Journal of Hydrology 519 (2014) 925–933

Contents lists available at ScienceDirect

Journal of Hydrology

journal homepage: www.elsevier.com/locate/jhydrol

Multi-objective optimization for construction of prediction interval of hydrological models based on ensemble simulations

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ARTICLE INFO

Article history:
Received 25 March 2014
Received in revised form 12 July 2014
Accepted 9 August 2014
Available online 19 August 2014
This manuscript was handled by Konstantine P. Georgakakos, Editor-in-Chief, with the assistance of Attilio Castellarin, Associate Editor

Keywords:
Prediction interval
Ensemble
Hydrological models
Multi-objective optimization

SUMMARY

Practice experience reveals that prediction interval is more reliable and informative compared to single simulation, as it indicates the precision of the forecast. However, traditional ways to implement the construction of prediction interval is very difficult. This paper proposed a novel method for constructing prediction interval based on a hydrological model ensemble. The excellent multi-objective shuffled complex differential evolution algorithm was introduced to calibrate the parameters of hydrological models so as to construct an ensemble of hydrological models, which ensures a maximum of the observed data to fall within the estimated prediction interval, and whose width is also minimized simultaneously. Meanwhile, the mean of the hydrological model ensemble can be used as single simulation. The proposed method was applied to a real world case study in order to identify the effectiveness of the construction of prediction interval for the Leaf River Watershed. The results showed that the proposed method is able to construct prediction interval appropriately and efficiently. Meanwhile, the ensemble mean can be used as single simulation because it maintains comparative forecasting accuracy as the traditional single hydrological model.

1. Introduction

Accurate and reliable flow forecasting is of great significance for the optimal management and utilization of water resources. Conceptual hydrological models, which are theoretical representations of a part of the hydrologic cycle, are widely used to perform flow predictions. In actual case applications, single simulation is more popular than prediction interval because of its convenience to implement. However, single simulation is of limited value because it merely indicates a single possible future value for the variable and does not convey information about the level of uncertainty which is intrinsic associated with forecasting (Goodwin et al., 2010). Compared to single simulation, prediction interval not only provides a range that observed flows are highly likely to lie within, but also has an indication of their accuracy called the confidence level (Quan et al., 2014). Prediction interval is more reliable and informative for decision makers to draw up plans than single simulation. Therefore a reasonable estimate of prediction interval for the flows provides valuable information in water resources problems (Liu and Gupta, 2007).

Traditional methods for the construction of prediction interval in the hydrology literature mainly are delta, Bayesian, generalized likelihood uncertainty estimation (GLUE) and bootstrap. The delta technique introduced by Chryssoloiuris et al. (1996) considers linearizing the model around a set of parameters, and constructing the prediction interval by the application of standard asymptotic theory to the linearized model (Kasiviswanathan and Sudheer, 2013b). However this method is based on the assumption that noise is homogenous and normally distributed which may not be true in real world problems (Ding and He, 2003). In the Bayesian method, each parameter in the model is considered as a probability distribution rather than a single value and therefore the outcome of the model will also be in distribution conditional form on the observed data. Although the Bayesian method has a strong supporting theory, it is still not popular because of the limitation of massive computational burden. In Bayesian technique, the Hessian matrix of the parameters needs to be calculated in each iteration. The GLUE method is based on Monte Carlo simulation where a model is run a large number of times with different parameter sets (Blasone et al., 2008a,b). A large number of model runs are made with many different randomly sampled parameter values from a

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http://dx.doi.org/10.1016/j.jhydrol.2014.08.026
0022-1694/

priori probability distribution based on modeler's knowledge of the system. The acceptability of each run is evaluated against observed values and, if the acceptability is below a certain subjective threshold, the run is considered to be non-behavioral and that parameter combination is removed from further analysis (Liu et al., 2010). Although GLUE may be easily implemented and does not require any changes to the source code of the simulation model, it also has very evident shortcomings, such as subjective choice of the likelihood function and truncation threshold used to separate behavioral and non-behavioral models. The bootstrap method is a computational procedure that uses intensive resampling with replacement, in order to reduce uncertainty (Efron and Tibshirani, 1993). The bootstrap method generates different realizations of a dataset to create bootstrap samples and their estimates can provide average and variability of the estimates (Tiwari and Chatterjee, 2010). The main advantage of the bootstrap method is its simplicity and ease of implementation (Kasiviswanathan et al., 2013a). However, bootstrap makes an assumption that an ensemble of models will produce a less biased estimate of the true regression of the targets. Implementation difficulties, special assumption about the data distribution, and massive computational requirements hinder the widespread applications of these methods (Quan et al., 2014).

Recently, a variety of multi-objective optimization algorithms have been introduced or designed for multi-objective parameter optimization of hydrological models (Gupta et al., 1998, 1999; Vrugt et al., 2003; Bekele and Nicklow, 2007; Guo et al., 2013). Compared to single-objective optimization, the multi-objective optimization will get a set of so-called "differently good solutions" (Pareto optimal solutions) that modelers would need to provide additional criteria to choose between them. There is a significant advantage to maintain the independence of the various objective functions, because multi-objective optimization will not only allow an analysis of the trade-offs among the different objective functions but also enable hydrologists to better understand the limitations of the current hydrologic model structure (Gupta et al., 1998). However, the multi-objective parameter optimization algorithms aforementioned in hydrology field are mostly used in single simulation.

A higher coverage probability and narrower forecasting width are always preferred in prediction interval. These two properties are conflicting with the optimization perspective, as a higher coverage probability will typically result in a wider forecasting width, while a narrower width will always lead to a lower coverage probability. Therefore, multi-objective optimization algorithms can be introduced to solve the optimization problem of the two conflicting objectives. Recently Kasiviswanathan et al. (2013a) employed Non-dominated Sorting Genetic Algorithm II (NSGA- II) multi-objective optimization algorithm to construct prediction interval for artificial neural network (ANN) rain-fall runoff models. In his research, the results illustrated that an ensemble of models, generated by multi-objective optimization algorithm, provided a good characterization of the uncertainty in rainfall-runoff model performance. Due to the powerful flow forecasting ability of conceptual hydrological models, the ensemble of conceptual hydrological models can also be used for the construction of prediction interval. Multi-Objective Shuffled Complex Differential Evolution (MOSCDE) has been demonstrated to be more efficient than NSGA- II by five frequently used benchmark test problems in Guo et al. (2013), which means MOSCDE is an efficient multi-objective algorithm. Therefore, MOSCDE algorithm is introduced in this paper to construct prediction interval for an ensemble of conceptual hydrological models, which ensures a maximum of the observed flows to fall within the estimated range, and whose width is also minimized simultaneously. Besides, the mean of the hydrological model ensemble can be used as single simulation. A single hydrological model calibrated by Shuffled Complex Evolution (SCE) is also developed to perform single simulation for comparison.

The remainder of this paper is organized as follows: Section 2 presents a brief description of theoretical background involved in this study. Section 3 proposes the methodology to construct prediction interval for an ensemble of hydrological models. In Section 4, a real world case study with results and discussions is revealed. Section 5 summaries the conclusions of this study.

2. Background

2.1. HYMOD hydrological model

The HYMOD conceptual hydrological model, which is introduced by Boyle (2000) and recently used by Guo et al. (2013), is used herein to illustrate the effectiveness of the proposed method of the prediction interval construction. This model consists of a simple two-parameter rainfall excess model connected with two series of linear reservoirs (three, identical, for the quick and a single reservoir for the slow response) in parallel as a routing component (Wagener et al., 2001). The structure of the HYMOD model is illustrated in Fig. 1.

The model requires the calibration of five parameters: the maximum storage capacity in the catchment C_{max}, the degree of spatial variability of the soil moisture capacity within the catchment b_{exp}, the factor distributing the flow between the two series of reservoirs *Alpha*, and the residence times of the linear quick and slow reservoirs R_q and R_s, respectively. The variable ranges of the five parameters are listed in Table 1. Readers may refer to Moore (1985) for detailed description of the HYMOD.

2.2. Shuffled Complex Evolution (SCE) algorithm

SCE algorithm is developed by Duan et al. (1992) for parameter optimization of conceptual rainfall-runoff models. It is an evolutionary-based procedure that simultaneously evolves a population of solutions (parameter sets) towards better solutions in the search space, trying to converge to the global optimum of the objective function (Blasone et al., 2007). The procedure starts with a random generation of an initial population of solutions in the feasible parameter space confined by the lower and upper bounds of the parameter values. Each individual solution is evaluated by the objective function which describes the correspondence between a model output variable and observed values. After the initialization, the parameter sets are then partitioned into several sub-samples, called complexes. The solutions in each complex are evolved according to the simplex search method (Nelder and Mead, 1965) in the attempt to replace the worst solutions of lowest fitness with better ones. In this phase, each complex is evolved independently for a certain number of generation. At last, all the individual solutions from the complexes are shuffled into a new population, from which new complexes are formed and evolved as before. This process is repeated until some stopping criteria are satisfied. The use of multiple complexes and their periodic shuffling operation provide the algorithm with an effective exploration of different region of attraction in the feasible space, thereby reducing the probability of falling into the local optimal (Guo et al., 2013). Studies have shown that the SCE algorithm is an effective and efficient optimization method for the calibration of hydrological models (Madsen, 2000, 2003; Eckhardt and Arnold, 2001; Ajami et al., 2004; Blasone et al., 2007; Zhang et al., 2013). In rainfall-runoff models applications, SCE algorithm has also been demonstrated to be superior to other search techniques, such as the Multiple Start Simplex, Genetic Algorithms and Simulated Annealing (Gan and Biftu, 1996; Cooper et al., 1997; Kuczera, 1997; Franchini et al., 1998). For more