal technique.

During the past decades, multi-objective evolutionary algorithms (MOEAs), which are solving multi-objective optimization problems based on evolutionary algorithms, have been thoroughly investigated mainly because of the fact that they can be suitably applied to find multiple Pareto-optimal solutions in one single simulation run [3-7]. PSO has been successfully used for the continuous nonlinear and discrete single-objective optimization problems, and seems particularly suitable for multi-objective optimization problems since it presents the high speed of convergence for single-objective optimization [8-12]. However, basic PSO is not appropriate to handling multi-objective problems in that there is no absolute global optimum in functions, which leads to complexity in defining a single gBest or pBest during each generation.

This paper presents a new particle swarm optimization algorithm to solve the above problems.

II. HIERARCHY PARTICLE SWARM OPTIMIZATION ALGORITHM (HPSO)

In daily generation planning objective functions in hydropower stations optimal operation, where the peaking capacity is the main concern and the power generation benefit taken into account, the highest priority is to minimize the peak of residual load process, followed by residual load process uniformed to the largest extent, and finally the maximization of total generation benefit of hydropower stations. Obviously, these can be seen as the hierarchy in the objective functions, and on the other hand contributing to the complex constraints in hydropower system operation.

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doi:10.4304/jcp.7.8.2039-2046
Particle swarm optimization (PSO) is a population based stochastic optimization technique developed by Dr. Eberhart and Dr. Kennedy in 1995, inspired by social behaviors of bird flocking or fish schooling [13]. PSO has been extensively applied in various optimization problems due to its unique searching mechanism, excellent convergence and simple implementation. In recent years, various studies have been published on multi-objective particle swarm optimization (MOPSO) in different fashion [14-17]. In this paper, a new PSO to slove hierarchy multi-objective multiple-objective operation optimizations, called Hierarchy particle swarm optimization algorithm (HPSO), is presented.

The main idea of HPSO is as follows:

(1) Since multiple-objective operation optimization of hydropower stations has obvious hierarchy and priority, according to this feature, the updating strategies of particle pBest and gBest are as follows: First, compute the objective function vector of j-th particle, then from high to low sort according to the objective function value of particle pBest and gBest. According to the sorting results to determine whether update the pBest and gBest of j-th particle. In other words, first, the objective function which has highest priority is sorted, and then the next highest priority is sorted when the objective function which has highest priority is equal, until it can be determined whether the pBest and gBest of j-th particle are updated.

(2) When hydropower stations take part in peak load regulating of power system during low flow period, because daily water consumption of hydropower stations is certain, the hydropower reservoir should impound water during the valley load of power system as much as possible, and increase output of stations during the peak load to obtain the maximum peak-energy capacity benefits.

(3) It is very difficult to solve multi-objective optimal regulation of cascade reservoirs due to complex constraints. Based on the characteristics of a cascade hydropower system, we change the constraints to the feasible region of the water level in cascade reservoirs, and then the evolution of the particles of the swarm is restricted to this region. Thereby, the constrained optimization problem is changed to unconstrained optimization problems.

The structure of HPSO is shown as follows:

**Step 1:** Initial algorithm parameters;
**Step 2:** Generate initial population in the feasible region of particles;
**Step 3:** Generate the next generation population:
FOR $j = 1$ TO POP SIZE
FOR $i = 1$ TO $N$
A. Compute the feasible region of particles $[x^1_j, x^N_j]$;
B. Compute the velocity limited region $[v^1_j, v^N_j]$;
C. Compute the position $x^t_j$ in $t + 1$ generation;
NEXT
**Step 4:** Judgment over the convergence of HPSO;
**Step 5:** Output the gBest particle.

where, POP_SIZE is population size.

(4) Accelerating genetic operator of HPSO

The particle's velocity in decision space is one of the important parameters to influence the rate of convergence of algorithm; it restricts the searching step and direction of particles during the evolutionary process. If the searching step is too small, the algorithm may trap in local optima, otherwise may cause particle oscillation around a position [9]. If the domain knowledge of optimum object can be obtained, it can guide the particles to the global optimal solution, so as to improve the converging speed obviously.

An accelerating genetic operator based on the characteristics of peaking operation of hydropower stations is designed, which can change the searching direction of particles by the particle's position during the evolutionary process. Specifically, if the particles are located on the peak or valley load of residual load process, the decision variable will be decreased or increase with a great probability, and the closer the peak or valley load, the greater the probability. The accelerating genetic operator is implemented by the following:

First of all, the decision variable of particles are normalized to [-1, 1] (let's call decision variable as p). Assuming the absolute value of p is greater a threshold value (such as 0.85), the particles are located on the peak load ($p > 0$) or valley load ($p < 0$), the maximal velocity of particles are set to 0 for the former, and the minimal velocity of particles are set to 0 for the latter. The greater of p of particles, the more the variation range of velocity is. So the searching step and direction are changed by limiting variation range of velocity. The realization of algorithm is as shown in Fig.1. where, $x_j^p = \frac{1}{M} \sum x_j^t$ is the average value of decision variable of j-th particle, R is random number between [0,1], sgn(·) is sign function, a is real number between [0,1]. The algorithm of velocity in HPSO degenerated to general PSO algorithm.

III. THE STRATEGIES TO IMPROVE THE PERFORMANCE OF THE ALGORITHM

A. Adaptive Inertia Weight Algorithm(AWA)

Inertia weight $w$ is the modulus that controls the impact of previous velocity on the current one, thus balancing exploration and exploitation in PSO, which means proper control of the inertia weight is crucial to find the optimum solution accurately and efficiently. In this paper, a adaptive inertia weight algorithm (AWA) is adopted to improve the performance of the algorithm. The inertia weight will be increased when the objective
values of particles close to accordance or tend to local optimum. Conversely, the inertia weight will be decreased. Meanwhile, for the particles which objective values are better than the mean value, the inertia weight will be set a smaller value to improve search accuracy, otherwise, for the particles which objective values are worse than the mean value, the inertia weight will be set a larger value to explore the search space.

The algorithm is used to encourage good particles (pairs) to revise their exploration to refine results by local search, and bad ones to modify searching space with large step. The algorithm is determined as follows.

\[
w_{i,j} = \begin{cases} \frac{w_{	ext{max}} + (w_{	ext{max}} - w_{	ext{min}})(f_{i,j} - f_{	ext{min},i})}{f_{	ext{avg},i} - f_{	ext{min},i}} & f_{i,j} \leq f_{\text{avg},i} \\ \frac{w_{	ext{max}}}{f_{	ext{avg},i}} & f_{i,j} > f_{\text{avg},i} \end{cases}
\]

where, \(w_{i,j}\) is inertia weight of \(i\)-th particle during \(t\)-th iterations, \(w_{\text{max}}\) and \(w_{\text{min}}\) are the minimum and maximum of inertia weight, respectively. \(f_{i,j}\) is the objective value of \(i\)-th particle during \(t\)-th iterations, \(f_{\text{avg},i}\) and \(f_{\text{min},i}\) are the average and minimum objective values of all particles during \(t\)-th iterations, respectively.

\[
p = \frac{x_i^{\text{old}} - x_i^{\text{new}}}{\max_{i \in [1,M]}(x_i^{\text{old}} - x_i^{\text{min}})}\times (-1)^{|p|}\times \frac{1}{x_i^{\text{old}}}
\]

\[
Y \leftarrow |p| > \alpha \text{ and } R < |p|
\]

\[
Y \leftarrow \text{true}
\]

\[
|y_i^{\text{old}},v_i^{\text{old}}| = [0,V_i]
\]

\[
|y_i^{\text{old}},v_i^{\text{old}}| = [-V_i,0]
\]

\[
x_i^{\text{new}} = x_i + (x_i - x^*_i)|\beta|^{-1}
\]

where, \(x_i\) is the \(j\)-th dimension vector of particle’s position, \(x^*_i\) is the \(j\)-th dimension upper boundary in decision space, \(\beta\) is a smaller integer, \(t\) is iteration count. When \(t = 1\), \(x_i^{\text{new}} = x^*_i\), that is, the MSLSA searches for optimal solutions from the upper boundary.

Step 2) For each local search point, the objective function values are calculated. Then the minimum objective function among all is taken as \(F_{\text{best}}\), and the corresponding \(x_i^{\text{new}}\) is taken as \(x_i^{\text{new}}\). The optimum values are updated as follows:

If \(F_{\text{new}} < F_{\text{best}}\) then \(F_{\text{best}} = F_{\text{new}}\) and \(x_i^{\text{best}} = x_i^{\text{new}}\), and the local searching of \(j\)-th dimension vector is broken. Otherwise, the iteration count \(t\) is incremented by one and the above procedure is repeated from step 1).

Step 3) Searching for optimal solutions from the lower boundary.

\[
x_i^{\text{new}} = x_i - (x_i - x^*_i)|\beta|^{-1}
\]

where, \(x_i\) is the lower boundary of \(j\)-th dimension in decision space. When \(t = 1\), \(x_i^{\text{new}} = x^*_i\), that is, the MSLSA searches for optimal solutions from the lower boundary.

Step 4) The objective function values are calculated. If \(F_{\text{best}}\) is better than \(F_{\text{new}}\), \(F_{\text{best}}\) and \(x_i^{\text{best}}\) are updated and the local searching of \(j\)-th dimension vector is broken. Otherwise, if maximum iteration for local search is not reached, the iteration count \(t\) is incremented by one and the above procedure is repeated from step 3).

Step 5) If maximum dimension is not reached, \(j\) is incremented by one and the above procedure is repeated from step 1). Otherwise, \(F_{\text{best}}\) and \(X_{\text{best}} = (x_1^{\text{best}}, x_2^{\text{best}}, \ldots, x_D^{\text{best}})\) are taken as the optimum results found by the MSLSA algorithm, where \(D\) is maximum dimension of decision space.

C. Hybridization of PSO with MSLSA

As a stochastic optimization algorithm, the solution process moves through a random trajectory to locate the optimum point. The trajectory may not be the same for
each run. A robust algorithm should locate the optimum solution irrespective of the starting point. Moreover, the stochastic optimization algorithms are good enough to locate the promising areas. If a promising area where the global optimum is residing is identified at the end of the optimization process, the algorithm is able to exploit the promising area to get global optimum. On the other hand, if the promising area with global optimum is identified at the earlier stages of the optimization, there is a possibility of missing that area without exploitation.

In addition, During the optimization process, the particles are flown according to their previous experience and the general PSO model implements this step by adjusting particles decision parameters to make them ‘closer’ to those of two other solutions: the best evaluated particle found so far by the population (gBest), and the best evaluated particle found previously by that particle (pBest), thus, the particle gBest is key factors to control the convergence performance of algorithm.

Considering the above fact, the MLSA is employed to search optimal solutions in gBest during in the process of evolution. The resultant PSO-MSLSA hybrid algorithm is robust in finding the global optimum for large dimensional nonconvex functions.

In order to make it evident to show the performance of PSO-MSLSA, comparative studies are completed in this section. While basic PSO algorithm (bPSO), NPSO-LRS [18], and PSO-MSLSA algorithm are introduced in experiments.

In experiments, bPSO, NPSO-LRS and PSO-MSLSA algorithms share part of parameters, while the number of particles is 50, maximum iteration count is set to 1000, the maximum inertia weight \( w_{\text{max}} = 0.9 \), the minimum inertia weight \( w_{\text{min}} = 0.4 \), \( c_1 = c_2 = 2.05 \). For PSO-MSLSA, \( \beta = 2 \), the maximum searching count of MLSA is 20.

To evaluate the efficiency and effectiveness of the algorithm for nonlinear programming problems, the following four benchmark problems are solved separately.

1. **Generalized Girewank function**

F1 : \( \min f(x) = \frac{1}{4000} \sum_{i=1}^{30} x_i^2 - \prod_{i=1}^{30} \cos \left( \frac{x_i}{\sqrt{i}} \right) + 1 \)

\[ |x_i| \leq 600, \quad \min f = f(0,0,\ldots 0) = 0 \]

2. **Generalized Rosenbrock function**

F2 : \( \min f(x) = \sum_{i=1}^{20} [100(x_{i+1} - x_i^2) + (x_i - 1)^2] \)

\[ |x_i| \leq 30, \min f = f(1,1,\ldots 1) = 0 \]

3. **Generalized Rastrigin function**

F3 : \( \min f(x) = \sum_{i=1}^{30} [x_i^2 - 10 \cos(2\pi x_i) + 10] \)

\[ |x_i| \leq 5.12, \min f = f(0,0,\ldots 0) = 0 \]

4. **Ackley function**

\[ F4 : \min f(x) = -20 \exp \left( -\frac{1}{2} \sqrt{\frac{1}{n} \sum_{i=1}^{n} x_i^2} \right) - \exp \left( \frac{1}{n} \sum_{i=1}^{n} \cos (2\pi x_i) \right) + 20 + e \]

\[ |x_i| \leq 32, \min f = f(0,0,\ldots 0) = 0 \]

For each benchmark problem, 30 independent runs are executed. Fig. II, III, IV, V display the best results produced by bPSO, NPSO-LRS, and PSO-MSLSA on four benchmark problems respectively. Table I, II, III, IV show the optimization statistical results considering the best, worst, average fitness and the variance of fitness of gBest particle in 30 independent runs.

The results show that PSO-MSLSA has the best capabilities in the rate and accuracy of convergence on all Benchmark problems, and the robustness of the PSO-MSLSA algorithm is the best also. Table III, IV show that the PSO-MSLSA algorithm can obtain high-precision solutions to Generalized Girewank function (F1), Generalized Rosenbrock function (F2) and Ackley function (F4) in 1000 iterations. Fig. II, III, V show that the converging speed of PSO-MSLSA algorithm is fast in the initial stage of iteration. However, there is the problem of slow convergence in the later stage of iteration.

Table III and Fig. IV show the all algorithms could not find the global optimum in 30 independent runs to Generalized Rastrigin function (F3). Therefore, more efficient local search method, such as chaos optimization search should be adopted to overcome the problem.

<table>
<thead>
<tr>
<th>Algorithms</th>
<th>bPSO</th>
<th>NPSO-LRS</th>
<th>PSO-MSLSA</th>
</tr>
</thead>
<tbody>
<tr>
<td>Best</td>
<td>5.0082</td>
<td>1.0281</td>
<td>4.6462e-7</td>
</tr>
<tr>
<td>Worst</td>
<td>13.909</td>
<td>1.1133</td>
<td>0.56061</td>
</tr>
<tr>
<td>Average</td>
<td>8.6403</td>
<td>1.068</td>
<td>0.12297</td>
</tr>
<tr>
<td>Variance</td>
<td>4.7317</td>
<td>0.00056115</td>
<td>0.018744</td>
</tr>
</tbody>
</table>

Figure 2. Comparison of algorithms applied to Generalized Girewank function.
IV. MULTI-OBJECTIVE SCHEDULING MODELS OF HYDROPOWER STATIONS

A. Objective Function

To maximize the capacity benefits of hydropower stations, the output of hydropower stations must replace the generating capacity of other stations as much as possible, namely, the peak of residual load process must be to reach the minimum. In order to improve the peak load regulation performance of hydropower stations, the residual load process must be as uniform as possible, that is, uniform load process is optimal load process in power system. Maximum power output not only maximizes electricity quantity benefits of hydropower stations, but meets the requirements of full use of basin water resources. So the scheduling models of hydropower stations are given by the following:

$$
\sum_{i=1}^{N} \sum_{t=1}^{T} (D(i) - \sum_{i=1}^{N} N_i(t)) = 0.00011016
$$

where, $D(i)$ stands for the given load process in power system, $N_i(t)$ is output power of $i$-th hydropower station at $t$-th time period, $N$ is number of hydropower stations, $T$ is number of periods. (4) stands for the residual load process in power system, which is the total load in the power system minus the output process of hydropower stations, and is facilitated by other stations in power system.

$$
\min \left\{ \max_{t=0\ldots T} [L(t)] \right\}
$$

TABLE II

<table>
<thead>
<tr>
<th>Algorithms</th>
<th>bPSO</th>
<th>NPSO-LRS</th>
<th>PSO-MSLSA</th>
</tr>
</thead>
<tbody>
<tr>
<td>Best</td>
<td>32173.6632</td>
<td>226.9497</td>
<td>0.00011016</td>
</tr>
<tr>
<td>Worst</td>
<td>171658.1319</td>
<td>1477.7534</td>
<td>3.9415</td>
</tr>
<tr>
<td>Average</td>
<td>99868.1404</td>
<td>795.0033</td>
<td>0.20209</td>
</tr>
<tr>
<td>Variance</td>
<td>2033019818</td>
<td>154115.8325</td>
<td>0.77479</td>
</tr>
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TABLE III

<table>
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<tr>
<th>Algorithms</th>
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<th>PSO-MSLSA</th>
</tr>
</thead>
<tbody>
<tr>
<td>Best</td>
<td>106.4519</td>
<td>19.2675</td>
<td>12.9345</td>
</tr>
<tr>
<td>Worst</td>
<td>195.7208</td>
<td>48.9771</td>
<td>21.8891</td>
</tr>
<tr>
<td>Average</td>
<td>160.3673</td>
<td>32.8711</td>
<td>17.0138</td>
</tr>
<tr>
<td>Variance</td>
<td>610.3449</td>
<td>52.2827</td>
<td>5.582</td>
</tr>
</tbody>
</table>

TABLE IV

<table>
<thead>
<tr>
<th>Algorithms</th>
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<th>NPSO-LRS</th>
<th>PSO-MSLSA</th>
</tr>
</thead>
<tbody>
<tr>
<td>Best</td>
<td>5.8975</td>
<td>3.0472</td>
<td>6.80E-05</td>
</tr>
<tr>
<td>Worst</td>
<td>8.9874</td>
<td>6.5487</td>
<td>0.00025121</td>
</tr>
<tr>
<td>Average</td>
<td>7.6471</td>
<td>4.2928</td>
<td>0.0001349</td>
</tr>
<tr>
<td>Variance</td>
<td>0.62157</td>
<td>0.77369</td>
<td>2.48E-09</td>
</tr>
</tbody>
</table>
\[
\min \left\{ \max_{i \in [1,t]} \{ L(t) \} - \min_{i \in [1,t]} \{ L(t) \} \right\} \quad (6)
\]

\[
\min \left\{ \sum_{j=2}^{T} \left| L(t) - L(t-1) \right| \right\} \quad (7)
\]

Equation (5) is used to minimize the peak value of residual load process. (6) is used to minimize the increasing trend of the peak and vale difference. (7) is used to uniform residual load process as much as possible. (5), (6) and (7) are used to maximize the peak-energy capacity benefits during scheduling period.

\[
\max \sum_{j=1}^{N} P_j(t) \cdot N_j(t) \cdot \Delta T \quad (8)
\]

Equation (8) is used to maximize the generation benefit of hydropower stations, where, \( P_j(t) \) is the generation price of \( i \)-th generator in \( t \)-th period, \( \Delta T \) is length of scheduling period.

B. Constraints

Hydropower Station Models. The generator net MW output is calculated as a non-linear function of head level and turbine discharge, the output power of the hydropower station at \( t \)-th period is as follows

\[
N_j = \frac{M}{\sum_{j=1}^{M} f(Q_j, h_j)} \quad (9)
\]

where, \( Q_j \) is discharge of \( j \)-th generator in \( t \)-th period, \( h_j \) is head level of hydropower station, and \( M \) is number of generators in the hydropower station.

Water Reservoir Balance. Water reservoir level at the end of a period depends on the water reservoir level at the beginning of the period, inflow during the period, and discharge for generation in the period and the spillage in the period. In terms of energy equivalent, water reservoir balance can be written as

\[
W_j = W_{t+1} + I_t + G_j(N_j) - SP \quad (10)
\]

where, \( W_j \) stands for water reservoir level in \( t \)-th period, \( I_t \) is expected inflow, \( G_j \) is generating flow which is non-linear function of output power \( N_j \), and \( SP \) is spillage in \( t \)-th period.

V. THE MULTI-OBJECTIVE DAILY GENERATION OPERATION OF THREE GORGES CASCADE HYDROPOWER STATIONS

A. Handling Constraints

It is very difficult to solve multi-objective optimal regulation of cascade reservoirs due to complex constraints. Based on the characteristics of cascade hydro system, we change the constraints to the feasible region of the water level in cascade reservoirs, and then the evolution of the particles of swarm is restricted in this region. Thereby the constrained optimization problem is changed to unconstrained optimization problems. The algorithm of calculating the discharge lower limit of hydropower station in upper reaches with the limit of the discharge in down reaches:

\[
Q\_i = V_0(Z_{D,i} - V_D(Z_{D,i}) + (Q_D - Q_g)\Delta T
\]

Step 1: calculating the feasible region of particles at \( t \)-th generation is shown as follows:

Step 2: calculating water level limit \( \bar{Z}_1 \) and \( Z_1 \) corresponding to \( Z_{t-1} \):

\[
\bar{Z}_1 = Z(V(Z_{t-1}) + (I_{t-1} - Q_1)\Delta T)
\]

\[
Z_1 = Z(V(Z_{t-1}) + (I_{t-1} - \bar{Q}_1)\Delta T)
\]

Step 3: calculating water level limit \( \bar{Z}_2 \) and \( Z_2 \) corresponding to \( Z_{t-1} \):

\[
\bar{Z}_2 = Z(V(Z_{t-1}) - (I_{t-1} - \bar{Q}_2)\Delta T)
\]

\[
\bar{\bar{Z}_2} = Z(V(Z_{t-1}) - (I_{t-1} - \bar{Q}_{2})\Delta T)
\]

Step 4: calculating water level limit \( \bar{Z}_3 \) and \( Z_3 \) with the generation upper and lower limit \( \bar{N}_t \) and \( N_t \), adopting trial-and-error method.

Step 5: assuming that the water level upper and lower limits are \( Z_{u_0} \) and \( Z_{l_0} \) at \( t \)-th period.

Step 6: calculating water level limit at \( t \)-th period:

\[
\bar{Z}_1 = \min (Z_{u_0}, \bar{Z}_1, \bar{Z}_2, \bar{Z}_3)
\]

\[
Z_1 = \max (Z_{l_0}, Z_1, Z_2, Z_3)
\]

where, \( Z_{l}, I_t, Z_{l} \), and \( Z_1 \) denote water level, reservoir runoff, upper limit and lower limit of water level at \( t \)-th period respectively, \( Z_{D} \), \( Q_D \) and \( Q_g \) stand for lower limit of water level, lower limit of discharge and inter-zone inflow of hydropower station in down reaches respectively, \( \tau \) is water arriving time of cascade hydropower stations, \( V(\_\_\_\_\_\_\_) \) is function that calculate reservoir capacity and \( Z(\_\_\_\_\_\_) \) calculate reservoir water level based on reservoir water level-capacity curve.

B. The Results of Regulation

The daily generation operation of Three Gorges cascade hydropower stations which takes into account the capacity and power generation benefits is studied with adopting HPSO algorithm.

As is predicted, the maximal load of Huazhong and Huadong interconnected power system is recorded in July in layout period, at 25835GW; The maximal load is 25835 GW, and the typical daily load difference between peak and valley is 9781 GW in summer season; The
maximal load is 24000 GW in winter, with a typical daily load difference between peak and valley of 9075 GW[5]. With such large proportion of thermal power capacity and shortage found in the regulating capacity in the interconnected power system, it is very necessary to study on reasonable operation mode of Three Gorges cascade hydropower stations to maximize the peak-energy capacity benefits and reduce the burden of peaking operation in interconnected power system.

As a seasonal storage reservoir, during flood season Three Gorges cascade hydropower stations mainly bear basic load of power grid, with a reservoir level of 145m for most of the time, so the productive head of hydropower station is lower than design head and reduces the output. During non-flood season, Three Gorges cascade hydropower stations have enough balancing storage to generate daily peak regulation capacity, but the constraints such as shipping limit the peak-sharing ability of Three Gorges cascade hydropower stations [5]. In the paper, the firm power of Three Gorges and Gezhouba hydropower stations are 499GW and 94.6 GW respectively, and generate basic load 130 GW; The ranges of water level of Three Gorges and Gezhouba reservoir do not exceed 0.3 m and 1m respectively within 1 hour; The discharge of Gezhouba reservoir is not less than 5300m3/s; The output factors of Three Gorges and Gezhouba hydropower stations are 8.5 and 8.4 respectively. The typical daily load curve of power system in the low-water period is as shown in Table 1.

The result of the peak load regulation of Three Gorges Cascade by adopting HPSO algorithm is as shown in Table 2. The load regulating operation process of the typical plan 3 and 5 are as shown in Fig. 2 and Fig. 3 respectively, where, horizontal axis stands for operation period and vertical axis stands for output of the cascade hydropower stations. From Table 2, the results can be seen that the load peak and off-peak difference of power system decrease 1723.78 GW by Three Gorges cascade hydropower stations, and Three Gorges stations are able to provide peaking output 1950.03 GW greatly. Fig. 2 shows that the highest system load can be cut down greatly, the major peak of residual load process is smooth obviously and the secondary peak has different degrees of weakening too. Therefore Three Gorges and Gezhouba stations have strong peaking capacity during winter season.

<table>
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VI. CONCLUSIONS

In this paper, a new particle swarm optimization algorithm solving hierarchy multi-objective optimization problems is proposed, and an optimal operation model for the hydropower stations, which can take into account capacity benefits and electricity quantity benefit, is established.

An accelerating genetic operator based on the characteristics of peaking operation of hydropower stations is designed, which can remarkably improve the convergence performance and search efficiency of HPSO algorithm. Furthermore, it is illustrated that the solution to the daily generation optimal operation of Three Gorges cascade hydropower stations with the purpose to increase capacity and power generation benefits is by adopting HPSO algorithm, and obtaining the peak-load regulation plan of Three Gorges cascade hydropower stations during low-flow period. The results suggest that the peak

FIGURE 2. THE PEAK LOAD REGULATION OF THREE GORGES CASCADE HYDROPOWER STATIONS. (PLAN 3).

FIGURE 3. THE PEAK LOAD REGULATION OF THREE GORGES CASCADE HYDROPOWER STATIONS (PLAN 5).
operation capability of Three Gorges cascade hydropower stations is applicable under reasonable operation plans.

The strategies to improve the performance of the algorithm are proposed.

(1) In PSO algorithm, the inertia weight is one of the key factors to find the optimum solution accurately and efficiently. An adaptive inertia weight algorithm (AWA), which can adaptively adjust the inertia weight of each particle based on the ability of global and local searching of the algorithms during iteration, is proposed.

(2) PSO algorithm fails to locate global minima for the complex multimimima functions, and the speed and accuracy of convergence are slow in the later stage of iteration, In this paper, the mutative scale local search algorithm (MSLSA) is proposed to search optimal solutions in gBest during in the process of evolution. The results of simulation have demonstrated that hybridization of PSO with MSLSA is valid.

ACKNOWLEDGMENT

Project supported by Guangdong Natural Science Fund, China (Grant No. 9151027501000039)

REFERENCES


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