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A parallel multi-objective particle swarm optimization for cascade hydropower reservoir operation in southwest China

Wen-jing Niu[a], Zhong-kai Feng[b,*], Chun-tian Cheng[c], Xin-yu Wu[c]

[a] Bureau of Hydrology, ChangJiang Water Resources Commission, Wuhan, 430010, China
[b] School of Hydropower and Information Engineering, Huazhong University of Science and Technology, Wuhan, 430074, China
[c] Institute of Hydropower and Hydroinformatics, Dalian University of Technology, Dalian, 116024, China

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ABSTRACT

Due to the expanding system scale and increasing operational complexity, the cascade hydropower reservoir operation balancing benefit and firm output is becoming one of the most important problems in China's hydropower system. To handle this problem, this paper presents a parallel multi-objective particle swarm optimization where the swarm with large population size is divided into several smaller subswarms to be simultaneously optimized by different worker threads. In each subtask, the multi-objective particle swarm optimization is adopted to finish the entire evolutionary process, where the leader particles, external archive set and computational parameters are all dynamically updated. Besides, a novel constraint handling strategy is used to identify the feasible search space while the domination strategy based on constraint violation is used to enhance the convergence speed of swarm. The presented method is applied to Lancang cascade hydropower system in southwest China. The results show that PMOPSO can provide satisfying scheduling results in different cases. For the variation coefficient of generation in 30 independent runs, the presented method can bettered the serial algorithm with about 66.67% and 61.29% reductions in normal and dry years, respectively. Hence, this paper provides an effective tool for multi-objective operation of cascade hydropower system.

1. Introduction

As one of the most significant renewable and clean šourcesöf energy, hydropower has been experiencing a rapid development period throughout the world in recent years [1–4]. China has abundant hydropower resources with a technical exploitation amount of about 400 G W [5]. To satisfy the huge energy demand caused by the booming economic development of China, a large number of hydroplants have been placed in service while many more are being under construction [6]. By the end of 2015, the total installed capacity of hydropower in China has reached up to about 320 G W, while the gross generation of hydropower exceeds 1.0 trillion kilowatt hours. Nowadays, China is entering a new era of large-scale hydropower system composed of numerous hydropower bases equipped with giant hydroplants and generating units [7]. Hence, due to the unprecedented system scale, the cascade hydropower reservoirs operation (CHRO) is becoming one of the most important and challenging tasks for China's power system [8–10].

Generally, the main goal of hydropower system operated by a central dispatching authority is to determine the optimal operation process of all hydroplants that can maximize the total generation benefit of system in the scheduling horizon [11–13], while satisfying a group of complex equality and inequality constraints, like water balance equations and output limits [14,15]. However, due to the limited water resources, the results obtained by conventional benefit maximization model tend to store more water so as to raise the water levels and hydraulic heads of hydropower system. This mode will help the system operate at high efficiency zones as long as possible, but inevitably lead to the risk that there is no enough water for energy supply in some periods [16]. To achieve a compromise between economy and reliability, the operation model that simultaneously considers energy production and firm output is becoming increasingly popular in the cascaded hydropower system of China [17]. Thus, to meet the actual demand of the CHRO problem, the multi-objective model balancing generation benefit and firm output is chosen as the focus of this paper.

* Corresponding author.
E-mail address: myfellow@163.com (Z.-k. Feng).

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Mathematically, the CHRO problem balancing generation benefit and firm output is classified as a multi-objective optimization problem (MOOP). To solve the MOOP problem, many effective algorithms have been successfully developed by researchers around the world [18–20], and these techniques can be broadly divided into two different groups: single-objective optimization and multi-objective optimization. In the first category, some conversion tricks (like weighting method, constraint method and penalty factor) are firstly adopted to transform the multi-objective problem into a single-objective optimization problem, and then some classical mathematical methods (like linear programming and dynamic programming) are employed to resolve it [21–23]. For instance, In Ref. [24], the weighting coefficient is incorporated into linear programming to allocate the quarter-hourly generation of hydro-thermal-nuclear plants among multiple power grids; Ref [25]. proposes a multi-objective ecological reservoir operation model combining the merits of statistical water quality models, multi-objective reservoir operations and a self-adaptive genetic algorithm; based on differential evolution and utility function; Ref [26]. proposes a multi-objective best compromise decision model for multi-objective real-time flood operations in multiple reservoir system; Ref [27]. proposes a novel search method fusing a feasible search space into the particle swarm optimization for multi-objective cascade reservoir optimization. Although the first group can effectively reduce the optimization difficulty in most cases, it is often affected by the artificial conversion coefficients and cannot provide enough information on the optimal tradeoff front [28]. In the second group, all the objectives are often simultaneously addressed by multi-objective evolutionary algorithms (MOEAs) [29–31], such as multi-objective particle swarm optimization (MOPSO), multi-objective differential evolution and non-dominated sorting genetic algorithm-II (NSGA-II). MOEAs have no strict requirements on the mathematical properties of optimization problems and can generate a group of non-dominated solutions in a single run, which has attracted a great of attention from scholars. For instance, Ref [32]. presents a multi-objective particle swarm optimization to handle hydropower system operation considering the maximization of gross generation and firm output; Ref [33]. uses a cascade reservoir input variable selection strategy to choose the most valuable input variables for decision-making in multiple-objectivity cascade reservoir operation; Ref [34]. uses MOEAs to derive operating rules for pumped water storage with the objectives of minimizing the water shortage index and maximizing the net revenues of consumed and produced energy; Ref [35]. uses a multi-objective reservoir optimal operation model to discuss the individual and joint effects of operation factors on the trade-off between flood control and water conservation. However, due to the loss of swarm diversity, it is difficult for MOEAs to avoid the premature convergence problem in many cases, which often produces dissatisfactory non-dominated set. In addition, the computational cost of MOEAs often increases sharply or even become intolerable with the expansion of problem scale [36–38]. Thus, some certain spaces to enhance the performance of MOEAs still exist in practice. Generally, the possible feasible ways include the improvement of search mechanism, exploration of new search strategies or utilization of efficient computing technique [39–41]. Here, the parallel computing technique is chosen to improve the search capacity of MOEAs.

With the rapid development of computer technology, the multi-core processor has become the standard configuration of personal computers, workstation and servers, providing the necessary hardware foundation for parallel computing [42]. In addition, many famous parallel frameworks represented by Fork/Join and MPI (message passing interface) have been developed by different organizations and companies [43], providing indispensable software basis for the implementation of parallel computing. Hence, in many scientific and engineering fields, the parallelization design has become a popular tool to reduce the execution time of traditional tasks [44–46]. For instance, Ref [47]. develops a parallel multi-swarm algorithm based on comprehensive learning particle swarm optimization for global numerical optimization problems; Ref [48]. develops a parallelized version of genetic algorithm for the optimal distribution of shopping centers; Ref [49]. uses parallel technique and progressive optimality algorithm to handle the peak operation problem of hydropower system; Ref [50]. verifies the feasibility of parallel computing in stochastic dynamic programming for long term operation planning of hydrothermal power systems. However, for the best of our knowledge, even to this day, there are still a few open reports about using the parallel technique to improve the computational efficiency of algorithms for cascade hydropower reservoir operation balancing benefit and firm output. Hence, for the purpose of enriching the existing optimization techniques, this paper aims at incorporating the advanced parallel technology into MOEAs for the hydropower operation problem.

Compared with other heuristic approaches, the particle swarm optimization (PSO) was found slow at the beginning, but will become effective when approaching to a higher model run iteration [51], which can effectively guarantee its global search capability. With the advantages of fewer computing parameters, higher execution efficiency and less computational burden, PSO has been widely adopted to address many complex engineering optimization problems. Moreover, the PSO method encoded in Java language has been successfully developed in our previous literatures [32], which will greatly promotes research progress. Thus, PSO was chosen as the standard method for parallelization, and the parallel multi-objective particle swarm optimization (PMOPSO) based on the Fork/Join framework is introduced to solve the complicated CHRO problem. The feasibility of PMOPSO was demonstrated by the simulations of Lancang hydropower system in several cases with dry, wet and real runoff. To be mentioned, for a given region, the dry years means that the runoff in the target hydrologic year is less than its average annual runoff, and the drought years denote a long period of below-average precipitation. Both of the drought years and dry years will lead to water resources shortages and harm to the local economy, ecosystem as well as agriculture.

Finally, to better understand this paper, the key points are summarized as below: (1) a practical model balancing power generation and firm output of hydropower system is presented; (2) based on the principles of MOPSO, small population and parallel computing, PMOPSO is proposed to diversify the population and reduce the execution time of MOPSO, which is the main contribution of this study to the field of optimization studies; (3) Based on the strict theoretical derivation, a novel constraint handling technique is used to ensure the feasibility of particles; (4) the proposed approach can obtain satisfactory results when applied to the optimal operation of Lancang cascade hydropower system in China.

The rest of this paper is organized as below. Section 2 gives the mathematical model of CHRO. The basic information of PMOPSO is introduced in Section 3. Then, Section 4 shows the details of PMOPSO for the CHRO problem. The results of different methods are compared in Section 5, while Section 6 shows the conclusions.