sis of the influence of loads distribution of hydropower stations on the results of optimization algorithms

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ABSTRACT: Aiming to solve the problem: the conventional loads distribution of hydropower stations calculated by single model corresponding to multiple optimal algorithms, the way that various models corresponding to multiple optimal algorithms are proposed in the paper. According to characteristics and tasks of hydropower station, loads distribution models should be chosen reasonably. Genetic Algorithms, Simulated Annealing Algorithm, Particle Swarm Optimization Algorithm are introduced different loads distribution models respectively to calculate examples that undertaking different tasks of hydropower stations. When the Particle Swarm Optimization Algorithm is applied to calculate the minimum flow consumption model, because of its fast convergence and strong optimization ability and other characteristics, it is regarded as the best one among the three algorithms; Simulated Annealing Algorithm is in the calculation of the maximum power output model reflecting the greater advantage.

1 BACKGROUND

The hydropower station achieves economic scheduling, which will increase economic efficiency about 1%~3% [1]and decrease the energy consumption. The speed and accuracy of optimization algorithms calculating the loads distribution of the hydropower stations is the key to ensure economic operation of hydropower station. However, calculation speed and accuracy of optimization algorithms depends on the algorithms themselves, but also rely heavily on models. Therefore, studying the effects of loads distribution model of hydropower stations on the optimization results is significant for operating the hydropower station economically. In this respect, domestic and foreign researchers formed a series of theories gradually after decades of hard working and practicing [3-11], such as nonlinear programming method, dynamic programming method. Although Nonlinear Programming and Dynamic Programming method have their own advantages, the problems should not be ignored including dimension of disaster, computation complex and slow. In addition, the type that a single model corresponds to various optimization algorithms and choosing a priority algorithm is used frequently in previous research in this area. In this paper, two basic models of loads distribution are introduced. One of the two models named minimum flow consumption model is used consuming the minimum water as the target function, and the other is the maximum power output model that generating maximum power is established for the objective function. Introducing Genetic algorithms, Simulated Annealing Algorithms and Particle Swarm Optimization in the two models respectively, and applying to examples. Analysis the results and explore loads distribution model effects on algorithms.

2 LOADS DISTRIBUTION MODELS OF HYDROPOWER STATIONS

Actually minimum flow consumption model has the "electric definite water" criteria and maximum power output model is the "water definite electric" criteria.

2.1 *Minimum flow consumption model(MFCM)*

2.1.1 *Objective function*

$$Q = \min \sum_{k=1}^{n} Q_k(N_k) \qquad (1)$$

where k=unit's number; Q_k =the flow consumption of unit k; N_k= the power output of unit k.

traints condition

a. Active power balance equation

$$N = \sum_{k=1}^{n} N_k \tag{2}$$

b. Power output should be constrained within the maximum and minimum power output capacities of units

$$N_{k\min} \le N_k \le N_{k\max} \tag{3}$$

where $N_{k\ min}$= minimum power output capacities of unit k; $N_{k\ max}$= maximum power output capacities of unit k.

2.1.3 *Constraints Processing*

To simplify the constraint and divert it from the constraints to unconstrained problems by introducing the penalty function to the objective function[12], while ensure its optimal solutions within the feasible region. Using $Q_k=N_k/(K_kH)$ replaced the Q_k in the formula (1) and added to the objective function (4):

$$\min Q = \sum_{k=1}^{n} \frac{N_k}{K_k H} + M \times \left(N - \sum_{k=1}^{n} N_k \right)^2 \tag{4}$$

Where M is the penalty factor, M=1000; K_k is the overall efficiency of unit k when the power output of unit k is equal to N_k

2.2 *Maximum power output model(MPOM)*

2.2.1 *Objective function*

$$N = \max_{Q_k \in D_k} \sum_{k=1}^{n} N_k \left(Q_k \right) \tag{5}$$

2.2.2 *Constraints condition*

a. Flow consumption balance equation

$$Q = \sum_{k=1}^{n} Q_k \tag{6}$$

b. Power output should be no more than the maximum power output capacities of units

$$0 \leqslant N_k \leqslant N_{k\max} \tag{7}$$

c. Flow constraint

$$Q_k \leqslant Q_{k\max} \tag{8}$$

Where $Q_{k\ \max}$ is the maximum flow discharge of unit k.

2.2.3 *Constraints Processing*

Penalty function is also introduced to the objective function. To ensure objective function variables consistency, objective function of N in the formula (5) should be replaced by Q. Thus, the objective function turns to be the formula (9):

$$\max N(Q) = \sum_{k=1}^{n} 9.81 \eta_k Q_k H_k + M*(Q - \sum_{k=1}^{n} Q_k)^2 \tag{9}$$

Where M is the penalty factor, M=1000; η_k is the mechanical efficiency of unit k.

3.1 *Genetic Algorithm*

Genetic Algorithm (Genetic Algorithm, abbreviated GA) is a search algorithm based on the theory of biological evolution. This algorithm draws its idea from the natural search and selection processes leading to the 'survival of the fittest' of individuals.

GA starts by generating randomly initial population. Then, the initial population is encoded, and evaluated by computing the value of the objective function[13]. Next, chosen better fitness individuals and abandoned the bad ones. Finally, a new population with higher average fitness is generated. The process will be repeated for the number of generations set by the user. The details process of distributing loads by Genetic Algorithm as shown in Figure.1.

3.2 *Simulated Annealing algorithm*

3.2.1 *The method of Simulated Annealing algorithm*

Simulated Annealing algorithm (Simulated Annealing, abbreviated SA) of the original idea was proposed in 1953, Kirkpatrick simulated annealing process based on the Metropolis[14]. The process was the solids melting the liquid gradually and cooling down to the lowest energy state. Kirkpatrick put the above theory successful application in the combinatorial optimization problems in 1983.

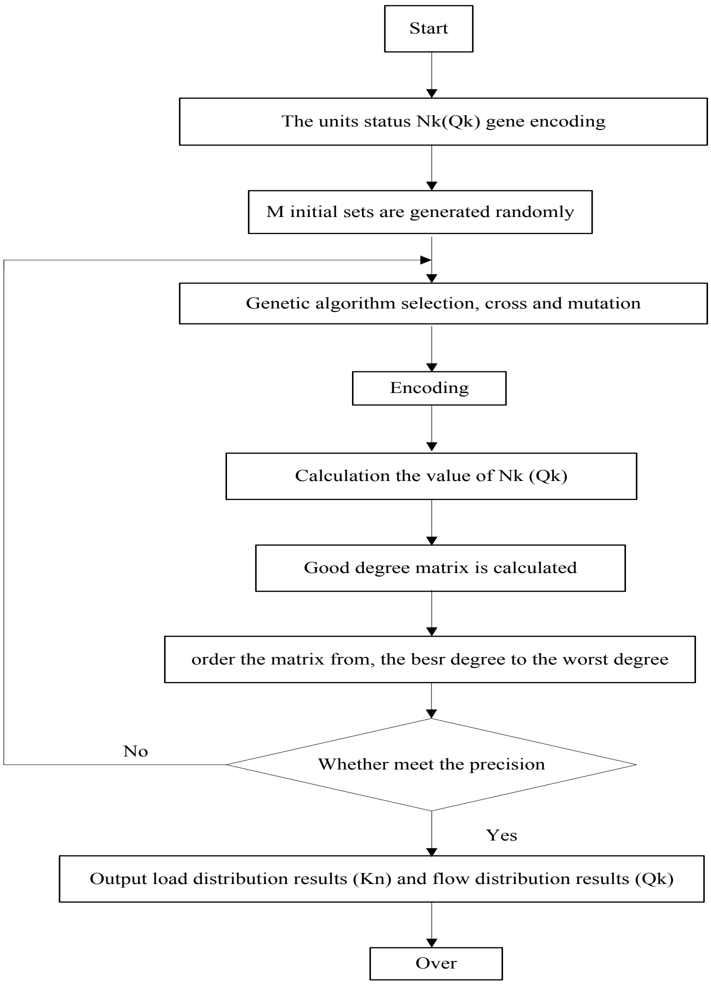

Figure.1 The process of distributing loads by Genetic Algorithm

process of distributing loads in hydropower station by using SA

a. Set the parameters: such as the initial temperature T, maximum iteration number, initial solution state S (is the starting point of the iterative algorithm);

b. Randomly disturb S in the given boundary conditions and Produce S' data;

c. Computation fitness incremental: Δf= F(S') - F(S);

d. If $\Delta f < 0$ is accepted as a new S' current solution,

or the exp(- Δf/T) should be calculated, if exp(- Δf/T)>rand(0,1) then accept S' as a new current solution, or unchanged;

e. If meet the termination condition is output current solution as the optimal solution;

f. If the current iteration number is less than the maximum iteration number, turn to step b or end program.

3.3 *Particle Swarm Optimization algorithm*

3.3.1 *The method of Particle Swarm Optimization algorithm*

Particle Swarm Optimization algorithm (Particle Swarm Optimization Algorithm, PSO) simulates the feeding behavior observed in bird flocks and it is a global optimization algorithm. PSO was first proposed by the Kennedy and computer science PhD Eberhart[16,17].

In PSO, each candidate solution is called a “particle”, and each of them has a speed parameter which decides their flight direction and distance. Each particle adaptive value is dynamically adjusted, after several iterations to find the optimal solution[18].

3.3.2 *The process of distributing loads in hydropower station by using PSO*

This algorithm is successively accomplished with the following steps[19]:

a. Set the values of the dimension space N and the sizes of the swarm (s can be taken randomly).

b. Initialize the iteration number k (in the general case is set equal to zero).

c. Evaluate for each agent, the velocity vector using its memory and equation (10), where pbest and sbest can be modified.

$$v_{ij}^{k+1} = \omega_j v_{ij}^{k} + c_1 r_1^{k}\left[(pbest)_{ij}^{k} - x_{ij}^{k}\right] + c_2 r_2^{k}\left[(sbest)_{ij}^{k} - x_{ij}^{k}\right] \quad (10)$$

d. Each agent must be updated by applying its velocity vector and its previous position using equation

$$x_{ij}^{k+1} = v_{ij}^{k+1} + x_{ij}^{k} \quad (11).$$

e. Repeat the above step (3, 4 and 5) until a convergence criterion is reached.

where are the position and the velocity vector of particle *i*, respectively at iteration $k+1$; learning factors c_1 et c_2 are acceleration coefficients for each term exclusively situated in the range of 0-2; ω_j is the inertia weight; r1,r2 $\in$ rand[0,1].

Hydroelectric power station A and B undertake different tasks, the parameters are shown in Table 1. Loads distribution model for hydropower station should be depended on the tasks of hydropower station. Hydropower station A is used to undertake flood control, irrigation, hydropower and other tasks. To balance utilization efficiency of A, reducing the power generation process flow loss is necessary. Therefore, the MFCM is chosen as the loads distribution model of hydropower station A. However, hydropower station B is run-of-river hydropower station. The power output of B depends on the amount of runoff flow. The MFCM is more appropriate to B.

Table.1 Hydropower parameters

Hydropower Station	Number of turbines	Total installed capacity	Firm power	Maximal water discharge capacity
		10^4kW	10^4kW	m^3/s
A	6	6*55	100	376
B	5	3*15+2*7	20	190

4.1 *Parameters setting*

To eliminate parameters on the effects of algorithms themselves, the parameters of algorithms are setting consistently when the algorithms calculate both minimum flow consumption and maximum power output. The main parameters are setting as follows: (1) the parameters of GA: population size N=50, maximum iterations number t_{max}=500, crossover rate P_c=0.8, mutation rate P_m=0.2; (2) the parameters of SA: initial temperature T=100, anneal cycle is 100; (3) the parameters of PSO: c_1=1.2, c_2=0.012; inertia weight ω= 0.0004.

4.2 *Analysis of the results*

Due to the randomness of optimization algorithm search, calculate the results repeatedly and take the mean value[20]. The final results are listed in Table.2 and Table.3

Table.2 The results of algorithms in MFCM

Algorithm	Flow m^3/s					
	312	315	317	319	322	325
GA	2195	2232	2239	2245	2250	2269
SA	2192	2212	2231	2240	2254	2272
PSO	2183	2198	2215	2216	2237	2265

Table.3 The results of algorithms in MPOM

Algorithm	Generating capacity 10^4kW						
	30	48	55	62	75	87	96
GA	13	22	25	29	34	43	47
SA	14	23	25	29	35	43	47
PSO	12	23	25	27	36	38	45

Table.2 shows PSO have the advantages because of the lower flow consumption. In the Table.3 the power output results from SA and GA are higher than PSO.

CM impact on the performance of algorithms

	MFCM			
Algorithm	Standard deviation	Stable iteration	Convergent iteration	Time s
GA	1.6	20	296	0.8
SA	1	110	300	0.1
PSO	0.8	102	150	1

Table.5 MPOM impact on the performance of algorithms

	MPOM			
Algorithm	Standard deviation	Stable iteration	Convergent iteration	Time s
GA	1.8	69	373	3.3
SA	1.1	213	318	0.1
PSO	0.9	200	300	1.9

Compared Table.4 with Table.5, there are great differences in the aspects of standard deviation, stability, convergence and computational speed between MFCM and MPOM. In terms of standard deviation, using GA, and SA, PSO for solving MFCM is significantly higher than that for MPOM. For the stable iteration, GA, SA, and PSO in MFCM stabilize ahead than in MPOM, which were steady ahead 49,103, 98 and account for 9.8%, 20.6%, 19.6% of the total respectively. Both in the terms of convergent iteration and computational speed, GA, SA, and PSO have the obvious superiority applied in MFCM than MPOM.

Due to parameters of the three algorithms are the same during applied in calculating the two models, which excludes the effect of parameter settings for the algorithms. Therefore, two models have different degrees of influence on the speed, accuracy, stability, convergence of GA, SA, PSO, especially in calculation speed. In addition, models effect on PSO greatly, and have less impact on another two algorithms.

5 . CONCLUSION

GA, SA, PSO are introduced into different models, to compute loads distribution of hydropower station, and optimal results are also analyzed comprehensively from standard deviation, stability, convergence and computational speed a comparative. The cases study shows that: (1) The performance of PSO is better than GA, SA for solving the MFCM; (2) SA applied to the MPOM has the greater advantage than GA, and PSO; (3) Models have different degrees of influence on the speed, accuracy, stability, convergence of algorithms; (4) Selected reasonable model according to the tasks of hydropower station and optimization algorithm depended models slightly, which can improve loads distribution computational speed to meet hydropower station scheduled rapidly, economically and exactly.

This paper only explores specially model impact on algorithm, and next, in-depth analysis of reasons affecting the model algorithms will be done.

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