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Reservoir Flood Control Operation Based on Adaptive Immune Differential Evolution Algorithm

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Abstract. Reservoir flood control operation (RFCO) is a high dimensional complex problem with multi-stages, multi-variables and multi-constraints, and its optimal solution is not easy to get. Differential evolution algorithm (DE) can be applied in RFCO, but its species diversity may sharply decline at the last evolution and lead into local optimal. Therefore, based on the adaptively controlling for mutation factor and crossover factor in each generation and immune clonal selection for better individuals, then adaptive immune differential evolution algorithm (AIDE) was proposed. And test function simulation verified the feasibility and efficiency of AIDE. Finally, AIDE was employed for RFCO and case study showed that AIDE could get better flood control benefit with fast convergence and high accuracy, moreover the outcomes of this research provided an effective way for RFCO.

1. Introduction

The aim of RFCO is to obtain a library of flow process and give full play of ensuring the safety of flood control with intelligent optimization technique according to given flood conditions [1]. RFCO problem is a complicated and combinatorial optimization problem with multi-stages, multi-variables and multi-constraints. The traditional optimization methods include dynamic programming (DP), progressive optimality algorithm (POA) with mature theoretical system, but there are obvious shortcomings, because the calculation speed of DP and POA will be significantly entered into “curse of dimensionality” problem with the increase of the number of the reservoir, the number of discrete points as well as the constraint conditions[2]. Recently, modern intelligent evolution algorithms have been applied in RFCO [1], such as genetic algorithm (GA), particle swarm optimization algorithm (PSO), but the convergence speed and convergence of the algorithms need further improvement and follow research [2].

DE [3] is a novel optimization algorithm based on group differences in efficient heuristic random search, has simple principle, high calculation speed and strong search capability, and were adopt for flood disaster evaluation [4] and reservoir hydropower optimal operation [5], but it also has the disadvantage of premature convergence and further improvement is needed to improve its searching ability. Therefore, based on the adaptive dynamic control mechanism for mutation parameter and crossover parameter in each generation and immune clonal selection for elite population, adaptive immune differential evolution algorithm (AIDE) was proposed to solve RFCO. Case study shows that AIDE can obtain good flood control benefit and provide an effective way for RFCO.

2. Reservoir flood control operation model

In the process of RFCO, the task of ensuring the safe of downstream will become more difficult when the peak flow increases, and even if the peak flow is more than the safety flow capacity of the reservoir or downstream river, the loss caused by the flood will sharply increase with the increase of the peak flow. Therefore, the traditional reservoir flood control is usually used to describe the quality of flood control sctableeme. According to the main principle of maximum flood peak elimination, the mathematical model of RFCO is shown as bellow [1][2]:

$$F = \min \sum_{t=1}^{T} Q_t^2 \tag{1}$$

where t_0 , t_T are respectively the start time and end time in flow process; Q_t is the flood discharge volume in the t -th period. And the constrain conditions of RFCO includes the following aspects:

(1) Reservoir flood control capacity limit:

$$\sum_{t}^{T}(I_t - Q_t)\Delta t = V_s \tag{2}$$

(2) Water balance equation:

$$V_t = V_{t-1} + (I_t - Q_t)\Delta t \tag{3}$$

(3) Reservoir upstream water level limit:

$$Z_{t,\min} \le Z_t \le Z_{t,\max} \tag{4}$$

(4) Discharge volume limit:

$$Q_{t,\min} \le Q_t \le Q_{t,\max} \tag{5}$$

(5) Water release ability limit of dam:

$$Q_t \le Q_{\max}(Z_t) \tag{6}$$

(6) Discharge flow variable range limit:

$$|Q_t - Q_{t+1}| \le \Delta Q_{\max} \tag{7}$$

in Eqs.(2)-(6), V_s is the reservoir flood control capacity, V_t is the reservoir storage in t -th period, I_t is flood inflow volume in t -th period; $Z_{t,\min}$ and $Z_{t,\max}$ is respectively the minimum and maximum upstream water level limit of t -th period; $Q_{t,\min}$ and $Q_{t,\max}$ is respectively the minimum and maximum discharge volume limit of t -th period; $Q_{\max}(Z_t)$ is the flood peak discharge ability limit of dam at level Z_t ; $\Delta Q_{\max}$ is maximum discharge flow variable limit.

3. Adaptive Immune Differential Evolution Algorithm(AIDE)

3.1. Differential evolution algorithm (DE)

The basic idea which DE scheme is based on is to generate new tail parameter vectors, and DE combines three operators, i.e. mutation, crossover and selection. The population of DE contains N D -dimensions real-valued parameter vectors defined as x_i^g , where g is the generation and i is the index of parameter vector. DE's strategy can be described as follows[5].

The mutation operation is adopted to obtain the new mutant vector v_i^{g+1} :

$$v_i^{g+1} = x_{r1}^g + F \cdot (x_{r2}^g - x_{r3}^g),\ i = 1, 2, \cdots, N \tag{8}$$

where integers r1, r2, r3 are different from each other in the range $[1, N]$; F is mutation factor in order to control the different variation amplification of the selected parameter vectors.

The crossover operation is used to increase the diversity of the population. The trail vector $u_i^{g+1}=(u_{i,1}^{g+1}, u_{i,2}^{g+1}, \ldots, u_{i,D}^{g+1})$ is generated in Eq.(9) from vector x_i^g and its mutant vector v_i^{g+1}

$$u_{i,j}^{g+1} = \begin{cases} v_{i,j}^{g+1}, \mathit{if}\ Rand(j) < CR)\ \mathit{or}\ j = Rnb(i) \\ x_{i,j}^{g+1}, \mathit{otherwise} \end{cases} \tag{9}$$

where $u_{i,j}^{g+1}$ is the j-th dimension of vector u_i^{g+1}, $j = 1, 2, \ldots, D$; $Rand(j)$ is a uniform random number generator between [0,1]. $Rnb(i)$ is a randomly chosen index within the range of [1,D]. And CR is the crossover constant and $CR \in [0,1]$.

Finally, the selection operation is used to select the better vector between x_i^g and u_i^{g+1} by their fitness.

3.2. AIDE

3.2.1. Adaptive dynamic control mechanism. In DE, the value of mutation factor F and crossover factor CR may influence the algorithm performance, so it is necessary to adaptively control F and CR. However, the relevant research are on the control at the population level, all vectors use the same adaptive control method, but this method could not fully reflect and use the differences information among the vectors [6].

Therefore, based on the research work of adaptive control [7], and consider the implementation of control parameters at the individual level, adaptive dynamic control strategy for each vector was set up with Eqs.(10)-(11) to ensure that as the generation g increases, the mutation factor decreases while the crossover factor increases to enhance the probability of obtaining the global optimum solution:

$$F_g^i = F_0^i / 2^{\exp\left(1 - G_{\max}/(g+1)\right)} \tag{10}$$

$$CR_g^i = CR_0^i \times 2^{\exp\left(1 - G_{\max}/(g+1)\right)} \tag{11}$$

where F_0^i and CR_0^i is the initial value of mutation factor and crossover factor respectively for the i-th vector; $G_{\max}$ is the maximum generation; F_g^i and CR_g^i is the value of mutation factor and crossover mutation in the g generation respectively for the i-th vector.

3.2.2. Immune clonal selection. DE would perform well with fast convergence speed for small dimensional problem. But when the problem is complicated and multidimensional, DE may lead to a higher probability of obtaining a local optimum [5]. So the research work employ immune theory for elite population so as to ensure that the search area is more comprehensive and may help DE to avoid premature convergence effectively. Immune clonal selection algorithm is a heuristic search algorithm, and has the advantage of good diversity and easy to escape from local extreme by using high frequency variation. And it includes clone, mutation and selection operators, and its detailed calculation procedure is as follows [8]:

Step 1: Select n better vectors from the current population to form the elite population, here set $n = 25\% * N$.

Step 2: clone the elite population to generate a temporary population S, and cloning formula N_c is calculated by Eq.(12):

$$N_c=\sum_{i=1}^{n} round(\frac{\beta\times n}{i}+b) \tag{12}$$

where β is a random value between 0 and 1; b is an integer constant and $b\geq 1$ so as to ensure that each antibody has a certain number of clones.

Step 3: high frequency variation for all the vectors in temporary population S with Eqs.(13)-(15):

$$y_{i,j}^{g}=x_{i,j}^{g}+p\times\eta\times x_{i,j}^{g}\times r_4-p\times\eta\times x_{i,j}^{g}\times r_5 \tag{13}$$

$$p=\begin{cases}1, & r_6\leq 0.5\\ 0, & else\end{cases},\ \ \eta\text{=1-}\exp\left(1-G_{\max}/\left(g+1\right)\right) \tag{14}$$

where $y_{i,j}^{g}$ is the j-th dimension of the new vector y_i^g; r_4, r_5 and r_6 is respectively random value between 0 and 1; η is clonal variation factor to ensure that at the starting stage the global search is performed to maintain the diversity of population, while at the late stage, local search is performed to ensure the search accuracy.

Step 4: select the n better vectors from the new vector y_i^g to replace elite population for next generation of DE.

3.3. Flowchart of AIDE

With the adaptive dynamic control mechanism for mutation factor and crossover factor of each vector and immune clonal selection, the flowchart of AIDE propose in the paper is as follows:

Step 1: Initialization. Set generation $g=0$, and initialize F_0^i and CR_0^i in the specified range.

Step 2: Adaptive dynamic control mechanism for control factor. Calculate the F_0^i and CR_0^i at generation g with Eq.(10) and Eq.(11), respectively.

Step 3: DE operation. Implement the mutation, crossover and selection operation for each vector with Eqs.(8)-(9), respectively.

Step 4: Immune clonal selection. When the generation g reaches the specified conditions, the clonal selection operation is performed for elite population according to Eqs. (12)-(14).

Step 5: Termination condition judgment. If g equal the maximum generation or accuracy is reached, output the optimal value, otherwise g=g+1 and go to **Step2**.

3.4. Benchmark function tests

In order to test the effect of AIDE, we use three well-known functions with their global optimum solution as follows.

(1) Sphere function

$$\min_x f(x)=\sum_{i=1}^{n}x_i^2,\ \ -5.12\leq x_i\leq 5.12,\ x^*=(0,0,...,0),\ f(x^*)=0 \tag{15}$$

(2) Griewank function

$$\min_x f(x)=\sum_{i=1}^{n}x_i^2/4000-\prod_{i=1}^{n}\cos(x_i/\sqrt{i})+1, |x_i|\leq 600, x^*=(0,0,...,0),\ f(x^*)=0 \tag{16}$$

(3) Schaffer's f7 function

$$\min_x f(x) = \sum_{i=1}^{n-1} (x_i^2 + x_{i+1}^2)^{0.25} \left[\sin(50(x_i^2 + x_{i+1}^2)^{0.1}) + 1 \right], |x_i| \le 100, x^* = (0,...,0), f(x^*) = 0 \tag{17}$$

The parameters of AIDE are NP=100, D=30, Gmax=1000, the initial mutation factor and crossover factor for each vector is respectively a random value in [0.6, 0.8] and [0.2, 0.4], and clonal selection operation is performed 200 times for elite population at every 20 generation. The parameters of PSO is same with 9 refs. The test results are shown in table 1 and each function is independently processed 50 times. And the convergence curves for each function are respectively shown in Fig.1-Fig.3.

Seen from table 1 and Fig.1-Fig.3, AIDE outperforms DE and PSO in solving all functions. AIDE can get rid of being trapped into local optimum effectively, as well as avoid premature effectively and get a better convergence precision. So, AIDE can be employed for RFCO.

Table1. Test function results for PSO, DE and AIDE

function	Algorithm	best	worst	average	standard deviation
	PSO	8.6933E-06	2.9085E-05	2.0736E-05	8.6983E-06
Sphere	DE	2.0866E-14	7.4657E-14	4.5321E-14	2.2246E-14
	AIDE	**5.5565E-37**	**1.1047E-32**	**4.6243E-33**	**5.7911E-33**
	PSO	3.2636E-03	3.5860E-02	1.6241E-02	1.4848E-02
Griewank	DE	7.1780E-11	7.6924E-09	1.6621E-09	3.3717E-09
	AIDE	**0**	**0**	**0**	**0**
	PSO	1.9247E+01	4.2492E+01	2.7679E+01	8.9475E+00
Schaffer's f7	DE	1.4172E+00	1.7270E+00	1.5900E+00	1.2222E-01
	AIDE	**6.0116E-06**	**3.7195E-05**	**1.7258E-05**	**1.3437E-05**

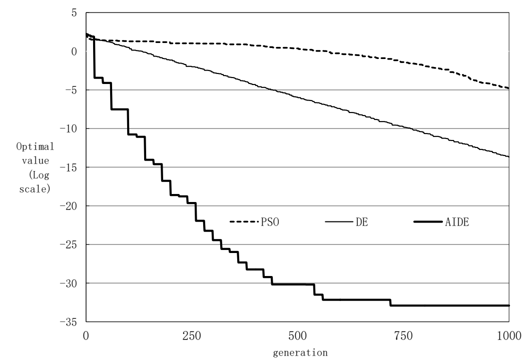

Figure 1. Convergence curve of function Sphere

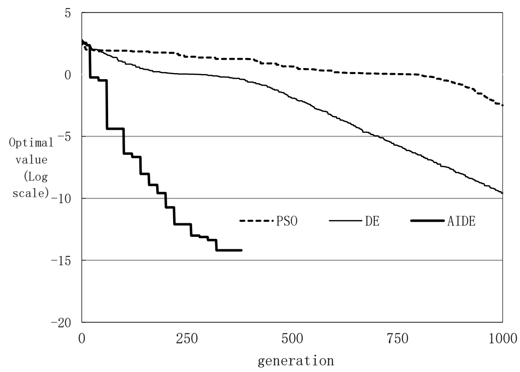

Figure 2. Convergence curve of function Griewank

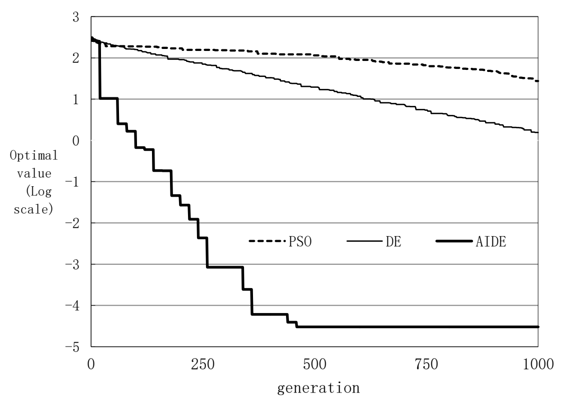

Figure 3. Convergence curve of function Schaffer's f7

4. Case study of RFCO based on AIDE

We have case study on RFCO of Dahuofang Reservoir in Hunhe River Basin, its catchment area is 5437 square kilometers. And its normal high water level is 131.5 m, flood control limit water level is 126.4 m, the final water level is not higher than 127.8 m, the flood control capacity is 1.187 billion cubic meters, downstream safety discharge is 1000 m^3/s, the maximum amplitude of discharge is 200 m^3/s [9].

In order to verify the feasibility and efficiency of AIDE, the AIDE is applied to the optimal operation of reservoir flood control of Dahuofang reservoir, and the flood process has 53 calculation periods and each period stand for 3 hours, and AIDE is compared with DE and PSO under the same initial conditions. For all the functions, AIDE parameters are NP=25, D=53, Gmax=300, the initial mutation factor and crossover factor for each vector is respectively a random value in [0.6, 0.8] and [0.2, 0.4], and clonal selection operation is performed 50 times for elite population at every 10 generation. The parameters of PSO is same with 9 refs. What's more, the levels at each time are taken as the decision variable to carry on the real number coding, according to the detailed calculation process of DE, PSO and AIDE.

Considering the randomness of the optimization algorithm, the optimal results of the 50 independent operations in which the objective function value and the average value are the closest are used as the scheduling results. The results of PSO, DE and AIDE are calculated in Table 2. Table 2 shows the maximum outflow calculation by AIDE compared with DE and PSO is greatly reduced, the peak clipping effect significantly, 62.6%, and the objective function value 1.6731×107is smallest than PSO and DE, whose objective function value is 1.6788×107 and 1.6773×107 respectively, and the results also suggested that DE and PSO need to be properly adjusted and improved so as to solve the problem of RFCO, while the proposed AIDE is feasible and effective for RFCO.

Table 2. Comparison of flood control operation results with PSO, DE and AIDE

Algorthm	Maximum outflow（m^3/s）	Peak clipping rate	Objective function value ($(m^3/s)^2$)
PSO	680	60.5%	1.6788×10^7
DE	668	61.2%	1.6773×10^7
AIDE	643	62.6%	1.6731×10^7

Nevertheless, Fig.4 shows the different optimization flood control results by the three algorithms. Obviously, discharge process of AIDE is smoother and more moderate, which is favorable for flood safety, which demonstrate that AIDE has better good advantage than DE and PSO for RFCO.

In addition, Fig. 5 shows the convergence curves of DE, PSO and AIDE, We can find out that at the initial stage they have little gap, but with the increase of evolutionary generation, the diversity of DE and PSO population decreased rapidly, and quickly premature convergence phenomenon to fall into the local optimal. While AIDE by using adaptive dynamic control mechanism and immune clonal selection to update and filter the particles which fall into local optimum, thus to increases the population diversity, the possibility to jump out of local optimum and can be better used to efficiently solve RFCO.

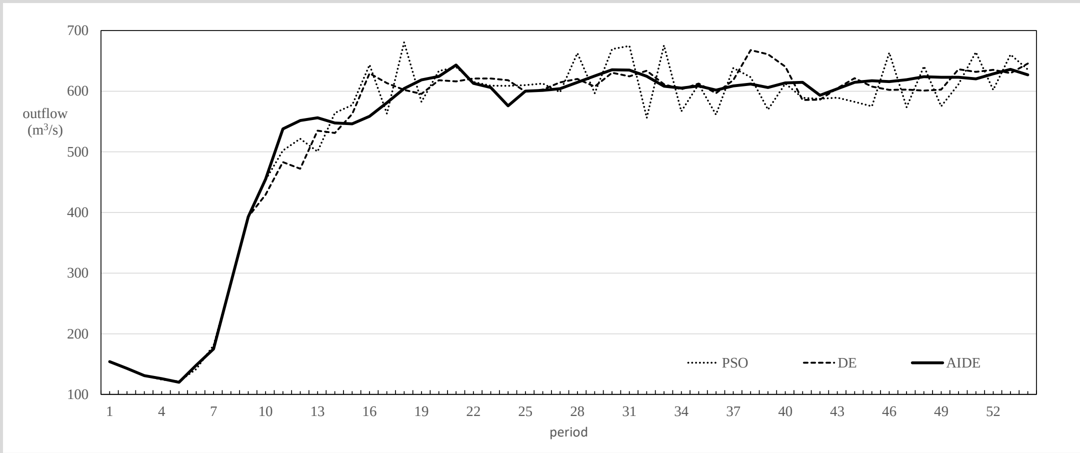

Figure 4. Outflow results of flood control optimal operation with different algorithm

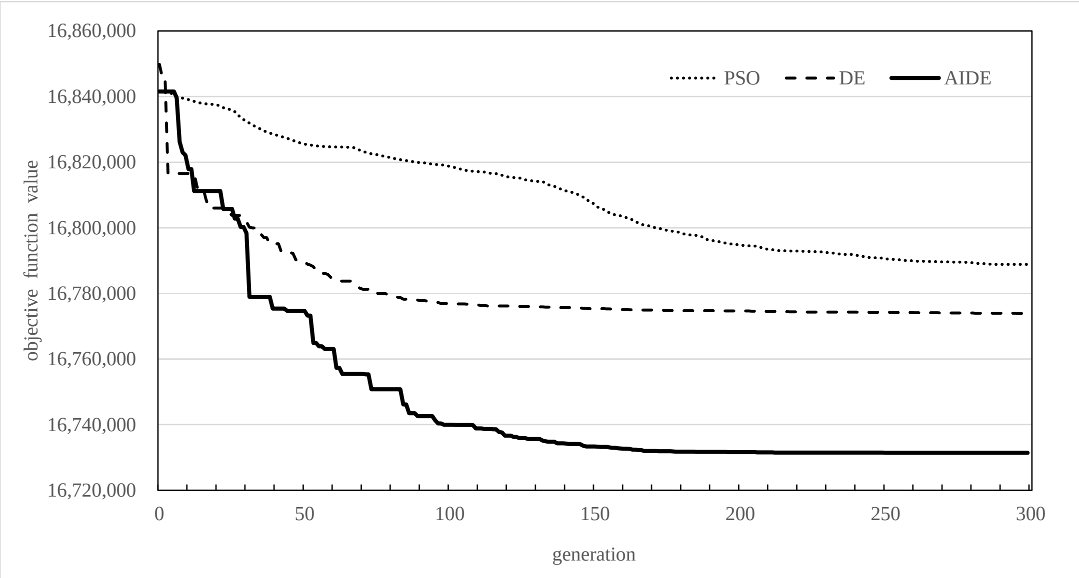

Figure 5. Convergence curve of flood control optimal operation with different algorithm

5. Conclusions

The optimal operation of reservoir flood control is strongly constrained and nonlinear. DE is applied to solve the RFCO problem, but according the fact that DE is premature convergence to local optimum, we have effective improvements for DE. So based on adaptive dynamic control mechanism for control factor of each vector at each generation and immune clonal selection for elite population on the specified conditions, adaptive immune differential evolution algorithm (AIDE) is proposed. Simulation results show the feasibility and efficiency of AIDE, and then AIDE is applied to RFCO, the application results show that AIDE has better results and higher precision than DE and PSO, thus provides an effective way for reservoir flood control optimal operation.

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