Prediction interval optimization of radial basis function artificial neural network streamflow forecast models

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Understanding the complex nature of rainfall-runoff process has opened many folds of modeling technique. It is still a challenging task in hydrologic modeling analyzing the inherent variability or uncertainty besides the improvement in model performance. To date, variety of hydrologic models have been developed which are mainly classified into physics based or data driven based approaches. The advantage of using physics based models represents the physical processes responsible for generating the flow. However, it often requires more information of catchment, and expertise of modeler. In addition, any changes in the catchment may alter the performance of the model because of the sensitivity of model parameters. Alternatively, the data driven models have produced reasonable estimate of streamflow forecasting compared to physics based models. The main advantage lies learning the underlined processes from historically measured data without explicit information of the system to be modeled. Though the data driven models might not include the physical processes in its computation, the accurate estimation of flood is mainly required, which encourages the application of these models. Over the last two decades, various types of data driven based flood forecast/rainfall-runoff models have been reported, in which Radial Basis Function Artificial Neural Network (RBFANN) model has been recognized as a promising tool while approximating the non-linear hydrologic processes. However, the point estimation of RBFANN sometimes lacks in explaining the underline variability or uncertainty associated with modeling, which reduces the reliability of the models. Hence the main focus of the present paper is to carry out the uncertainty analysis of RBFANN. The RBFANN has a parameter called spread, which needs to be determined carefully, since it identifies appropriate model parameters of ANN (i.e. weights and biases). In general, the RBFANN uses a default constant spread value (named as Static RBFANN in this study) which leads to a point prediction of model output. However any improper selection of spread value might lead to over and/or poor generalization of ANN models. In this paper, a multi-objective optimization method is proposed for estimating the upper and lower values of spread (named as Stochastic RBFANN), which in turn train two sets of weights and biases for forecasting the upper and lower bounds of model output in the form of prediction interval (PI). The proposed modeling approach is demonstrated through streamflow forecasting using the hourly rainfall and runoff data collected from Kolar river basin, India. The comparison between Static and Stochastic RBFANN models indicates that the performance of these models is similar. However, the Stochastic RBFANN modeling approach produces prediction interval that indicate the level of uncertainty. The multi-objective optimization function comprised of two indices such as percentage of coverage (POC) and average width (AW), which are generally used to evaluate the model prediction uncertainty was formulated. The prediction interval (Fig.1) for various flow domains resulted in different magnitude of prediction uncertainty. The high flow series contained only 7 percentage of observation in the prediction interval compared to low (77%) and medium flow (79%) in the model validation. As uncertainty can be directly related to the reliability, the information from the prediction interval is necessary for the careful identification of model output, in specific to the decision making on the flood forecast. Overall, the quantification of prediction uncertainty in RBFANN provides valuable information, which clearly illustrates the strong and weak points while forecasting the streamflow.

Fig. 1 Prediction interval corresponding to upper and lower bound values of spread

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