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An adaptive particle swarm optimization algorithm for reservoir operation optimization

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ABSTRACT

Reservoir operation optimization (ROO) is a complicated dynamically constrained nonlinear problem that is important in the context of reservoir system operation. In this study, improved adaptive particle swarm optimization (IAPSO) is proposed to solve the problem, which involves many conflicting objectives and constraints. The proposed algorithm takes particle swarm optimization (PSO) as the main evolution method. To overcome the premature convergence of PSO, adjusting dynamically the two sensitive parameters of PSO guides the evolution direction of each particle in the evolution process. In the IAPSO method, an adaptive dynamic parameter control mechanism is applied to determine parameter settings. Moreover, a new strategy is proposed to handle the reservoir output constraint of ROO problem. Finally, the feasibility and effectiveness of the proposed IAPSO algorithm are validated by the Three Gorges Project (TGP) with 42.23 bkW power generation and XiLuoDo Project (XLDP) with 30.10 bkW. Compared with other methods, the IAPSO provides a better operational result with greater effectiveness and robustness, and appears to be better in terms of power generation benefit and convergence performance. Meanwhile, the optimal results could meet output constraint at each interval.

1. 1 Introduction

The water resource crisis is increasingly becoming challenging and complicated, posing a dilemma for stakeholders desiring effective water allocation. Reservoir operation optimization (ROO) facilitates not only water resource allocation that yields maximum benefits with respect to multiple objectives in areas such as agriculture, energy, and industry but also rational water exploitation and hydropower generation. Moreover, for obtaining solutions to ROO problems, advanced computational technology and improved algorithms are used for enhancing the computation efficiency. ROO can be used for formulating, analyzing, and solving operation optimization problems in water resource planning [20].

Most methods used for ROO analysis involve conventional optimization algorithms and various metaheuristic algorithms. Over the past several decades, a wide range of methods have been proposed to solve ROO problems. Those reported to be effective are linear programming (LP) [14], nonlinear programming (NLP) [3,31], quadratic programming (QP) [25] and Lagrangian relaxation (LR) [10,15]. Dynamic programming (DP) is a powerful optimization technique that is applied to ROO and is considered a conventional optimization algorithm in reservoir operation. Among the traditional optimization techniques for reservoir operation, DP [32] boasts high popularity. In other methods, there may be difficulties in finding the optimal solution. In the case of LP, the nonlinear and unsmooth characteristics of ROO problems are often ignored during linearization, generating large errors in the optimal operation. In NLP and QP, the objective function should be continuous and differentiable. Moreover, some approximations are necessary in the formulation when NLP and QP are used, and they may lead to inaccurate solutions when an objective function that is continuous and differentiable is used. In LR, Lagrange multipliers with an updating strategy are used, and therefore, the method suffers from oscillations in the optimal result. In DP, the high dimensionality of the problem poses difficulties and might not converge within a reasonable time, especially for large-scale hydropower systems.

Owing to the lack of computational efficiency in the case of conventional optimization algorithms, modern heuristic stochastic search algorithms such as the genetic algorithm (GA) [34], evolutionary programming (EP) [3], simulated annealing (SA) [4] particle swarm optimization (PSO) [13], and the differential evolution algorithm (DE) [18] have been extensively used to solve the ROO problem without any restriction on the unsmooth and nonconvex characteristics of the problem. Although these methods do

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not always guarantee the globally optimal solution, a suboptimal (near the global optimal) can be provided. Due to easy implementation and good properties in optimization, these algorithms have drawn a widely attention in the world. Because of the increase in the complexity of ROO with the dimensionality, a large-scale ROO problem with an enormous number of variables and constraints must be decomposed into sub-problems to enhance the robustness of the algorithms search. Therefore, ROO problems can be alternatively solved by the PSO.

Particle swarm optimization (PSO) [8] is one of the most representative algorithms among modern artificial intelligence techniques. As a population-based evolutionary algorithm, PSO has demonstrated good properties of fast convergence in optimization of ROO problem [5,24]. However, the problem of premature convergence caused by falling into local optima still exists in PSO algorithm. Focus on the drawbacks of method mentioned above, an improved adaptive particle swarm optimization (IAPSO) is proposed in this paper. Moreover, IAPSO lacks of a mechanism to deal with the constraint of ROO problem effectively. Though the tradition penalty function method can be easily implemented to solve the various constraints of ROO problem, but could not guarantee optimal PSO moving to feasible regions. To overcome the drawback of penalty function method, a new strategy is proposed based on feasible rules to solve the constraint of ROO problem, which can satisfy the firm output constraint of ROO problem fully. IAPSO approach incorporating both computational efficiency and optimal decisions is presented for the Three Gorges Project (TGP).

The remainder of this paper is organized as follows. Section 2 presents the formulation of the ROO problem. Section 3 explains the improved optimal algorithms. The application of the proposed optimal algorithm is shown in Section 4. In Section 5, the results of the study are presented and discussed. Finally, conclusions are provided in Section 6.

2. Formulation of problems

ROO is aimed at maximizing water resource benefits as much as possible by determining an optimal plan for a hydropower station over the operation period, while satisfying all kinds of physical and operational constraints. Generally, the objective function and associated constraints of the ROO problem can be formulated as follows.

2.1. Objective functions

The major objective of ROO is to maximize the reservoir benefits, which are mainly related to hydropower generation and water supply. Hydropower generation is a significant benefit derived from a reservoir system, and it is related to a given operation of the hydropower station for T intervals as follows:

$$F = \max \sum_{t=1}^{T} AO^t H^t M^t \quad \text{or} \quad F = \max \sum_{t=1}^{T} N^t M^t \tag{1}$$

where F is the total hydropower generation for all operation intervals, A is the comprehensive output coefficient, O^t is the rate of outflow from the reservoir in the t-th operation interval, H^t is the average reservoir storage level in the t-th operation interval, T is the number of intervals over the operating horizon, M^t is the period of the t-th operation interval, and N^t is the reservoir output in the t-th operation interval.

Recently, multi-objective ROO has become popular. This was developed as a technique to resolve conflicting objectives and it converts the ROO into a multi-objective problem. Besides hydropower generation, other objectives are taken into account, such as flood control, navigation, benefits of supply of water to downstream rivers, and the maximization of water supply for civil or agricultural uses. These objectives may be incompatible with each other. Traditionally, multi-objective optimization problems have been solved using weighting methods or ε-constraint methods. A single objective is obtained as the weighted sum of many objectives. The optimal Pareto set is obtained by varying the weights associated with each objective and solving the problem sequentially. DeJong [7] used the weighting method [6] to integrate multiple objectives into a single objective. In this approach, the need to compare incompatible objectives significantly complicates the selection of the weights. The ε-constraint method retains one objective as the primary and treats the others as constraints, so all but one of the objectives is incorporated into the constraint set. The objectives included in the constraint set are varied parametrically from the lower bound to the upper bound.

The main objective of this study is to maximize power generation under certain constraints. To easily implement the algorithm for solving an ROO problem, we usually adopt an external penalty function to convert a constrained optimization problem into an unconstrained one. A reservoir operation system involves complicated procedures, and for simplification, we consider only the two most vital objectives, which are flood prevention and power generation (with irrigation, navigation, etc. ignored). Although reservoir operation should be cost-effective, it is important to ensure its reliability and safety. Generally, during the flood season, the reservoir operation maintains the storage at a fixed level (reservoir inflow is equal to reservoir discharge). Hence, reliable output from the hydropower station and maximum power generation during the nonflood season are considered in this study. We design the fitness function with penalty terms, which augment the objective function with penalty values associated with infeasible solutions:

$$f(V) = F(V) + M \cdot \min\{N - N_{\mathrm{inf}}, 0\} \tag{2}$$

where $f(V)$ is the fitness value, $F(V)$ is the total hydropower generation for all operation intervals, M is a penalty weight, and N_{inf} is the minimum output.

2.2. Constraints

The reservoir operation problem is subjected to equality and inequality constraints.

A. The water volume balance equation is:

$$V^t = V^{t-1} + (I^t - O^t) \cdot M^t; \quad t = 1, 2, \ldots, T \tag{3}$$

where V^{t+1} is the reservoir storage volume in the $t+1$th operation interval, V^t is the reservoir storage volume in the t-th operation interval, I^t is the inflow rate of the reservoir in the t-th operation interval, O^t is the outflow rate in the t-th operation interval, and M^t is the duration of the t-th operation interval. The equation describes the water balance under the assumption that there is no water loss from bed leakage.

B. The other constraints can be written as:

$$(V, Z, O, N)_l^t \le (V, Z, O, N)^t \le (V, Z, O, N)_u^t \quad t = 1, 2, \ldots T \tag{4}$$

where V, Z, O, and N are the reservoir storage volume, storage level, discharge, and output capacity, respectively, while l and u are the lower and upper reservoir limits in the t-th operation interval, respectively.

3. Methodology

3.1. Overview of particle swarm optimization

Particle swarm optimization (PSO) is proposed by Kennedy and Eberhart [8,16], which is a simple and powerful heuristic method