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Research papers

Assessing the weighted multi-objective adaptive surrogate model optimization to derive large-scale reservoir operating rules with sensitivity analysis

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A B S T R A C T

The optimization of large-scale reservoir system is time-consuming due to its intrinsic characteristics of non-commensurable objectives and high dimensionality. One way to solve the problem is to employ an efficient multi-objective optimization algorithm in the derivation of large-scale reservoir operating rules. In this study, the Weighted Multi-Objective Adaptive Surrogate Model Optimization (WMO-ASMO) algorithm is used. It consists of three steps: (1) simplifying the large-scale reservoir operating rules by the aggregation-decomposition model, (2) identifying the most sensitive parameters through multivariate adaptive regression splines (MARS) for dimensional reduction, and (3) reducing computational cost and speeding the searching process by WMO-ASMO, embedded with weighted non-dominated sorting genetic algorithm II (WNSGAII). The intercomparison of non-dominated sorting genetic algorithm (NSGAII), WNSGAII and WMO-ASMO are conducted in the large-scale reservoir system of Xijiang river basin in China. Results indicate that: (1) WNSGAII surpasses NSGAII in the median of annual power generation, increased by 1.03% (from 523.29 to 528.67 billion kW h), and the median of ecological index, optimized by 3.87% (from 1.879 to 1.809) with 500 simulations, because of the weighted crowding distance and (2) WMO-ASMO outperforms NSGAII and WNSGAII in terms of better solutions (annual power generation (530.032 billion kW h) and ecological index (1.675)) with 1000 simulations and computational time reduced by 25% (from 10 h to 8 h) with 500 simulations. Therefore, the proposed method is proved to be more efficient and could provide better Pareto frontier.

1. Introduction

Water is essential in our life (Valipour and Singh, 2016). The long-term optimal operation of the large-scale reservoir system and the way of using the renewable water has attracted substantial attention over the past decades in water resources management (Valipour, 2012; Yannopoulos et al., 2015). The large-scale reservoir operation involves a time-consuming decision making process because of non-commensurable (even conflicting) objectives and high dimensionality (Liu et al., 2011a; Marino and Loaiciga, 1983; Oliveira and Loucks, 1997). An efficient multi-objective optimization algorithm is required to derive the large-scale reservoir operating rules effectively.

For deterministic reservoir operation, it is impossible to obtain the optimal solution in a large-scale reservoir system because of the curse of dimensionality (Liu et al., 2011b). Parameter simulation optimization (PSO), which predefines a rule curve shape and determines parameters through optimization algorithms (Celeste and Billib, 2009), is widely used to derive the large-scale reservoir operating rules. Various functional forms have been applied to reservoir operating rules, such as linear regression (Liu et al., 2014; Zeng et al., 2015) and support vector machine (Zhang et al., 2015). The aggregation-decomposition model coupled with piecewise linear regression is widely used in cascade hydropower systems (Li et al., 2014). The aggregation method can transform a

Abbreviations: AGDP, aggregation-decomposition method; COR, conventional operating rules; SA, Sensitivity analysis; MARS, multivariate adaptive regression splines; LH, Latin Hypercube; MC, Monte Carlo; NSGAII, non-dominated sorting genetic algorithm II; WNSGAII, weighted non-dominated sorting genetic algorithm II; WMO-ASMO, weighted multi-objective adaptive surrogate model optimization; GLP, Good Lattice Point; RGS, ranked Gram-Schmidt algorithm; GPR, Gaussian processes regression.

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multi-reservoirs system into an equivalent virtual reservoir (Turgeon, 1980). Valdes et al. (1992) proposed the aggregation in power units rather than water units in hydropower system. The decomposition method, which decentralizes the total decision into individual reservoirs, is often used together with the aggregation method (Terry and Sales, 1986). Neutral networks (Saad et al., 1996, 1994), theoretical analysis (Lund and Guzman, 1999) and fixed proportion have been successfully used as decomposition forms.

Sensitivity analysis (SA) can screen out the most sensitive parameters on model performance to decrease complexity (Griensven et al., 2006; Saltelli et al., 2004). SA has been widely used in the field of water resources, such as hydrological model (Gan et al., 2014) and reservoir operating rules (Chu et al., 2015). There are many SA methods which can be selected, including global and local sensitive analysis methods. Li et al. (2013) concluded that global SA methods were suitable for complex models to identify sensitive parameters from the insensitive ones. Among different kinds of SA methods, multivariate adaptive regression splines (MARS) was proved to be a stable SA method (Gan et al., 2014).

However, despite dimension reduction by SA, the computational burden involved in the large-scale reservoir system must be considered for two reasons: (1) the multi-objective optimization usually requires a large number of model runs to obtain the optimal Pareto frontier (Li et al., 2016) and (2) running the operation for a multiyear and large-scale reservoir system is time consuming. Although many multi-objective optimization algorithms have been used for several decades, such as NSGAII (Deb et al., 2002) and MOSCEM (Vrugt et al., 2003), it is difficult to implement these algorithms to obtain the Pareto optimal sets for large-scale reservoir system because of high computational cost (Chu et al., 2015). The weighted crowding distance was proposed to guide the searching process towards the non-dominated region, replacing the classical crowding distance (Gong et al., 2015b).

Surrogate model, also called metamodeling, can mimic complex model to reduce computational burden of optimization. Razavi et al. (2012) summarized research on surrogate model in water resources, such as groundwater optimization problems (Johnson and Rogers, 2000) and water distribution system design and optimization (Behzadian et al., 2009). For multi-objective surrogate model optimization, some researchers transformed multi-objective problem into single-objective problem through some scalarization methods. For example, Gong et al. (2015a) used three weighing functions to convert the multi-objective problem into a single-objective problem in land surface models. Three multi-objective surrogate model based optimization methods, ParEGO (Knowles, 2006), SUMO (Gorissen et al., 2010) and SMS-EGO (Ponweiser et al., 2008), which transformed multi-objective problem into multiple single-objective problems, were compared with two classical evolutionary algorithms, NSGAII and SMS-EMOA (Beume et al., 2007) in multi-reservoir operation (Tsoukalas and Makropoulos, 2015). The results indicated that the surrogate model based optimization performed better than the classical evolutionary algorithms, and SUMO outperformed ParEGO and SMS-EGO. Gong et al. (2015b) developed a multi-objective adaptive surrogate modeling based optimization algorithm, which can keep better balance of convergence and diversity with adaptively selecting the most representative sample points.

Based on the above mentioned researches, we can know that NSGAII has been widely used in reservoir optimization operation. Surrogate model and sensitivity analysis have been applied to reservoir operation due to the computational burden and high dimension. However, little work has been done about multi-objective reservoir optimization operation using WNSGAII coupled with adaptive surrogate model. Furthermore, integration of sensitivity analysis and adaptive surrogate model has not been done in previous research. The purpose of this paper is to use the WMO-ASMO that incorporates the weighted crowding distance and the adaptive surrogate model to derive the optimal large-scale reservoir operating rules under sensitivity analysis, compared with the classical evolutionary algorithms. Particularly, the weighted crowding distance could guide the searching process and the adaptive surrogate model solves the computational large-scale reservoir simulation. WMO-ASMO obtains the optimal Pareto frontier more efficiently and effectively than two evolutionary algorithms, with a case study in the derivation of large-scale reservoir operating rules of Xijiang river basin in China.

2. Methodology

As shown in Fig. 1, this paper proposes an improved multi-objective optimization method for the derivation of large-scale reservoir operating rules. The methodological processes are summarized below.

(1) Reservoir simulation model. The large-scale reservoir operating rules are predefined by aggregation-decomposition method (AGDP), coupled with piecewise linear regression. The parameters of piecewise linear operating rules are selected as the model inputs, while the annual hydropower generation and the ecological index are the outputs (Section 2.1).
(2) Sensitivity analysis (SA). MARS method is used to screen out the important parameters with Latin Hypercube and Monte Carlo sampling techniques. Sensitive parameters are optimized through multi-objective optimization algorithms and other parameters are fixed according to the default parameters (Section 2.2).
(3) Multi-objective optimization. The surrogate model GPR is applied to the multi-objective optimization to evaluate its efficiency. WNSGAII is integrated into GPR to update surrogate model. The weighted multi-objective adaptive surrogate model optimization (WMO-ASMO) is compared with the typical NSGAII and WNSGAII (Sections 2.3 and 2.4).
(4) Pareto frontier. Results of three multi-objective optimization algorithms are analyzed to determine the appropriate multi-reservoir operating rules.

Above all, reservoir simulation model and multi-objective optimization are the most important parts. The detailed explanation should be focus on Sections 2.1 and 2.4.

2.1. Aggregation-decomposition model

Since the high dimensionality of a large-scale reservoir system cannot be solved by the deterministic optimization model (Anand et al., 2013), an aggregation-decomposition method (AGDP) should be considered. The aggregation-decomposition model is to aggregate all the reservoirs to determine the total output, then allocates it to the individual reservoirs (Heever and Grossmann, 2002).

2.1.1. Aggregated reservoir

Supposing the drainage area is large and the flows change greatly with season, the reservoirs in different branches and different seasons can be aggregated as several aggregated reservoirs, respectively. An aggregated reservoir can retain and describe some features of the reservoirs in the same branch without considering their interactions. The reservoirs are aggregated in energy units rather than water units due to variation of head and unit efficiency for hydropower reservoirs (Valdes et al., 1992; Zhou et al., 2015).