Maximizing Hydropower Generation in Flood Control Operation using Preference Based Multi-objective Evolutionary Algorithm

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Abstract. Reservoir flood control operation (RFCO) is a challenging optimization problem with multiple objectives which are conflicting with each other. In this work, a tri-objective optimization model which maximizes hydropower generation during flood control is investigated and a multi-objective optimizer based on decomposition technique and the decision maker’s preference information is developed. Experimental studies on typical floods at Ankang reservoir indicate the effectiveness of the proposed algorithm. It successfully provides preferred scheduling plans with more hydro-power generations than those considering the safety objectives only.

1. Introduction
Reservoir flood control operation (RFCO) problem is a nonlinear and non-convex optimization problem. It involves multiple long-term and short-term objectives which are conflicting with each other [1]. During the process of flood control, the safety of both upstream and downstream are of course the two major issues. Research works have been done to guarantee the flood control safety by minimizing the peak values of discharge water volume and the upstream water level simultaneously [2]. However, few efforts have been devoted to maximizing the hydropower generation in flood control operation. This work considers the objective of hydropower generation in flood control and investigates a tri-objective optimization model for RFCO problem.

As a consequence of the rapid progress in the last few years in multi-objective optimization techniques [3], more and more research efforts have been devoted to optimizing the conflicting optimization objectives in RFCO problems simultaneously, instead of converting it into single objective optimization problem as before. Yu et al. developed a multi-objective fuzzy decision-making model for RFCO problem [4]. Kim et al. proposed a multi-objective optimizer for RFCO problem using genetic algorithm [5]. Nagesh-Kumar et al. presented a particle swarm optimization algorithm to optimize the reservoir operation policies [6]. Afshara et al. suggested a multi-objective optimizer for RFCO problem using ant colony optimization algorithm [7]. Li et al. developed a shuffled frog leaping algorithm for multi-objective RFCO problem [8]. Qin et al. proposed a bi-objective model for RFCO problem and developed a cultured differential evolution algorithm to solve it [2]. Qi et al. developed an immune inspired algorithm for multi-objective RFCO problem [9]. Luo et al. suggested a hybrid multi-objective algorithm for RFCO problem by combing the particle swarm optimization and the estimation of distribution algorithm together [10].

Despite the success of multi-objective optimization algorithms for RFCO problem, almost all of them were developed with the aim of obtaining a set of trade-off solutions that approximates the entire Pareto front (PF) which is the set of all the best trade-off solutions. Few efforts have been devoted to incorporate the decision maker’s (DM) preference into multi-objective optimizers for RFCO problems, although the preference based multi-objective optimization is not brand new in the community of multi-criteria decision making [11]. According to our previous investigations [9][12], multi-objective RFCO problems have irregularly shaped
PFs which pose a big challenge to multi-objective optimization algorithms [13]. Moreover, in multi-objective RFCO problems, the difficulties of obtaining solutions at different PF regions could be various. In this case, multi-objective optimizers can hardly obtain a set of non-dominated solutions with good enough coverage on the PF. Instead, algorithms can converge to different PF regions on different flood instances without control. Such situation becomes even worse when solving a tri-objective optimization model for RFCO problem which considers hydropower generation in flood control.

Since it is challenging and unnecessary to approximate the entire PF in multi-objective RFCO problems, a preference based optimizer which obtains trade-off solutions at the preferred PF region could be a promising substitute. In our previous work, we considered the final upstream water level (FUWL) preference in bi-objective RFCO problem and developed a preference based selection mechanism for immune inspired multi-objective optimizer [14]. On the other hand, we developed preference based multi-objective optimization algorithm using decomposition technique and applied it to solve bi-objective RFCO problem. In this algorithm, the DM’s preference information is expressed by using the light beam search preference model [17] in the objective space. However, in RFCO problem, the FUWL preference is implicit, it is difficult to articulate in the objective space by using existing preference representation techniques. This paper extends our previous work and contributes in three aspects. 1) The objective of hydropower generation is considered in flood control and a tri-objective optimization model for RFCO problem is developed. 2) A preference modeling method which converts the FUWL preference into a preferred region in the objective space is designed. 3) According to the preferred region which is dynamically determined by the proposed preference modeling method, a preference based multi-objective evolutionary algorithm is developed for RFCO problem.

The remainder of this paper is organized as follows. Section 2 describes the tri-objective optimization model for RFCO problem. Section 3 presents the preference modeling method for presenting the FUWL preference in RFCO problem. Section 4 describes the flowchart of the proposed algorithm. Section 5 verifies the effectiveness of the proposed algorithm. Section 6 conclusions this paper.

2. Multi-objective Model for RFCO Problem

Taking the hydropower generation and the FUWL preference into consideration, this work investigates the following tri-objective optimization model for RFCO problem.

\[
\begin{align*}
\text{Minimize} & \quad F(Q) = (f_1(Q), f_2(Q), f_3(Q)) \\
& \quad f_1(Q) = \max(Z_t), \quad t = 1, 2, L, T \\
& \quad f_2(Q) = \max(Q_t), \quad t = 1, 2, L, T \\
& \quad f_3(Q) = 1/E \\
\text{Subject to:} & \\
& \quad Z_{\text{min}} \leq Z_t \leq Z_{\text{max}} \\
& \quad 0 \leq Q_t \leq Q_{\text{max}} \\
& \quad V_t = V_{t-1} + I_t - Q_t \\
& \quad Z_t \to Z_{fL} \\
\end{align*}
\]

(1)

where \(Q = (Q_1, Q_2, \ldots, Q_T)\) is the water release volumes at \(T\) scheduling periods. Each \(Q_t\) \((t = 1, 2, \ldots, T)\) has a non-negative value no larger than \(Q_{\text{max}}\). \(Z_t\) is the upstream water level of the \(t\)-th scheduling period, it has a value between \(Z_{\text{min}}\) and \(Z_{\text{max}}\). \(V_t\) and \(I_t\) are respectively the reservoir storages and the reservoir’s inflow volume of the \(t\)-th scheduling period. \(Z_{fL}\) is the final target upstream water level at the end of the scheduling. \(E\) is the hydropower generation, it can be calculated as following.
\[
E = \sum_{i=1}^{N} (N_i \cdot \Delta t) \quad (2)
\]

\[N_i = K \cdot Q_i \cdot H_i\]

where \(\Delta t\) is the time interval of the scheduling period, \(K\) is the efficiency coefficient. \(Q_i\) and \(H_i\) are respectively the water release volume and the water head of the \(i\)-th scheduling period. The average output \(N_i\) has a lower bound \(N_{\text{min}}\) and an upper bound \(N_{\text{max}}\).

In the optimization model in equation (1), \(f_1(Q)\) means the highest upstream water level. It should be minimized to guarantee the safety of the upstream side. \(f_2(Q)\) is the largest water release volume. We minimized it to protect the downstream side. \(f_3(Q)\) is the reciprocal of hydropower generation. We convert the maximization of hydropower generation during flood into minimization of its reciprocal.

3. Presentation of DM’s Preference

The proposed preference modeling method converts the FUWL preference into a preferred region in the objective space. At each iteration of the multi-objective optimization algorithm for RFCO problem, the individuals whose final upstream water levels lie in between \(Z_{FL} - Z_{PT}\) and \(Z_{FL} + Z_{PT}\) are identified from the evolving population to form the preferred solution set \(S^{\text{P}}\). According to \(S^{\text{P}}\), the preferred region \(P^{\text{P}}\) can be determined by a middle point \(M = (M_1, M_2, M_3)\) and a veto threshold vector \(V = (V_1, V_2, V_3)\) as following.

\[
P^{\text{P}} = \{Q \mid f_1(Q) - M_1 \leq V_1 \text{ and } f_2(Q) - M_2 \leq V_2\} \quad (3)
\]

\[
M = \left\{F(Q) \mid \min \left\{\|FL(Q) - Z_{FL}\|, Q \in S^{\text{P}}\right\}\right\} \quad (4)
\]

\[
V = \{(V_1, V_2, V_3) \mid V_1 = 1.2 \hat{V}_1, V_2 = 1.2 \hat{V}_2, V_3 = \infty\} \quad (5)
\]

\[
\hat{V}_i = \max \left\{\|f_i(Q) - M_i\|, Q \in S^{\text{P}}, i = 1, 2\right\} \quad (6)
\]

As shown in equation (3), the preferred region is defined based on the first two objectives, because the objective value of hydropower generation is the larger the better. In equation (4), \(FL(Q)\) denotes the final upstream water level of the individual \(Q\). The middle point is defined as the objective vector of the individual whose final upstream water level is the closest to \(Z_{FL}\). The veto threshold vector extends the calculated result \(\hat{V}\) by 20\%. The motivation behind this extension is to provide better coverage of the preferred region.

Based on the definition of the preferred region, a measure of preference level, denoted as \(PL(Q)\), is defined on each individual \(Q\) to rank the preference degree of individuals.

\[
PL(Q) = \sqrt{\sum_{i=1}^{3} \left(\frac{f_i(Q) - M_i}{V_i}\right)^2} \quad (7)
\]

4. The Proposed Algorithm

Due to its simplicity and efficiency, the multi-objective evolutionary algorithm based on decomposition (MOEA/D) has achieved a great success and attracted a lot of attention [17]. MOEA/D decomposes the target multi-objective optimization problem (MOP) into a number of scalar optimization sub-problems by employing an aggregation approach with a set of evenly scattered weight vectors. And then, these decomposed sub-problems are solved simultaneously in a collaborative manner by using an evolutionary algorithm.

Given the target MOP with \(m\) objectives \(f_1(x), \ldots, f_m(x)\) and a weight vector \(\lambda = (\lambda_1, \ldots, \lambda_m)\), \((\sum_{i=1}^{m} \lambda_i = 1, \lambda_i \geq 0\),
\( i = 1, \ldots, m \) the weighted Tchebycheff aggregation approach decomposes the target MOP into the following scalar optimization problem.

\[
g^e(x|\lambda, \lambda^e) = \min_{x \in \Omega} \max_{i = 1}^{m} \{ |f_i(x) - z_i^e| \} \tag{8}
\]

In which, \( \lambda^e = (1, \ldots, 1) \) starting from \( z^e \) has an intersection with the PF of the target MOP, then the intersection point is the optimal solution of the scalar optimization sub-problem with weight vector \( \lambda^e \). We have also defined the WS-transformation which is a map from \( \lambda \) to \( \lambda^e \) as following [13].

\[
\lambda^e = WS(\lambda) = \left( \frac{1}{\lambda_1}, \ldots, \frac{1}{\lambda_m} \right)
\]

It should be noted that the WS-transformation is self-inverse (i.e. \( \lambda = WS(\lambda^e) = WS(WS(\lambda)) \)). Based on this property, if we want to obtain some non-dominated solutions located within preferred PF region, we can generate some scalar optimization sub-problems with specific weight vectors which take those preferred solutions as optimal solutions. That is the basic idea of the preference based MOEA/D (p-MOEA/D) we developed in our previous work [15]. p-MOEA/D guides the search of MOEA/D towards the preferred PF region by removing scalar sub-problems from unwanted PF areas and add new ones into the preferred region.

This work inherits the preference based weight adjustment strategy in p-MOEA/D, design a new preference modeling method for representing the FUWL preference in tri-objective RFCO problem, and develop a preference and decomposition based multi-objective optimizer for RFCO problem (PD-RFCO). At each iteration, PD-RFCO maintains the following. 1) An evolving population with \( N \) individuals \( \{ \mathbf{x}_i \}_{i=1}^{N} \), each \( \mathbf{x}_i \) records the current solution \( \mathbf{x}^e \) to the \( \mathbf{x} \)-th scalar sub-problem and its objective values \( FV_i \). 2) A set of \( N \) weight vectors \( \Lambda = \left\{ \lambda^e, \ldots, \lambda^N \right\} \) and a neighborhood list for each subproblem \( B = \{ B_1, \ldots, B(N) \} \). 3) An estimated ideal point \( \mathbf{z}^e \). 4) An external population \( EP \). The pseudo code of the proposed algorithm is as follows.

| Algorithm 1: PD-RFCO |
|----------------------|
| **Input:** Population size \( N \), external population size \( N^e \), neighborhood size \( T \), initial middle point \( M^p \) and veto threshold vector \( V^p \), maximal number of adjusted scalar sub-problems \( N^d \), iteration interval \( T^f \), and the maximal function evaluation number \( FE_{\text{max}} \). |
| **Output:** \( \{ \mathbf{x}^e, \ldots, \mathbf{x}^N \} \) and \( \{ FV^e, \ldots, FV^N \} \) |
| 1. **Initialization** \( \{ \Lambda, B, \text{pop}, \mathbf{x}^e, EP, M, V \} \); |
| 2. \( \text{Gen} = 0 \); |
| 3. **While** function evaluations \( < FE_{\text{max}} \) do |
| 4. Evolving \( \{ \text{pop}, \mathbf{x}^e \} \); |
| 5. UpdateEP \( \{ EP, \text{pop}, N^e \} \); |
| 6. UpdatePreferredRegion \( \{ EP, M, V, S^e \} \); |
7. \textbf{If} \(|E| > N\) and \(|S^+| > 2\) and Gen mod \(I^{WA} = 0\) \textbf{do}

8. RemoveSubproblems\(\{N^{WA}, M, V, pop, A, B\}\);

9. AddNewSubproblems\(\{N^{WA}, M, V, pop, A, B\}\);

10. \textbf{End If}

11. Gen++;

12. \textbf{End While}

13. \textbf{Return} \(\{x^1, \ldots, x^N\}\) and \(\{FV_1, \ldots, FV_N\}\)

In algorithm 1, the initialization step (line 1) and the evolving step (line 4) are exactly the same as those in MOEA/D [17]. In this work, the simulated binary crossover and the polynomial mutation are employed to generate new individuals. The ideal point is also updated in the evolving step.

In the UpdateEP step (line 5), non-dominated solutions are first identified from the union set of current \(EP\) and \(pop\), giving rise to a temporary set of \(NS\). If the size of \(NS\) is no larger than \(N_E\), then copy \(NS\) to \(EP\). Otherwise, calculate the preference level of each individual in \(NS\) using to equation (7), and update \(EP\) by the individuals with the first \(N_E\) smallest preference levels in \(NS\).

In the UpdatePreferredRegion step (line 6), the preferred individuals with preference levels smaller than 1 are first identified from \(EP\) to form the population \(SP\). If \(SP\) contains more than two individuals, then update the middle point \(M\) and the veto threshold vector \(V\) according to equations (4) and (5-6) respectively.

In the RemoveSubproblems step (line 8), \(N^{WA}\) scalar sub-problems are removed from the evolving population. It chooses the scalar sub-problems that will be removed according to their preference neighbor distances. The ones locate outside the preferred PF region will be selected in priority. However, when preferred solutions will have to be removed, the ones with smaller crowding distances will be selected in the first place.

In the AddNewSubproblems step (line 9), \(N^{WA}\) individuals in the external population will be recalled into the evolving population and new weight vectors will be generated and added to the sub-problem set. On the contrary to the RemoveSubproblems step, the preferred solutions with smaller crowding distances will be selected in priority. When there are not enough preferred solutions, the ones with smaller preference neighbor distances will be selected in the first place.

5 Experimental Studies

In this section, typical floods at Ankang reservoir on the Hanjiang river in Shanxi Province of China are investigated. The Ankang reservoir has a maximum water capacity of 2.585 billion cubic meters, a normal water level of 330 meters, a flood control limit level of 325 meters, a dead water level of 300 meters and a designed discharge capacity of 37474 cubic meters per second. The annual hydropower generation of Ankang station is about 2.857 billion KWH.

The parameters of the proposed PD-RFCO are set as follows. The evolving population size \(N\) is set to 100 and the external population size \(N_E\) is set to 250. The neighborhood size \(T\) is set to 10. The initial middle point \(M^0=(325,10000,\cdot)\) and the veto threshold vector \(V^0=(4,1000,\cdot)\). The maximal number of adjusted scalar sub-problems \(N^{WA}\) is set to 20. The iteration interval of weight adjustment \(I^{WA}\) is set to 500. The maximal function evaluation number \(F_{E\text{max}}\) is set to 10^6 times. The final target upstream water level at the end of the scheduling \(Z_{FLZ}\) is set to 325. The preference threshold \(Z_{PT}\) is set to 2.
Figure 1. Forecasted inflow of investigated floods.

Figure 1 is the forecasted water inflow volumes of the investigated floods. The flood on August 28, 2003 (left) lasts for 44 hours, it has two flood peaks and relatively low maximum inflow volumes per second. The flood on October 1, 2005 (right) lasts for 73 hours, it has one higher flood peak and larger total water volumes.

Figure 2. Obtained non-dominated solutions.

Figure 2 illustrates the Pareto optimal solutions obtained by the proposed PD-RFCO. The estimated Pareto fronts in this figure are obtained by running MOEA/D-AWA [13] with 6,000,000 function evaluations over 30 runs. It can be seen that the estimated PFs are complex in shape for both of the two flood instances. PD-RFCO successfully converge to a preferred region on the estimated PF. When looking at the distribution of the obtained non-dominated solutions within the preferred region, it has a much simpler shape comparing with the entire PF. Since the PF shape has a significant influence on the difficulty of a MOP, it is very challenging for a multi-objective optimizer to approximate the entire PF of the tri-objective RFCO problem. If we focus the search effort of the algorithm on a sub-region which is less complex in shape, the problem becomes easier. In addition, it is unnecessary to obtain non-dominated solutions that cover the entire PF, because only the ones within the preferred region are likely to be put into practice. Therefore, computing
efforts are more efficiently used the proposed PD-RFCO.

Figure 3 is the discharge volumes of the non-dominated solutions obtained by PD-RFCO. It can be seen that the scheduling schemes have maximum discharging volumes of less than 6000 m$^3$/s and 15000 m$^3$/s respectively for the two investigated floods, which are much lower than the peak inflow volumes of the two floods, say 12200 m$^3$/s and 21000 m$^3$/s respectively. Therefore, the proposed PD-RFCO successfully provides scheduling schemes that reduce the flood peak significantly.

Figure 3. Discharge volumes of obtained solutions.

Figure 4. Upstream water levels of obtained solutions.

Figure 4 shows the upstream water levels of the non-dominated solutions obtained by PD-RFCO. As shown in this figure, the final upstream water levels of the curves locate evenly within 2 meters above and below the flood control limit level of 325 meters as expected. These results indicate that PD-RFCO successfully obtains a set of preferred non-dominated solutions which evenly scattered over the specified preferred region.

Figure 5. Comparisons on hydropower generation.
Experimental studies have been conducted to make a comparison between the tri-objective optimization model for RFCO in equation (1) and the existing bi-objective optimization model which does not consider hydropower generation and minimizes \( f_1(Q) \) and \( f_2(Q) \) in equation (1) only. Figure 5 compares the hydropower generation of the non-dominated solutions obtained by PD-RFCO for solving the two optimization models respectively. In the box plots in this figure, the bottom and top of the box are respectively the first and third quartiles. The band inside the box is the second quartile, say the median. The ends of the whiskers represent the minimum and maximum of all the hydropower generation data. It can be seen that the boxes for the tri-objective model (right) are higher than those for the bi-objective model (left). This indicates the fact that by considering the maximization of hydropower generation in flood control, the optimizer can provide scheduling schemes with more hydropower generations.

6. Conclusions

In this work, a tri-objective optimization model which maximizes hydropower generation in flood control is developed for reservoir flood control operation (RFCO) problem. Considering the final upstream water level (FUWL) preference in RFCO problem, a new preference modeling method is designed by converting the FUWL preference into a preferred region in the objective space. The preference model is then incorporated into the algorithmic framework of the decomposition based multi-objective optimization algorithm (MOEA/D), giving rise to a preference and decomposition based multi-objective optimizer for RFCO problem (PD-RFCO).

Experimental studies have been done on two typical floods at Ankang reservoir to verify the effectiveness of the proposed PD-RFCO. Experimental results indicate that PD-RFCO obtains a set of non-dominated solutions which evenly scattered over the specified preferred region. And the scheduling schemes provided by PD-RFCO reduce the flood peak significantly. Comparison studies on multi-objective optimization models which consider and not consider the objective of hydropower generation have also been conducted. The results indicate that by considering the maximization of hydropower generation in flood control, the optimizer can provide scheduling schemes with more hydropower generations.

7. Acknowledgments

This work was supported by the National Natural Science Foundation of China under Grant Nos. 61303119 and 61202040, the Science and Technology Program of Shaanxi Province under Grant Nos. 2014KJ09-07 and 2015KJXX-30.

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