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Fusing feasible search space into PSO for multi-objective cascade reservoir optimization

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ABSTRACT

This study proposes a multi-objective optimization model of two cascade reservoirs in the Upper Yellow River basin for increasing social well-beings in general while simultaneously mitigating ice/flood threats. We first develop a strategy of dimensionality reduction and constraint transformation to largely diminish the complexity of the optimization system and next propose a novel search method that fuses a Feasible Search Space (FSS) into the Particle Swarm Optimization (PSO) algorithm, i.e. FSS-PSO, to effectively solve the optimization problem. To investigate the applicability and effectiveness of the proposed method, this study compares the FSS-PSO model with historical operation. The results indicate that the proposed model produces much better performances in all the objectives than historical operation. To assess the superiority and efficiency of the proposed FSS-PSO, the classical PSO and the Chaos Particle Swarm Optimization (CPSO) are also implemented to compare their computation time and convergence rates. The results demonstrate that the FSS-PSO improves the efficiency of the PSO and the CPSO by 72% and 55% accordingly and the convergence rate of the FSS-PSO is the fastest among the three algorithms. The results suggest that the proposed dimensionality-reduction strategy coupled with the FSS-PSO algorithm is a promising tool for water resources management under multi-objective joint reservoir operation and the proposed method could be easily implemented in the context of multi-objective optimization.

1. Introduction

The Yellow River is "China's Mother River" because its basin is the cradle of the Chinese civilization. The complex topography, fragile environment and prominent contradiction in various sectors make a considerable increase in flood and ice disasters over its upper basin, which threatens lives and property in downstream areas. As known, the Yellow River is famous for its sedimentation problems, where the suspended sediment has formed a secondary suspended river [25,28,32]. Reservoirs are the most effective water storage facilities in alleviating the uneven spatio-temporal distribution of water resources. As known, the purposes of most reservoirs built along the River in the past decades were only to generate hydropower in response to socio-economic development needs. With the rapid increase in water demand driven by population growth coupled with socio-economic development, the imbalances in water supply and demand, the tasks of flood and ice control and other factors have caused a dramatic change in the purposes of reservoir operation. Nonetheless, re-allocating the limited water resources of multi-purposed reservoirs is a great challenge, if not impossible.

System analysis is a very useful tool for assessing the impacts of policies and managing complex systems. Many engineering problems involve multiple competing objectives and prospective solutions. In the last decades, various classical nonlinear optimization methods have been used with effective and competent performance when tackling these problems. However, they usually require gradient information about the objective functions and constraints, which, in general, are difficult to solve and would easily fall into local optimal solutions. Recently, several meta-heuristic approaches, such as evolutionary algorithms (EA) [10,44], harmony search (HS) [18], biogeography-based optimization (BBO) [5] and particle swarm optimization (PSO) [42,45], have been proposed and utilized in order to handle diverse optimization tasks [4,17,19,30,31]. While these meta-heuristic methods produce better performances over classical optimization approaches in complex multi-objective problems, they are plagued by their own limitations such as premature convergence to a local optimal solu-

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tion rather than a global on [35]. As known, in high dimensional problems, only a small percentage of solutions can converge to the entire Pareto optimal front, termed as the "curse of dimensionality" [16]. Deb and Saxena [14] indicated that the ability to fully explore surfaces in greater than five dimensions was highly limited. Consequently, more research efforts must be developed in this direction if many-objective problems are to be solved.

Various meta-heuristic approaches have revealed superior performance in dealing with complex hydrological operation systems [3,8,11,20,23,24,34,39]. Lately, swarm intelligence algorithms have become popular in solving reservoir planning and management problems, for example, the genetic algorithm (GA) [9,12,22,27,36,37]; artificial neural network (ANN) [6,13]; ant colony optimization (ACO) [1]; and the PSO [2,7,21,26,36]. Even through efficient swarm intelligence algorithms satisfactorily applied to many optimization problems, the PSO algorithm, however, has its own flaws, e.g. early maturity, slow convergence rates, or difficult to handle constraint optimization problems. For this reason, a number of studies have been proposed to improve the efficiency and/or effectiveness of the PSO algorithm through adjusting its code mode, inertia weight, maximum speed limit of particles, mutation operators, neighborhood operations, boundary conditions [15,29,33,44]. Some of the studies used hybrid (mixture and parallel) algorithms, for instance PSO with immune algorithms, simulated annealing algorithms and chaos algorithms, to improve search effectiveness [38,40,41].

In this study we aim to find a suitable water and sediment regulation strategy for multi-objective reservoir operation through searching a set of optimal solutions for two pivotal cascade reservoirs in the Upper Yellow River basin. We propose a dimensionality-reduction and constraint transformation procedure coupled with a novel search strategy that fuses a Feasible Search Space (FSS) into the PSO algorithm, i.e. an improved PSO algorithm (FSS-PSO), to effectively search optimal solutions. Our research findings would suggest optimal operation strategies for water and sediment conservation and provide the referential impacts of water allocation on sediment control. The rest of the present article is structured as follows: Section 2 is dedicated to the mathematical representation of cascade reservoirs with the explanation of the implementation procedure of the proposed FSS-PSO algorithm; Section 3 explains the study watershed and model construction; Section 4 presents and discusses the experimental results, comparison and evaluation of the performance of the investigative methods. Finally, the conclusion of the implementation of the proposed method is presented in the last Section.

2. Methods

Water resources management often involves very large scale measures, complex processes and regulations. It is a great challenge to make efficient water resources management that optimizes a real-practical system under the great uncertainty of hydro-meteorological conditions. We propose a multi-objective optimization model for the joint operation of two cascade reservoirs in the Upper Yellow River basin for decision makers to increase social well-beings while simultaneously mitigate ice/flood threats. We first derive a mathematical model that considers four objectives: water and sediment regulation; ice and flood control; power generation; and water supply, and then provide a clear perspective of all the consideration and physical constraints conditions. To solve the complex problem, a dimensionality-reduction and constraint transformation procedure is proposed while a novel and effective search method, i.e. FSS-PSO, is developed and evaluated. The core idea of the FSS-PSO is to intelligently handle the objectives and constraints through intelligibly refining the feasible search space. To assess the proposed FSS-PSO, the classical PSO and the chaos particle swarm optimization (CPSO) are also implemented to compare the computation time and convergence rates of the three algorithms. The research flowchart of this study is illustrated in Fig. 1. A detailed description of the methods adopted in this study is shown as follows.

2.1. Building a multi-objective model and its transformation

The multi-objective optimization problem can generally be expressed as follows.

$$\text{Minimize/Maximize} F(X) = [F_1(X), F_2(X), .., F_k(X)] \quad (1)$$

$$\text{subject to} G_i(X) \leq 0, i = 1, 2, .., m.$$

$$H_j(X) = 0, j = 1, 2, .., p,$$

where $F(X)$ is a vector of objective functions; G_i (X) and H_j (X) are constraints; k is the number of objective functions; m is the number of inequality constraints; and p is the number of equality constraints. X is a vector of decision variables.

A common solution for multi-objective optimization problems is to determine a Pareto optimal set. However, the difficulty in finding a representative Pareto front set would arise significantly as the dimension increases. To solve the problem, we propose to reduce the number of objectives and to identify any constraint that actually restrains the FSS for the stated objectives. The mathematical expression of objectives and constraints of an optimization model can be generally classified into two types: equality and inequality. The inequality objectives must be strictly satisfied in the search process, and thus they could be transformed into strong constraints. As a result, the number of objectives of the multi-objective optimization model could be reduced, which would decrease the dimension as well as the difficulty in searching the optimal solution.

The controllable variables for reservoir operation can be classified into three categories: discharge; water level; and power generation. We, thus, classify the constraints into the three categories based on their features. These constraints are further divided into two types: transformable constraint; and non-transformable constraint. Transformable constraints can be directly converted into decision variables while non-transformable constraints are, in general, the implicit functions of optimization variables, which cannot be converted into decision variables. The category of controllable variables and the classification of constraints are listed in Table 1 .

2.2. Refining feasible search space (FSS)

In this study, the non-transformable constraints (i.e. power generation output) can be decomposed into E_1 and E_2, in which E_1 is a composite function addressing the composition of relations between water head and generated flow while E_2 is a composite function in relation to the power generation output of different power generating units. The targets of E_1 and E_2 are to make the maximum generation benefit in a dispatch period. The concept of refining the FSS is presented in Fig. 2, and the relevant process is addressed as follows.

2.2.1. Process description

First of all, the whole dispatch period $[0, T]$ is equally divided into T intervals. In our case, the whole dispatch period is one year and the intervals are of a monthly scale. The FSS can then be refined (filtered) sequentially by cross-examining the objectives and transformable constraints in the pairs of consecutive sub-periods. The process of refining the FSS of the whole dispatch period begins with