#### Available online www.jocpr.com

## Journal of Chemical and Pharmaceutical Research, 2013, 5(9):542-548



Research Article

ISSN: 0975-7384 CODEN(USA): JCPRC5

# The multi-object optimal dispatcher research of cascade hydropower stations based on MSM-SANGA

## Tinghong Zhao, Huimin Hou and Yu Wang

School of Energy and Power Engineering, Lanzhou University of Technology, Gansu, Lanzhou, China

#### **ABSTRACT**

It has very important significance in the process of cascade hydropower stations optimal scheduling that give consideration to the generating capacity benefits and guarantee output power. However, considering the two indicators at same time makes the optimal operation problem of cascade hydropower stations as a multi-objective, strong coupling, complex constraints, so greatly increased the difficulty of solving. This paper put forward a kind of master-slave model self-adaptive niche genetic algorithm(MSM-SANGA), this algorithm is made by one master algorithm and several sub-algorithm, and the individual Euclidean distance criterion can self-adaptive change with the incremental evolution; finally, the MSM-SANGA is applied to solving the cascade hydropower stations multi-objective optimal scheduling problem that considers two main momentum indicators such as the maximum generating power capacity and the minimum guarantee output power etc., the calculation results show, this algorithm can be effectively applied to solving multi-objective optimization scheduling problem of cascade hydropower stations, with fast speed and high precision.

**Keywords:** Multi-object optimal dispatcher, cascade hydropower stations, master-slave model, niche genetic algorithm

#### INTRODUCTION

The generation power capacity and guarantee output are the two main kinetic energy indicators considered optimal generation scheduling of hydropower station. The optimal operation research of cascade hydropower stations will usually guarantee output as the constraint condition, and the pursuit of power generation benefit as the optimization goal, without considering the guaranteed output capacity benefit. Just to draw up the reasonable scheduling scheme, improve the reliability of power supply and the market competitiveness of the cascade hydropower stations under the condition of electricity market; it has very important significance that considers generation power efficiency and guarantee output at same time in the course of cascade hydropower stations optimization scheduling. In recent years, some scholars have carried out the research[1][2][3] on multi objective optimal scheduling problem of cascade hydropower stations, these research transform the multi-objective problem to single objective problem through using the constraint method or weighting method, this method is methods for solving multi-objective problems, simple and effective, is a kind of common using but also has some disadvantages: (1) the solving efficiency is low, each calculation can only be a scheduling scheme, in order to get a set of non dominated scheduling scheme, need carry on multi-calculation; (2) it is sensitive to Pareto front shape, can't good to process concave section in front of Pareto, the scheduling scheme calculated by multi-calculation does not guarantee mutual non inferior, thus this method is restricted in reality using course[4].

As a kind of improved GA, the niche genetic algorithm (NGA) has inherited the advantage of the GA, with very high ability to search for excellent in the overall situation and the restrains speed, and is excellent performance in keeping solution diversified. But the traditional NGA has two following questions: (1) The individuals Euclidean distance criterion is generally established as fixed value in advance, which can't development and change with

evolution course, so can't give full play to the ability that algorithm keep colony diversified; (2) When keep the variety of solution, unable to avoid the procreation of the inferior solution, so reduce the efficiency of convergence and operation.

Although NGA has been widely used to solve single objective optimization problems, but has not been used to solve multi-objective optimal problem, and if using the simply NGA to solving multi-objective optimization problem, can not meet the requirements of speed and accuracy of solving. Therefore this paper put forward a master-slave model self-adaptive NGA, at first, construct the model of algorithm as master-slave model, then improve the individual Euclidean distance criterion to self-adaptive change with the evolution. At last, apply the MSM-SANGA to solving the multi-objective optimal problem of cascade hydropower stations, so to prove this algorithm is suitability and superiority in solving the multi-objective optimal problem of cascade hydropower stations.

#### THE MASTER-SLAVE MODEL NGA

#### The Niche Genetic Algorithm:

Niche is a concept from the biology, refers to a kind of living environment of organism in the specific environment, namely in the course of evolution, organism always live together to reproduce in the same species as a group, and survival in specific geographical areas, thus forming a kind of living environment in specific environment. NGA applied this kind of thought in the traditional genetic algorithm, in order to improve the optimal calculation results of GA. The NGA's basic idea is to form a niche by setting the Euclidean distance, as follows: firstly make an individual Euclidean distance criterion L, and then judge the Euclidean distance between each two individuals of the population, if the distance is less than L, compare two individual fitness, and applying a strong penalty function for the individual with smaller fitness, reducing its fitness, then the individual with smaller fitness among the two comparison individuals becomes worse, so as to increase probability of this individual being eliminated in the evolutionary process, namely in the Euclidean distance criterion L only retain an excellent individuals. This method can better maintain the diversity of the population, and enable the individual from the whole constraint space dispersion, thus overcoming the shortcomings of the traditional GA into local optimum [5].

#### The master-slave model self-adaptive niche genetic algorithm:

(1) The model of master-slave model self-adaptive niche genetic algorithm

NGA mainly includes steps such as selection, crossing, variation and niche competition, etc., this paper construct the niche genetic algorithm to a master-slave structure, namely constituted by a main algorithm(M-algorithm) and multiple sub-algorithms(S-algorithm), structure model as shown in figure 1. The main algorithm carry on first choice operation; each sub-algorithm carry on crossover, variation and niche competition; in each sub-algorithm, the crossover probability and variation probability are set different values.

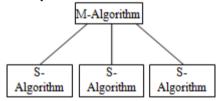


Fig.1 The structure of MSM-NGA

(2) The self-adaptive settle of Euclidean distance criterion

In the calculation process of NGA, individual Euclidean distance criterion setting is one key factor, if improper setting, will greatly affect the niche algorithm convergence speed and efficiency, in order to improve the convergence speed and efficiency, setting the Euclidean distance criterion to dynamic change is very necessary. Self-adaptive setting Euclidean distance as follows:

When the evolution time t=1, adopt the maximum Euclidean distance between as niche radius, and when the evolution time t>1, according to the average of Euclidean distance of individuals in upper generation to set up the adaptive Euclidean distance criterion of this generation. The function as follows:

$$L_{t} = \begin{cases} f_{\text{max}} - f_{\text{min}} & t = 1 \\ \overline{L}_{t-1} = \sum_{i=1}^{\mu+\lambda-1} \sum_{j=1}^{\mu+\lambda} d_{ij} / C_{\mu+\lambda}^{2} & t > 1 \end{cases}$$

$$i = 1, 2..., \mu + \lambda - 1; \quad j = i+1, ..., \mu + \lambda.$$

In function:  $L_t$  is the Euclidean distance criterion of the t generation;  $\overline{L}_{t-1}$  is the average Euclidean distance of the t-1 generation;  $C_{\mu+\lambda}^2$  is the combination calculation to get 2 from  $\mu+\lambda$ , namely is the number of Euclidean distance when calculate the Euclidean distance in  $\mu+\lambda$  pieces of individuals.

(3)The solving steps of master-slave adaptive niche genetic algorithm

According to structure of the master-slave model niche genetic algorithm, the solving steps of this algorithm as follows:

S1: The M-algorithm generated initial population P(t) with  $\mu$  pieces of individuals, calculate the fitness of each individual  $f_i(i=1,2,\ldots,\mu)$ .

S2: The M-algorithm ranked the individuals in descending order according to the size of fitness, memory former  $\lambda$  ( $\lambda < \mu$ ) pieces of individuals. Then send the population P(t) to each S- algorithm;

S3: Each S-algorithm carry on choosing, crossing and variation operation according to the crossing and variation probability on population P(t), produce new population P'(t) separately.

S4: Each S-algorithm incorporate  $\mu$  pieces of individuals in new population  $P'_i(t)$  with the  $\lambda$  pieces of individuals that memorized in front of, form a new population  $P''_i(t)$ .

S5: Each S-algorithm carry on niche selection calculation to  $\mu + \lambda$  pieces of individuals in the population  $P_i^{\prime\prime}(t)$ , the specific operation as follows:

①Calculating the Euclidean distance between two individuals  $X_i, X_j$  in population

$$P_i''(t): d_{ij} = ||X_i - X_j|| = \sqrt{\sum_{k=1}^n (x_{ik} - x_{jk})^2}, \quad i = 1, 2, \dots, \mu + \lambda - 1; \quad j = i + 1, \dots, \mu + \lambda.$$

② When  $||X_i - Y_j|| < L_i$ , compare fitness size of individuals  $X_i, Y_j$ , and carry on a strong penalty to the individual with lower fitness, obtained  $\mu + \lambda$  pieces of individuals that has been niche elimination calculation;

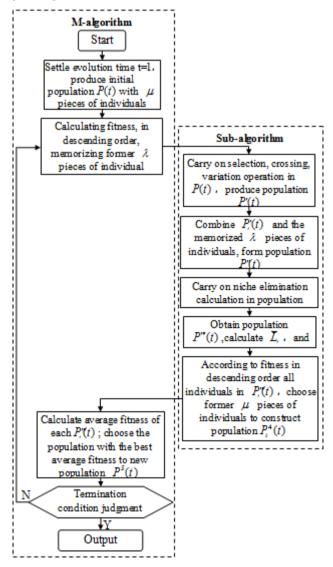


Fig.2. The procedure of algorithm implementation

\_\_\_\_\_

S6: Each S-algorithm combination above  $\mu + \lambda$  pieces of individuals to population, calculate the average of all Euclidean distance of  $\mu + \lambda$  pieces of individuals, as the niche elimination calculation criterion of next generation; and ranking in descending order the  $\mu + \lambda$  individuals according to the new fitness, getting former  $\mu$  pieces of individuals to form a new kind of population  $P_i^4(t)$ .

S7: Each S-algorithm send the new population  $P_i^4(t)$  to M-algorithm, the M-algorithm calculates the average fitness of each populations, and then selected the population with best fitness, named  $P^5(t)$ ;

S8: M-algorithm carry on termination condition judgment using the selected population  $P^5(t)$ . If the termination condition is not satisfied, then update the evolution time t = t + 1, and make the population  $P^5(t)$  that produced in step S7 as the initial population P(t) of the next generation evolutionary computation, and then go to step S2 to start a new round of calculation. Until the termination condition is satisfied, then output results, the algorithm terminates.

# THE MATH'S MODEL OF CASCADE HYDROPOWER STATIONS MULTI-OBJECTIVE OPTIMAL SCHEDULING

#### **Goal function:**

This paper take the maximum generating capacity and maximum guaranteed output power of cascade hydropower stations optimal scheduling as the objective function to solving the cascade hydropower stations multi-objective optimal scheduling problem.

1)The maximum generating capacity

$$f_1 = \max E = \sum_{t=1}^{T} \sum_{m=1}^{L} \sum_{m=1}^{M_n} p_m^l(t) \Box \Delta t$$
 (1)

In function: W is the maximum in overall scheduling scheme. E is the total generating power capacity.  $p_m^l(t)$  is the output power of l station m turbine in t period ( $10^4 \text{kW}$ );  $\Delta t$  is the time value of t period; T is the total number of time period. L is the total number of cascade hydropower stations.  $M_l$  is the total number of turbines in l stations.

2)The maximum guarantee output power

$$f_2 = \max N = \max\{\min N(t)\}\tag{2}$$

$$t = 1, 2, ..., T$$
;  $N(t) = \sum_{l=1}^{L} N_{l}(t)$ 

In function: N is the guaranteed output power of cascade hydropower stations. N(t) is the total guaranteed output power of cascade hydropower stations in t period.

#### **Constraint conditions**

①water level constraint:

$$Z_{l}^{\min}(t) \leq Z_{l}(t) \leq Z_{l}^{\max}(t)$$

2 output power constraint:

$$N_l^{\text{m i}}(t) \leq N_l(t) \leq N_l^{\text{max}}(t)$$

3 flow constraint:

$$Q_l^{\min}(t) \leq Q_l(t) \leq Q_l^{\max}(t)$$

4 water balance constraint:

$$V_{l}(t+1) = V_{l}(t) + I_{l}(t) Q (t_{l})$$

⑤The hydraulic connections between the cascade reservoir:

$$I_{l}(t) = Q_{l-1}(t-\tau) + q_{l}(t)$$

In function:  $Z_l^{\min}(t)$ ,  $Z_l^{\max}(t)$  are the upper and lower limit water level of l station in t period respectively.  $N_l^{\min}(t)$ ,  $N_l^{\max}(t)$  are the upper and lower limit output power l station in t period respectively.  $Q_l^{\min}(t)$ ,  $Q_l^{\max}(t)$  are the upper and lower limit output flow l station in t period respectively.  $V_l(t)$ ,  $V_l(t+1)$  are the initial capacity and ultimate capacity l station in t period respectively.  $I_l(t)$ ,  $Q_l(t)$  are the input flow and output flow l station in t period respectively. l station in l period respectively. l station l is the using time that the

water flow flows from l-1 station to l station,  $q_i(t)$  is the interval inflow of l station in t period..

#### **EXAMPLE VERIFICATION**

This paper take the Three Gorges cascade hydropower stations as an example for simulation test. Three Gorges cascade hydropower stations includes Three Gorges and Gezhouba two hydropower stations. The installing capacity of Samxia hydropower station is  $182 \times 10^4$  kW, guarantee output is  $499 \times 10^4$  kW, the average generating power capacity of many years is 847×10<sup>8</sup>kW • h; About Gezhouba hydropower station, the installed capacity is 271.5×10<sup>4</sup>kW, the guaranteed output is 104×10<sup>4</sup>kW, the average generating power capacity of many years is 139×108 kW • h. Three Gorges hydropower station is the cascade leading reservoir, with incomplete adjustment ability, Gezhouba hydropower station is anti regulating reservoir in cascade hydropower stations, with daily regulating ability. According to the Samxia cascade dispatching rules, Samxia reservoir begin to regulate from at normal water level 175m at the beginning of the year, and January to April water level is not less drawdown of dry season level 155M. Began to lower the water level at May and lower water level to flood limited water level 145m at the beginning of June, and reservoir maintained the water level 145m to operation from June to September. At the end of September began to fill with water, and at the end of October storage to normal water level to operation, the final level of scheduling period is defined as a normal water level 175m. Gezhouba hydropower station operated in dry season according to 65m water level, and operated in flood season according to 65.5m water level. This paper selects typical inflow process of flat water years (inflow frequency is 50%) as the inflow of Three Gorges cascade hydropower stations, uses MSM-SANGA algorithm to solving the Multi-objective scheduling optimization problem of cascade hydropower stations.

In concrete calculation, the initial parameters are as follows: population size M is 60; the number of iteration T is 300; crossing probability  $p_c$  is 0.65, 0.7, 0.75; variation probability  $p_m$  is 0.001, 0.003, 0.005; the concrete calculation result as Table.1 shows, the calculation time is 68s.

Scheme	Annual energy output	Firm capacity	Abandoned water
Number	$/ (10^8 \text{kW h})$	/ (10kMW)	$/10^{8} \text{m}^{3}$
1	1024.36	654.9	846.9
2	1024.85	653.0	847.1
3	1025.37	650.9	847.4
4	1025.78	648.7	847.4
5	1026.21	646.9	847.6
6	1026.68	644.8	847.6
7	1026.92	642.6	850.8
8	1027.16	640.6	851.2
9	1027.61	638.1	854.8
10	1027.79	635.0	857.6
11	1027.94	631.8	859.6
12	1028.22	629.2	863.3
13	1028.48	627.2	866.1
14	1028.76	624.7	868.0
15	1029.08	621.8	869.8
16	1029.48	618.6	871.2
17	1029.61	615.3	872.0
18	1029.82	612.8	872.9
19	1029.92	609.9	873.5
20	1030.02	606.8	874.1

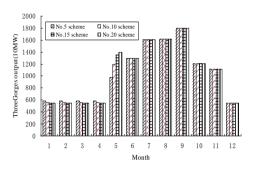
Table.1 The dispatcher results of Three Gorges cascade hydropower stations

It is can be seen from Table.1, under the condition that meet the minimum guarantee output of Three Gorges and Gezhouba hydropower stations, cascaded total generating capacity increased from  $1024.36 \times 10^8$  kW•h to  $1030.02 \times 10^8$ kW • h, guarantee output decreased from  $654.9 \times 10^3$  kW to  $606.8 \times 10^3$ kW, the inversely proportional relation between volume guarantee output and total generation capacity is obvious.

Further more, carry on comparative analysis that choose 5, 10, 15, 20 four typical scheme. It can be seen from Fig.3-5, all scheduling schemes are the same from July to December, the variation of the cascade generation capacity, ensuring output variation and waste water fully reflected in the period from January to May with less input water. For the Three Gorges power station, with less input water from January to May, need to reduce capacity of reservoir, increase the flow to improve the guarantee output. At the end of May, according to the requirements for flood control, all schemes are need to lower the water level to 145m.

It can be seen from Fig.3, Fig.4, the Three Gorges power station guarantee output is more low, then the average

water level of reservoir of January to May is more high, average water head is more high, so in the former 5 months, under the conditions that the total water consumption are same, the total generating capacity is more large. The increasement of generating capacity is focused in May, to make up the decreasement of power capacity. For the June and August with the largest input water, the Three Gorges power station generate electricity according to the expected output, abandoned water all happen in this two months, so the scheme of Three Gorges power station abandoned water are equal in all scheme. In October, in order to raise the water level to increase later generation power capacity, all schemes quickly increase the water level of reservoir to 175m, and has been maintained operation in 175m.



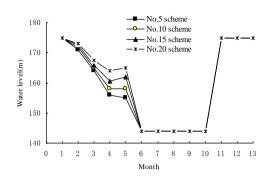


Fig.3 Three Gorges output process comparison

Fig.4 Three Gorges water level process comparison

As runoff hydropower stations, The output power of Gezhouba power station depends entirely on the upstream of Three Gorges hydropower station, under the condition that ignore the interval inflow, the control of Three Gorges hydropower station generation power referral flow determine the output process of the Three Gorges and the Gezhouba two power stations at same time. It can be seen from the four schemes of Gezhouba output process in Fig.5, from January to April, Gezhouba output power process gradually increase with the increase of Three Gorges power station's reference flow; on the other hand, The output power of Gezhouba hydropower station maintain good synchronization with the Three Gorges hydropower station in every scheme, and under the conditions that meet the different cascade guarantee output power, the output power of Three Gorges hydropower station is more large, the output power of Gezhouba hydropower station is more large. The above analysis shows the interval coupling relationship among the annual generation electricity, the guarantee output power and abandoned water of every power station in cascade hydropower stations, typical scheduling process to meet the requirements of Three Gorges cascade dispatching rules, explain the solution set is reasonable and effective.

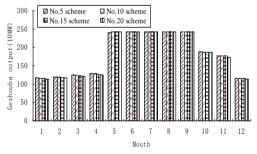


Fig.5 Gezhouba output process comparison

#### **CONCLUSION**

The generating capacity and guarantee output power are the two main indicators considered optimal generation scheduling of hydropower station. The former optimal operation research of cascade hydropower stations usually take guarantee output power as the constraint condition, while take the pursuit of the largest generation capacity benefit as the optimization goal, without considering the capacity benefit of guarantee output. For to make the reasonable scheduling scheme, improve the reliability of power supply and the market competitiveness of cascade hydropower stations under the condition of electricity market. Thus giving consideration to the generating capacity benefits and guarantee output power has very important significance in the process of cascade hydropower stations optimal scheduling. However, considering the two indicators at same time makes the optimal operation problem of cascade hydropower stations as a multi-objective, strong coupling, complex constraints, so greatly increased the difficulty of solving. This paper, in view of the above characteristics, improved the traditional genetic algorithm, the individual Euclidean distance criterion is settled to self-adaptive change with the evolution procedure, and the

algorithm is made the master-slave model, the master algorithm realized the selection, crossing operation in former period, the sub-algorithm realized the niche elimination calculation, so as to establish a master-slave model adaptive niche genetic algorithm(MSM-ANGA); Finally, the MSM-ANGA is applied to solving the cascade hydropower stations multi-objective optimal scheduling problem that considers two main momentum indicators such as the maximum generating capacity and the minimum guarantee output power etc., the calculation results show, the algorithm can be effectively applied to solving multi-objective optimization scheduling problem of cascade hydropower stations, with fast speed and high precision.

#### Acknowledgement

This paper obtains the support of National Natural Science Foundation subsidized project (51069004) and the Excellent Young Teachers Fund of Lanzhou University of Technology (Q201008), just expresses my gratitude to them.

#### REFERENCES

- [1] HUANG Qiang, SHEN Jin. Systems Engineering-Theory & Practice, 1997,17(1):75-82.(in Chineses)
- [2] GAO Shichun, TAO Zicheng. Journal of Hydroelectric Engineering. 2007, 26(4):1-4. (in Chineses)
- [3] LIU Ning. *Journal of Hydraulic Engineering*. **2008**, 38(3):264-271. (in Chineses)
- [4] DEBK. Multi-objective optimization using evolutionary algorithm. Chichester Wiley, UK, 2001.
- [5] FU Xiaowei, Gao Xiaoguang, Kuang Aixi. Journal of System Simulation. 2008,20(21):5940-5944.