Optimal Scheduling of the Cascade Hydropower Station and the Solution Based on an Improved PSO Algorithm

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ABSTRACT: *In order to overcome the defect of particle swarm optimization(PSO) that it is easy to be trapped in local optimum, this paper presented a hybrid-advanced strategy, which combined the dual fitness method, dynamic neighborhood operator and randomly dynamically adjusting inertia weight convergence of particles. This calculation example showed that this advanced strategy could increase the local convergence ability and accelerate the convergence of particles. Thus it was a simple and effective approach to solve nonlinear programming problems with complex and constraint conditions. This paper discussed the correlative issues in optimal scheduling of the cascade hydropower station and established a long-term optimal scheduling mathematics model of the cascade hydropower station based on the consideration of the electricity price in wet and dry season. Besides, it sought the solution by the application of improved PSO algorithm. The actual calculation results from the cascade hydropower station show that this model can help coordinate power generation and water consumption, and decrease profitless spill water of cascade hydropower station. This model can not only keep up a balanced power output in the dry season, but meet the need of flood mitigation and water storage in wet season, which is beneficial to a stable operation of the power system. The advanced PSO algorithm is a simple and effective approach to long-term optimal scheduling of cascade hydropower station based on the strength of quick calculation and precise convergence.*

Keywords: Cascade Hydropower Station, Optimal Scheduling, Improved PSO Algorithm.

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1. Introduction

With the development of power resources on a large scale, cascade hydropower stations are constantly built in regions with abundant hydroenergies in China. More and more attention has been attached on the exploration of joint optimal scheduling of cascade hydropower stations. It is shown from experience that the joint cascade optimal scheduling can increase the electricity by 2%~5.5% compared with the ordinary scheduling. The joint scheduling plays an important role in improving the efficiency of

hydroenergies and increasing the benefits of hydropower stations 1]. Besides, according to the open power generation side market, power enterprise, as a market entity, takes the maximization of its own profits as the main goal. No matter from the perspective of improving the efficiency of hydropower resources, or from the enterprise's pursuit of the maximization of profits, the joint optimal scheduling of cascade hydropower station is a necessary task at present.

2. Summary of PSO Algorithm

PSO algorithm is a heuristic algorithm based on swarm intelligence raised by Kennedy and Eberhart in 1995 to simulate the biological behavior of swarms. It provides some guidance on the optimal search by the swarm intelligence from the cooperation and competition within particle swarm. PSO algorithm is derived from the research on birds foraging. Birds often come about, disperse and gather together suddenly in foraging for something to eat. With unpredictable behavior, these birds maintain consistent as a whole, and there is always a proper distance between each two birds. Based on the behavior research on groups of similar creatures, a social information sharing mechanism was found within these creature groups, which placed an advantage on the evolution of swarms. This is the basis of PSO algorithm.

In PSO algorithm each particle has a sort of ability of perception. It is able to perceive the particle at the local optimal location around itself, and the existence of particles at the global optimal location in the whole swarm. Besides, based on the present status, it is able to adjust the behavior in the next step, and then perform some certain intelligence in the whole swarm. In solving the problem of optimization, each particle can be considered as a potential solution in the solution space. A global optimal solution in need can be finally available with a random adjustment of these potential solutions and repeated iterations. PSO algorithm retains a global research strategy based on population, and adopts the model of velocity and displacement. It is quite easy to operate. It can adjust the search strategy by following the present search conditions with its unique memory in a dynamic way. It is a much more effective parallel algorithm including merits like few adjustable parameters and quick convergence [2-4].

A standard PSO algorithm adopts the following equation to update the location and speed of particles:

$$v_i^{k+1} = wv_i^k + c_1 r_1 \left(p_i^k - x_i^k\right) + c_2 r_2 \left(p_g^k - x_i^k\right) \tag{1}$$

$$x_i^{k+1} = x_i^k + v_i^{k+1} \tag{2}$$

Where in w refers to the weight; c_1, c_2 refer to the coefficient which are usually obtained as 2; r_1, r_2 refer to two random numbers between 0 and 1; P_i^k refers to the optimum in iteration No. k; P_g^k refers to the optimum in all iterations.

3. Strategy of Improving The PSO Algorithm

So as to overcome the defect of local optimum and early convergence, this paper conducted a research on several aspects, including the design of fitness, the mechanism of optimization search, the choice and adjustment of inertia weight. Besides, this paper adopted a hybrid-advanced strategy of PSO algorithm, including the adjustment of fitness, dynamic neighborhood operator and inertia weight [2].

3.1 Design of Fitness

In seeking a solution of complex constraints in nonlinear optimization, there is always an infeasible solution, which depends on the disposal of constraints. It is easier to solve this problem by adopting the method of double fitness [3].

Fitness shows the adaptation from the individual x to environment, which can be divided into two categories, one is the objective fitness from the optimized objective functions, and the other is the constraint fitness from the constraint functions. Objective fitness can be presented as follows:

$$F_{obj}(x) = f(x) \tag{3}$$

Constraint fitness can be presented as follows;

$$F_i(x) = \begin{cases} 0 & g_i(x) \le 0 \\ g_i(x) & g_i(x) > 0 \end{cases} \tag{4}$$

Then, the total fitness can be presented as follows:

$$F_{con}(x) = \sum_{i=1}^{m} F_i(x) \tag{5}$$

In the process of evolution, double fitness can be applied to evaluate the particles. First of all, we should compare the constraint fitness among particles. Particles with sound fitness are higher in the list. When there is an equal fitness between two particles, we should further compare the fitness of their objective functions and those with sound fitness are higher in the list. Compared with the ordinary penalty functions, it can effectively avoid the defects of penalty coefficient which is yet to be certain. This method enjoys a virtue that the feasible solution is always better than the infeasible solution in fitness, which enables the feasible solution to be obtained from the optimization process. Then the optimum feasible solution will be obtained from the evolutionary operation of these feasible solutions and some sound infeasible solutions. In this case, we can integrate the entry into feasible region with the acquisition of optimal solution. Besides, the fitness is above zero without the need to change the optimization object and without the need to set the weight of constraint fitness and objective fitness. In a word, it is quite easy and self-evident to operate.

3.2 Dynamic Neighborhood Operator

There are some studies showing that PSO algorithm is quicker to work out a sound solution than other evolutionary algorithms. But with the increase of iterations, PSO algorithm cannot search much more precisely. The neighborhood operator enables PSO algorithm to improve its own computing performance for it can maintain the diversity of particle swarm and effectively avoid an early convergence. In the particle neighborhood with a good fitness, there are supposed to be particles with better fitness and a dynamic neighborhood operator to improve the performance of standard PSO algorithm. In the initial stage of optimization, the neighborhood of one particle is simply itself. With the increase of iterations, the neighborhood is also gradually larger and finally will include all particles [5].

The global extremum p_g in standard PSO algorithm is replaced by the local extremum l_{best} with the increase of local neighborhood, namely the l_{best} will take the place of p_g in equation (1). Then the local state will further be updated.

3.3 A Dynamic Adjustment Strategy of Inertia Weight

In PSO algorithm, the inertia weight w keeps a balance between the ability of global search and local search in algorithm. A larger w is the symbol of a stronger ability of global search and a weaker ability of local search. Otherwise, a w smaller is the symbol of a stronger ability of local search and a weaker ability of global search. The adaptive LDW (Linear Descend Weight) strategy adjusting inertia weight enables the PSO algorithm to enjoy a stronger ability of search in the initial stage of iteration. It can constantly search for new regions and then enhance its ability of development, which enables the algorithm to conduct a careful search around the optimal solution.

LDW strategy enjoys two defects. On the one hand, the ability of local search in the initial stage of iteration is quite weak. Although the initial particle has reached the global optimum, it is always missed. While in the later stage of iteration, it is easy to be trapped into the local extremum due to a weak ability of global search. On the other hand, it is quite difficult to predict the maximum iterations and then it will affect the regulation function of this algorithm.

Although a fuzzy system is applied to regulate the inertia weight, it also requires the expert knowledge to establish some fuzzy rules. Before a complex system is optimized, it is found that the expert knowledge is always so poor to be acquired and it is quite complex to be realized.

This paper adopted a SIW (Stochastic Inertia Weight) strategy which was defined as:

$$\beta = F_{obj}^{k} - F_{obj}^{k-10} / F_{obj}^{k-10} \tag{6}$$

Where in F_{obj}^{k} refers to the global or local optimal fitness in the iteration No.k; F_{obj}^{k-10} refers to the global or local optimal fitness in the iteration No. k - 10; β refers to the relative rate of change of optimal fitness within ten iterations.

Inertia weight w was obtained according to the following equation, a variable which can randomly adjust.

$$\begin{cases} \omega = \alpha_1 + 0.5r & \beta \geq 0 \\ \omega = \alpha_1 + 0.4r & \beta < 0 \end{cases} \tag{7}$$

Where in both α_1 and α_2 refer to the selected parameters, which are generally obtained as $\alpha_1 = 0.5, \alpha_2 = 0.4$; r is a random number well-distributed in the interval [0,1].

SIW strategy can randomly obtain the value of w. It can be found from equation (1) that the historical speed of particle has a random effect on the present speed. W is able to make an adaptive adjustment with the change of optimal fitness, and then it can regulate the ability of global and local search more flexibly. The randomly obtained w is similar to mutation operators of genetic algorithm to some extent, which is beneficial to maintaining the diversity of population.

3.4 Steps to Improve the PSO Algorithm [6]

1) Initialize a swarm of particles including a random location and speed

2) Calculate and evaluate the constraint and objective fitness of each particle.

3) Put the objective fitness of all particles and the optimal location they have undergone into comparison. A sound result will be considered as the present optimal location.

4) Calculate the rate of change of the optimal objective fitness and then determine the inertia weight based on the result.

5) Calculate the neighborhood scope of all particles. In a local pattern, compare their fitness with the optimal location they have undergone in neighborhood. With a sound result, the index number of l_{best} should be reset, otherwise the P_g will be adopted.

6) Update the speed and location of particles based on equation (1) and (2).

7) When failing to reach the maximum iterations or a fairly sound fitness, back to step 2, or stop the iteration and type out the calculation result.

4. The Long-Term Optimal Scheduling Mathematical Model of Cascade Hydropower Station

The study of middle and long-term primal scheduling of hydropower station and its reservoir is related to several problems such as the formulation and implementation of the optimal scheduling of hydropower station and its reservoir in a long period (season, year or decades). In essence, it is in line with the inflow into reservoir and with the requirement of comprehensive utilization, while taking account of the operation feature of hydraulic turbine set and the effect of electricity price, formulating and implementing the middle and long-term optimal scheduling of hydropower and its reservoir so as to achieve the maximized profits [7].

On the premise of meeting the requirement of a safe and reliable cascade hydropower station and other constraints, optimization principle is to choose the allocation strategy of water power which helps to maximize the benefits of power generation in scheduling cycle from the whole cascade hydropower station by increasing the profits in dry season and increasing the profits in wet season as well [8].

A long-term optimal scheduling mathematical model of cascade hydropower station based on the above optimization principles.
1) Objective function:

$$\max \ f = \max \left[\sum_{t=1}^{T} \left[\sum_{i=1}^{N_h} A_i Q_t^i H_t^i \right] M_t p_t \right] \tag{8}$$

Where in T refers to the time intervals of scheduling; N_h refers to the power generating units; A_i refers to the comprehensive output coefficient in the unit No, i; Q_t^i refers to the power discharge in the time interval No.t and unit No. i; H_t^i refers to the head of power generation in the time interval No.t and unit No.i; M_t refers to the time length in the time interval No.t; and P_t refers to

the electricity price in the time interval No.t.

2) Constraint conditions include the constraint of water balance, the constraint of output in hydropower station, constraint of water storage in reservoir, constraint of discharge volume in reservoir, constraint of floor control, constraint of volume control in lower reaches, constraint of a firm output, and constraint of water storage in the entire scheduling cycle and non-negative conditions [9].

5. Application of the Improved PSO Algorithm on The Solution of Mathematical Model

The long-term optimal scheduling mathematical model of cascade hydropower station is related to the problem of single objective nonlinear programming in math, which is not only under the constraint of equation, but under the constraint of many inequations. This paper applied the improved PSO algorithm to seek a solution, and it should at first formulate the method of encoding and initialization. This paper took the water level in cascade hydropower station as a decision variable, and then connected power discharge from all hydropower stations together in the sequence of time and number so as to make up a particle. The location vector is shown in equation (9), while the velocity vector is shown in equation (10), namely the velocity of water level change of all hydropower stations at different time intervals. Wherein v_t^i refers to the velocity of water level change of hydropower station No.i and at time interval No.t. In seeking a solution of this model, the location vector of each particle all corresponds to a scheduling plan.

$$X=\left[L_1^1,\ L_2^1,\cdots,L_T^1,\ L_1^2,\ L_2^2,\cdots,L_T^2,\cdots,L_1^{N_h},\ L_2^{N_h},\cdots,L_T^{N_h}\right]^T \tag{9}$$

$$V=\left[v_1^1,\ v_2^1,\cdots,v_T^1,\ v_1^2,\ v_2^2,\cdots,v_T^2,\cdots,v_1^{N_h},\ v_2^{N_h},\cdots,v_T^{N_h}\right]^T \tag{10}$$

Where in L refers to the water level of power station; T refers to the time intervals of scheduling; N_h refers to the number of power stations; v refers to the velocity of water level change. Particles initialize the location and velocity based on equation (11) and (12); r_3 and r_4 refer to two well-distributed random numbers in the interval [0,1].

$$L_t^i = L_{t\min}^i + r_3\left(L_{t\max}^i - L_{t\min}^i\right) \tag{11}$$

$$v_t^i = 0.2\, r_4\left(L_{t\max}^i - L_{t\min}^i\right) \tag{12}$$

The specific steps of applying the improved PSO algorithm to seek the solution of the scheduling model are listed as follows:

1) Water level is chosen as a control variable, and initializes a swarm of particles, including the random location and velocity of change

2) Based on the principle of water balance, calculate and evaluate the constraint and objective fitness of each particle.

3) Put the objective fitness of all particles and the o7ptimal location they have undergone into comparison. A sound result will be considered as the present optimal location.

4) Calculate the rate of change of the optimal objective fitness and then determine the inertia weight based on the result

5) Calculate the neighborhood scope of all particles. In a local pattern, compare their fitness with the optimal location they have undergone in neighborhood. With a sound result, the index number of l_{best} should be reset, otherwise the p_g will be adopted.

6) update the speed and location of particles based on equation (1) and (2)

7) When failing to reach the maximum iterations or a fairly sound fitness, back to step 2, or stop the iteration and type out the calculation result.

6. Example of Application

A real cascade hydropower station in south China is taken as the object of study. This cascade hydropower station enjoys two levels. The I hydorpower station enjoys the ability of annual regulation, while the II station enjoys the ability of daily regulation [10].

In the I hydropower station, the normal water level is 1139.6 cm, the dead storage level is 1112.2 cm; the effective capacity is 8.5million m^3; the maximum water area is 4,570,000m^2; the maximum depth is 34.6m; the water diversion flow is designed to be 1.9m^3/s; the head is designed to be 360 m, the maximum head is 383 m; the total capacity of the station is 6,400kW with two units which bear the regulation functions in the local independent grid; and the firm power is 2MW. In the II hydropower station, the effective capacity is 21,000m^3; the water diversion flow is designed to be 2.73m^3/s; the head is designed to be 220 m; the total capacity of the station is 5,000kW with two units; and the firm power is 1,700kW. The firm output from the whole cascades is 3,700kW.

Month	Inflow discharge /(m3°s-1)	Monthly discharge /m	Power discharge /(m3°s-1)	Spilled discharge /(m3°s-1)	Average output/ kW
1	0.53	1138.4	0.63	0	2060
2	0.47	1135.2	0.64	0	2065
3	0.46	1130.9	0.64	0	2062
4	0.49	1126.6	0.65	0	2055
5	0.56	1120.9	0.79	0	2457
6	1.53	1112.5	1.88	0	5771
7	3.74	1131.7	1.90	1.82	5780
8	4.90	1135.0	1.90	2.86	5780
9	3.23	1135.0	1.90	1.69	5780
10	2.79	1135.0	1.90	0.50	5780
11	1.59	1139.6	1.59	0	5173
12	0.88	1139.6	0.88	0	2866

Table 1. Optimized calculation results in the I Hydropower Station

Month	Inflow discharge/ (m3°s-1)	Monthly discharge /m	Power discharge /(m3°s-1)	Spilled discharge /(m3°s-1)	Average output /kW
1	0.26	756.6	0.95	0	1855
2	0.22	756.6	0.96	0	1860
3	0.21	756.6	0.96	0	1863
4	0.22	756.6	0.98	0	1898
5	0.27	756.6	1.21	0	2334
6	1.02	756.6	2.73	0.17	5000
7	1.74	756.6	2.73	2.73	4346
8	2.01	756.6	2.73	4.04	1459
9	1.49	756.6	2.73	2.34	4564
10	1.28	756.6	2.73	0.95	5000
11	0.73	756.6	2.30	0	4425
12	0.41	756.6	1.33	0	2578

Table 2. Optimized calculation results in the II Hydropower Station

Data of runoff on behalf of year is adopted for calculation. Months between July and October are the wet season, months between May and November are the temperate season and months between December and April in the next year are the dry season. In temperate season, the reference electricity price is applied as 0.3 yuan/ (kW° h). In wet season, the electricity price is charged at 75% of reference price; in dry season, the electricity price is charges at 150% of reference price. The parameters of this improved PSO were set as follows: the particle swarm was 100, $c_1 = c_2 = 2$, $\alpha_1 = 0.5$, $\alpha_2 = 0.4$; the maximum iteration was 1000; calculation was carried on ten times respectively; and the average value was obtained as the optimum. The final optimized calculation results were shown in table 1 and table 2.

In order to compare the computing performance of the improved PSO algorithm, under the same computing conditions, a genetic algorithm solution model was applied. In this model, the mutation and crossover rate were 0.1 and 0.2 respectively; the maximum iteration was 1000; calculation was carried on ten times respectively and the average value was obtained as the final optimum. The comparison with these calculation results was shown in table 3.

7. Conclusion

The long-term optimal scheduling of cascade hydropower station is such a complicated nonlinear programming problem. It should not only take account of the operation feature of the cascade hydropower station, but the requirement of flood control. In the wet and dry season, a higher power generation is not supposed to be the symbol of greater benefits. This example of application shows that this optimal scheduling model in this paper enables a stable and regular output in the dry season and a stable operation of power system. Besides, this model can improve the efficiency of water resources and increase the benefits of power generation from cascade hydropower station. The improved PSO algorithm can effectively seek the solution of the optimal scheduling of cascade hydropower station. It is quite easy to operate and quite worth spreading for application.

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