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Multi-objective Immune Algorithm with Preference-Based Selection for Reservoir Flood Control Operation

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Abstract In reservoir flood control operation, the safety of upstream and downstream of the dam are the main two optimization goals with conflicts. In addition, the irrigation water demands is also an important issue considered by decision makers. Therefore, the dispatching schemes that meet the final water level constraint are preferred. Considering such preference in decision making, a novel preference-based selection operator is developed and combined with immune inspired optimization technique to form the proposed multi-objective immune algorithm with preference- based selection (MOIA-PS) for reservoir flood control operation. The unique of MOIA-PS is that it intends to obtain a set of preferred Pareto optimal solutions that located within a part of preferred area on the Pareto front rather than to find a good approximation of the entire Pareto front as most existing methods did. Experimental results on four typical floods at the Ankang reservoir have indicated that the preferred non-dominated solutions are distributed within a local area of preferred PF region. And the newly designed preference-based selection operator can guide the search of MOIA-PS towards the preferred PF region. Comparing with the outstanding multi-objective evolutionary algorithm NSGAII and the immune inspired multi-objective optimization algorithm NNIA, the proposed MOIA-PS obtains more non-dominated solutions that densely and evenly scattered within the preferred area of the Pareto front. MOIA-PS can find finding dispatching schemes that not only reduce the flood peak significantly and guarantee the dam safety well but also satisfy the irrigation water demands. It is a more efficient use of the computing efforts.

Keywords Reservoir flood control operation · Multi-objective optimization · Artificial immune algorithm · Preference

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1 Introduction

Floods in river system are serious natural disasters that occur frequently in China and have huge destructive power. In order to prevent floods, dams and reservoirs are built to store and control flood water. They play important roles in minifying flood peaks, reducing flood damages, reserving flood for irrigation, generating hydropower and et al. (Schanze et al. 2006). Reservoir flood control operation (RFCO) is a nonlinear non-convex optimization problem which involves continuous and interdependent decision variables and multiple objectives (Hajkowicz and Collins 2007). In RFCO problem, more than one conflicting tasks, such as minimizing downstream damage and keeping dam safety within reasonable limits, are taking into consideration. It can be modeled as a multi-objective optimization problem (MOP).

A MOP with n decision variables and m objectives can be mathematically formulated as following:

$$\begin{array}{ll} \text{Minimize} & \mathbf{F}(\mathbf{x}) = [f_1(\mathbf{x}), f_2(\mathbf{x}), \ldots, f_m(\mathbf{x})] \\ \text{Subject to} & \mathbf{x} \in \Omega \end{array} \tag{1}$$

where $\Omega \in \mathbf{R}^n$ is the feasible region of the decision space, and $\mathbf{x} = \{x_1, x_2, \cdots, x_n\} \in \Omega$ is the decision variable vector. The target function $\mathbf{F}(\mathbf{x}): \mathbf{x} \rightarrow \mathbf{R}^m$ consists of m real-valued continuous objective functions $f_1(\mathbf{x}), f_2(\mathbf{x}), \ldots, f_m(\mathbf{x})$ and $\mathbf{R}^m$ is the objective space. Since there is no single solution that can optimize all the objectives of the MOP at the same time, the best tradeoffs among the objectives are termed as Pareto optimal solutions, and the set of all the Pareto optimal solutions in the decision space and the objective space are termed as the Pareto set (PS) and the Pareto front (PF) respectively (Deb 2001). As it is very time-consuming to obtain the entire PF, the goal of a multi-objective optimization algorithm is to find a finite number of Pareto optimal solutions on PF that decision makes are interested in.

With the advantage of producing a set of Pareto optimal solutions in a single run, evolutionary algorithms (EAs) have been recognized to be very successful in solving the MOPs. Since Schaffer's pioneer work on evolutionary multi-objective optimization (EMO) (Schaffer 1985), a number of multi-objective evolutionary algorithms (MOEAs) had been developed. According to Coello's overview of works on EMO (Coello 2006), the traditional MOEAs are categorized into two generations by their characteristics. The first generation MOEAs, like MOGA (Carlos and Peter 1993), NPGA (Jeffrey et al. 1994) and NSGA (Srinivas and Deb 1994), are characterized by the use of selection mechanisms based on non-dominated sorting and fitness sharing to maintain diversity. The second generation MOEAs like SPEA (Zitzler and Thiele 1999), SPEA2 (Zitzler et al. 2002), PAES (Knowles and Corne 2000), PESA (Corne et al. 2000), PESAII (Corne et al. 2001) and NSGA-II (Deb et al. 2002), are characterized by the use the elitism strategy. MOEAs in this period more or less share the same framework as that of NSGA-II, however, in recent years many new researching developments have been made in this field. The multi-objective evolutionary algorithm based on decomposition termed as MOEA/D was developed by Zhang and Li (2007). In MOEA/D, the target MOPs are decomposed into a number of scalar optimization sub-problems which are optimized simultaneously.

Artificial immune systems (AIS) attempt to extract ideas from the biological immune system to develop computational tools for dealing with science and engineering problems. It has been used to solve various types of problems such as fault diagnosis, computer security, pattern recognition, scheduling and optimization. More and more researches indicate that comparing with EAs artificial immune algorithms can maintain better population diversity and thus not easy to fall in to local optimal in the field of optimization computing (Dasgupta et al. 2011). As far as multi-objective optimization is concerned, MISA by Coello and Cortes (2005) may be the first attempt to solve general multi-objective optimization problems using artificial immune systems. Hu (2010) developed a multi-objective immune system based on a multiple-affinity model. Gong et al. (2008) proposed a multi-objective immune algorithm with non-dominated neighbor-based selection (NNIA), which consists of a novel non-dominated neighbor-based selection strategy, crowding-distance based proportional cloning, simulated binary crossover and static hyper-mutation operator. Then its improved version of NNIA, namely NNIA2, was suggested by Yang et al. (2010). NNIA2 introduced adaptive ranks clone and k-nearest neighbor list strategies to improve the diversity of evolution population.

In recent years, the multi-objective evolutionary algorithms (MOEAs) have been widely applied to solve the multipurpose reservoir operation problems and achieved various degrees of success. Many research works have been done by optimizing different MOP models for reservoir operation. Kim et al. (2006) applied NSGA-II to four interconnected reservoir operation in the Han River Basin. Li et al. (2007) developed an efficient macro-evolutionary multi-objective genetic algorithm (MMGA) for optimizing the rule curves of multipurpose reservoir. Chang and Chang (2009) applied the NSGA-II algorithm to examine the operations of a multi-reservoir system in Taiwan. Hakimi-Asiabara et al. (2010) proposed a self-learning genetic algorithm (SLGA) to derive optimal operating policies for a three-objective multi-reservoir system. Ahmadi et al. (2014) applied NSGA-II algorithm to extract real-time reservoir optimal operation rules. Ashkan et al. (2014) employed the multi-objective NSGAII-ALANN algorithm to extract the best set of reservoir operation decisions. Besides evolutionary algorithms, other nature inspired meta-heuristic algorithms, such as multi-objective evolutionary algorithms (MOEAs), multi-objective particle swarm optimization algorithms (MOPSO), multi-objective differential evolution algorithms (MODE), multi-objective ant colony optimization algorithms (MOACO) and multi-objective frog leaping algorithms (MOFLA), have also been applied to reservoir flood control operation. Nagesh Kumar and Janga Reddy (2006) presented an elitist-mutated particle swarm optimization (EMPSO) to derive reservoir operation policies for multipurpose reservoir systems. Baltar and Fontane(2008) presented an implementation of multi-objective particle swarm optimization (MOPSO) and applied it to multipurpose reservoir operation problem with up to four objectives. Guo et al. (2013) proposed an improved non-dominated sorting particle swarm optimization algorithm (I-NSPSO) to handle the multi-reservoir operation problem. Peng et al. (2014) presented a multi-objective optimization model for the coordinated regulation of flow and sediment in cascade reservoirs and applied the catfish effect particle swarm optimization algorithm to solve the model. Janga Reddy and Nagesh Kumar (2006, 2007) proposed a multi-objective genetic algorithm (MOGA) and a multi-objective differential evolution (MODE) and applied them to Bhadra Reservoir system respectively. Qin et al. (2010) proposed a multi-objective cultured differential evolution (MOCDE) to deal with the reservoir flood control operation problem. Afshara et al. (2009) presented a non-dominated archiving ant colony optimization (NA-ACO) algorithm and used to optimize reservoir operating policy with multiple objectives. Li et al. (2010) presented a novel multi-objective shuffled frog leaping algorithm (MOSFLA) and applied to solve the reservoir flood control operation problem for the Three Gorges reservoir.

When using multi-objective optimization techniques to solve RFCO problem, not all the obtained non-dominated solutions are interested by the decision maker because the scheduling schemes that fix the upstream water level constraint at the end of the flood are preferred (Qi et al. 2012, 2014). It would be a waste of computing efforts for a multi-objective optimization algorithm to obtain non-dominated solutions that are of no interest to the decision maker. Instead, if we incorporate the preference information to guide the search towards the preferred region of the PF, the algorithm could be much more efficient. According to the time that algorithm interacts with the decision maker, multi-objective optimization methods can be classified into priori methods, posteriori methods, and interactive methods (Kim et al. 2012). In RFCO problem, the preference information is quite clear. Thus, a priori method in which preference information is given by the decision maker before the solution process is developed in this work for solving multi-objective RFCO problem. The main contributions of this work are as follows.

1) A novel selection operator which considers the preference of irrigation water demands in decision making is developed to guide the search of a multi-objective optimization algorithm for RFCO problem towards the preferred area on Pareto front.
2) A multi-objective immune algorithm with preference-based selection (MOIA-PS) for reservoir flood control operation is proposed. It intends to obtain a set of preferred Pareto optimal solutions that located within a part of preferred area on the Pareto front rather than to find a good approximation of the entire Pareto front as most existing methods did.

Experimental results have indicated that the proposed MOIA-PS can successfully convergence to the preferred region of the PF, and thus is much more efficient than multi-objective immune algorithm without preference.

The remainder of this paper is organized as follows. Section 2 gives the multi-objective optimization model for reservoir flood control operation. Section 3 presents the details of the proposed preference-based selection operator for solving RFCO problem. Section 4 describes the newly developed algorithm MOIA-PS. Section 5 presents and analyzes the experimental results. Section 6 concludes this work.

2 Multi-objective Optimization Model for RFCO Problem

The task of reservoir flood control operation is to guarantee the safety of both upstream and downstream of the dam and reservoir during flood. To ensure the safety of the dam and its upstream side, the upstream water level cannot go too high. As for the safety of the downstream side, the discharging downstream flow cannot be too large. When encountering a flood with a given total volume, these two optimization goals are conflict with each other. Therefore, the RFCO problem is a typical multi-objective optimization problem. The safety of the upstream side involves to the flood water volume stored in the reservoir, it can be represented by the maximum upstream water level of the dam. As for the downstream side, the discharge volume of the dam is the critical issue. Its safety can be evaluated by the maximum discharge volume of the dam (Qin et al. 2010). In this paper, the multi-objective optimization model for RFCO problem is modeled as follows. It takes the discharge volumes of the dam as the decision variables and serves two optimization goals.

$$\begin{aligned} \text{Minimize} \quad & F(Q) = (f_1(Q), f_2(Q)) \\ f_1(Q) &= \min[\max(Z_t)] \; t = 1, 2, \cdots, T \\ f_2(Q) &= \min[\max(Q_t)] \; t = 1, 2, \cdots, T \end{aligned} \tag{2}$$

where, T is the total scheduling periods of the RFCO problem. The decision vector Q=(Q_1,Q_2,…,Q_T) represents the dam's discharge volumes of each scheduling periods. Z_t means the dam's upstream water level of the t-th scheduling period. The first optimization goal $f_1(Q)$ is to minimize the highest upstream water level during the T scheduling periods, taking discharge volumes as variables. Minimize the optimization goal of $f_1(Q)$ is to make the reservoir store no large flood water volume and ensure the safety of the dam and its upstream side. The second optimization goal $f_2(Q)$ is to minimize the largest discharge volume during the scheduling periods. It expects the reservoir store as much flood water volume as possible to protect the dam's downstream side.

The multi-objective optimization model for RFCO problem has four constrains and can be described as follows:

(1) Water balance equality limit

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

where, V_t and V_{t-1} are the reservoir storages of the t-th and (t–1)-th period, respectively; I_t and Q_t are the reservoir inflow and discharge volume of the t-th period, respectively.

(2) Reservoir upstream water level limit

$$Z_t^{\min} \le Z_t \le Z_t^{\max} \tag{4}$$

where, $Z_t^{\min}$ and $Z_t^{\max}$ are the minimum and maximum limit of reservoir upstream water level of the t -th period.

(3) Discharge volume limit

$$Q_t^{\min} \le Q_t \le Q_t^{\max} \tag{5}$$

where, $Q_t^{\min}$ and $Q_t^{\max}$ are the minimum and maximum limit of reservoir discharge volume of the t -th period.

(4) Final reservoir water level limit

$$Z_T \rightarrow Z_{FT} \tag{6}$$

where, Z_T is the final upstream water level, Z_{FT} is the flood limit water level. It is a soft constraint that needn't to be satisfied accurately.

3 The Preference-Based Selection Operator

Considering the demand of irrigation and water supply, scheduling schemes with given upstream water level at the end of the flood are likely to be adopted by the decision maker. In the above described multi-objective optimization model for RFCO problem, the constraint of upstream water level at the end of the flood is not involved. It is treated as preference information in this work. As the upstream water level at the end of the flood is implied in the scheduling schemes, it is unable to provide preference information by defining a preferred region on the PF of the RFCO multi-objective problem in the object space. Thus, the reference points based method for expressing preference information, which is common used in most of the preference inspired multi-objective optimization algorithm (Deb et al. 2006), cannot be applied to the RFCO problem directly. In this work, a new preference based selection operator using non-dominated sorting (Deb et al. 2002) is developed for multi-objective RFCO problem.

The selection operator is the key technique in the multi-objective optimization algorithm. Different form the single-objective optimization problem, the multi-objective optimization problem does not have a unique solution that optimizes all the object function simultaneously. It is important to determine which solution should survive and which one should die out in a multi-objective evolutionary algorithm when these two are both non-dominated solutions. Deb et al. (2002) developed a sorting method for multi-objective evolutionary algorithm, the common used non-dominated sorting method. Figure 1 illustrates the basic idea of the non-dominated sorting method, taking bi-objective optimization problem for example.

The non-dominated sorting method provides a rule of ordering individuals in the population base on the non-domination. As is shown in the Fig. 1a, the non-dominated individuals in the population are assigned to the rank 1. Remove individuals with rank 1 from the population, the remaining non-dominated individuals are assigned to the rank 2. Continue this operation and assign each solution to a rank equal to its non-domination level. According to the non-dominated sorting method, when two solutions have different non-domination ranks, the one with lower rank is better. When the two solutions have the same non-domination rank, the decision maker usually prefers the one that is located in a lesser crowded region. In order to estimate the density of solutions surrounding a particular solution in the population, we calculate the average distance of two points on either side of this point along each of the objectives. This quantity which is termed as the crowding distance of the individual is assigned to the perimeter of the cuboid formed by using its nearest neighbors as the vertices. As is shown in Fig. 1b, we can get the crowding distance of individual A and B by calculating the perimeters of the two cuboids shown with dashed boxes. It can be seen that, individual A has larger crowding distance than B, thus A is better than B although they have the same non-domination rank.

Based on the non-dominated sorting method, a selection operator using preference information is developed and introduced into the multi-objective immune algorithm for solving the RFCO problem. Given the flood limit water level Z_{FL}, the final upstream water level after dispatching Z_T is expected to fall back to flood limit water level, to cope with following possible floods and satisfy the irrigation water needs. In order to describe this preference information, a positive preference threshold Z_{PT} must be provided by the decision maker. In other words, the solutions whose final upstream water level Z_T located between $Z_{FL}-Z_{PT}$ and

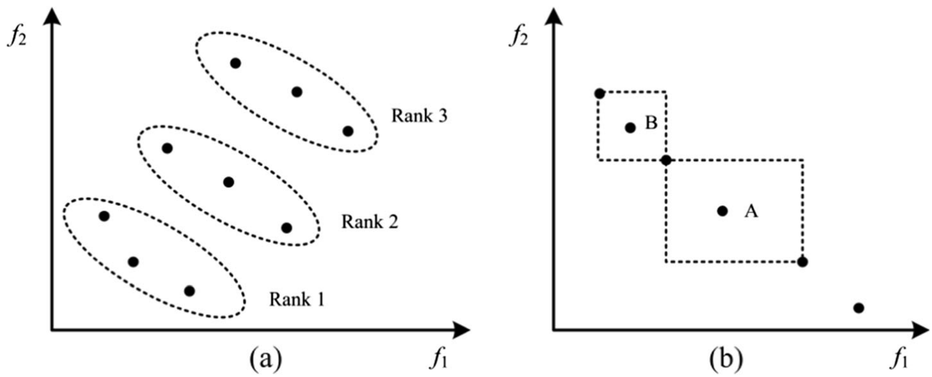

Fig. 1 Basic idea of the non-dominated sorting method: **a** concept of non-domination rank; **b** calculation of crowding distance

$Z_{FL}+Z_{PT}$ are preferred by the decision maker. Given a population *pop* with size N_1 as an input, the preference-based selection operator works as following, giving rise to the output population *pop′* with maximum size of N_2.

Algorithm 1 The Preference-Based Selection Operator

Input: Z_{FL}, Z_{PT}, *pop*, N_1, N_2.
Output: *pop′*.

Step 1 For each individual $\mathbf{A}_i(i=1,2,\cdots,N_1)$ in population *pop*, calculate the final upstream water level Z_T^i. Keep all the individuals in *pop* that satisfies $Z_{FL}-Z_{PT}\le Z_T^i\le Z_{FL}+Z_{PT}$ to form the new population P';

Step 2 if the size of P' is no larger than N_2 then let $pop'=P'$, output *pop′*. Otherwise, continue;

Step 3 For each individual $\mathbf{A}_j$ ($j=1,2,\cdots,N'$, N' is the size of P') in P', calculate the values of the following two function f_1 and f_2, in which CD($\mathbf{A}_j$) means the crowding distance of individual A_j in P';

$$f_1 = \left|Z_T^i - Z_{FL}\right|, f_2 = 1/\mathrm{CD}\left(\mathbf{A}_j\right)$$

Step 4 Viewing f_1 and f_2 as the two object function of individuals in P', select the first N_2 individuals from P' by using the non-dominated sorting method, giving rise to *pop′*, then output *pop′*

According to the character of the RFCO problem, the above algorithm 1 gives a preference-based selection method to preserve solutions that meet the constraint of the final upstream water level limit and have large crowding distance. By considering these two targets which are determined by f_1 and f_2 in the step 3, a new multi-objective model is built for the preference-based selection. Finally, the non-dominated sorting method is employed to select a specified number of individuals in the step 4.

4 The Algorithm

In this section, we introduce the newly proposed preference-based selection operator into the framework of the non-dominated neighbor immune algorithm (NNIA) (Gong et al. 2008) and developed a multi-objective immune algorithm with preference-based selection (MOIA-PS) for reservoir flood control operation. Inspired by clonal selection principle of the biological immune system, NNIA is an effective and robust immune algorithm for multi-objective optimization problem. The antibody coding and fitness assignment can be described as follows.

Given an antibody population $\mathbf{P}$, each of its members $\mathbf{A}=\{a_1,a_2,\cdots,a_n\}$ is the coding of the decision variable $\mathbf{x}=\{x_1,x_2,\cdots,x_n\}$ in the mathematical model of Eq. (1). NNIA adopts real-valued presentation, that is, $a_i=x_i$, $i=1,2,\cdots,n$. So, $\mathbf{A}=\{a_1,a_2,\cdots,a_n\}$ must be in the feasible region Ω. The affinity of antibody $\mathbf{A}$ is defined as its crowding-distance in the population $\mathbf{P}$:

$$Affinity(\mathbf{A}|\mathbf{P}) = \mathrm{CD}(\mathbf{A},\mathbf{P}) \tag{7}$$

The crowding-distance of antibody $\mathbf{A}\in\mathbf{P}$ can be defined as:

$$\mathrm{CD}(\mathbf{A},\mathbf{P}) = \sum_{i=1}^{k}\frac{\zeta_i(\mathbf{A},\mathbf{P})}{f_i^{\max}-f_i^{\min}} \tag{8}$$

In which, $f_i^{\max}$ and $f_i^{\min}$ are the maximum and minimum value of the i-th object function. Note the boundary antibody set of the i-th objective function by Bd_i, then:

$$Bd_i = \left\{\mathbf{A}\middle|\mathbf{A}\in\mathbf{P}, \forall A'\in\mathbf{P} : f_i(\mathbf{A}) = \min\left\{f_i\left(\mathbf{A}'\right)\right\} or \max\left\{f_i\left(\mathbf{A}'\right)\right\}\right\} \tag{9}$$

$$D_A = \min\left\{f_i\left(\mathbf{A}'\right)-f_i\left(\mathbf{A}''\right)\middle|\mathbf{A},\mathbf{A}',\mathbf{A}''\in\mathbf{P},\mathbf{A}\notin Bd_i : f_i\left(\mathbf{A}''\right) < f_i(\mathbf{A}) < f_i\left(\mathbf{A}'\right)\right\} \tag{10}$$

$$\zeta_i(\mathbf{A},\mathbf{P}) = \begin{cases} 2\times\max\left\{D_{A'}\right\}, & \text{if } \mathbf{A},\mathbf{A}'\in\mathbf{P},\mathbf{A}\in Bd_i,\mathbf{A}'\notin Bd_i \\ D_A, & otherwise \end{cases} \tag{11}$$

Using the crowding-distance of antibody **A** in the population **P**, the density of antibodies surrounding **A** can be estimated. Antibodies with larger crowding-distances will have higher affinities and will be more likely to survive and proliferate.

Base on the above coding scheme, the proposed algorithm MOIA-PS works as follows.

Algorithm 2 Multi-objective Immune Algorithm with Preference-based Selection (MOIA-PS)

Input: Max_{FE} the maximum number of function evaluations, n_D: the maximum size of dominant population, n_A: the maximum size of active population, cs: the clone size.

Output: D_{t+1} as the resulting approximate Pareto-optimal set.

Step 1 **Initialization:** Generate initial antibody population $\mathbf{P}_0 = \left(\mathbf{A}^1,\cdots,\mathbf{A}^{n_D}\right)$ with size n_D at random and evaluate the objective functions. Set the initial active population $\mathbf{V}_0$ and the clone population $\mathbf{C}_0$ as empty sets. Set the iteration time t=0.

Step 2 **Activation:** Select n_A individuals from the current population $\mathbf{P}_t$ to form the active population $\mathbf{V}_t$ by using the following steps:

Step 2.1 Identify dominant antibodies in $\mathbf{P}_t$, copy all the dominant antibodies to form the temporary dominant population **TP**. If the size of **TP** is not greater than n_A, let $\mathbf{V}_t$= **TP**, go to Step3. Otherwise, go to Step 2.2;

Step 2.2 Apply the preference-based selection operator described in algorithm 1 on **TP**, giving rise to **TP′** with maximum size of n_A. Note the size of **TP′** as $N_{\mathrm{TP}'}$. If $N_{\mathrm{TP}'} < n_A$, add **TP′** to $\mathbf{V}_t$ and select the remaining $n_A-N_{\mathrm{TP}'}$ antibodies from **TP**−**TP′** using the non-dominated sorting method to form $\mathbf{V}_t$, then go to Step 3. Otherwise, let $\mathbf{V}_t$=**TP′**, go to Step 3.

Step 3 **Proportional Cloning:** Get the clone population $\mathbf{C}_t$ by applying the proportional cloning to $\mathbf{V}_t$. The clone size of the i-th antibody $\mathbf{A}^i$ in $\mathbf{V}_t$ is proportional to its affinity and can be calculated by Eq. (12):

$$q_i = \left\lceil cs\times\frac{Affinity\left(\mathbf{A}^i|\mathbf{V}_t\right)}{\sum_{j=1}^{n_A}Affinity\left(\mathbf{A}^i|\mathbf{V}_t\right)}\right\rceil \tag{12}$$

where i=1,2,⋯,n_A and n_A is the size of population of $\mathbf{V}_t$. $\lceil x\rceil$ returns the smallest integer no less than x. The antibody affinity has been defined by Eq. (7).

Step 4 **Immune Genetic Operation:** Perform the simulated binary crossover and the polynomial mutation operator (Deb et al. 2002) on each antibody in clone population $\mathbf{C}_t$, giving rise to the offspring antibody population $\mathbf{C}_t^{'}$

Step 5 **Update the current population:** Select n_D antibodies from $\mathbf{P}_t \cup \mathbf{C}_t^{'}$ by using the non-dominated sorting method to form $\mathbf{P}_{t+1}$.

Step 6 **Stopping Criteria:** If the number of function evaluation $\geq Max_{FE}$, output non-dominant antibodies in the population $\mathbf{P}_{t+1}$. Otherwise, $t=t+1$. Go to Step 2.

The selection operator is one of the key issues of a population based evolutionary algorithm for optimization, especially for multi-objective optimization. The essence of selection is the allocation of computing resources. In the proposed MOIA-PS, the survival ability of an antibody is determined by three aspects, including the non-domination rank, the crowding distance and the satisfaction of the final upstream water level constraint. The activation step of the algorithm reflects the influences of the tree factors to the survival ability of antibodies. In the proportional cloning of the algorithm, antibodies with high affinity values will have more proliferating offspring. In which, the affinity of an antibody is determined by its non-domination rank and crowding distance. In conclusion, the key innovation of the proposed algorithm is the development of the selection operator based on the preference information of RFCO problem.

5 Application to Multi-objective Reservoir Flood Control Operation

Ankang Reservoir is the biggest hydrojunction project in Shaanxi Provence of China, which is located on the upper reach of Hanjiang River with the map shown as Fig. 2.

Fig. 2 Map of Hanjiang River basin and AnKang Reservoir

Ankang Reservoir consists of reservoir, hydropower station, and navigation structures, which has comprehensive benefits of flood control, power generation, shipping, and other aspects, and flood control is its main task. The maximum storage of Ankang Reservoir is 23×10^8 m^3, the dam height 128 m, the design flood water level 333 m, the check flood water level 337.05 m, the normal water level 330 m,the flood limit water level 325 m, the dead water level of 300 m, the design flood peak discharge 36700 m^3/s, the check flood peak discharge 45000 m^3/s, the maximum discharge 37474 m^3/s, the storage coefficient is less than 5 %. Therefore, the Ankang Reservoir faces a conflict of flood control between reservoir and downstream area in the flood season and it is of much significance to make reasonable flood control operation schemes in respect of protecting the safety of Ankang Reservoir and its downstream area. In the study, the proposed MOIA-PS is applied to solve the reservoir flood control operation for Ankang Reservoir.

In this work, we use discharge volume as the decision variable to encode the particles in the MOIA-PS algorithm. Each antibody in the population can be coded as a series of discharge volumes during T scheduling periods, that is $\mathbf{A}=\{a_1,a_2,\cdots,a_T\}$ where a_t (t=1, 2, …, T) is the discharge volume of the individual in the t-th period. The parameters of the MOIA-PS algorithm are set as following. The maximum size of dominant population n_D is set as 20, the maximum size of active population n_A is set as 10, the clone size cs is set as 3, and the flood control limit level Z_{FL} is 325 m. The preference threshold Z_{PT} is set to different values to form different versions of

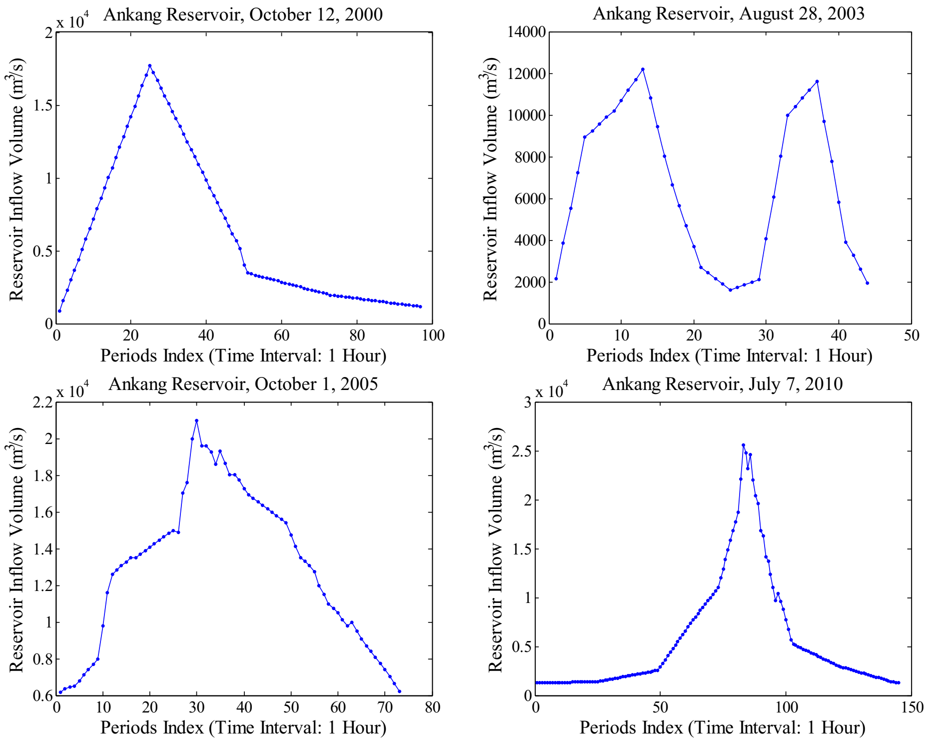

Fig. 3 Inflow volumes of floods at Ankang Reservoir

MOIA-PS. MOIA-PS (1 m) and MOIA-PS (2 m) represent the MOIA-PS with the preference threshold of 1 and 2 respectively. More specifically, MOIA-PS (1 m) will only find non-dominated solutions whose final upstream water level located between 324 m and 326 m. For MOIA-PS (2 m), the numbers of is between 323 m and 327 m. In order to validate the efficiency of the proposed algorithm, MOIA-PS is compared with NSGA-II and NNIA. One of the comparing algorithms NSGA-II is recognized as an efficient and robust multi-objective evolutionary algorithm. Another comparing algorithm NNIA (Coello and Cortes 2005) provides the multi-objective immune algorithm framework that the proposed MOIA-PS follows, it concerns no preference information.

To be fair, MOIA-PS, NNIA and NSGA-II employs the same crossover and mutation operators which are used in the original version of NSGA-II (Deb et al. 2002). The population sizes of NSGA-II and NNIA are both set as 20 in the following comparisons. The stop criteria of the algorithms compared are set as follows, each simulation continues until the total function evaluation number reaches the maximum value 20000.

The multi-objective model for RFCO problem which is to be solved has been defined in section 2. In these experimental studies, four typical floods that respectively occurred on October 12, 2000, August 28, 2003, October 1st, 2005 and July 7,

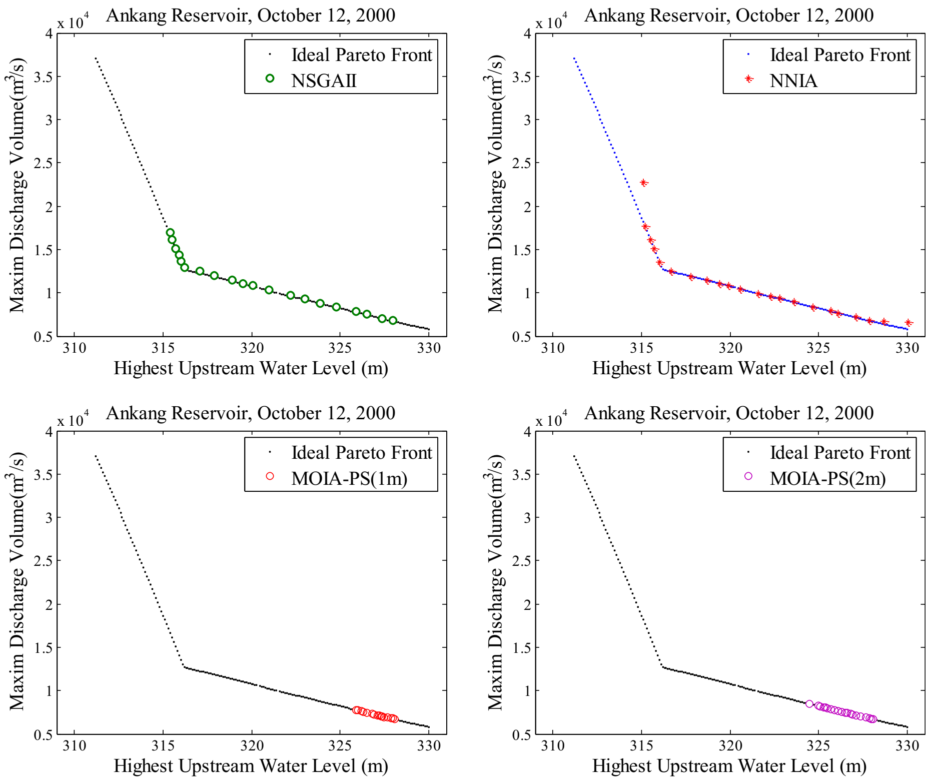

Fig. 4 Pareto optimal dispatching schemes obtained by the compared algorithms for the flood on October 12, 2000

2010 at the Ankang reservoir are investigated. Figure 3 illustrates the reservoir inflow volumes of these four floods. It can be seen in these figures that the floods on October 12, 2000, October 1st, 2005 and July 7, 2010 have one flood peak. The inflow volumes of these floods have different curve shape, maximum inflow volumes per second and total water volumes. Different from these three floods, the flood on August 28, 2003 has two flood peaks with relatively low maximum inflow volumes per second.

Figures 4, 5, 6, 7, 8, 9, 10 and 11 illustrate the experimental results of the four compared algorithms, which are NSGA-II, NNIA, MOIA-PS (1 m) and MOIA-PS (2 m), in solving the four multi-objective RFC problems. In Figs. 2, 6, 8 and 10, the ideal Pareto fronts of the four multi-objective RFCO problems are the non-dominated solution sets obtained by running NNIA with 2,000,000 function evaluations over 30 runs. The total dispatching times of the floods on October 12, 2000, October 1st, 2005 and July 7, 2010 are 97 h, 44 h, 73 h and 145 h. Their dispatching time intervals are set as 6 h, 3 h, 4 h, and 6 h respectively to control the number of the decision variables.

As is shown in Fig. 4, NNIA provides a set of dispatching schemes with better diversity than those obtained by NSGA-II. The Pareto optimal solutions found by NNIA cover wider part of the ideal Pareto front than NSGA-II, especially within the

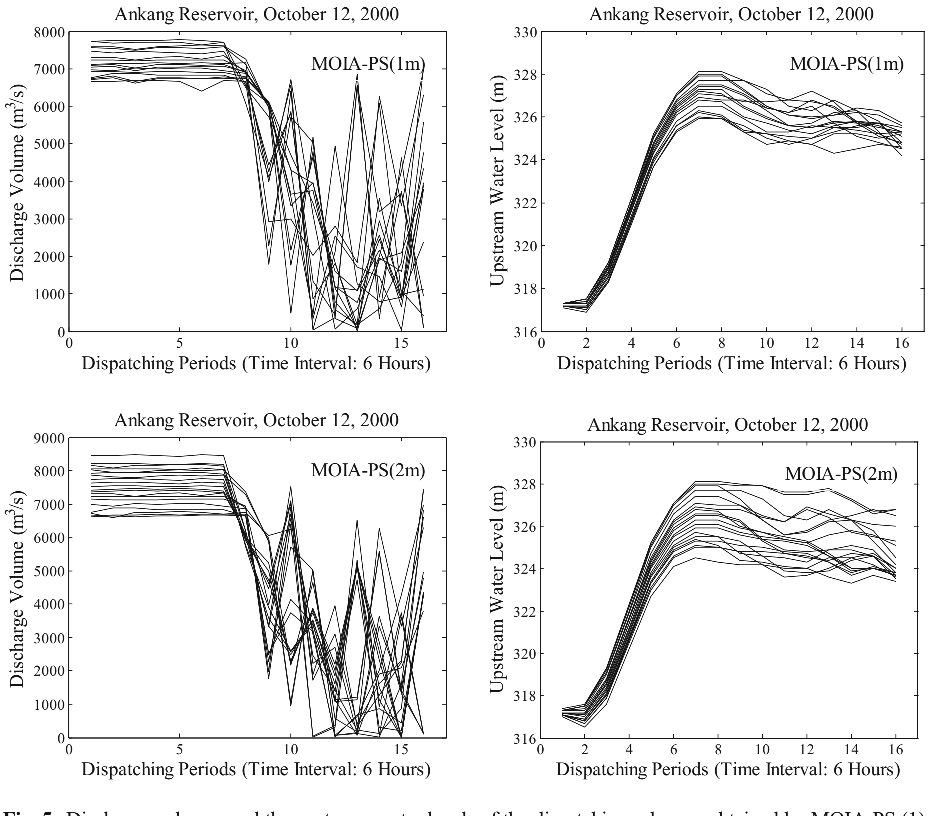

Fig. 5 Discharge volumes and the upstream water levels of the dispatching schemes obtained by MOIA-PS (1) and MOIA-PS (2) for the flood on October 12, 2000

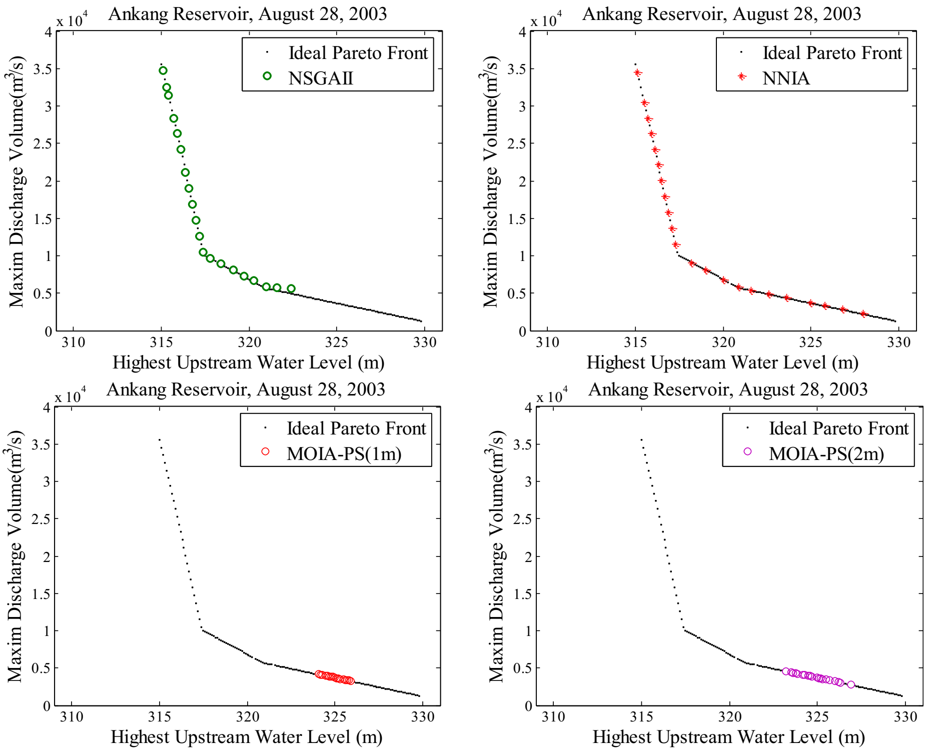

Fig. 6 Pareto optimal dispatching schemes obtained by the compared algorithms for the flood on August 28, 2003

preferred region whose highest upstream water levels lie between 320 m and 300 m. MOIA-PS (1 m) and MOIA-PS (2 m) converge to the preferred part of the Pareto front successfully. Therefore, comparing with NNIA, the proposed MOIA-PS can provide more candidate dispatching schemes that satisfies the upstream water level constraint at the end of the flood. It is a more efficient use of the computing efforts of the algorithm.

Figure 5 illustrates the discharge volumes and the upstream water levels of the dispatching schemes obtained by MOIA-PS (1) and MOIA-PS (2). It can be seen that, at end of the flood, the upstream water levels of the dispatching schemes provided by MOIA-PS (1) locate evenly within the preferred region, between 324 m and 326 m. As for MOIA-PS (2), the final upstream water levels of the dispatching schemes lie between 323 m and 327 m. On the other hand, the dispatching schemes provided by MOIA-PS (1) and MOIA-PS (2) have their maximum discharging volumes less than 8000 m^3/s and 9000 m^3/s, which is about half of the maximum inflow volume of the reservoir 17730 m^3/s. This demonstrates the fact that the proposed MOIA-PS can significantly reduce the flood peak and the flood damages.

Figures 6 and 7 illustrate the dispatching schemes provided by the compared algorithms for the flood on August 28, 2003. Different from the flood on October 12, 2000, this flood has two flood peaks and a maximum inflow volume 12200 m^3/s which is much lower.

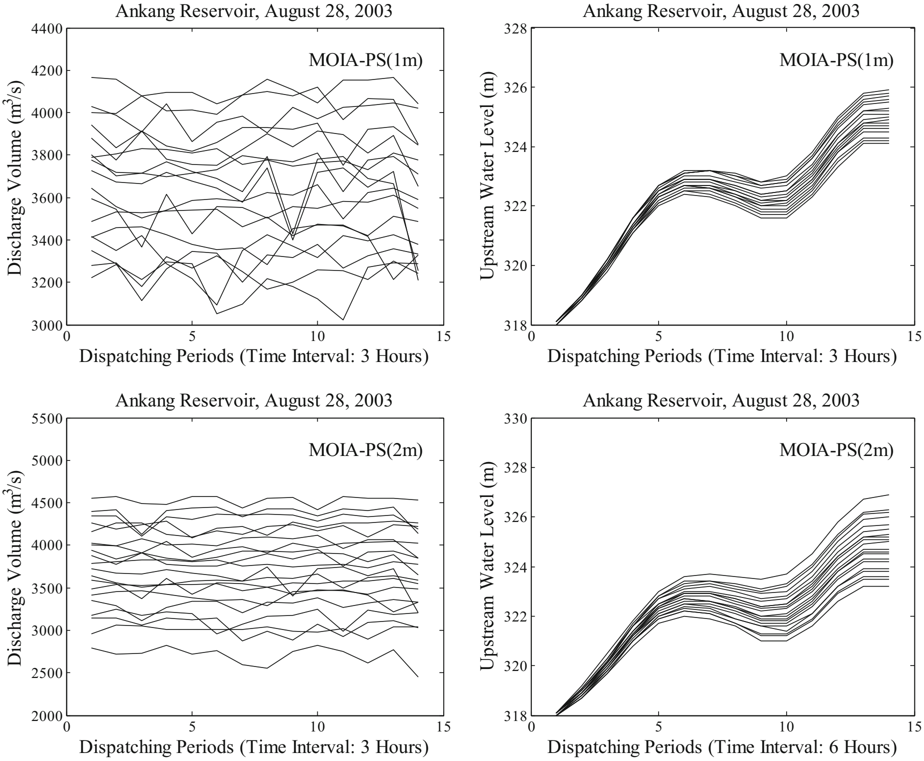

Fig. 7 Discharge volumes and the upstream water levels of the dispatching schemes obtained by MOIA-PS (1) and MOIA-PS (2) for the flood on August 28, 2003

From Fig. 6, it can be seen that NSGA-II fails to obtain solutions within the preferred region of the Pareto front. On the other hand, NNIA performs well, and provides a set of uniformly distributed non-dominated solutions which covers the whole ideal Pareto front of the problem. MOIA-PS (1) and MOIA-PS (2) also converge to the preferred regions with different sizes. We can come to the similar conclusion that MOIA-PS can provide much stronger decision support than NNIA.

As is shown in Fig. 7, MOIA-PS (1) and MOIA-PS (2) obtain dispatching schemes with stable discharge volumes for the flood on August 28, 2003 whose inflow volume curve has relatively minor fluctuation. It shows that the dispatching schemes provided by MOIA-PS keep the downstream reservoir free from the effects of the upstream flood. As for the upstream water level, the curves climb up steadily to the final water level about 325 m, which will not pose any threat to the safety of the dam.

Figures 8 and 9 show the performances of the compared algorithms on the flood on October 1st, 2003. This flood is a challenging flood hydrograph which has one flood peak with maximum inflow of 21000 m^3/s and a high total inflow water volume. For such a difficult problem, the ideal Pareto front is a sharp turning curve whose convex corner angle is smaller than that of a relatively simpler problem. That is to say, at the preferred region of the Pareto front, one optimization goal gets bad rapidly with the

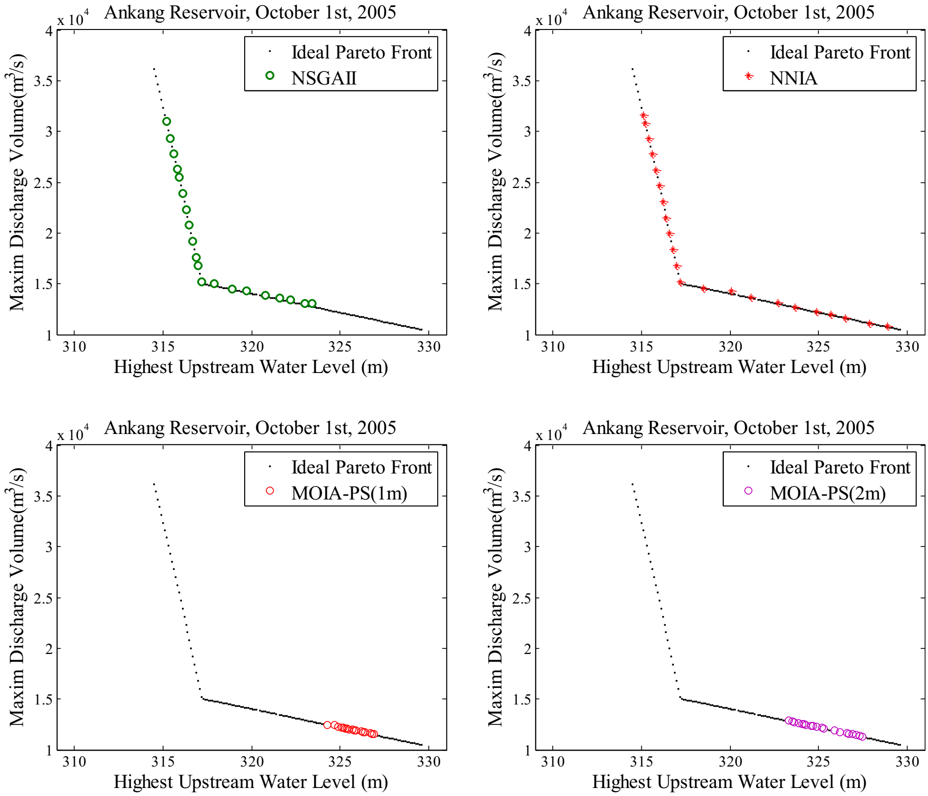

Fig. 8 Pareto optimal dispatching schemes obtained by the compared algorithms for the flood on October 1st, 2005

other optimization goal improves, which raises a great challenge to the optimization algorithms for flood control operation.

As is shown in Fig. 8, NNIA performs much better than NSGA-II on this difficult problem. It obtains a set of evenly scattered and widely spread non-dominated solutions that covers the preferred region of the ideal Pareto front notably better than NSGA-II. MOIA-PS (1) and MOIA-PS (2) converge to the preferred regions tightly, they provide dense and evenly distributed solution sets within preferred regions with different preference thresholds.

Figure 9 shows the details of the dispatching schemes obtained by MOIA-PS (1) and MOIA-PS (2) for the flood on October 1st, 2005. It can be seen that MOIA-PS successfully reduce the flood peak down to no more than 14000 m^3/s. At most of the dispatching time, from the beginning, the discharge volumes of the dispatching schemes remain stable. While at the end of the dispatching periods, the discharge volumes decrease rapidly to meet the constraint of the final upstream water level limit. The upstream water levels of the dispatching schemes never get too high. At the beginning, the upstream water levels remain at low values to allow for the inflow of flood waters. While at the end of the flood, the upstream water levels climb up to satisfy the irrigation water needs.

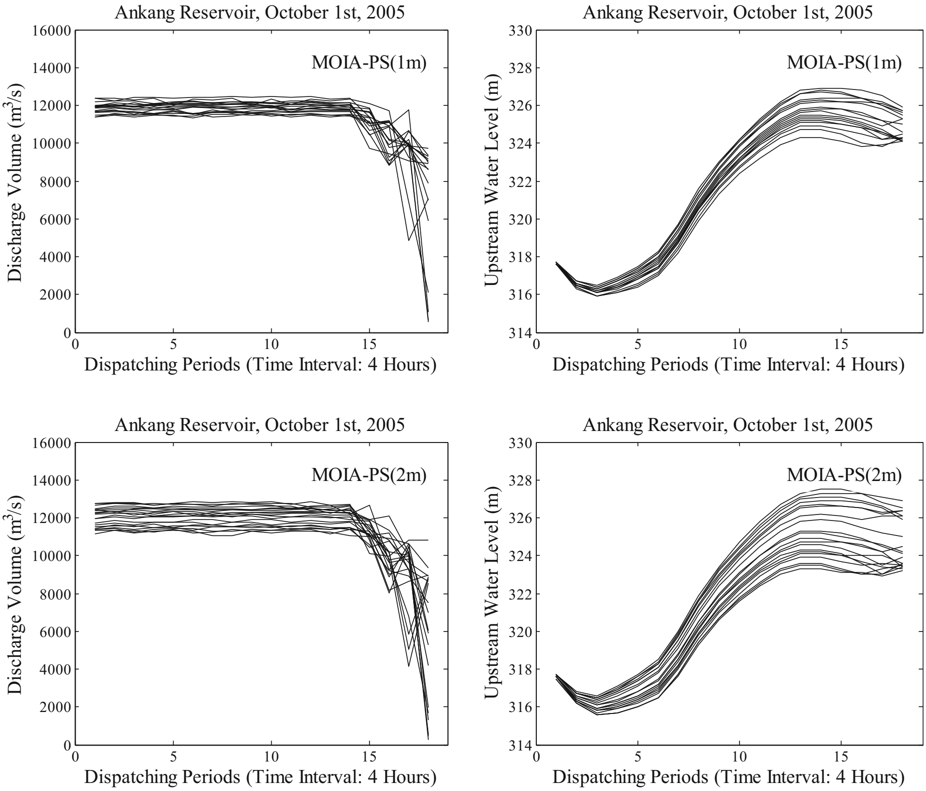

Fig. 9 Discharge volumes and the upstream water levels of the dispatching schemes obtained by MOIA-PS (1) and MOIA-PS (2) for the flood on October 1st, 2005

Figures 10 and 11 illustrate the dispatching results of the compared algorithms for the flood on July 7, 2010. This flood has the highest flood peak among the four investigated floods, its flood peak happens in a sudden, with a maximum inflow volume up to 25537 m^3/s.

As is shown in Fig. 10, NSGA-II converges to the knee part of the Pareto front curve and it fails to converge tightly to the ideal Pareto front. As for NNIA, the non-dominated solutions spread wider over the ideal Pareto front. Especially at the preferred region, they locate close to the ideal Pareto front and distribute evenly.

As for the discharge volumes and the upstream water levels which are shown in Fig. 11, we can come to the similar conclusion as that of the flood on October 1st, 2005. The only difference is that the upstream water levels of the dispatching schemes for this flood decline significantly at the beginning of the dispatching periods to prepare for the sudden increase of the inflow water volume.

From the experimental results the analyses above, we can come to the following conclusions. 1) The preferred non-dominated solutions whose final upstream water levels are close to certain value to cope with the irrigation demands are distributed within a local area on the Pareto front, termed as the preferred PF region. 2) The newly designed preference-based selection operator can guide the search of a multi-

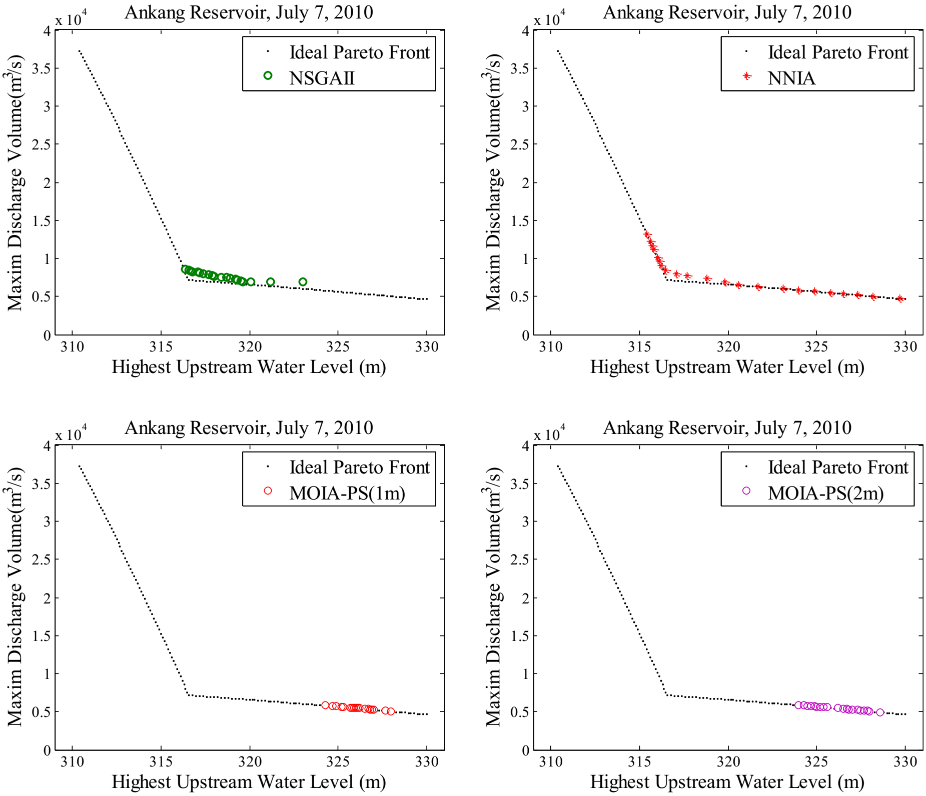

Fig. 10 Pareto optimal dispatching schemes obtained by the compared algorithms for the flood on July 7, 2010

objective optimization algorithm for reservoir flood control operation problem towards the preferred PF region. 3) By using the preference-based selection operator, MOIA-PS devotes its computing efforts to solutions that meet the constraint of the final upstream water level limit, and thus provides more candidate dispatching schemes that preferred by the decision makers.

When looking at the details of the dispatching schemes provided by MOIA-PS, we can come to the conclusion that the proposed MOIA-PS can significantly reduce the flood peak. At the same time, it guarantees the upstream water levels never get too high to threaten dam safety and satisfies the upstream final water level constraint for the irrigation purpose.

6 Conclusions

Reservoir flood control operation is the problem of planning and scheduling the dams and reservoirs during floods. It is a type of complex optimization problem that involves continuous and interdependent decision variables and multiple objectives. Following the immune inspired multi-objective optimization algorithm framework, a preference-based immune algorithm named MOIA-PS is proposed in this work for solving multi-objective reservoir flood control operation problems. To cope with the needs of irrigation, the dispatching schemes with certain

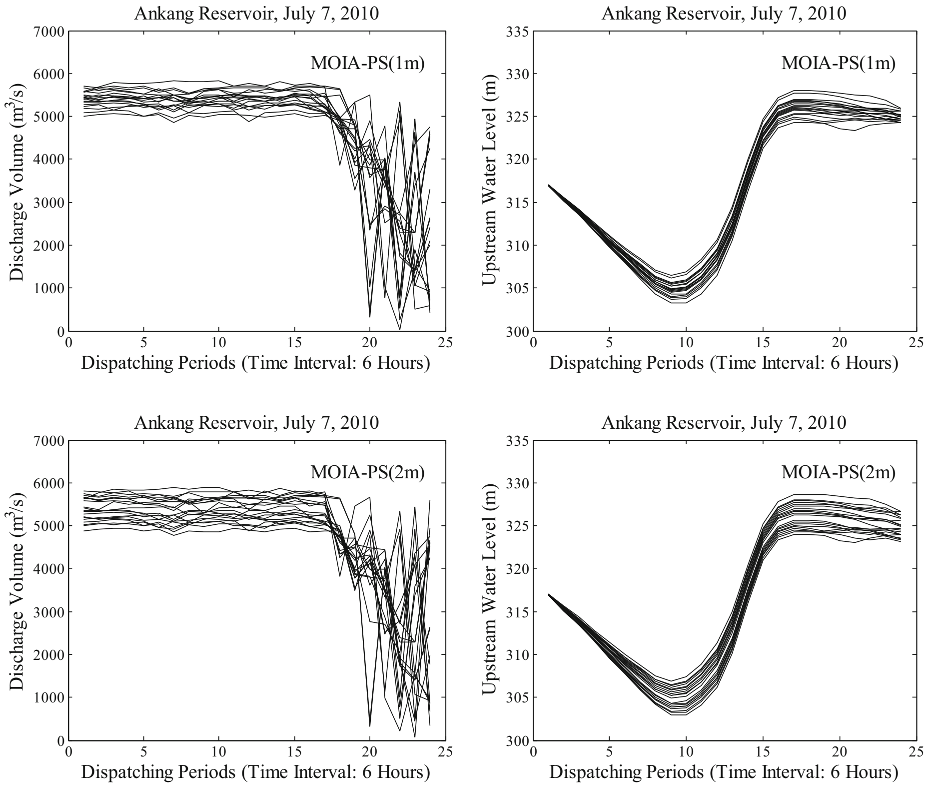

Fig. 11 Discharge volumes and the upstream water levels of the dispatching schemes obtained by MOIA-PS (1) and MOIA-PS (2) for the flood on July 7, 2010

given upstream water level at the end of the flood are preferred by the decision makers. Based on this prior information, the affinity of antibody in MOIA-PS is determined by three aspects, including the non-domination rank, the crowding distance and the satisfaction of the final upstream water level constraint. With the preference based selection operator, MOIA-PS was expected to obtain non-dominated solutions that are located at the preferred region of the Pareto front.

Experimental results on four typical floods at the Ankang reservoir have indicated that the preferred non-dominated solutions are distributed within a local area of preferred PF region. With the help of the newly designed preference-based selection operator which guides the search towards the preferred PF region, the proposed MOIA-PS successfully obtains more non-dominated solutions that densely and evenly scattered within the preferred area of the Pareto front than the compared algorithms NSGAII and NNIA. The dispatching schemes provided by MOIA-PS can reduce the flood peak significantly and guarantee the dam safety well. MOIA-PS can provide much stronger decision support than the compared algorithms. Moreover, it is an efficient utilization of the computing efforts.

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