Multi-objective optimization pollination algorithm based on game theory for joint dispatching of basin reservoir group

WANG Runying

1 College of Water Conservancy and Hydropower Engineering, Hohai University, Nanjing, Jiangsu, 210098, China
* wry6888@126.com

Abstract. In order to solve the multi-objective joint dispatching problem of watershed and reservoir, and overcome the shortcoming of single element heuristic intelligent algorithm, based on the analysis of the convergence, stability and applicability of the algorithm, an Improved Flower Pollination Algorithm (IFPA) combined with the reality of basin reservoir group is proposed. In IFPA, the elements in traditional Flower Pollination Algorithm (FPA) and the basic elements in game theory are mapped one by one. Two strategies (initializing the pollen operator with chaotic sequence and inverse learning transforming the population) are introduced into traditional FPA respectively and are gamed to optimize the problem. Function tests show that the convergence speed and optimization accuracy of IFPA are 15% and 10% higher than those of the traditional FPA respectively. IFPA is applied to the basin reservoir group dispatching and the actual dispatching results are consistent with the related literature. The study shows that IFPA is superior to the traditional FPA and can be used in multi-objective problem group joint dispatching of basin reservoir group.

1. Introduction

With the development and utilization of water resources, a number of reservoir group systems have been built in different watersheds in China, and the optimal operation of reservoir groups is becoming a hot research topic at present[1]. In recent years, many meta-heuristic intelligent algorithms have been used to solve watershed optimal dispatching problems, such as artificial neural network, differential evolutionary algorithm[2], ant colony algorithm, Tabu search algorithm[3], simulated annealing algorithm, cultural algorithm, particle swarm optimization, leap frog algorithm[4,5], artificial fish swarm algorithm, intelligent water droplet algorithm[6], artificial bee swarm algorithm, artificial immune algorithm[7] and drosophila algorithms, etc. However, these meta-heuristic intelligent optimization algorithms also have some shortcomings, such as long computation time, precocity and local optimal phenomenon. Therefore, it is necessary to explore new algorithms. Flower Pollination Algorithm (FPA) possesses advantages of simple structure, fewer parameters and strong searching ability and it is easy to realize in code[8]. However, in solving high dimensional problems, shortcomings such as slow convergence rate and local optimal phenomenon do exist with this algorithm.

In this paper, an Improved Flower Pollination Algorithm (IFPA) is proposed, in which the elements in FPA and the basic elements in game theory are mapped one by one, and two strategies (pollen operator with initializing chaotic sequence and inverse learning by transforming the population) are gamed to search for optimization. Tested IFPA is verified by a project case[8].
2. Methods

2.1. IFPA Model based on Game Theory

2.1.1. Improvement of FPA Model

In order to harmonize the elements of game theory with the elements of pollen algorithm, each element is matched one by one, as shown in Table 1.

| Element | Game theory | FPA |
|---------|-------------|-----|
| Participant | Game-agents, whose purpose is to maximize their utility level through the completion of various schemes | Pollen gametes participating in independent optimization in FPA, and all pollination gametes are selected as a main body |
| strategy | The alternative scheme for each participant under the given game information | The improved optimization strategy prepared in advance during optimization of pollen gametes |
| result | The results of each player in a game usually relate to two aspects: 1. Single participant's own policy of choice. 2. A set of policies selected by all participants | Pollen gametes will get the optimal value or the more coordinated value after continuous optimization |

2.1.2. Game Model of IFPA

Participant set \(\{N|N = 1,2\}\) is used to define two optimization queues \(\{\text{queue}_1, \text{queue}_2\}\) and two strategies \(\{\text{scheme}_1, \text{scheme}_2\}\). \(\text{queue}_i\) is the main participant in Game problem. The ultimate goal of the game is to get the best result. Each queue corresponds to the strategy set \(\text{scheme}_j, \{S_j|S_j = \text{scheme}_1, \text{scheme}_2\}\). Game results are expressed in terms of \((q_1, q_2)\), and \(q_1, q_2\) are the adaptive value of \(\text{queue}_1\) and \(\text{queue}_2\) respectively, as shown in

\[
q_i = \frac{a_{1j}}{a_{1j} + a_{2j}} \text{best}_j + SC_{ij}
\]

(1)

where, \(SC_{ij}\) is the optimal fitness value of queuei under strategy j, \(a_{ij}\) is the average fitness value of queuei under strategy j, \(\text{best}_j\) is the optimal fitness generated by using the strategy j as shown in equation (2). \(\frac{a_{1j}}{\sum_i a_{ij}}\) means that when two queues play with the same policy, the queue with high average fitness will obtain better results from the strategy.

\[
\text{best}_j = \max(\text{SC}_{1j}, \text{SC}_{2j})
\]

(2)

2.1.3. Solution of IFPA Game Model

The results of different queues are defined as \(\{R_k|R_k = R_1, R_2\}\). The results \(R_i\) of the queue \(i\) usually are related to two aspects, one is a single policy selected by a participant and the other is a set of policies selected by all participants. In the game process, the pay-utility matrix is used to represent the advantages and disadvantages of different policy combinations, as shown in equation (3) and Table 2.

\[
R_1 = \left(\frac{a_{11}}{a_{11} + a_{21}}\text{best}_1 + SC_{11}, \frac{a_{21}}{a_{11} + a_{21}}\text{best}_1 + SC_{21}\right)
\]

\[
R_2 = (\text{best}_1 + SC_{11}, \text{best}_2 + SC_{21})
\]

\[
R_3 = (\text{best}_2 + SC_{12}, \text{best}_1 + SC_{21})
\]

\[
R_4 = \left(\frac{a_{12}}{a_{12} + a_{22}}\text{best}_2 + SC_{12}, \frac{a_{22}}{a_{12} + a_{22}}\text{best}_2 + SC_{22}\right)
\]

(3)
Performance of IFPA and FPA is shown in Table 3. \( t \)-test is used to perform statistical analysis of the test results. If IFPA is statistically better than FPA, it is indicated by “+”; otherwise it is indicated by “-”. From Table 3, we can see that as to functions \( f1 \sim f4 \), IFPA is superior to FPA in functions \( f1 \sim f3 \), and FPA is only better in \( f4 \) than IFPA. As to functions \( f5 \sim f10 \), IFPA is superior to FPA in functions \( f5 \sim f9 \), FPA is better than IFPA in \( f10 \). In conclusion, test results show that IFPA can improve the performance of FPA on single-peak and multi-peak test functions effectively.
Table 3. Test results

| function | Mean Error, standard deviation, ± |
|----------|----------------------------------|
|          | FPA                              | IFPA                              |
| $f_1$    | 1.38E-3, 1.78E-36                | 9.47E-19, 0.00E+00, +              |
| $f_2$    | 5.23E-16, 7.14E-16               | 1.18E-95, 1.76E-95, +              |
| $f_3$    | 1.45E-05, 1.65E-05               | 1.38E-152, 1.98E-152, +            |
| $f_4$    | 4.02E+00, 4.45E+00               | 8.44E+00, 1.06E+00, −              |
| $f_5$    | 5.66E+03, 6.94E+02               | 2.28E+03, 5.11E+02, +              |
| $f_6$    | 9.97E+01, 2.55E+01               | 0.00E+00, 0.00E+00, +              |
| $f_7$    | 1.33E−02, 5.15E−03               | 0.00E+00, 0.00E+00, +              |
| $f_8$    | 1.66E+00, 3.55E−01               | 1.67E−15, 1.68E−15, +              |
| $f_9$    | 2.22E−13, 3.15E−13               | 3.66E−20, 5.29E−20, +              |
| $f_{10}$ | 1.15E−03, 3.83E−04               | 3.31E−02, 4.62E−02, −              |

The convergence curves of typical functions are shown in Figure 1. It can be seen that the convergence rate of IFPA is faster than that of FPA, and the convergence rate of IFPA is at least 15% higher than that of the traditional pollination algorithm, and the precision of optimization of IFPA is increased by about 10% comparing with the analytical solution.

3. An engineering example

3.1. Project Overview
A reservoir group includes reservoir A, reservoir B and reservoir C, basic parameters of cascade hydropower stations of which are shown in Literature [8]. Reservoir A is incomplete annual regulating, of which the monthly water level amplitude does not exceed 30 m and the water level at the end of July does not exceed 836.2 m. The hydropower stations of reservoir B and reservoir C are both run-off river hydropower stations.

3.2. Joint dispatching model
In this paper, maximum generation model is adopted and the objective of maximizing the minimum output force is transformed into a constraint condition by using the constraint method. The objective function is [11]

$$E = \max \sum_{t=1}^{T} \left[ \sum_{i=1}^{n} K_{i,t} \cdot Q_{i,t} \cdot H_{i,t} - \sigma_t \cdot \lambda \cdot |\varepsilon - K_{i,t} \cdot Q_{i,t} \cdot H_{i,t}| \right] \cdot M_t$$

where, $E$, $n$, $i$ are the total energy output of cascade hydropower stations during the year, the total amount of hydropower stations and the number of power station, respectively. $T$ is the number of periods calculated in the year, in this paper,$T=12$. $t$ is the calculating period number. $K_{i,t}, Q_{i,t}$ and $H_{i,t}$ represent the integrated power generation coefficient, power flow and net head of the $t$ interval of the $i$ power station, respectively. $M_t$ is the duration of the interval of $t$. $\varepsilon$ is the minimum output after the maximization of the assumption. $\lambda$ is an invariant, which is taken as $10^4$ in this paper. $\sigma_t$ is a variable defined as 1 and 0.
Water balance constraints are set as
\[ V_{it+1} = V_{it} + 3600(q_{it} - Q_{it} - S_{it}) \cdot \Delta t \] (8)

Flow balance constraints are set as
\[ q_{i+1,t} = Q_{i,t} + S_{i,t} + q'_{i,t} \] (9)

Reservoir water storage constraints are set as
\[ V_{i,t}^{\min} \leq V_{i,t} \leq V_{i,t}^{\max} \] (10)

Reservoir discharge flow constraints are set as
\[ Q_{i,t}^{\min} \leq Q_{i,t} + S_{i,t} \leq Q_{i,t}^{\max} \] (11)

Power plant discharge constraints are as
\[ Q_{i,t}^{\min} \leq Q_{i,t} \leq Q_{i,t}^{\max} \] (12)

Water balance constraints are set as
\[ V_{i,t+1} = V_{i,t} + 3600(q_{i,t} - Q_{i,t} - S_{i,t}) \cdot \Delta t \] (8)

Flow balance constraints are set as
\[ q_{i+1,t} = Q_{i,t} + S_{i,t} + q'_{i,t} \] (9)

Reservoir water storage constraints are set as
\[ V_{i,t}^{\min} \leq V_{i,t} \leq V_{i,t}^{\max} \] (10)

Reservoir discharge flow constraints are set as
\[ Q_{i,t}^{\min} \leq Q_{i,t} + S_{i,t} \leq Q_{i,t}^{\max} \] (11)

Power plant discharge constraints are as
\[ Q_{i,t}^{\min} \leq Q_{i,t} \leq Q_{i,t}^{\max} \] (12)

The above-mentioned variables are non-negative variables (\( \geq 0 \)).

In equation (8) ~ (13), \( V_{i,t} \) and \( V_{i,t+1} \) are the water storage capacity of power station \( i \) at the beginning and end of the time interval \( t \) respectively, \( q_{i,t} \) is reservoir inflow of power station \( i \), \( S_{i,t} \) is surplus water discharge of power station \( i \), \( q'_{i,t} \) is incoming flow between power station \( i \) and \( i+1 \); \( V_{i,t}^{\min} \) and \( V_{i,t}^{\max} \) are the minimum and the maximum water storage capacity of power station to be guaranteed of power station \( i \) respectively. \( Q_{i,t}^{\min} \) is the minimum discharge to be guaranteed of power station \( i \), \( Q_{i,t}^{\max} \) is the maximum allowable discharge of power station \( i \), \( Q_{i,t}^{\min} \) and \( Q_{i,t}^{\max} \) are the minimum and the maximum power discharge of power station \( i \), respectively, \( N_{i,t}^{\min} \) and \( N_{i,t}^{\max} \) are the minimum and the maximum allowable output of power station \( i \).

3.3. Algorithm implementation process

Step 1: Two pollen gametes (\( queue_1 \) and \( queue_2 \)) are randomly generated in the search space with the same number of gametes \( n_{num} \), initialize the boundary condition. Initialize the model parameter \( \gamma \) and \( \lambda \), transition probability \( p \) and the maximum number \( l_{max} \) of iterations. Initialize the vector \( L_j \), in which each element is taken from \( \text{Levy} \) distribution. Initialize two strategies. Search for the best \( MAXJT \) generation independently. Initialize the global optimal solution \( f_{best} \). For the optimal operation of cascade hydropower stations, random gamete \( X_n \) is generated by \( X_{n,t} = Z_{t}^{\min} + \omega_1 (Z_{t}^{\max} - Z_{t}^{\min}) \) in which \( Z_{t}^{\min} \) and \( Z_{t}^{\max} \) represent the water level limit of reservoir during the period of \( t \). \( \{\omega_1 \} \omega_1 \in (0,1) \) is a set of random number which is a uniform distribution.

Step 2: Take objective function as the fitness function. At each iteration, the optimal fitness value \( SC_{ij} \) and the average fitness value \( ag_{ij} \) are calculated separately by using the strategy \( j \) to optimize the queue \( i \) and record the pollen operator \( X_n \) of queue \( i \) corresponding to the optimal fitness value \( SC_{ij} \) and the optimal fitness value \( best_j \) of the strategy \( j \).

Step 3: Generate \( rand \). Global or local pollination is carried out and pollen gametes are processed according to various constraints. If the new pollen gamete is better, it is renewed.

Step 4: For each queue \( i \), calculate the result \( R_i \) according to the payment utility matrix, and calculate the final result \( R_k^* \) of the population.

Step 5: Calculate the optimal strategy combination \( R \).

Step 6: For each queue \( i \), search for the best \( MAXJT \) generation independently under the selected optimal strategy \( j \) according to equation (5), and obtain the optimal solution.

Step 7: Determine whether its optimal solution for each queue \( i \) is less than the global optimal solution \( f_{best} \). If it is, update \( f_{best} \).

Step 8: Determine whether the current number of iterations has reached the maximum number of iteration \( MAXDT \). If it is, output the existing global optimal solution \( f_{best} \). Otherwise, turn to step 2.
The parameter values are set as $\gamma = 0.1$, $\lambda = 1.5$, $p = 0.8$, $num = 100$, and the maximum iteration number 3000 is set as the condition to determine when to end.

3.4. Simulation results and Analysis of typical years

The run-off process from June to May in hydrologic year of 2012 and 2013 is selected to simulate optimization dispatching[8]. The results of IFPA are shown in Table 4.

Table 4. Optimization results of IFPA

| Month | $z_t^*$ (m) | $Q_t^a$ (m$^3$/s) | $Q_t^b$ (m$^3$/s) | $Q_t^c$ (m$^3$/s) | $Q_t^d$ (m$^3$/s) | $Q_t^e$ (m$^3$/s) | Cascade output (MW) |
|-------|--------------|--------------------|--------------------|--------------------|--------------------|--------------------|---------------------|
| 6     | 805.4        | 2620               | 2316               | 0                  | 2381               | 2381               | 0                   |
| 7     | 833.5        | 3918               | 2775               | 404                | 3320               | 2411               | 900                 |
| 8     | 839          | 2351               | 2215               | 0                  | 2315               | 2315               | 0                   |
| 9     | 839          | 2033               | 2033               | 0                  | 2133               | 2133               | 0                   |
| 10    | 845          | 1993               | 1723               | 0                  | 1766               | 1766               | 0                   |
| 11    | 845          | 895                | 895                | 0                  | 900                | 900                | 0                   |
| 12    | 841.5        | 606                | 705                | 0                  | 715                | 715                | 0                   |
| 1     | 835.4        | 459                | 724                | 0                  | 733                | 733                | 0                   |
| 2     | 821.6        | 404                | 761                | 0                  | 773                | 773                | 0                   |
| 3     | 803.7        | 428                | 820                | 0                  | 827                | 827                | 0                   |
| 4     | 791.9        | 533                | 893                | 0                  | 903                | 903                | 0                   |
| 5     | 791          | 1169               | 116                | 0                  | 1181               | 1181               | 0                   |

$z_t^*$ denotes the water level at the end of the month.
$Q_t^a$ denotes the reservoir inflow discharge.
$Q_t^b$ denotes the power discharge.
$Q_t^c$ denotes the surplus water discharge.

Water storage and water supply are achieved in the reservoir group from June to October and from December to April, respectively. In May and November, there is no storage and no supply, and the process of water level variation and output is roughly consistent with the required operation. The optimal dispatching results of IFPA are reasonable.

3.5. Performance comparison and Analysis of algorithms

In order to compare IFPA with other traditional algorithms, the runoff process of the hydrological year from June 2014 to May of 2015 is simulated with FPA and traditional Progressive Optimality Algorithm (POA) respectively. The searching step of POA is set as 0.02 m and the maximum number of iterations is 15000 times. Initial reservoir water level is determined according to equal storage capacity and dropping. The simulated results of different algorithms are shown in Table 5.

Table 5. Comparison of Optimization Results of Different Algorithms

| Algorithm | Minimum Output (MW) | Maximum Output (MW) | Average Output (MW) | Standard Deviation (MW) | Cascade Energy Output (10^8kW·h) | Operation Duration (s) |
|-----------|---------------------|---------------------|---------------------|------------------------|----------------------------------|------------------------|
| IFPA      | 1421                | 1421                | 1421                | 0                      | 231                              | 3.1                    |
| FPA       | 1421                | 1421                | 1421                | 0                      | 223.4                            | 53.3                   |
| POA       | 1231                | 1426                | 1386.7              | 79                     | 224.1                            | 1.2                    |

Table 5 shows that as to IFPA, the minimum output value of the reservoir group is 1421 MW, the output force is uniform from December to April, the power generation of the cascade is 231.0×10^8kW·h. The calculation time of IFPA is only 3.1s and the convergence rate of IFPA is faster. As to FPA, the optimization results also satisfy the requirements, but the convergence rate of FPA is slower and the optimization accuracy is lower than IFPA, the power generation is 223.4×10^8kW·h. As to POA, the optimization results fail to meet the requirements of the cascade output force, the output force fluctuates greatly from December to April, and the annual power generation of the cascade is also relatively low. Therefore, the proposed IFPA is obviously superior to the traditional FPA and POA for the multi-objective optimization problem of cascade hydropower stations.
4. Conclusions
The results of calculation show that the convergence speed and the optimization precision of IFPA are 15% and 10% higher than the traditional FPA respectively and the engineering example is in good agreement with the related literatures. The study shows that IFPA is superior to the traditional FPA and IFPA can be used for multi-objective joint dispatching of basin reservoir group.

References
[1] XU, G. Research on Yalong River’s Long-term Scheduling Based on Improved Ant Colony Optimization Algorithm[J]. China Rural Water and Hydropower, 2013(02):141-145+147.
[2] QIN, H., ZHOU, J., WANG, G., ZHANG, Y. Multi-objective optimization of reservoir flood dispatch based on multi-objective differential evolution algorithm[J]. Journal of Hydraulic Engineering, 2009, 40(5):513-519.
[3] BOYER, V., ELKIHEL, M., BAZDE. Heuristics for the 0-1 Multidimensional Knapsack Problem [J]. European Journal of Operational Research, 2009, 199(3): 658-664.
[4] QIN, H., ZHOU, J., et al. Multi-objective Cultured Differential Evolution for Generating Optimal Trade-offs in Reservoir Flood Control Operation[J]. Water Resources Management, 2010, 24(11): 2611-2632.
[5] JI, C., LI, J., ZHANG, X., ZHANG, Y. Optimal operation of cascade reservoirs based on immune-shuffled frog leaping algorithm [J]. Systems Engineering - Theory & Practice, 2013, 33(8): 2125-2132.
[6] DARIANE, A.B., SARANI, S. Application of Intelligent Water Drops Algorithm in Reservoir Operation [J]. Water Resources Manage, 2013(27): 4827-4843.
[7] ZUO, X., MA, G., XU, G., TAO, C. Artificial immune system and its application in short-term optimal scheduling of hydro-plants in cascade reservoirs [J]. Advances in Water Science, 2007, 18(2): 277-281.
[8] JIANG, F., ZHAN, Y., LIU, G., HUANG, W., MA, G. Improved Flower Pollination Algorithm for Multi-objective Optimization of Cascaded Hydropower Stations [J]. Water Power, 2018, 44(1): 90-93+113.
[9] YANG, M., LIU, J. Hybrid optimization algorithm based on game theory [J]. Application Research of Computers, 2016, 33(08): 2350-2352+2362.
[10] Yao X, Liu Y, Lin G. Evolutionary programming made faster [J]. IEEE Transactions on Evolutionary Computation, 1999, 3(2): 82-102.
[11] WANG, J., HUANG, W., MA, G. Multi-objective Optimization of Cascade Hydropower Stations Based on Improved Partheno-genetic Algorithm [J]. Journal of Sichuan University (Engineering Science Edition), 2014, 46 (S2): 1-6.