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# *Application of Chaos Particle Swarm Optimization in Short-Term Optimal Scheduling of Reservoirs*

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***Abstract:*** This paper combines particle swarm algorithm and chaos algorithm to solve the short-term optimal scheduling problem of reservoir. It takes advantage of the fast convergence velocity of the particle swarm optimization algorithm and the ergodicity and randomness of chaotic motion to modify the traditional particle swarm optimization algorithm, which gets rid of the shortcomings that particle swarm optimization algorithm easily falls into local extreme points in the later stage, while maintaining the search rapidity in the early stage. Through example calculation, the results show that the algorithm is obviously superior to the traditional particle swarm optimization algorithm in terms of convergence and stability, which is an effective search algorithm.

## 1. Introduction

Optimal scheduling of hydropower station is a kind of complex combinatorial optimization problem. In the optimal scheduling of hydropower reservoirs, the commonly used model solving methods include: dynamic programming (DP), genetic algorithm (AG), stepwise optimization (POA), particle swarm algorithm (PSO), etc. [1-5]. However, when used to solve the optimal scheduling problem of hydropower stations, dynamic programming has the shortcomings of dimension disaster and too long solution time [6]; genetic algorithm has unique advantages in handling complex objective functions, but still encounters problems when dealing with numerous constraints and convergence velocity [7]; if there are more than two reservoirs, the computer memory occupied by the gradual optimization algorithm will increase accordingly, leading to greatly reduced calculation velocity [8]; the traditional particle swarm optimization algorithm easily falls into the local minimum point in the later stage of evolution, and the achievable accuracy of the algorithm is poor.

This study makes full use of the advantages of particle swarm optimization algorithm in fast convergence velocity and ergodicity of chaotic motion, and proposes a hybrid algorithm based on chaos thought-chaos particle swarm optimization for application in the short-term optimal scheduling of reservoirs. For its characteristics: using the fast convergence of particle swarm optimization algorithm and the ergodicity and randomness of chaos search, it not only ensures the algorithm convergence velocity, but also effectively avoids the premature convergence of the traditional particle swarm optimization algorithm.

## 2. Mathematical model establishment [9]

### 2.1. Objective function

The research object is a regulating reservoir. The inflow sequence of the reservoir is known, and the selected objective is to maximize the daily power generation revenue while meeting the constraints.

$$E = Max\sum_{t=1}^{T}(A \cdot Q_t \cdot H_t \cdot M_t \cdot P_t) \tag{1}$$

Where: $E$ ——Daily power generation revenue of the power station (yuan);

$A$——The comprehensive output coefficient of the power station;

$Q_t$ ——The power generation flow rate (m3/s) of the power station in the time period $t$;

$H_t$——The average net water head of power generation in the time period $t$ (m);

$M_t$——Number of hours in the time period $t$;

$P_t$——The electricity price for the time period $t$ (yuan/MW.h).

### 2.2. Constraints

(1) Water balance constraint

$$V_{t+1} = V_t + (q_t - Q_t - S_t)\Delta t \qquad \forall t \in T \tag{2}$$

Where: $V_{t+1}$ ——the water storage capacity of the power station reservoir at the end of time period $t$ ($m^3$);

$V_t$——the water storage capacity of the power station reservoir at the beginning of time period $t$ ($m^3$);

$q_t$——the inbound flow of the power station during the time period $t$ ($m^3/s$);

$S_t$——the abandoned water flow of the power station in the time period $t$ ($m^3/s$);

$\Delta t$—— Calculation period length (s).

(2) Reservoir storage capacity constraint

$$V_{t,min} \le V_t \le V_{t,max} \qquad \forall t \in T \tag{3}$$

Where: $V_{t,min}$ ——The minimum water storage capacity of the reservoir that should be guaranteed by the power station during the time period $t$ ($m^3$);

$V_t$——Reservoir water storage capacity ($m^3$) of the power station in the time period $t$;

$V_{t,max}$ ——The maximum water storage capacity of the reservoir allowed by the power station during the time period $t$ ($m^3$, usually based on the consideration of reservoir safety, such as the water storage capacity corresponding to the normal high water level of the reservoir, etc.).

(3) Reservoir discharge flow constraint

$$Q_{t,min} \le Q_t \le Q_{t,max} \qquad \forall t \in T \tag{4}$$

Where: $Q_{t,min}$ ——the minimum discharge flow rate ($m^3/s$) that should be guaranteed by the power station in the time period $t$;

$Q_{t,max}$ ——the maximum allowable discharge flow ($m^3/s$) of the power station in the time period $t$.

(4) Power station output constraint

$$N_{min} \le A \cdot Q_t \cdot H_t \le N_{max} \quad \forall t \in T \tag{5}$$

Where: $N_{min}$ ——The allowable minimum output of the power station (MW, depending on the type and characteristics of the turbine);

$N_{max}$ ——The installed capacity (MW) of the power station.

(5) Non-negative conditional constraint

All the above variables are non-negative variables (≥0).

## 3. Algorithm introduction

### 3.1. Particle Swarm Optimization

Particle swarm optimization algorithm is a swarm-based evolutionary algorithm, with its idea derived from artificial life and evolutionary computing theory. PSO is sourced from the study on the predation behavior of birds. A group of birds is randomly searching for food. If there is only one piece of food in this area, the simplest and most effective strategy for finding food is to search the surrounding area of the bird currently closest to the food. Particle swarm optimization algorithm starts from a set of random solutions and searches for the optimal solution through iteration. It assigns each particle in the particle swarm two characteristics of position and velocity; the position of each particle is used as a possible solution to the problem to be solved; the objective function (solved by the position coordinates of the particle) is used as the fitness to measure quality of each particle in the swarm. Using the two characteristics of position and velocity, the particle continuously updates its position in the solution set space by tracking two extremums (individual extremum and global extremum), so as to find the optimal solution to the problem [10].

With the continuous improvement of the PSO optimization algorithm, the commonly used formulas for updating particle velocity and position are as follows:

$$V_{i+1} = w V_i + c_1 r (p_{Best} - P_i) + c_2 r (g_{Best} - P_i) \tag{6}$$

$$P_{i+1} = P_i + V_{i+1} \tag{7}$$

Where: $P_i$ is the position of the current particle; $P_{i+1}$ is the position of the next-generation particle; $V_i$ is the moving velocity of the current particle; $V_{i+1}$ is the moving velocity of the next-generation particle; $w$ is the inertia factor; $c_1$ and $c_2$ are learning factors; $r$ is a random number generated on [0,1]; $p_{Best}$ is individual extremum (the optimal position found by the particle itself); $g_{Best}$ is the global extremum (the optimal position currently found by the entire population). In addition, the rate of each dimension in the update process of particles (composed of $n$ dimensional space) should be limited to $[-V_{max}, V_{max}]$.

### 3.2. Chaos Optimization Algorithm

Chaos is a pervasive nonlinear phenomenon whose behavior is complex and random-like, but with delicate inherent regularities. Due to the ergodicity of chaos, optimization search using chaotic variables is more advantageous than blind random search, which can avoid the shortcoming that optimization algorithm falls into local optimum. The chaos optimization algorithm is to use the randomness, ergodicity and regularity of these chaotic variables for optimization search in the solution set space. Easy to jump out of the local optimal solution, it does not require optimization problem to have continuity and differentiability. The Logistic mapping [11] of formula (8) is selected to generate chaotic variables. Where, $u$ is the control parameter, 0 < $y_i$ <1. It has been proved that when $u$ = 4, formula (8) is completely in a chaotic state.

$$y_{i+1} = u * y_i * (1 - y_i) \tag{8}$$

Where: $y_i$ is the iterative value of variable $y$ in the $i$ th iteration; $y_{i+1}$ is the iterative value of variable $y$ in the $i+1$-th iteration; $u$ is the control parameter.

### 3.3. Chaos Particle Swarm Optimization

Optimal scheduling of hydropower stations is a strongly constrained, nonlinear, multi-stage combinatorial optimization problem. The optimal scheduling of hydropower stations is expressed as: finding a sequence of water level changes ($Z_1$, $Z_2$, ..., $Zn$) that maximizes power generation under various constraints. When the model is solved by the chaos particle swarm algorithm, a particle is an operation strategy of the hydropower station. The element of particle position vector is the water level of the reservoir at the end of each period, and the element of velocity vector is the fluctuation velocity of the water level of the reservoir at the end of each period. Water level change of the reservoir at the end of each period must meet various constraints in the above model. In order to increase the initial feasible solution, this paper uses a penalty function to convert the constraints into no constraints. The algorithm steps are as follows:

Step 1: Within the allowable water level variation range of each time period, use the Logistic mapping of formula (8) to randomly generate $m$ groups of water level change sequence $(Z_1^1, Z_2^1, \cdots, Z_D^1), \cdots, (Z_1^m, Z_2^m, \cdots, Z_D^m)$ at the end of the time period, and randomly generate $m$ groups of water level fluctuation velocity change sequence $(V_1^1, V_2^1, \cdots, V_D^1), \cdots, (V_1^m, V_2^m, \cdots, V_D^m)$ at the end of the time period. That is, randomly initialize $m$ particles. The $\vec{p}_k$ coordinates of the particle $k$ are set as the current position of the particle $\vec{p}_k = Z_t^k (k = 1,2,\cdots,m; t = 1,2,\cdots D)$, and its corresponding individual extremum $E(k)$ is calculated according to the formula (1). Find the largest one of the $m$ individual extremums so there is the global extremum $E_g = \max\{E(k), k = 1,2,\cdots m\}$. Record the serial number $l$ of the best particle, and set it as the position of the particle $\vec{g}_{best} = Z_t^l (t = 1,2,\cdots,D)$.

Step2: Calculate the objective function value of each particle according to formula (1). If it is superior to the current individual extremum $E(k)$ of the particle, set $\vec{P}_{best}$ as the position of the particle, and update the individual extremum. If the best of all individual extremums is superior to the current global extremum $E_g$, then set $\vec{P}_g$ as the particle's position and update the global extremum.

Step3: Update the respective velocity and position of the particles according to formulas (6) and (7).

Step4: Calculate the fitness variance of the population. $f_i$ is the fitness of the $k$ th particle (here, the power generation) [12], $\overline{f}$ is the average fitness of particles in the current particle swarm, $\sigma^2$ is the population fitness variance of the particle swarm, $\sigma^2 = \sum\left[\left(f_k - \overline{f}\right)/ f\right]^2$. Where, $f$ is the normalization factor,

$$f = \begin{cases} \max\left\{\left|f_k - \overline{f}\right|\right\}, \left(\max\left\{\left|f_k - \overline{f}\right|\right\} \geq 1\right) \\ 1, \left(other\right) \end{cases} \tag{9}$$

If the variance is smaller than the set value, use the Logistic mapping to update the particle's position. Otherwise, use formula (6) to update the particle's position.

Step5: Check whether the iteration termination condition is met. If the current number of iterations reaches the preset maximum number of iterations, or reaches the minimum error requirement, the iteration is terminated and the result is output. Otherwise, go to Step 2 for further iteration.

When the iteration is terminated, the position of the global extreme point is recorded as the optimal scheduling line of the reservoir.

## 4. Calculation example

In order to verify the feasibility and effectiveness of the above algorithm, a reservoir is taken as an example for calculation, and the parameters are set as w=0.9, c1=c2=2. The reservoir is mainly used for power generation, and the comprehensive utilization requirements are relatively simple. The water level-storage capacity of the hydropower station, the downstream water level-discharge flow, and the expected output curve of the unit are known. The normal storage level of the reservoir is 2650m, the dead water level is 2600m, the output coefficient is 8.6, the installed capacity is 240,000 kW, the maximum flow rate is 47.24m$^3$/s, the water level at the beginning of the scheduling period is 2640m, and the daily water consumption is 800,000 m$^3$. Referring to the time-of-use electricity price policy of Sichuan Province, the electricity price factor is set to 1.335 during the peak period of electricity demand, 0.5 during the trough period of electricity demand, and 1.0 in other cases. The base electricity price is 308 yuan/MW.h. Price factor of each specific period in a day is: 0.500 from 0:00 to 7:00; 1.335 from 7:00 to 11:00; 1.000 from 11:00 to 19:00; 1.335 from 19:00 to 23:00; 0.5000 from 23:00 to 24:00.

The scheduling period of the model is one day. With 15 minutes as a period, it is divided into 96 periods, and the reservoir water level is discreted into 250 state points in each period. Dynamic programming, PSO and chaotic particle swarm are used for solution respectively, with the results shown in Figure 1 and Table 1.

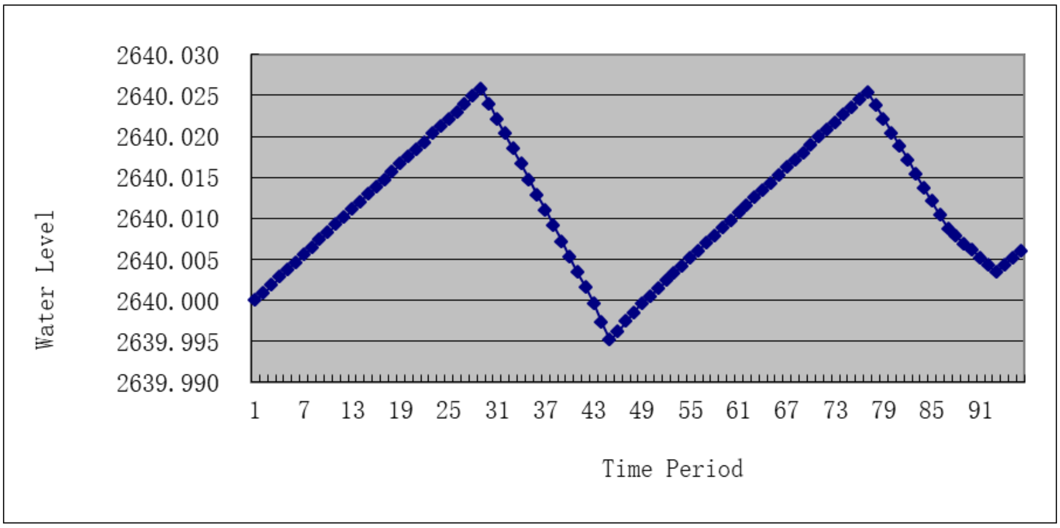


Figure 1: Diagram of the diurnal variation process of the reservoir water level.

Table 1: Dynamic programming, PSO, chaos particle swarm comparison table.

| Optimization algorithm | Number of discrete points | Power generation revenue/yuan | Optimization calculation time/s |
|---|---|---|---|
| Dynamic programming | 250 | 482170.7 | 10.4 |
| Particle swarm | 250 | 481121.9 | 5.2 |
| Chaos Particle Swarm | 250 | 481961.4 | 3.7 |

As can be seen from Figure 1, the reservoir stores water during the low electricity price period, but releases water during the high electricity price period, and no water abandonment occurs, which increases the power generation revenue. It can be seen from Table 1 that when the discrete points of the storage capacity are consistent, the solution result of the chaos particle swarm optimization algorithm is 481961.4 yuan, which is only 209.3 yuan less than that of the dynamic programming algorithm, but the calculation time is only 1/3 of that of dynamic programming algorithm. Compared with the traditional particle swarm algorithm, the solution results are slightly superior, and the calculation time is shorter, which shows that chaos particle swarm algorithm can easily jump out of the local optimal solution, with good convergence and stability.

## 5. Conclusion

This paper proposes a chaos particle swarm optimization algorithm for solving the short-term optimal scheduling problem of reservoirs. This algorithm improves the traditional particle swarm optimization algorithm, which demonstrates the following advantages: fast calculation velocity, high search efficiency; good convergence performance, easiness in jumping out of the local optimum solution; simple principle, easy programming.

Chaos particle swarm optimization algorithm is an improvement to the traditional particle swarm optimization algorithm, which not only ensures the convergence speed of the algorithm, but also effectively avoids the premature convergence of the traditional particle swarm optimization algorithm, achieving good results in solving the short-term optimal scheduling problem of reservoirs. The optimal scheduling of cascade hydropower station groups based on the chaos particle swarm algorithm demands for further research.

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