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A novel chaotic differential evolution algorithm for short-term cascaded hydroelectric system scheduling

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ABSTRACT

A novel chaotic differential evolution (CDE) algorithm of optimal scheduling of short-term cascaded hydroelectric system based on improved logistic map is presented to maximize the expected generation benefit in a day, which uses the water discharge as the decision variables combined with the death penalty function. According to the principle of expected power generation, the proposed approach makes use of the ergodicity, symmetry and stochastic property of improved logistic chaotic map for enhancing the performance of differential evolution (DE) algorithm. The improved logistic map between $(-1,1)$ is utilized to explore globally around the best individual until the lagged ones are close to best one. Meanwhile, the fitness value of objective function is handled by a piecewise linear interpolation function (PLIF). The new hybrid method has been examined and tested on a practical cascaded hydroelectric system. The experimental results show that the effectiveness and robustness of the proposed CDE algorithm are better than existing algorithms.

1. Introduction

The objective of short-term cascaded hydroelectric system scheduling is to determine the optimal operation schedule of cascaded hydro plants that maximizes the hydro production profit in a predefined short-term period while satisfying the various constraints. It is one of the important and difficult nonlinear optimization problems in the power system because many complex constraints of hydraulic and electrical aspects must be taken into account for solving this problem [1]. In an interconnected multi-reservoir power system, the water resources available for electrical generation are represented by the inflows to the hydro power plants and the water stored in their reservoirs [2–4]. Hence, it makes the problem very complicated for existed link between a dispatching decision taken in a given stage and the future consequences of this decision along the whole dispatching horizon. Many traditional mathematical approaches have been used to solve this problem, such as network flow [5], mixed-integer quadratic programming [6], and dynamic programming [7,8]. Meanwhile, as an alternative to conventional methods, modern heuristic evolution techniques including genetic algorithm [9], particle swarm optimization (PSO) [1,10,11], and differential evolution (DE) [12,13] have been developed for solving the short-term scheduling problem of cascaded hydroelectric system. However, there are several drawbacks in those approaches to some extent, including dimensionality difficulty, premature phenomena and trapping in the local optimum lead to these methods no longer suitable for handling complex cascaded hydro system.

As a heuristic algorithm, chaotic optimization algorithm (COA) using chaotic variables instead of random variables have received more and more attention [14]. Based on the properties of ergodicity, symmetry and randomness, huge amounts of numerical examples assert that COA can more easily escape from local optimum in comparison with other stochastic optimization algorithms although the mathematical theory cannot be formulated [15,16]. Nevertheless, all simple COAs need a large quantity of iterations to achieve the global optimum and suitable initial value because of their sensitivity to the initial conditions. Thus, the simple COA algorithm is hard to achieve rapid the global optimum for solving the complex optimization problem [17,18].

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In order to improve the performance of COAs, a novel hybrid optimization method known as chaotic differential evolution (CDE) was introduced by Coelho and Mariani in 2006 [19]. They combined the simple DE algorithm with the generator of logistic chaos sequences and sequential quadratic programming technique to solve the model of economic dispatch with valve-point effect. Due to easy implementation, superior performance and quick convergence, CDE algorithms have obtained much attention and wide application in different fields, including economic dispatch [19], hydrothermal generation scheduling [20–22], image contrast enhancement [23], nonlinear function optimization [24,25], flood disaster evaluation [26],Coordination of directional overcurrent relays [27], islanded micro-grid [28], and resource-constrained project scheduling [29].

This paper introduces a novel two-phased CDE algorithm using improved logistic map within symmetrical region to deal with short-term scheduling problem of cascaded hydroelectric system. The proposed hybrid method uses simple DE algorithm in the first evolution phase and the chaotic sequences generated by improved logistic map nearby the current optimal value in the second evolution phase. Based on the ergodicity, symmetry and stochastic property of improved logistic chaotic map, the novel hybrid method introduces the death penalty function to process the constraints and piecewise linear interpolation function(PLIF) to implement the objective function. The application of chaotic sequences within symmetrical region instead of random variables in DE is a powerful strategy to diversify the population and enhance the performance of DE in preventing premature convergence to local optima. A practical cascaded hydroelectric system is applied to examine and test the effectiveness and robustness of the proposed CDE algorithm. The numerical results show that the novel hybrid method is promising and great superiority in comparison with PSO, existing DE and CDE algorithms.

The remainder of the paper is organized as follows. Section 2 provides the mathematical formulation of short-term cascaded hydroelectric system scheduling. The simple DE, and two kinds of CDE algorithms are described in Section 3. Section 4 shows a practical numerical example, and Section 5 outlines the conclusions and future research.

2. Problem formulation

2.1. Objective function

For maximizing the energy production, the object of short-term cascaded hydro-system scheduling is to maximize the total generation benefit in a short period under lots of complex constrained conditions. The model of objective function is formulated as follows:

$$\max f = \sum_{i=1}^{N}\sum_{t=1}^{T} A_i Q_i(t) H_i(t) \tag{1}$$

where N is the number of hydro plants; T is the length of term; A_i is the power generation coefficient of hydro plant i; $Q_i(t)$, $H_i(t)$ are the water discharge and net head of hydro plant i at time t, respectively.

2.2. Constrained conditions

In order to solve foregoing model, we will consider the following constrained conditions in a cascaded hydro-system.

1. Water dynamic balance equation with travel time

$$\begin{cases} V_1(t+1) = V_1(t) + q_1(t) - Q_1(t) - S_1(t) \\ V_i(t+1) = V_i(t) + q_i(t) + Q_i(t-\tau) - Q_i(t) - S_i(t) \end{cases} \tag{2}$$

2. Hydro plant power generation limits

$$P_{i,min} \leqslant P_i(t) \leqslant P_{i,max} \tag{3}$$

3. Reservoir storage volumes upriver water level limits

$$Z^t_{i,min} \leqslant Z_i(t) \leqslant Z^t_{i,max} \tag{4}$$

4. Hydro plant discharge limits

$$Q^t_{i,min} \leqslant Q_i(t) \leqslant Q^t_{i,max} \tag{5}$$

In the equations above, τ is water travel time; $V_i(t), q_i(t), S_i(t)$ are reservoir storage volume, natural inflow into reservoir and water spillage of hydro plant i at time t, respectively; $P_{i,min}, P_{i,max}, P_i(t)$ are minimum, maximum power generation of hydro plant i and power generation of hydro plant i at time t; $Z^t_{i,min}, Z^t_{i,max}, Z_i(t)$ are minimum, maximum upriver water level and upriver water level of hydro plant i at time t; $Q^t_{i,min}, Q^t_{i,max}, Q_i(t)$ are minimum, maximum water discharge of hydro plant i and water discharge of hydro plant i at time t.

3. A novel CDE algorithm

3.1. Traditional DE

Differential evolution (DE) is one of the most recent population-based stochastic evolutionary optimization techniques. Storn and Price first proposed DE in 1995 [30] as a heuristic method for minimizing nonlinear and nondifferentiable continuous space functions. As other evolutionary algorithms, the first generation is initialized randomly and further generations evolve through the application of certain evolutionary operator until a stopping criterion is reached [31]. The theoretical framework of DE and its modified forms [32] are very simple to solve nonlinear continuous optimization problems, and have been applied to various scientific fields [33–39]. The simple optimization procedure of DE algorithm [31] can be depicted in more detail below with reference of following 5 steps.

3.1.1. Algorithm DE

Step 1: Let a population size M, crossover probability P_c, evolution generation T_{max}, scaling factor F, and initial evolution generation $k = 0$ in the d-dimensional space. Initialize the population with random vector $X(0) = (x_1(0), \ldots, x_M(0))$, in which the mth individual $x_m(0) = (x_{m1}(0), \ldots, x_{md}(0))$. The initial optimal objective value is $f(x_b(0))$ in the optimal position $x_b(0) = (x_{b1}(0), \ldots, x_{bd}(0))$.

Step 2: Choose five distinct random integers r_1, r_2, r_3, r_4, r_5 from the set $\{1, \ldots, M\}$ and random integer $j_{ra} = 1, \ldots, d$. The new point is found from nearby the best position using the following crossover rule:

$$x'_{mj}(k) = \begin{cases} v_{mj}(k), & \text{if } r_{mj} < P_c \text{ or } j = j_{ra} \\ x_{mj}(k) & \text{else} \end{cases} \tag{6}$$

(1) DE/rand/1

$$v_{mj}(k) = x_{r_1,j}(k) + F(x_{r_2,j}(k) - x_{r_3,j}(k)) \tag{7}$$

(2) DE/best/1

$$v_{mj}(k) = x_{bj}(k) + F(x_{r_1,j}(k) - x_{r_2,j}(k)) \tag{8}$$

(3) DE/rand/2

$$v_{mj}(k) = x_{r_1,j}(k) + F((x_{r_2,j}(k) - x_{r_3,j}(k)) + (x_{r_4,j}(k) - x_{r_5,j}(k))) \tag{9}$$