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Reservoir flood control operation using multi-objective evolutionary algorithm with decomposition and preferences

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ABSTRACT

In this paper we propose a preference-based multi-objective optimization model for reservoir flood control operation (RFCO). This model takes the water preserving demand into consideration while optimizing two conflicting flood control objectives. A preference based multi-objective evolutionary algorithm with decomposition, named MOEA/D-PWA, is developed for solving the proposed RFCO model. For RFCO, it is challenging to define the preferred region formally, as the preference information is implicit and difficult to formulate. MOEA/D-PWA estimates the preferred region dynamically according to the final water level of solutions in the population, and then guides the search by propelling solutions towards the preferred region. Experimental results on four types of floods at the Ankang reservoir have illustrated that the suggested MOEA/D-PWA can successfully produce solutions in the preferred region of the Pareto front. The schedules obtained by MOEA/D-PWA can significantly reduce the flood peak and guarantee the dam safety as well. The proposed MOEA/D-PWA is also efficient in term of computational cost.

1. Introduction

Flood disaster is considered as one of the world's most common natural disasters. To reduce from flood damages, dams and reservoirs are constructed to regulate water flow and reduce flood peaks [1]. Reservoir flood control operation (RFCO) problem is a nonlinear non-convex optimization problem that involves multiple long-term and short-term objectives [2]. During the flood season, the safety of both upstream and downstream, which are conflict with each other, becomes the major problem in RFCO. Due to the conflict between objectives, the RFCO problem can be modeled as a multi-objective optimization problem (MOP) [3].

At present, most research works on RFCO transform the multi-objective optimization task into single-objective ones by combining multiple objectives using weighted sum methods [4,5], or choosing the primary criterion as the only objective while keeping the others as constraints [6,7]. The main shortcoming of these methods is that they often assume the weights are known a prior, and the solutions produced by these methods are not necessarily always the best trade-off solutions. Such problems could become even worse when joint schedule among multiple reservoir is required. Recently, more research efforts have been devoted to solving the original RFCO problem by using advanced multi-objective optimization techniques [8,9]. These approaches optimize the conflicting objectives in RFCO problem simultaneously and generate a set of trade-off solutions which are termed as non-dominated solutions to the multi-objective RFCO problem. Given a diverse set of candidate solutions, a decision maker can make a more informed decision on whether solution is the most appropriate one for a given situation.

Most existing multi-objective methods for solving RFCO problems attempt to obtain a set of trade-off solutions, either with or without any preference information. However, only selected solutions from this set will be finally chosen by the decision makers [10]. In the RFCO problem, non-dominated solutions, whose final upstream water levels at the end of operating horizon are close to the final target level, will be preferred by decision makers. The main challenge of incorporating preference information into multi-objective RFCO approaches is that the final upstream water level (FUWL) preference is difficult to articulate, neither in the objective space nor in the decision space of the MOP, by using existing preference representation techniques [11,12]. This paper proposes a new preference-based model for multi-objective RFCO problem by determining the preferred region in the objective space dynamically according to the FUWL preference information. This preference model is then combined with a decomposition based multi-objective evolutionary algorithm to guide the search towards the preferred region.

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With the advantage of obtaining a set of non-dominated solutions in a single run, multi-objective evolutionary algorithms (MOEAs) offers a significant advantage over traditional multi-criteria methods [13]. Since the pioneering work of Schaffer [14], a number of MOEAs have been developed. Recently, Zhang et al. combined conventional decomposition approaches with MOEAs, and developed the multi-objective evolutionary algorithm based on decomposition (MOEA/D) [15]. MOEA/D decomposes the target MOP into a number of scalar optimization sub-problems by using aggregation approaches and then optimizes them simultaneously by using an evolutionary algorithm. Research works have shown that MOEA/D can produce high-quality solutions on continuous and combinatorial problems [16]. It performs well on problems with complex Pareto-sets [17], and can be easily combined with preference information by dynamically adapting the decomposing weight vectors of scalar optimization sub-problems [18]. With a refined set of weight vectors, MOEA/D is able to focus its search efforts on the preferred region.

In this work, a multi-objective evolutionary algorithm with decomposition and preference, named MOEA/D-PWA, is developed for solving multi-objective RFCO problem. The main contributions of this work are as follows:

1. Considering the final upstream water level preference, a new preference-based model which determines the preferred region in the objective space dynamically is developed for multi-objective RFCO problem.
2. Based on the proposed preference model, a preference based weight adjustment method is developed and incorporated into the framework of MOEA/D to guide the search towards the preferred region, giving rise to he proposed MOEA/D-PWA for solving multi-objective RFCO problem.

The remainder of this paper is organized as follows. Section 2 summarizes existing works on multi-objective RFCO problem. Section 3 describes the multi-objective optimization model with preference for RFCO problem. Section 4 presents the proposed preference model. Section 5 introduces the preference based weight adjustment method under the framework of MOEA/D. Section 6 describes the workflow of the proposed MOEA/D-PWA. Section 7 verifies the effectiveness of MOEA/D-PWA and presents some discussions on it. Finally, Section 8 concludes this paper.

2. Related works on multi-objective RFCO

Reservoir flood control operation (RFCO) is a challenging problem that involves interdependent decision variables and multiple nonlinear objectives [19]. Due to the complexity of the water resource management system, there is no uniform model for RFCO problem. For a long time, the RFCO problem was modeled as single objective optimization problems for simplicity. Recently, there has been a growing interest in considering multiple objectives in RFCO problem simultaneously, owing to the great progress of multi-objective optimization techniques. Different from single objective optimizer, a multi-objective algorithm for RFCO problem optimizes the conflicting objectives in RFCO problem at the same time and generates a set of non-dominated solutions which provides the decision maker with more comprehensive information about the problem.

In the past few years, different multi-objective optimization models and optimizers for RFCO problem have been developed. Yu et al. [20] developed a fuzzy decision making system for multi-objective RFCO problem. Kim et al. [21] investigated the four interconnected reservoir operation problem at the Han River Basin and developed the multi-objective evolutionary algorithm to solve it. Using multi-objective genetic algorithm [22], Janga-Reddy et al. proposed their optimizer for RFCO problem at the Bhadra Reservoir. Nagesh-Kumar et al. [23] suggested an elitist-mutated particle swarm optimization algorithm to refine the reservoir operation policies. Baltar et al. [24] proposed a optimization model with four objectives for RFCO problem and developed an optimizer based on particle swarm optimization technique. Chang et al. [25] developed a multi-objective evolutionary algorithm to solve the RFCO problem in a parallel reservoir system in Taiwan. Based on the ant colony optimization algorithm, Afshara et al. [26] presented a multi-objective optimizer for refining the reservoir operating policy. Following the algorithmic workflow of shuffled frog leaping algorithm, Li et al. [27] proposed a multi-objective optimization algorithm for RFCO problem at the Three Gorges reservoir. Hakimi-Asiabara et al. [28] developed a genetic algorithm with self-learning for deriving optimal operating policies for three-objective multi-reservoir system. Qin et al. proposed a bi-objective optimization model for RFCO problem and then developed a cultured differential evolution algorithm [8] to solve it. Based on the artificial immune system and the character of multi-objective optimization problems in the decision space, Qi et al. [3] developed a multi-objective immune algorithm with Baldwinian learning for RFCO problem. Guo et al. [29] developed particle swarm optimization algorithm with a non-dominated sorting to handle the multi-reservoir operation problem. Zhou et al. [30] developed an integrated adaptive optimization model for derivation of multipurpose reservoir operating rule curves including ecological operating rule curve under future climate change which is predicted by a support vector machine model [31–34]. Ashkan et al. [35] incorporated artificial neural network into multi-objective evolutionary algorithm, giving rise to an optimizer to extract the best set of reservoir operation decisions.

At present, almost all of the existing algorithms for multi-objective RFCO problems were developed with the aim of obtaining a set of non-dominated solutions that approximates the entire Pareto front (PF) which is the whole set of the best trade-off solutions. Few works have been done on the study of incorporating decision maker's preference into multi-objective optimizers for RFCO problems, although the preference based multi-objective optimization is not new in the field of multi-criteria decision making [36]. Due to the complexity of 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, they are likely to converge to different PF regions on different flood instances without control. On the other hand, it is time-consuming and unnecessary to approximate the entire PF, because only a small portion of solutions on PF are preferred by the decision maker. Therefore, this work focuses on how to represent the preference information specified by the decision maker, and how to incorporate the decision maker's preference into a decomposition based multi-objective optimizer to guide the search towards a preferred PF region.

3. Multi-objective model for RFCO problem

Considering the FUWL preference, the multi-objective model for RFCO problem can be mathematically described as follows [8,3].

In which, $\mathbf{Q}=(Q_1, Q_2, \ldots, Q_T)^T$ denotes the water release volumes at T scheduling periods. Each Q_t ($t=1, 2, \ldots, T$) must have a non-negative value no larger than its upper bound $Q_{\max}$. Z_t is the upstream water level of the tth scheduling period, it has a lower bound $Z_{\min}$ and a upper bound $Z_{\max}$. V_t and V_{t-1} are the reservoir storages of the tth and the $(t-1)$th scheduling period. I_t is the