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Multi-objective Ecological Operation of Reservoir in Luanhe River Based on Improved Particle Swarm Optimization

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ABSTRACT

River ecosystem is one of the most important ecosystems, and it provides many ecosystem services for human beings. However, river health has also been damaged by over-exploitation and water pollution. In the process of reservoir operation, the ecological flow demand of rivers should be fully considered and multi-objective ecological dispatch of reservoirs should be implemented. On basis of the traditional particle swarm optimization (PSO), the improved PSO with adaptive random inertia weights (ARIW) is proposed to deal with the problem of ecological optimal operation of reservoir in the paper. According to the evolutionary process, based on the probability distribution density function of triangle, the inertia weight can be adjusted randomly and adaptively to meet the global or local optimization requirements. By typical mathematical function, the improved PSO algorithm is compared with traditional PSO and genetic algorithm (GA), and is proved to be more efficient and accurate. Taking Panjiakou Reservoir on the main stream of Luanhe River in China as an example, the multi-objective ecological optimal dispatch of reservoir has been analysed and calculated with the improved PSO algorithm under different target years, considering flood control, water supply, and ecological demand. The research results can provide reference for developing rationally Luanhe River water resources, and making scientifically ecological dispatch plan of Panjiakou reservoir.

INTRODUCTION

River ecosystem is one of the most important ecosystems for human survival. A healthy river ecosystem has stability and sustainability, and has a good ability for adjusting and restoring under the external pressure and disturbance. It can provide many ecosystem services such as water, food and transportation for human production and living (Zhang et al. 2015, Hao et al. 2014). However, when the rivers contribute to the development of human society, they have also been damaged. Water resources depletion, water quality deterioration and other problems are widespread in China. It is urgent to protect river ecosystems. It is an important measure to carry out reservoir ecological dispatch to guarantee river ecosystem health.

In the past, various researchers applied a series of typical methods such as linear programming, nonlinear programming, dynamic programming, etc., to solve multipurpose reservoir operation problems (Zhao et al. 2014, Zhao et al. 2011, Liu et al. 2011). In fact, reservoir system is a complex and non-linear system, and the problems of multipurpose reservoir operation are far more complex than for single object regulation. In spite of improvement of these traditional algorithms, it is difficult to achieve satisfied performance for such a reservoir system with traditional optimization methods. Generally, the problems of multipurpose reservoir operation that have nonconvexities in domain and nonlinear relationships in objectives and constrains are complex, and the linear programming method is not fit. Dynamic programming and stochastic dynamic programming have been applied into many fields including optimal operation of reservoir, but these approaches face the problem of the dimensionality disaster. As far as traditional nonlinear programming is concerned, slow convergence rate and large amounts of calculation time are the shortage of the method. In addition, nonlinear programming easily falls into local optimal solutions (Bai et al. 2015, Huang et al. 2004).

In recent years, many heuristic algorithms have been applied into optimization. By the evolution techniques, the optimal problem can be treated better and described more realistically. Some optimal models and algorithms, which are easy in handling the nonconvex and nonlinear relationship, are provided. In the multiple dimension optimization calculation categories, genetic algorithm (GA) (Goldberg et al. 1989) and particle swarm optimization (PSO) (Eberhart et al. 1995) are used widely, and some operation models of reservoir are established base on these algorithms. For example, Oliveira & Loucks (1997) derived multi-reservoir operation rules based on genetic algorithms. Wardlaw & Sharif (1999) made a study of alternative formulations of GA for reservoir. Chen et al. (2008) established the large scale system model based on particle swarm optimization to optimal allocation of water resources in irrigation areas. Chang et al. (2010) developed the modified adaptive PSO to deal with optimal operation of hydropower station. Yang et al. (2016) proposed the Multi-objective operating rules for Danjiangkou reservoir in China under climate change. Chang et al. (2013) employed the PSO and GA as tools to research the optimization of water resources utilization. Swarm intelligence algorithms or evolutionary algorithms (Cheng et al. 2012), such as GA and PSO, have become popular in the optimal operation and improved management of reservoir system.

According to the new mechanism, the model of PSO with adaptive random inertia weights (ARIW) is applied into solving problems for multipurpose reservoir system. To test the usefulness of PSO with ARIW, it is tested firstly by the Rastrigin function that is the one of classic nonlinear functions. To show the practical utility, operation model for reservoir based on PSO with ARIW is then applied into an existing reservoir, namely the Panjiakou reservoir in Hebei Province, China.

PARTICLE SWARM OPTIMIZATION

Traditional Particle Swarm Optimization

The swarm intelligence, which is used to describe algorithms and distributed solutions, is inspired by the collective behaviour of animals and insects. PSO is a kind of swarm intelligence technology for deal with multiple dimension optimal problems. In 1995, Eberhart and Kennedy originally put forward the particle swarm optimization algorithm, which is inspired by the social behaviour of bird flock in catching food process (Shi et al. 1998). PSO is like other evolutionary methods in some aspects, such as GA. PSO is initialized by generating randomly many feasible solutions, which are described by vectors. By a given heuristic rule, the parent population will be evolving to new generation, and search for optimum by updating generations. Different algorithm has different heuristic rule. In contrast to GA, the basic PSO has not genetic operators which are applied to generate a new generation of candidate solutions. The evolution is driven by the exchange of information between individuals and population. In evolution process, each particle adjusts its velocity to its own previous best position and towards the best position attained by all particle's trajectories. It will be easy to deal with the optimal problem of nonlinearity and nonconvexity with the standard PSO.

Suppose that the search space is n dimensional, the i^{th} feasible solution called particle is described by n dimensional vector, $X_i = (x_{i1}, x_{i2},\ldots, x_{in})$. The previous best position of the i^{th} particle is represented as $XP_i = (xp_{i1}, xp_{i2},\ldots, xp_{in})$, which corresponds to the individual optimum P. The best particle in the swarm is denoted as $XG_i = (xg_{i1}, xg_{i2},\ldots, xg_{in})$, which corresponds to the popular optimum G. The velocity that represents the change of particle is denoted as $V_i = (v_{i1}, v_{i2},\ldots,v_{in})$. The superscripts of variants represent the iteration number, and the evolution of swarm is manipulated as follows:

$$v_{id}^{k+1} = wv_{id}^{k} + c_1 r_1 (xp_{id}^{k} - x_{id}^{k}) + c_2 r_2 (xg_{d}^{k} - x_{id}^{k}) \quad \ldots(1)$$

$$x_{id}^{k+1} = x_{id}^{k} + v_{id}^{k+1} \quad \ldots(2)$$

Where $d = 1,2,\ldots,n$; $i = 1,2,\ldots,N$; N is the size of the particle swarm; w is inertial weight; c_1 and c_2 are positive constant parameters, generally let $c_1 = c_2 = 2.0$; r_1, r_2 are random numbers, which subject to uniform distribution in [0,1]; and k is iteration number.

By equation (1) and (2), each particle will oscillate in the feasible region (search space), between its own previous best position and the best solution of swarm, attempting to reach the new optimal position in its trajectory. In order to avoid escaping the constrains space in updating process because of the fast velocity, in evolution process, restricting the velocity of each particle into an interval, $|v_{id}| \le v_{\max}$, $v_{\max}$ is the maximum speed, which can be obtained by trial. The inertia weight w is to control the impact of local and global searching ability. A large inertia weight facilitates global search, while small inertia is helpful to local exploration. It is very important to select suitable value of inertia weight w for reduction of iteration times and optimal effect. The standard PSO usually uses the strategy of linear decreasing weight (LDW) for regulation weight of particle (Shi et al. 1998) as follows:

$$w^k = (w_{ini} - w_{end})(K_{\max} - k) / K_{\max} + w_{\mathrm{end}} \quad \ldots(3)$$

Where, k is the iteration number; $K_{\max}$ is the maximal iteration number; w^k is the inertia weight after iteration of k times; w_{ini} is the initial inertia weight of particle; w_{end} is the inertia weights corresponding to the iteration number $K_{\max}$. Even though PSO is faster than other evolutionary algorithms in searching optimal solution, it faces still premature convergence and poor fine-tuning capability of the final solution. Using the LDW strategy, in the early evolutionary phases,

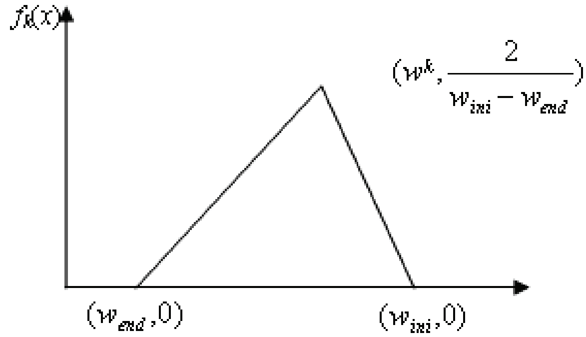

Fig. 1: Probability density of random inertial weights.

particle attends to fall into local optimum as small inertia weight, while particle may miss the optimal solution because of poor fine-tuning results from large inertia weight.

PSO Algorithm with Adaptive Random Inertia Weights

The inertia weight is randomly generated by triangle probability distribution density function. The distribution density function is updated automatically with the evolution. In the early searching phases, the possibility of achieving the larger weight values is great to facilitate global search. With the increase of the iteration number, the probability of attaining the smaller weight values will get great, tending to facilitate local exploration.

The w^k is calculated using formulation (3), $k = 0,1,2,\ldots, K_{max}-1$, and the probability distribution density function can be established by linking the points (w_{ini}, 0), (w_{end}, 0), (w^k, $2/(w_{ini} - w_{end})$) to get a triangle, whose area equals 1 exactly. When $k = 0$, the triangle is an instructing triangle. The figure of probability distribution density function is shown as Fig. 1.

The probability distribution function can be deduced by distribution density function. Suppose that $F_X(x)$ is the distribution function of random variable X, and random variable U subjects to uniform distribution in [0,1], then

$$X = F_X^{-1}(U) \qquad \ldots(4)$$

It is easy to generate a series of random numbers by computer program, $u_1,u_2,\ldots,u_m$, which subject to uniform distribution in interval from 0 to 1. Random numbers of random variable X can be achieved as follows:

$$x_i = F_X^{-1}(u_i) \qquad i = 1,2,\cdots,m \qquad \ldots(5)$$

The step-by-step process of PSO with ARIW is demonstrated as below:

Step 1 (Initialization of particles): The initial position of all the particles is produced randomly within the limits of each component of vector that represents one particle. Velocity vector for each particle is generated randomly. Each particle of swarm is initialized with random position vectors $X^0{}_i$, and random velocity vectors $V^0{}_i$.

Step 2 (Calculation of fitness degree): The fitness degree y_i of each particle is calculated by the given objective function. According to the fitness degree, initial personal best value P_i and global best value G are picked out.

Step 3 (Updating the personal best value): Comparing y_i with the current personal best P_i, the new personal is updated. If the best fitness degree of the i^{th} particle is better than the current P_i, then P_i is to be changed to the fitness degree of the i^{th} particle and this particle is as the current personal optimal solution XP_i.

Step 4 (Updating the global best value): It is similar to calculate the personal best value. If the best fitness value of a particle in the swarm is better than the current G, then G is to be changed to the value of searching point of the corresponding particle contributing to the best fitness degree. The particle corresponding to the G is updated as the new global optimal solution XG.

Step 5 (Calculation of random inertia weight): By generating m random numbers subject to uniform in [0,1] and using above equations, inertia weight of each particle is evaluated.

Step 6 (Modification of each particle): The searching point of each particle is updated by equations (1) and (2).

Step 7 (Termination criteria): steps 2 to 6 are repeated until either the pre-set iteration maximum is reached or the calculation accuracy is satisfied.

Test of PSO with ARIW

Rastrigin function is multimodal function that has many local minima. The global minimum that equals 0 is located in the position $X^* = (0,0,..,0)$. Rastrigin function with n dimension is described as follows:

$$f(X) = \sum_{d=1}^{n} (x_d^2 - 10\cos(2\pi x_d) + 10) \qquad -5.12 < x_d < 5.12 \quad \dots(6)$$

In this paper, suppose that the test functions are 10 dimensional; size of the swarm is N=30; the maximal velocity is 10; PSO other parameters c_1=c_2=2.0, w_{ini}=0.9, and w_{end}=0.4. In order to compare the performance for the PSO with ARIW, standard PSO with LDW and GA, three testing methods are suggested. Firstly, on the condition of the given calculation accuracy, compare the number of iterations. In the paper, number of iterations is $K_{\max}$=10000, and models will be run for 100 trials. The average of iteration numbers is taken as the index to evaluate efficiency in different methods. Secondly, giving the maximal evolutionary generations, analyse the calculation accuracy in different algorithms. At last, on the condition of the same parameters and accuracy, calculate and compare the probability of achieving to the global optimum by 100 trials.

According to the given parameters, probability distribution function and corresponding density function, which are used to generate random inertia weight, are evaluated as follows:

$$F_0(x) = \begin{cases} 0 & x \le 0.4 \\ 4(x-0.4)^2 & 0.4 < x \le 0.9 \\ 1 & x > 0.9 \end{cases} \quad \dots(7)$$

$$F_0^{-1}(x) = 0.4 + 0.5\sqrt{x} \qquad 0 \le x \le 1 \quad \dots(8)$$

$$F_k(x) = \begin{cases} 0 & x \le 0.4 \\ \dfrac{2}{w^k - 0.4}x^2 - \dfrac{1.6}{w^k - 0.4}x + \dfrac{0.32}{w^k - 0.4} & 0.4 < x \le w^k \\ -\dfrac{2}{0.9 - w^k}x^2 + \dfrac{3.6}{0.9 - w^k}x - \dfrac{w^k + 0.72}{0.9 - w^k} & w^k < x \le 0.9 \\ 1 & x > 0.9 \end{cases} \quad \dots(9)$$

$$F_k^{-1}(x) = \begin{cases} 0.4 + \sqrt{0.5x(w^k - 0.4)} & 0 \le x \le 2(w^k - 0.4) \\ 0.9 - \sqrt{0.5(1-x)(0.9 - w^k)} & 2(w^k - 0.4) \le x \le 1 \end{cases} \quad \dots(10)$$

Where, $k = 1, 2, \dots, K_{\max}$-1.

The test results by three methods are presented in Table 1 and Table 2.

The data in these tables show clearly that the PSO with ARIW can reach the best solution, with least number of function evaluations and higher precision as compared to other models. The detailed discussion is following:
(1) It is very clear to know that the PSO with ARIW in performance is better than other algorithms, by three different testing methods, according to the results of Tables 1 to 2. Particularly, when the accuracy demanded is same, the number of iterations calculated by ARIW mechanism is much less than the calculation number by LDW. Algorithm based on the ARIW mechanism can automatically regulate suitable weight for each particle, by the evolution process.
(2) The best results calculated by PSO with ARIW in 100 trials are picked out. For Rastrigin function, the best solution is X^* = 3.586×10^{-10}, 4.732×10^{-11}, -4.675×10^{-10}, -4.321×10^{-10}, -5.794×10^{-10}, 3.635×10^{-11}, 4.299×10^{-10}, 9.017×10^{-11}, 4.118×10^{-10}, 4.711×10^{-11}), and the global minimum is $f(X^*)$ = 0.0000. By comparing with theory optimum of testing functions, the calculation outcomes are satisfied.

APPLICATION OF THE IMPROVED PSO

Introduction of Panjiakou Reservoir

To calculate the practical effect of the proposed model, an existing reservoir, namely Panjiakou Reservoir, was taken up as a case study. The Panjiakou Reservoir is in the mainstream of the Luanhe River, in Hebei province, China. The reservoir has the total storage capacity of 29×10^8 m^3 and the water-spread area at full reservoir level is about 70 km^2. The Panjiakou Reservoir is multipurpose and serves for flood control, water supply, hydropower generation and ecological water demand of river. In these served objects, hydropower generation subjects to water supply. Only during the process of water supply, hydropower is generated according to the discharge and water level of the reservoir. The detailed information related to regulation of Panjiakou Reservoir is described below:

(1) The process of water demand: The primary areas of water supply from Panjiakou Reservoir are Tianjian and

Table 1: Comparison of evolution generations among different methods at certain accuracy.

Accuracy	GA	LDW	ARIW
1	6645	5794	4718

Table 2: Comparison of accuracy among different methods at certain evolution generations.

Iterations number	GA	LDW	ARIW
2000	2.8465	2.7173	2.4844

Tangshan, which are the important cities. According to the data of actual monthly water supply from 1983 to 2002, the averages of monthly water supply for many years are evaluated as given in Table 3.

(2) The ecological water demand of Luanhe River: In the paper, ecological water demand of each month was evaluated using Tennant methods, considering ecological base flow, the river evaporation and water leakage and so on. The monthly ecological water demand is calculated as given in Table 4.

(3) Rules of flood control of Panjiakou Reservoir: In major flood period (21 July~15 August), if the water level of reservoir is below 216 m, the main task is storing water, with ensuring the water demand of downstream; while the water level is between 216 to 222 m, reservoir discharges flood steadily by the 10000 m^3/s; when the water level is in the interval from 222 to 225 m, the release of reservoir is controlled by the 28000 m^3/s; and while the water level is beyond 225 m, all flood discharge facilities of reservoir are opened entirely.

In later flood season (16 August~30 September), the water level raised gradually to 222 m from 16 August to 31 August, and the highest water level of reservoir can be controlled in 225 m from 1 September to 30 September.

(4) Water leakage and evaporation of reservoir: By observation and experience of many years for Panjiakou Reservoir, the water leakage and evaporation can be estimated to be about 16.4×10^4 m^3 every day.

Mathematical Model Formula

The two objectives considered in the model are minimization of the deficits for water supply and ecological water of river, and the regulation rules of flood control are taken as one of the constraints. Because of the limitation of water storage in reservoir, the two objectives are conflicting. To handle these multipurpose, a weighted approach is adopted in this study. By giving the weights to the objects, multipurpose problem is transferred to single objective question. The object function is following:

$$\text{ob} = \min(a \cdot f(x_1,x_2,\cdots,x_m) + b \cdot g(y_1,y_2,\cdots,y_m)) \quad \ldots(11)$$

Where, $f(x_1,x_2,\cdots,x_m)$ is object of water supply, which reflects the comprehensive extent of water deficits for water supply, and is calculated by the following equation.

$$f(x_1,x_2,\cdots,x_m) = \sqrt{\sum_{i=1}^{m}(x_i - w_i)^2} \quad \ldots(12)$$

Where, x_i is the actual water supply of each calculation period (10^8 m^3); w_i is the water demand of each period (10^8 m^3); and m=18, is the number of calculation periods. From July to September, the length of calculation period is 10 days, and the rest calculation periods are evaluated by the interval of a month. $g(y_1,y_2,\ldots,y_m)$ is the ecological water object, reflecting the integral deficits extent of ecological water, and is evaluated as follows:

$$g(y_1,y_2,\cdots,y_m) = \sqrt{\sum_{i=1}^{m}(y_i - s_i)^2} \quad \ldots(13)$$

Where, y_i is the actual water released to the river in each calculation period (10^8 m^3); s_i is the ecological water demand of river in each period (10^8 m^3); the number of calculation periods m=18. a, b are the weight coefficients, represent the importance of object s for decision maker subject to the following constrains:

(1) Water level of reservoir:

$$Z_{\min,i} \le Z_i \le Z_{\max,i} \quad \ldots(14)$$

Where, Z_i is water level of the i^{th} calculation period (m); $Z_{\min,i}$ is the allowed lowest water level (m); $Z_{\max,i}$ is the allowed highest water level (m).

(2) Discharge limits:

$$0 \le x_i \le w_i \quad 0 \le y_i \le q_{\max} \quad \ldots(15)$$

Where, $q_{\max}$ is the discharge capacity of each period (10^8 m^3).

(3) Mass balance equation:

$$V_{t+1} - V_t = (Q_t - q_t) \cdot \Delta t \quad \ldots(16)$$

Where, V_{t+1} is the reservoir storage in the end of period (10^8 m^3); V_t is the reservoir storage in the beginning

Table 3: Average of monthly water supply (108 m3) from Panjiakou Reservoir.

Month	1	2	3	4	5	6
Water	0.35	0.07	0.91	0.53	1.13	1.12
Month	7	8	9	10	11	12
Water	0.40	0.48	0.84	0.49	0.54	0.72

Table 4: Ecological water demand of Luanhe River (10^8 m^3).

Month	1	2	3	4	5	6
Water	0.178	0.19	0.312	0.337	0.208	0.38
Month	7	8	9	10	11	12
Water	1.76	2.424	0.988	0.551	0.363	0.23

of period (10^8 m^3); Q_t is the inflows average during the period (m^3/s); q_t is the release average during the period (m^3/s); $\varDelta t$ is the length of calculation period.

(4) Rules of flood control: In flood season, reservoir regulations obey the rules of flood control.

Regulation Results

According to historical data of the inflows of Panjiakou Reservoir, three typical years were chosen, which respectively represent the low flow year, normal flow year and high flow year, and the periods corresponding to typical years are July 1981 to June 1982, July 1993 to June 1994, and July 1994 to June 1995. The multipurpose ecological regulation model of Panjiakou Reservoir is solved using PSO with ARIW, for three typical years.

(1) Low flow year: The inflows of Panjiakou reservoir in low flow year are given in Table 5.

The initial water level that is also the allowed lowest level during regulation was 164.48 m, which was achieved by the end water level of reservoir in 30 June, 1981. Let the weight of water supply object=0.9, the weight of the object for ecological water=0.1. By PSO with ARIW, the regulation results of Panjiakou Reservoir are as given in Table 6.

Water deficits of each month are shown Figs. 2-3.

(2) Middle flow year: The inflows of Panjiakou Reservoir in middle flow year are presented in Table 7.

The initial water level that is also the allowed lowest level during regulation is 208.73 m, which is achieved by the end water level of reservoir on 30 June, 1993. Weights of the objects are same with values of low flow year, respectively. The regulation results of Panjiakou Reservoir are as given in Table 8.

Water deficits of each month in middle flow year are shown in Figs. 4-5.

(3) High flow year: The inflows of Panjiakou Reservoir in high flow year are as given in Table 9.

The initial water level that is also the allowed lowest level during regulation is 213.13 m, which is achieved by the end water level of reservoir on 30 June, 1995. Weights of tow objects are same with values of low flow year, middle flow year. Using the improved PSO to solve the regulation model of Panjiakou Reservoir, results are as given in Table 10.

According to the calculation results for three typical years, it is easy to draw the following conclusions: In high flow year, by optimal regulation for Panjiakou Reservoir, the requirement of water supply can be fulfilled, and the

Table 5: Inflows of Panjiakou Reservoir in low flow year.

No.	Period	Water (10^8 m^3)
1	Early July	0.1520
2	Middle July	0.2220
3	Late July	0.5830
4	Early August	0.1587
5	Middle August	0.2546
6	Late August	0.2805
7	Early September	0.2297
8	Middle September	0.3030
9	Late September	0.3887
10	October	0.7727
11	November	0.4821
12	December	0.3026
13	January	0.2268
14	February	0.2658
15	March	0.5704
16	April	0.6286
17	May	0.3537
18	June	0.8303

Table 6: Regulation results of Panjiakou Reservoir in low flow year.

Period	Water supply (10^8 m^3)	Ecological water (10^8 m^3)	Water level (m)
Early July	0.1290	0.0066	164.4800
Middle July	0.1290	0.0766	164.4800
Late July	0.1419	0.4230	164.4800
Early August	0.1423	0.0000	164.4800
Middle August	0.1548	0.0834	164.4800
Late August	0.1703	0.0921	164.4800
Early September	0.2133	0.0000	164.4800
Middle September	0.2800	0.0066	164.4800
Late September	0.2800	0.0923	164.4800
October	0.2727	0.0208	168.6631
November	0.3793	0.0800	168.4064
December	0.4200	0.0217	166.5753
January	0.0205	0.0113	167.9942
February	0.0335	0.0728	169.0675
March	0.6875	0.0451	167.0107
April	0.1882	0.0555	170.1893
May	0.7393	0.0057	165.9912
June	0.8899	0.0465	164.4800

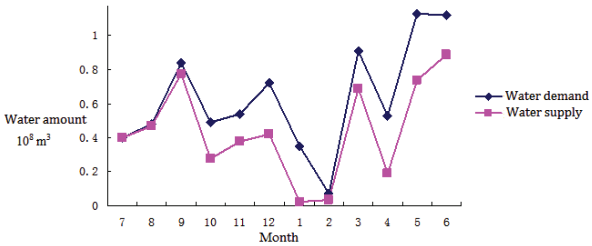

Fig. 2: Water deficit of each month in low flow year.

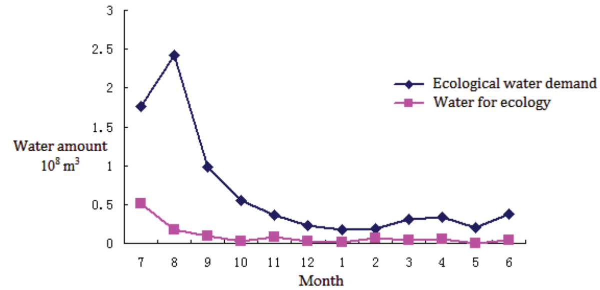

Fig. 3: Ecological water deficit of each month in low flow year.

Table 7: Inflows of Panjiakou Reservoir in middle flow year.

No.	Period	Water (10^8 m^3)
1	Early July	0.5235
2	Middle July	1.8023
3	Late July	2.2656
4	Early August	3.6091
5	Middle August	2.5993
6	Late August	1.2993
7	Early September	0.6274
8	Middle September	0.8672
9	Late September	0.5012
10	October	1.3479
11	November	0.9953
12	December	0.566
13	January	0.4085
14	February	0.4302
15	March	0.6186
16	April	1.0012
17	May	0.822
18	June	0.3161

Table 8: Regulation results of Panjiakou Reservoir in middle flow year.

Period	Water supply (10^8 m^3)	Ecological water (10^8 m^3)	Water level (m)
Early July	0.1290	0.3781	208.7300
Middle July	0.1290	1.6568	208.7300
Late July	0.1419	2.1057	208.7300
Early August	0.1548	3.4379	208.7300
Middle August	0.1548	2.4281	208.7300
Late August	0.1703	1.1109	208.7300
Early September	0.2800	0.3310	208.7300
Middle September	0.2800	0.5708	208.7300
Late September	0.2800	0.2048	208.7300
October	0.4057	0.1094	210.3341
November	0.4953	0.0953	210.9975
December	0.6104	0.0929	210.6496
January	0.2789	0.0593	210.6890
February	0.0561	0.0524	211.1973
March	0.9006	0.1893	210.2263
April	0.4742	0.0233	211.0741
May	1.0036	0.0562	210.5387
June	1.0856	0.0746	208.7300

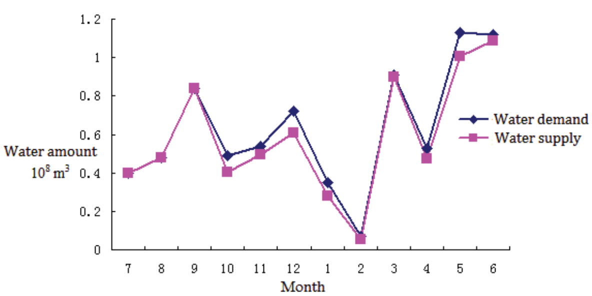

Fig. 4: Water deficit of each month in middle flow year.

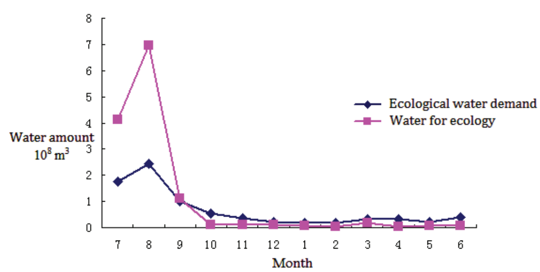

Fig. 5: Ecological water deficit of each month in middle flow year.

Table 9: Inflows of Panjiakou Reservoir in high flow year.

No.	Period	Water (10^8 m^3)
1	Early July	0.3393
2	Middle July	0.5319
3	Late July	3.0473
4	Early August	5.9128
5	Middle August	1.8991
6	Late August	1.5059
7	Early September	1.0206
8	Middle September	0.6249
9	Late September	1.0583
10	October	2.6076
11	November	1.4466
12	December	0.7827
13	January	0.5594
14	February	0.4284
15	March	0.7688
16	April	0.9787
17	May	0.5485
18	June	0.9722

Table 10: Regulation results of Panjiakou Reservoir in high flow year.

Period	Water supply (10^8 m^3)	Ecological water (10^8 m^3)	Water level (m)
Early July	0.1290	0.1938	213.1300
Middle July	0.1290	0.3864	213.1300
Late July	0.1419	2.8874	213.1300
Early August	0.1548	5.7416	213.1300
Middle August	0.1548	1.7278	213.1300
Late August	0.1703	1.3175	213.1300
Early September	0.2800	0.7242	213.1300
Middle September	0.2800	0.3285	213.1300
Late September	0.2800	0.7619	213.1300
October	0.5510	0.4900	215.8820
November	0.3630	0.5400	216.7286
December	0.230	0.7200	216.3578
January	0.1780	0.3500	216.3274
February	0.1900	0.0700	216.5315
March	0.3120	0.9100	215.6712
April	0.3370	0.5300	215.7782
May	0.2080	1.1300	214.2832
June	0.3800	1.1200	213.2067

ecological water demand can be satisfied. Ecological water deficits are happened only in few periods in flood season. In these periods of deficit, as the inflows are less than ecological water demand, release flood by the inflow amount to keep current water level; in middle flow year, by regulation, the water needs in season can be mainly met, but water supply is lacking in non-flood season; in low flow year, water demands cannot be satisfied whether water supply or ecological water. By optimal calculation using improved PSO, the extent of water deficits will be flatted to reduce the destructions deriving from water shortage.

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