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A hybrid multi-objective PSO–EDA algorithm for reservoir flood control operation

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ABSTRACT

Reservoir flood control operation (RFCO) is a complex multi-objective optimization problem (MOP) with interdependent decision variables. Traditionally, RFCO is modeled as a single optimization problem by using a certain scalar method. Few works have been done for solving multi-objective RFCO (MO-RFCO) problems. In this paper, a hybrid multi-objective optimization approach named MO-PSO–EDA which combines the particle swarm optimization (PSO) algorithm and the estimation of distribution algorithm (EDA) is developed for solving the MO-RFCO problem. MO-PSO–EDA divides the particle population into several sub-populations and builds probability models for each of them. Based on the probability model, each sub-population reproduces new offspring by using PSO based and EDA methods. In the PSO based method, a novel global best position selection method is designed. With the help of the EDA based reproduction, the algorithm can lean linkage between decision variables and hence have a good capability of solving complex multi-objective optimization problems, such as the MO-RFCO problem. Experimental studies on six benchmark problems and two typical multi-objective flood control operation problems of Ankang reservoir have indicated that the proposed MO-PSO–EDA performs as well as or superior to the other three competitive multi-objective optimization algorithms. MO-PSO–EDA is suitable for solving MO-RFCO problems.

1. Introduction

Flood disaster is one of the most serious, frequent and wide-spread natural disasters, especially in China. Influenced by monsoons from both Pacific and India oceans, 60% to 80% rainfalls in China are concentrated in the flood season, which increases the frequency and destruction strength of flood disaster. Reservoir plays an important role in flood management during flood seasons, it helps to minify flood peaks, reduce flood damages, and reserve flood [1].

Reservoir flood control operation (RFCO) is an important area of research in water resource management. As it involves more than one conflicting tasks, such as minimizing downstream damage and keeping dam safety within reasonable limits, the RFCO can be modeled as a multi-objective optimization problem (MOP) [2]. Further more, RFCO is a complicated decision problem with multi-objective, multi-scales, multiple constraints and multi-stage, it is a MOP with continuous and interdependent decision variables.

Traditionally, RFCO was treated as a single objective optimization problem by dealing with each optimization task sequentially or converting the MOP into single optimization problem with a mixed target function [3]. Many optimization techniques were also employed to solve this single objective RFCO problem. Some of them are heuristic algorithms, such as linear programming [4], dynamic programming [5] and non-linear programming [6]. With the development of computational intelligence, some nature inspired optimization techniques have been gradually applied to reservoir operation [7]. Genetic algorithm (GA) [8–10] is the representative approach of this type. These works have shown the significant potential of GA in water resources management and clearly demonstrated the advantages of GA over traditional techniques in terms of computational requirements. Ant colony optimization (ACO) algorithm which is inspired by the foraging behavior of some ant species was presented to solve continuous four reservoir operation problem [11]. Most recently, particle swarm optimization was also used for solving the reservoir operation problem [12].

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As RFCO is a MOP, it is not possible to find a single scheme simultaneously optimizing all objectives. Instead, the solution to RFCO becomes a set of good trade-offs between the multiple objectives. The trade-offs between the conflicting objectives are known as Pareto optimal schemes, for which any single objective cannot be improved without compromising at least one of the others. All the Pareto optimal schemes form the Pareto set (PS) of the RFCO and the Pareto optimal front (PF) is thus defined as the corresponding objective vectors of the schemes in Pareto optimal set. For solving RFCO, the above mentioned single-objective optimization algorithms have a drawback in common, they are usually sensitive to the shape or continuity of the PF of RFCO [13]. For example, non-convex parts of the Pareto front cannot be recovered by optimizing convex combinations of the objective functions. Superior to single-objective optimization algorithms, a multi-objective optimization algorithm can obtain a set of Pareto optimal schemes within a single run, which provides more information to decision makers.

In recent years, a variety of newly developed methods have been proposed to solve MOP. Multi-objective optimization has been one of the hottest research areas in the field of meta-heuristic and swarm intelligence techniques [14]. These multi-objective optimization techniques have also been employed to solve RFCO with multiple objectives and achieved various degrees of success. Chen et al. [15,16] summarized decision making problems of flood control and proposed multi-objective decision making theory, model and methods. Based on the fuzzy optimum model, Hou [17], Yu [18] and Fu [19] developed fuzzy decision-making methods concerning multiple objectives. Zhou et al. [20] introduced the theory of information entropy into fuzzy optimum model and proposed an entropy weights based multi-objective decision making approach for RFCO problem. Qin et al. proposed a multi-objective optimization model for RFCO problem and solved the optimization model using multi-objective differential evolution algorithm [21] and multi-objective cultured differential evolution algorithm [2] respectively. These two approaches were population based multi-objective optimization algorithms which can provide a set of Pareto optimal solutions with good diversity in a single run.

RFCO problem is a complex MOP because its decision variables are interdependent of one another [22]. So far, all of the above mentioned multi-objective optimization algorithms for solving RFCO problem simply employ the conventional reproduction operators designed for single-objective optimization algorithms. Few works have been done to improve the searching efficiency of the algorithm according to the characteristic of MOP, especially when decision variables of the target MOP are interdependent.

Particle swarm optimization (PSO) is a population based stochastic optimization technique inspired by social behavior of bird flocking or fish schooling which aim to find food. The process in PSO involves both social interaction and intelligence so that particles learn from their own experience and from experiences of other particles around them [23]. In past several years, PSO has been successfully applied in many research and application areas. It is demonstrated that PSO gets better results in a faster, cheaper way compared with other methods. Recently, there has been a growing interest in multi-objective particle swarm optimization (MOPSO) which investigates PSO techniques for handling MOPs [24].

In this work, a hybrid multi-objective optimization algorithm combining PSO and estimation of distribution algorithm (EDA), simply MO-PSO–EDA for short, is developed to solve multi-objective RFCO problem. Although PSO converges fast, it is easy to fall into local optimum. Thus PSO is not suitable for solving complex optimization problems like RFCO problem whose decision variables are interdependent. In order to overcome the shortcoming of PSO, an EDA based reproduction method is introduced into MOPSO to form the proposed MO-PSO–EDA. EDA is an evolutionary computation optimization paradigm based on probabilistic modeling of promising solutions [25]. EDA aims to extract the distribution model of the population and discover the variable linkage information to benefit offspring generation. It has been proved that if the variable interaction structure of the probability model used in EDA is properly chosen, EDA could converge to global optimal solutions [26]. By taking the advantage of EDA [27], MO-PSO–EDA is expected to be suitable for solving multi-objective RFCO problem.

The remainder of this paper is organized as follows. Section 2 introduces some backgrounds include the MOP model and the workflow of the PSO algorithm. Section 3 gives the multi-objective optimization model for reservoir flood control operation. Section 4 presents the details of the proposed hybrid multi-objective PSO–EDA algorithm for solving RFCO problem. Section 5 briefly presents and analyzes the experimental results to validate our proposed approach. Section 5 concludes this paper and outlines future research work.

2. Related backgrounds

This section gives a brief introduction of the background of MOP. A literature review of the multi-objective PSO algorithm and its applications to the reservoir operation problems has been conducted.

2.1. The model of multi-objective optimization problem

A multi-objective optimization problem (MOP) with n decision variables and m objectives can be mathematically formulated as following:

$$\begin{aligned} &\text{Minimize} \quad \mathbf{F}(x) = \left\{f_1(\mathbf{x}), f_2(\mathbf{x}), \ldots, f_m(\mathbf{x})\right\} \\ &\text{Subject to} \quad \mathbf{x} \in \Omega \end{aligned} \tag{1}$$

where Ω is the feasible region of the n-dimensional decision space, $\mathbf{x} = \{x_1, x_2, \ldots, x_n\} \in \Omega$ is the decision variable vector. The objective function $\mathbf{F}(\mathbf{x})$ consists of m objective functions $f_1(\mathbf{x}), f_2(\mathbf{x}), \ldots, f_m(\mathbf{x})$ and $\mathbf{R}^m$ is the objective space.

The objectives of MOP often conflict with each other. In other words, improvement of one objective may lead to deterioration of another. Therefore, a single solution that optimizes all objectives simultaneously does not exist. Suppose x_A and x_B are two solutions of a MOP, x_B is called to be dominated by x_A, or x_A dominates x_B, noted as $x_A \prec x_B$, if and only if $f_i(x_A) \le f_i(x_B)$, $\forall\, i = 1, 2, ..., m$, and there exist a $j \in \left\{1, 2, ..., m\right\}$, which makes $f_j(x_A) < f_j(x_B)$. A solution $\boldsymbol{x}^*$ is a Pareto optimal solution, if there is no other feasible solution that dominates it. The set of all Pareto optimal solutions is called the Pareto optimal set (PS), which can be mathematically formulated as $PS \triangleq \{x^* | \neg \exists x \in \Omega, x \prec x^*\}$. The collection of corresponding objective vectors of the solutions in PS is called the Pareto optimal front (PF), that is $PF \triangleq \{F(x), x \in PS\}$.

Science it is impossible to find the whole PS of continuous MOPs, we aim at finding a finite set of Pareto optimal vectors which are uniformly scattered along the true PF, and thus good representatives of the entire PF.

2.2. The multi-objective particle swarm optimization algorithm

Particle swarm optimization (PSO) is a population-based stochastic optimization method which is inspired by the social behavior of bird flocking [23]. Due to its good performance and low computational cost, PSO has attracted significant researching attentions. In PSO algorithm, solutions are regarded as particles which are endowed with fitness values and velocities. A particle in the PSO system flies through the decision space of the target optimization problem by adjusting its velocity and position according to its own experience, represented by its personal best (pbest), as well as the