An improved artificial fish swarm algorithm for optimal operation of cascade reservoirs

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***Abstract*—Based on traditional artificial fish swarm algorithm (AFSA), an improved artificial fish swarm algorithm (IAFSA) is proposed and used to solve the problem of optimal operation of cascade reservoirs. To improve the ability of searching the global and the local extremum, the vision and the step of artificial fish are adjusted dynamicly in IAFSA. Moreover, to increase the convergence speed, the threshold selection strategy is employed to decrease the individual large space gap between before and after update operation in the local update operation. The validity of IAFSA is proved by case study and the threshold parameters of IAFSA are rated.**

***Index Terms*—Reservoir operation, Optimization, Hydroelectric power generation**

I. INTRODUCTION

Under the call of energy conservation, renewable resources, such as hydropower, wind power, biomass power and garbage power, have become the priority to be utilized to participate in the operation of electric power. Furthermore, this idea encourages generating more power by hydropower and requires improving the utilization ratio of the hydropower. Consequently, high requirements are also put forward to the optimization operation of reservoirs. How to perform the optimization operation of reservoirs and utilize the water power resource effectively has become a hot issue.

The optimization operation of cascade reservoirs, a complex mathematical optimization control problem of a nonlinear dynamic system with a large number of constraints, has been drawn much attention to many researchers. So far there are many traditional algorithms, such as linear programming [1], nonlinear programming [2], network flow programming [3], dynamic programming [4], and lagrangian relaxation [5], etc., have been used for the optimization operation of cascade reservoirs. However, these algorithms have the disadvantages of dimensionality curse, unstable convergence or complexity and so on. Nowadays, some intelligent optimization algorithms have been successfully applied, such as tabu search algorithm [6], simulated annealing algorithm [7], genetic algorithm [8], ant colony algorithm [9] and particle swarm optimization algorithm [10], etc.

Artificial fish swarm algorithm (AFSA) is a novel method for searching the global optimum, which is typical application of behaviorism in artificial intelligence [11]. It is a random search algorithm based on simulating fish swarm behaviors which contains preying behavior, swarming behavior and following behavior. It constructs the simple bottom behaviors of artificial fish (AF) firstly, and then makes the global optimum appear finally based on animal individuals' local searching behaviors. This algorithm has strong ability of avoiding the local extremum and achieving the global extremum, its usage is flexible and convergence speed is fast. It doesn't need the characteristics such as the grads value of objective function, thus it has a certain adaptive ability for search space, which belongs to swarm intelligence algorithm essentially.

However, this algorithm has several disadvantages such as the blindness of searching at the later stage and the poor ability to keep the balance of exploration and exploitation, which reduce its probability of searching the best result. In this paper, an improved AFSA (IAFSA) is proposed to overcome these defects. The improved algorithm can adjust the search range adaptively and have better ability to keep the balance of exploration and exploitation. To verify the effectiveness of IAFSA for obtaining reservoir operating polices, IAFSA is applied to a cascade reservoirs system, namely the Baishan-Fengman reservoirs system in Jilin province, China.

II. MATHEMATICAL MODEL FOR THE OPTIMIZATION OPERATION OF CASCADE RESERVOIRS

According to the inflow process, the optimization operation of cascade reservoirs takes the power discharges as the decision variables, and takes the maximal gross power generation in one scheduling period as the target. Suppose there are n hydropower stations in cascade power stations, as shown in Fig.1.

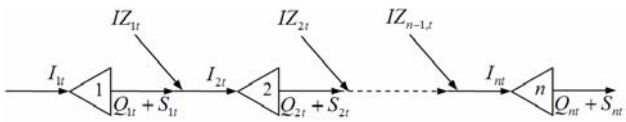

Figure 1. The sketch of cascade power stations

A. Objective function:

$$\max E = \max\{3600 \cdot \sum_{p=1}^{n}\sum_{t=1}^{T}(Q_{pt} \cdot M_t / R_{pt})\} \qquad (1)$$

doi:10.4304/jcp.6.4.740-746

Where, E is the gross power generation of cascade power stations; Q_{pt} is the power discharge of power station p in interval t; M_t is the number of hours in interval t; R_{pt} is the mean water rate of power station p in interval t, its unit is m^3/kW·h; n is the number of the reservoirs; T is total time-interval for calculation.

B. Constraints:

Water balance equations constraint

$$V_{p,t+1} = V_{pt} + (I_{pt} - Q_{pt} - S_{pt})\Delta t \tag{2}$$

Storage capacity constraint

$$V_{pt\min} \le V_{pt} \le V_{pt\max} \tag{3}$$

Correlation equation

$$I_{p+1,t} = Q_{pt} + S_{pt} + IZ_{pt}\text{；}\quad I_{1t} = IZ_{1t} \tag{4}$$

Turbine discharge constraint

$$Q_{pt\min} \le Q_{pt} \le Q_{pt\max} \tag{5}$$

Spillway capacity constraint

$$0 \le S_{pt} \le S_{pt\max} \tag{6}$$

Boundary constraint

$$V_{p1} = V_{p1c}\text{；}\quad V_{p,T+1} = V_{p,T+1,c} \tag{7}$$

Outflow from reservoir constraint

$$q_{pt\min} \le Q_{pt} + S_{pt} \le q_{pt\max} \tag{8}$$

Output of power station constraint

$$N_{p\min} \le 3600 \cdot Q_{pt} / R_{pt} \le N_{p\max} \tag{9}$$

Relationship between water level and storage capacity

$$V_{pt} = U_p(Z_{pt}) \tag{10}$$

Where, $V_{p,t+1}$ is the storage capacity at the end of the interval t; V_{pt} is the storage capacity at the beginning of the interval t; I_{pt} is the mean inflow of reservoir p in interval t; S_{pt} is the surplus water of reservoir p in interval t; $S_{pt\max}$ is the spillway capacity of reservoir p in interval t; Δt is the duration of interval t; $V_{pt\min}$ is the required minimal storage capacity of reservoir p at the beginning of interval t; $V_{pt\max}$ is the permissible maximal storage capacity of reservoir p at the beginning of interval t; $Q_{pt\min}$ is the minimal power discharge of power station p in interval t; $Q_{pt\max}$ is the maximal power discharge of power station p in interval t. Considering the power discharge of cascade reservoirs and the agricultural and industrial water-supply in downstream, when $Q_{pt} < Q_{pt\max}$, $S_{pt} = 0$. While $Q_{pt} = Q_{pt\max}$, $S_{pt} \ge 0$. V_{p1c} and $V_{p,T+1,c}$ are the storage capacity of reservoir p at the beginning and at the end of the optimization scheduling period, respectively. $q_{pt\min}$ is the minimal water discharge of reservoir p in interval t; $q_{pt\max}$ is the safety discharge at lower river in interval t; $N_{p\min}$ is the minimal output of power station p; $N_{p\max}$ is the maximal output limit of power station p; Z_{pt} is the water level of reservoir p at the beginning of interval t; U_p represents the function of the relationship between the water level and the storage capacity of reservoir p.

In the optimization operation model of cascade power stations mentioned above, the objective function is used to obtain the maximal gross power generation under the decision variables Q_{11}, Q_{12}, …, Q_{nT}, which is a $n \cdot T$-dimension vector. Since the power discharge Q_{pt} is the implicit function of the water level Z_{pt}, the problem can be transformed into getting the maximal gross power generation under Z_{11}, Z_{12}, …, Z_{nT}.

The constraints, which are difficult to be reckoned in feasible region, can be expressed by using penalty function. Then the objective function can be expressed as follows

$$\max F(Z) = \max\{E(Z) - \sigma_1 \sum_{i=l-l_0+1}^{l} (h_i(Z))^2 - \sigma_2 \sum_{j=u-u_0+1}^{u} [\max\{0, -g_j(Z)\}]^2\} \tag{11}$$

$$\text{s.t.}\quad h_i(Z) = 0,\quad i = 1,2,\ldots,l-l_0$$
$$g_j(Z) \ge 0,\quad j = 1,2,\ldots,u-u_0$$

Where, $E(Z)$ is the original objective function. $Z = (Z_{11}, Z_{12}, \ldots, Z_{nT})^{\mathrm{T}}$ is a $n \cdot T$-dimension vector. l, u is the number of equality and inequality constraints. σ_1 and σ_2 are penalty factors. The feasible region of Eq.(11) can be written as follows

$$Scope = \{Z \mid h_i(Z) = 0, i = 1,2,\ldots,l-l_0;\ g_j(Z) \ge 0, j = 1,2,\ldots,u-u_0\} \tag{12}$$

III. AFSA AND IAFSA

AFSA, a new population-based evolutionary computation technique inspired by the natural social behavior of fish schooling and swarm intelligence was first proposed in 2002 [11].

A. Principle of AFSA

In water, fish can find the area with more nutritional by individual search or following other fish. Therefore, the water area where the number of fish is the most is generally the most nutritional. According to this characteristic, AF model is presented which imitates preying behavior, swarming behavior and following behavior. These three typical behaviors are described as follows:

(1) *Preying behavior*: This is a basic biological behavior that tends to the food. Generally fish perceives the concentration of food in water by vision or sense to determine the movement and then chooses the tendency.

(2) *Swarming behavior*: Fish will assemble in groups naturally in moving process, which is a kind of living habits to guarantee the existence of the colony and avoid dangers. While swarming, they obey the following three principles: ① Compartmentation principle: to avoid congestion with other fellows. ②Unification principle: to move approximately toward other fellows' average moving direction. ③ Cohesion principle: to move approximately toward the center of near fellows.

(3) *Following behavior*: In moving process of the fish swarm, when a single fish or several ones find food, the neighborhood fellows will trail and reach the food quickly.

In AFSA, the food consistence in water is defined as the objective function, and the state of an AF is the variable to be optimized. Preying behavior is that AF moves randomly according to its fitness value, thus it is an optimization of individual extremum and belongs to self-studying process; it keeps the diversity of colony. Swarming behavior and following behavior are processes of AF interaction with surrounding environment. These two processes can ensure that it will not be too crowded for an AF with other fellows and the moving direction of AF is consistent with the average moving direction of other near fellows which are moving towards the colony extreme, the convergence of colony can be kept. Therefore, AFSA is also one optimization method based on swarm intelligence. After doing the above mentioned behaviors, AF gets to the place where food consistence is the biggest. During the whole optimization process of AFSA, self-information and environment information are fully used to adjust the search direction to achieve the balance of diversity and convergence.

B. Description of AFSA

In AFSA, AF model based on behaviors is constructed by multiple parallel pathways architecture, and this model encapsulates the self-state and the behavior of AF. The process of algorithm is the self-adaptive behavior of AF. The algorithm iterates once means AF moves once.

(1) Structure of AFSA and definitions

Suppose that the search space is D -dimensional and m fish form the colony. The state of AF can be expressed by vector $X=(x_1,x_2,\cdots,x_D)$, where x_i ($i=1,2,\cdots D$) is the variable to be searched for the optimal value; the food consistence at present position of AF can be represented by $Y=f(X)$, and Y is the objective function; the distance between AFs can be expressed as $d_{i,j}=\|x_i-x_j\|$; *Visual* represents the vision distance; *Step* is the maximal step length and δ is the crowd factor.

The key of the optimization operation of cascade reservoirs based on AFSA lies in the structure of AF model. According to the above definition and mathematical model for the optimization operation of cascade reservoirs, the state of AF can be expressed with vector X=(Z_{11} , Z_{12} , …, Z_{nT}), the distance between AFs can be expressed as:

$$d_{ij}=\left[\sum_{p=1}^{n}\sum_{t=1}^{T}(Z_{pt}^{i}-Z_{pt}^{j})^2\right]^{1/2},$$

and the food consistence at present position of AF can be represented by Eq. (1).

(2) Description of the behaviors

① Preying behavior

Suppose that an AF's current state is X_i . We randomly select a new state X_j in its visual field. If $Y_i<Y_j$ in the maximum problem, it goes forward a step in this direction; otherwise, select a state X_j randomly again and judge whether it satisfies the forward condition. If it can't satisfy after *try_number* times, it moves a step randomly. When the *try_number* is small in preying behavior, AF can swim randomly, which makes it flee from the local extreme value field. The pseudocode is as follows:

```
float Artificial_fish::prey()
{
  isChange=true;
  for (i=0;i<try_number;i++)
  {
    X_j = X_i + [Random(1)×2−1]×Visual ;
    if (Y_i < Y_j)
```

$$X_{i|next}=X_i+[Random(1)\times 2-1]\times Step\times\frac{X_j-X_i}{\|X_j-X_i\|};\quad(13)$$

```
    isChange=false;break;
  }
  if(isChange)
```

$$X_{i|next}=X_i+[Random(1)\times 2-1]\times Step;\quad(14)$$

```
}
```

② Swarming behavior

An AF with the current state X_i seeks the fellow's number in its current neighborhood where satisfy $d_{i,j}<Visable$; and calculate their center position X_c , Y_c denotes the food consistence of the center position and n_f denotes the number of fellows of X_i in the near fields, if $n_f\geq 1$, X_j explores the center position of its fellow. If $Y_c/n_f>\delta Y_i$, which means that the food consistence of the fellow's center is high and surroundings is not very crowded, forward a step to the fellow centers. Otherwise AF executes the preying

behavior. If n_f =0, AF executes the preying behavior. The pseudocode is as follows:

```
float Artificial_fish::swarm()
{
    n_f = 0; X_c = 0;
    for ( j=0; j<m; j++ )
        if ( d_{i,j} < Visable ) { n_f ++; X_c += X_j; }
        if( n_f = 0 ) prey();
        else{
            X_c = X_c / n_f;
            if ( Y_c / n_f > δY_i )
                X_{i|next} = X_i + Random(Step) · (X_c − X_i) / ||X_c − X_i||;   (15)
            else
                prey();
        }
}
```

③ Following behavior

An AF with the current state X_i seeks the fellow's number in its current neighborhood where satisfy $d_{i,j} < Visable$, and find the maximal position $X_{\max}$, $Y_{\max}$ is the maximal value of its fellows in the near fields and n_f denote the number of fellows of $X_{\max}$ in the near fields. If $n_f = 0$ or $Y_c / n_f > \delta Y_i$, which means that the fellow $X_{\max}$ has high food consistence and the surrounding is not very crowded, forward a step to the fellow $X_{\max}$. Otherwise AF executes the preying behavior. The pseudocode is as follows:

```
float Artificial_fish::follow()
{
    Y_max = −∞; n_f = 0;
    for ( j=0; j<m; j++ )
        if ( d_{i,j} < Visable && Y_j > Y_max )
        { Y_max = Y_j; X_max = X_j; }
        for ( j=0; j<m; j++ )
            if( d_{max,j} < Visual ) n_f ++;
        if ( n_f = 0 or Y_max / n_f > δY_i )
            X_{i|next} = X_i + Random(Step) · (X_max − X_i) / ||X_max − X_i||;   (16)
        else
            prey();
}
```

(3) Selection of the behaviors

The behavior of $X_i(iter)$ ($iter$ is the current iterative number) is determined by the hunger degree of AF. Here, the hunger degree is represented by energy. If the energy of $X_i(iter)$ is lower than

$$Energy(iter) = \frac{1}{m} \cdot \sum_{i=1}^{m} Y_i(iter)$$

AF takes the following behavior to get food in the area with high food consistence to obtain energy; If the energy of $X_i(iter)$ is higher than $Energy(iter)$, AF is not hunger, thus it chooses the swarming behavior to avoid harmful animals. If AF takes the following behavior and the swarming behavior unsuccessfully, it will execute the preying behavior.

(4) Bulletin

Bulletin is used to record the optimal state and the food consistence at present position of AF. Update the bulletin with the better state of AF, the final value of the bulletin is the optimal value of the problem, the state of which is the optimal solution of the system.

C. Improved AFSA

(1) Improvement of Visual and Step

The AFSA demonstrate that *Visual* has great influence on the three behaviors and the convergence of the algorithm. When *Visual* is larger, AF has strong global search ability and fast convergence speed; and when *Visual* is smaller, AF has strong local search ability. The bigger the *Step* is, the faster the convergence will be, though the oscillation sometimes appears; In contrast, the smaller the *Step* is, the slower the convergence will be, whereas the solving accuracy is higher.

According to the above mentioned, the more difficultly a function is optimized, the more the global search ability of this function should be improved. Moreover, after the position of the optimal solution is allocated, the local search ability also should be improved. Therefore, to improve the global search ability and the convergence speed of AFSA, larger *Visual* and larger *Step* are taken in prior period to make AF search in a larger scope in IAFSA. With the searching proceeds, *Visual* and *Step* decrease gradually, then the local search carries out in adjacent domain of the optimal solution, which consequently increases the local search ability and the solving accuracy of the algorithm. In this improved algorithm, *Visual* and *Step* are adjusted dynamically by following equations:

$$\begin{cases} Visual = Visual \times \alpha + Visual_{\min} \\ Step = Step \times \alpha + Step_{\min} \\ \alpha = \exp(-30 \times (iter / T_{\max})^s) \end{cases} \quad (17)$$

Where, $iter$ is the current iterative number, $T_{\max}$ is the maximal iterative number. In general, the initial value of

Visual is the maximum of the search scope. *Visual* and *Step* and are piecewise functions, which keep maximum in prior period, then decease gradually, finally keep minimum. The value of α is Show in Fig.2.

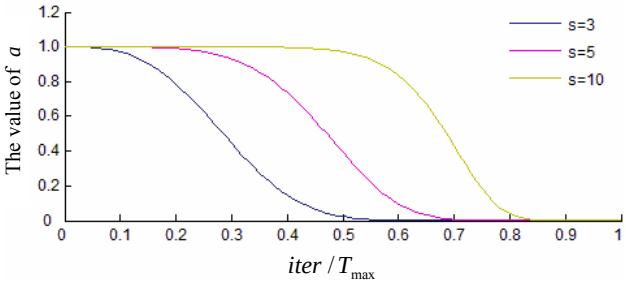

Figure 2. The value of α

(2) Improvement of update operation

In AFSA, When the algorithm carries out update operation to each fish, the component in each dimension of X_i will be processed randomly by Eq. (13) ~ (16), which makes the position of X_i change greater after update operation. With increasing of the dimensions, the position change of X_i increases. Therefore, though this update operation can enlarge the search scope of solution space, the global optimal solution will be easily skipped, which decreases the rapidity of convergence and accordingly increase the calculation time.

Therefore, to reduce the individual large space gap between before and after update operation, an improvement based on threshold selection strategy is conducted in IAFSA. The basic idea of this strategy is that during update operation of the component of X_i in dimension j by Eq. (13) ~ (16), a random criterion is introduced: When the random value is not larger than the threshold q_0, the moving distance of the component in dimension j is determined by Eq. (13) ~ (16); When the random value is larger than the threshold q_0, the component of X_i in dimension j is not changed. This strategy can decrease the space gap between before and after update operation of X_i, which is good for fast convergence.

D. Steps of IAFSA

The steps of the optimization operation of cascade reservoirs based on IAFSA are as follows:

(1) Initialization of the parameters: The number of AF is *m*, the scope of vision is *Visual*, $Visual_{\min}$, the maximum of moving step length is *Step*, $Step_{\min}$, crowd factor is δ, the maximal try number is *try_number*, the threshold value is q_0, the maximal iterative number is $T_{\max}$.

(2) Initialization of the position vectors of the swarm: For operation problem of cascade reservoirs, the search space is equal to the total number of release combinations. Each decision variable represents a parameter to be optimized in the model. The initial positions of all AF have to be generated randomly within the limit specified for each decision variable. Moreover, the initial search points are the initial random release values. In this step, each AF vector represents one operation process of the cascade reservoirs, and the water level at each interval is denoted by the coordinates of the AF vectors. Set initial iterative number $iter$ =0.

(3) Initial evaluation of the fitness function: Calculate the food consistence of initial AF Y and compare them, then put the biggest food consistence into the bulletin, and conserve the state and the value of Y.

(4) Calculate *Visual* and *Step* by Eq. (17).

(5) AF executes the swarming behavior, the following behavior, or the preying behavior according to its energy.

(6) Checks the self-state and the bulletin. If the self-state is superior to the bulletin, then the bulletin is replaced.

(7) Judge the terminate condition: If the iterative number reaches the maximal iterative number $T_{\max}$, then output the result (the value of bulletin). Otherwise, execute $iter = iter + 1$, and turn to step (4).

IV. Generation Of Initial AF Swarm And The Feasible Region

The detail procedures of the generation of initial AF are as follows:

(1) Considering the influence of Q_{pt} on S_{pt}, the value range of Q_{pt} is determined firstly:

Upper bound:

$$\min\{Q_{pt\max}, (V_{pt} - V_{p,t+1,\min})/\Delta t + I_{pt}\} \tag{18}$$

Lower bound:

$$\max\{Q_{pt\min}, (V_{pt} - V_{p,t+1,\max})/\Delta t + I_{pt}\} \tag{19}$$

If "*Upper bound*" < "*Lower bound*", let "*Upper bound*" = "*Lower bound*"= $Q_{pt\max}$, then generate an initial Q_{pt}^0 of Q_{pt} randomly in this value range.

(2) Determine the value range of S_{pt}:

Upper bound:

$$\min\{S_{pt\max}, (V_{pt} - V_{p,t+1,\min})/\Delta t + I_{pt} - Q_{pt}^0\} \tag{20}$$

Lower bound:

$$\max\{S_{pt\min}, (V_{pt} - V_{p,t+1,\max})/\Delta t + I_{pt} - Q_{pt}^0\} \tag{21}$$

Then generate an initial S_{pt}^0 of S_{pt} randomly in the value range.

(3) Determine the initial value of $V_{p,t+1}$ after obtaining the initial value of Q_{pt} 和 S_{pt}, that is

$$V_{p,t+1}^0 = V_{pt} + (I_{pt} - Q_{pt}^0 - S_{pt}^0)\Delta t \tag{22}$$

Each AF obtains the variation process of the initial storage capacity like above mentioned, and then the initial AF swarm can be obtained accordingly. The initial

AF swarm must satisfy the water balance Eq.(2) and the corresponding constraints Eq.(3) ~ (6), which make each AF of the initial AF swarm in the feasible region and accelerate the convergence.

The initial AF swarm satisfies Eq. (7) $V_{p1}=V_{p1c}$, but it does not always satisfies the ending condition $V_{p,T+1}=V_{p,T+1,c}$. Without regard to the ending condition, large numbers of the pilot calculation are carried out for the model. The results show that, to obtain the maximum electric benefit, the model is inclined to use all the water generate electricity, which is likely to make the water level minimum at the terminal stage of the calculation. According to this characteristic, the ending condition is changed into inequation, i.e. $V_{p,T+1}\geq V_{p,T+1,c}$. Here, the initial AF swarm also satisfies Eq. (7).

Based on the above mentioned, when inequation (8) and inequation (9) are difficult to be reckoned in Eq.(11), the feasible region can be express as

$$Scope=\{\ V_{p,t+1}=V_{pt}+(I_{pt}-Q_{pt}-S_{pt})\Delta t\ ;$$
$$V_{pt\min}\leq V_{pt}\leq V_{pt\max}\ ;\ Q_{pt\min}\leq Q_{pt}\leq Q_{pt\max}\ ;\ 0\leq S_{pt}\leq S_{pt\max}\ ;$$
$$V_{p1}=V_{p1c}\ ;\ V_{p,T+1}\geq V_{p,T+1,c}\ \} \qquad (23)$$

V. CASE STUDY

Baishan reservoir and Fengman reservoir are all have the function of seasonal regulation. Banshan reservoir is in the upstream of Fengman reservoir and there is a local inflow into Fengman reservoir. The dead water level, the normal water level, the limited water level and the maximal permissible storage water level at post-freshet period of Baishan reservoir are 380m, 413m, 413m and 416m, respectively. And the maximal water discharge of Baishan reservoir is 1500m^3/s, the firm output is 16.7×10^{4}kW, the maximal power output is 155×10^{4}kW. For Fengman reservoir, the dead water level, the normal water level, the limited water level and the maximal permissible storage water level at post-freshet period are 242m, 261m, 261m and 263.5m, respectively. And the maximal water discharge of Fengman reservoir is 1126.5m^3/s, the firm output is 16.6×10^{4}kW, the maximal power output is 60.25×10^{4}kW. To ensure the safety of these two reservoirs, it is needed that the water levels in July and August must be lower than the limited water level. And these two reservoirs are permitted over storage to the maximal permissible storage water level at post-freshet period after September. In view of multipurpose use, Fengman reservoir also supplies the water at the discharge of 120 m^3/s to agricultural irrigation, navigation and industry.

A. Performance test of IAFSA

The inflow process of Baishan-Fengman cascade reservoirs from 1987 to 1988 are used to validate the effectiveness of IAFSA. The initial water level and the termination water level of each reservoir are all the dead water level; the minimal output of each hydropower station is the firm capacity; the calculation interval is defined as month, that is T =12. During the calculation, P4-1.6G personal computer is used. Its memory size is 512M, the operation system is WinXP, and the algorithm is realized by Java.

The parameters of the IAFSA: The number of AF m=50, $Visual$=40, $Visual_{\min}$ =0.4, $Step$=0.4, $Step_{\min}$ =0.1, δ =0.618, try_number=4, q_0 =0.07, $T_{\max}$ =1000. The termination criterion is defined as follows: the absolute value of the difference between two adjacent iterations of 50 iterations is less than 10×10^{4}kW·h. To avoid the accidental circumstance, 100 times simulations have been done, then the average value is obtained. The optimization operation result is shown in TableI.

TABLE I. COMPARISON OF THE RESULTS OF DIFFERENT MODELS IN YEAR 1987-1988

	AFSA	IAFSA	PSO	DP
Power generation (×10^{4}kW·h)	477932	485020	484572	488605
Calculation time	7.1s	6.2s	6.7s	8.4h

To demonstrate the validity of IAFSA, comparison has been done between it and traditional DP algorithm[12], which is shown in TableI. For traditional DP algorithm, the number of the discrete points of two reservoirs are all 200, the total power generation is 488605×10^{4}kW·h. The average power generation of IAFSA under 100 times simulations is 485020×104kW·h, which has a difference of 0.73% with that of DP. The difference can be accepted. Furthermore, IAFSA increases the solution speed greatly and there is no curse of dimensionality. The calculation time of DP with 200 discrete points is 8.4 hours, and the average calculation time of IAFSA under 100 times simulations is only 6.2 seconds.

B. Rating of the threshold

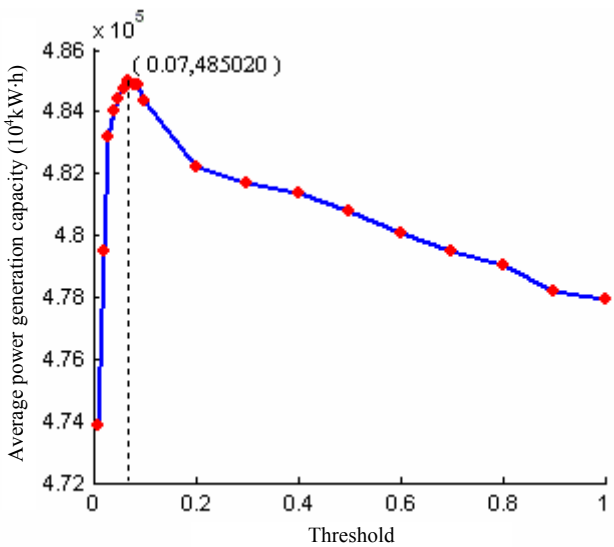

Figure 3. Relationship between the average power generation capacity and the threshold

Fig.3 shows the average power generation capacity under different thresholds. From this figure, it can be seen that the maximum generating capacity can be found by IAFSA when the threshold is between 0.06 and 0.09. And the recommended value of the threshold q_0 is 0.07.

C. Further performance test of IAFSA

To further verify the efficiency of IAFSA for the optimization operation of the cascade reservoirs, the power generation dispatching of the cascade reservoirs from 1986 to 1987 are performed in this paper. TableII lists the results of IAFSA and DP, respectively. Comparing the results between IAFSA and DP, it is found that for DP, when the number of the discrete points of two reservoirs are all 200, the power generation capacity is 642843×10^4kW·h; For IAFSA, the average power generation capacity under 100 times simulations is 640568×10^4kW·h. The difference between IAFSA and DP is 0.35% , which can be accepted.

TABLE II. COMPARISON OF THE RESULTS OF DIFFERENT MODELS IN YEAR 1986-1987

	AFSA	IAFSA	PSO	DP
Power generation ($\times10^4$kW·h)	634032	640568	637905	642843
Calculation time	5.7s	5.1s	5.5s	7.9h

VI. CONCLUSIONS

Aiming at the disadvantages of AFSA, such as the blindness of searching at the later stage and the poor ability to keep the balance of exploration and exploitation, etc., an improved AFSA (IAFSA) suitable for optimization operation of cascade reservoirs is proposed. The results demonstrate that the capability of IAFSA has greater improvement than that of AFSA and the optimization operation results of IAFSA are satisfied.

ACKNOWLEDGEMENTS

This research is supported by “Specialized Research Fund for the Doctoral Program of Higher Education” (20100041120004), “Open Research Fund of State Key Laboratory of Hydrology-Water Resources and Hydraulic Engineering, Hohai University” (2009490211), “the Fundamental Research Funds for the Central Universities” (1100-893345).

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