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Offline training for improving online performance of a genetic algorithm based optimization model for hourly multi-reservoir operation

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ABSTRACT

A novel framework, which incorporates implicit stochastic optimization (Monte Carlo method), cluster analysis (machine learning algorithm), and Karhunen-Loeve expansion (dimension reduction technique) is proposed. The framework aims to train a Genetic Algorithm-based optimization model with synthetic and/or historical data) in an offline environment in order to develop a transformed model for the online optimization (i.e., real-time optimization). The primary output from the offline training is a stochastic representation of the decision variables that are constituted by a series of orthogonal functions with undetermined random coefficients. This representation preserves covariance structure of the simulated decisions from the offline training as gains some "knowledge" regarding the search space. Due to this gained "knowledge", better candidate solutions can be generated and hence, the optimal solutions can be obtained faster. The feasibility of the approach is demonstrated with a case study for optimizing hourly operation of a ten-reservoir system during a two-week period.

1. Introduction

The optimization of hourly multi-reservoir operation is essential to many short-term routines such as determining the hourly operation strategy of the reservoir in a power-scheduling problem (Gil et al., 2003). Energy marketing also requires hourly reservoir operation for incorporating energy price changing at every hour (Olivares and Lund, 2011). Power schemes that combine hydropower with wind generation and/or other renewable sources often consider hourly or sub-hourly time steps for accurate representations on the variation of power resources (Wang and Liu, 2011; Deane et al., 2014). Moreover, hourly reservoir operations are increasingly being considered for environmental objectives. For instance, hourly fluctuations in water surface elevation and flow discharge are essential for spawning activity of some fish species (Chen et al., 2015; Stratford et al., 2016). Maintaining hourly regime of environmental flows has gained increasing attention due to its benefit to the biota of river ecosystem (Meile et al., 2011; Shiau and Wu, 2013; Horne et al., 2017). Optimizing hourly multi-reservoir operation, however, is a challenging task due to the complexity of the search space, which result from the large number of decision variables (e.g., thousands). The optimization problem may be solved in an offline environment assuming all information are known. This offline optimization is normally accompanied by high computational cost and therefore, may not be acceptable for the online optimization, i.e., an efficient optimization preformed in a real-time manner.

Genetic Algorithms (GA) and its variants have been widely applied to multi-reservoir operation during the last two decades (Oliveira and Loucks, 1997; Wardlaw and Sharif, 1999; Reed et al., 2013; Tsoukalas and Makropoulos, 2015; Lerma et al., 2015; Gibbs et al., 2015) owing to its robustness, effectiveness and global optimality properties. However, most applications of the GA on reservoir operation focus on long term planning and management with monthly time step or short-term optimization with a daily time step. Like other metaheuristics methods, GA works by iteratively

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moving to better positions in the search-space, which are sampled using some probability distribution (e.g., normal) defined around the current position. The embedded randomness is a key element for global optimality, however, results in a slow convergence. For the GA-based model, the computational cost for optimizing hourly multi-reservoir operation may be too expensive to perform an efficient online optimization in real-time. To reduce the computation cost, some decomposition techniques have been adopted. Gil et al. (2003) perform a time hierarchical decomposition on a short-term hydrothermal generation scheduling problem and a set of expert operators (expert knowledge of the system and a priority list) is incorporated in the GA. Zoumas et al. (2004) proposed six problem-specific genetic operators, essentially a combination of local search techniques and expertise on the problem, to enhance the online performance of the GA for a hydrothermal coordination problem. Although useful in certain contexts, these techniques tend to be very problem-dependent and difficult to apply to general problems.

Machine-learning approaches, such as Reinforcement Learning (RL) and Cluster Analysis (CA) have been increasingly used to improve the performance of the optimization model, despite that many machine-learning approaches are optimization problems per se. In fact, machine-learning approaches and optimization algorithms have become frequently coupled for solving complex problems (Bennett and Parrado-Hernández, 2006). Lee and Labadie (2007) used the RL to improve the performances of a stochastic optimization model for operating a two-reservoir system on Geum River (South Korea). Castelletti et al. (2010) applied a tree-based learning method for optimal operation of reservoirs in Lake Como water system (Italy). Though different machine-learning approaches are implemented, the basic idea is to interact with the experience (e.g., historical data) or environment (e.g., feedback) and learn from these interactions. The pilot researches of Lee and Labadie (2007) and Castelletti et al. (2010) showed promising results for using machine learning to improve the performance of the optimization model. However, their researches focus on long term planning using offline optimization. The computational cost of optimizing one reservoir is approximately 1.5 h in a regular computing environment (Castelletti et al., 2010), which is infeasible to implement for hourly multi-reservoir operation in real time.

The performance of the online optimization can be improved through the offline optimization (De Jong, 1975). The offline optimization is normally used to determine the current state and the control law for the online optimization and reduce the online control algorithm to a lookup table (Bemporad et al., 2002; Pannocchia et al., 2007). This strategy applied successfully to the small problems for which the number of decision variables is manageable, however, no longer practically feasible for large problems with thousands of controls (Wang and Boyd, 2010). Chasse and Sciarretta (2011) combined an offline optimizer with an online strategy for energy management problem. The offline optimization estimated two tuning parameter for the online optimization and therefore, allowing a better performance for the online optimization. However, an adaptation rule, which can be problem-specific, is needed for linking the offline optimization with the online optimization in order to account for future information uncertainty. Ravey et al. (2011) used offline optimization to predict a control strategy and then adapt online control strategy for real time energy management. An extra GA optimizer is implemented for the online optimization to improve the performance. Among those works, offline optimization is used to provide a priori for the online optimization but some extra efforts are normally required in the online optimization due to uncertainty/variability of the future information. A novel framework based on offline training is proposed herein to improve the performance of online optimization for hourly multi-reservoir operation. The framework trained the online optimization through intensive offline optimization, in which many inflow scenarios that account for future information are included. No extra procedure is required for the online optimization after the offline training process is completed and therefore, provide a more generic solution for different applications. The framework combine implicit stochastic optimization (Monte Carlo method), cluster analysis (machine learning algorithm), and Karhunen-Loeve expansion (dimension reduction technique) in an offline environment and develop a transformed model for the online optimization. The transformed model preserves the covariance structure of the obtained ‘historical’ optimal solutions, which can be thought as gaining *knowledge* from the training process. Candidate solutions that are generated by the transformed model (i.e., the trained model) share similar statistical properties with the historical optimal solutions and therefore, the trained model finds optimal solutions faster given similar input data. The framework is applied to train a multi-objective optimization model for hourly operation of a ten-reservoir system. The performance of the trained model is compared against the untrained model (zero training). The sensitivity on the number of the training times is also investigated. The major contribution of the study is (1) develop a novel framework for training optimization model in an offline environment, (2) the trained model significantly improve the online performance of optimization and (3) discover an optimal number of model training times for a relatively good performance with relatively less training budget.

2. Optimization model for hourly reservoir operation

2.1. Reservoir system

A reservoir system on the Columbia River in the United States, which comprises 10 reservoirs, is used as a test case. Sketch of the ten-reservoir system is shown in Fig. 1. The reservoir system provides multiple operational purposes including power generation, ecological and environmental requirements and recreation (Schwanenberg et al., 2014; Chen et al., 2016).

We consider an operational horizon as two weeks, specifically from August 25th to September 7th due to the data availability. The time step of the decisions is hourly. The decision variables are the outflows of each reservoir at each hour during the optimization horizon, which resulting in 3360 variables in total.

2.2. Objectives

Two objectives related to power generation are explicitly considered and expressed in the following:

$$\text{Objetive1: } \mathit{Minimize} \sum_{t=1}^{T_h} \left(\min\left(0, \sum_{i=1}^{Nr} \left(PG_t^i\right) - PD_t \right)\right) \tag{1}$$

$$\text{Objetive2: } \mathit{Maximize} \sum_{T_d=1}^{14} \left(\sum_{hr=6}^{22} \left(\max\left(0, \sum_{i=1}^{Nr} PG_{hr}^i - PD_{hr} \right)\right)\right) \tag{2}$$

where PG is hydropower generated in the system (MWh), PD is power demand in the region (MWh). The variable t denotes time in hours and T_h is the optimization period (3360 h). The index i represent reservoirs in the system and N_r is total number of reservoirs. h_r means heavy load hours (HLH) for a day (typically from 06:00 to 22:00 h). The quantity T_d corresponds to the optimization period in days (14 days in our case).