Evaluation of Several Algorithms in Forecasting Flood

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Abstract. Precise flood forecasting is desirable so as to have more lead time for taking appropriate prevention measures as well as evacuation actions. Although conceptual prediction models have apparent advantages in assisting physical understandings of the hydrological process, the spatial and temporal variability of characteristics of watershed and the number of variables involved in the modeling of the physical processes render them difficult to be manipulated other than by specialists. In this study, two hybrid models, namely, based on genetic algorithm-based artificial neural network and adaptive-network-based fuzzy inference system algorithms, are employed for flood forecasting in a channel reach of the Yangtze River. The new contributions made by this paper are the application of these two algorithms on flood forecasting problems in real prototype cases and the comparison of their performances with a benchmarking linear regression model in this field. It is found that these hybrid algorithms with a "black-box" approach are worthy tools since they not only explore a new solution approach but also demonstrate good accuracy performance.

1 Introduction

Numerical models for flood propagation in a channel reach can broadly be classified into two main categories: conceptual models [1-5]; and, empirical models based on system analysis or "black-box" approach. Huge amount of data are usually required for calibration of these conceptual models. In many cases, a simple "black-box" model may be preferred in identifying a direct mapping between inputs and outputs. During the past decade, several nonlinear approaches, including artificial neural network (ANN), genetic algorithm (GA), and fuzzy logic, have been employed to solve flood forecasting problems. Smith and Eli [6] applied a back-propagation ANN model to predict discharge and time to peak over a hypothetical watershed. Tokar and Johnson [7] compared ANN models with regression and simple conceptual models. Liong *et al.* [8] employed an ANN approach for river stage forecasting in Bangladesh. Cheng and Chau [9] employed fuzzy iteration methodology for reservoir flood control operation. Chau and Cheng [10] performed a real-time prediction of water stage with ANN approach using an improved back propagation algorithm. Chau [11] calibrated flow and water quality modeling using GA. Cheng *et al.* [12] combined a fuzzy optimal model with a genetic algorithm to solve multiobjective rainfall-runoff model calibration. Chau [13-14] performed river stage forecasting and rainfall-runoff correlation with particle swarm optimization technique. Cheng *et al.* [15] carried out long-term prediction of discharges in Manwan Reservoir using ANN models.

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In this paper, two hybrid algorithms, namely, genetic algorithm-based artificial neural network (ANN-GA) and adaptive-network-based fuzzy inference system (ANFIS), are applied for flood forecasting in a channel reach of the Yangtze River. To the knowledge of the authors, these types of algorithms have never been applied to hydrological and water resources problems. The new contributions made by this paper are the application of these two algorithms on flood forecasting problems in real prototype cases and the comparison of their performances with a benchmarking linear regression (LR) model in this field.

2 Genetic Algorithm-Based Artificial Neural Network (ANN-GA)

A hybrid integration of ANN and GA, taking advantages of the characteristics of both schemes, may be able to increase solution stability and improve performance of an ANN model. A genetic algorithm-based artificial neural network (ANN-GA) model is developed here wherein a GA [16] is used to optimize initial parameters of ANN before trained by conventional ANN. In the GA sub-model, the objective function used for initializing weights and biases is represented as follows:

$$\min J(W,\theta) = \sum_{i=1}^{p} \left| Y_i - f(X_i, W, \theta) \right| \tag{1}$$

where W is the weight, θ is the bias or threshold value, i is the data sequence, p is the total number of training data pairs, X_i is the ith input data, Y_i is the ith measured data, and $f(X_i, W, \theta)$ represents simulated output. The main objective of the sub-model is to determine optimal parameters with minimal accumulative errors between the measured data and simulated data.

3 Adaptive-Network-Based Fuzzy Inference System (ANFIS)

In this study, the output of each rule is taken as a linear combination of input variable together with a constant term. The final output is the weighted averaged of each rule's output. The fuzzy rule base comprises the combinations of all categories of variables. As an illustration, the following shows a case with three input variables and a single output variable. Each input variable (x, y, and z) is divided into three categories. Equally spaced triangular membership functions are assigned. The categories are assigned: "low," "medium," and "high." The number of rules in a fuzzy rule base is c^n, where c is the number of categories per variable and n the number of variables. The optimal number of categories is obtained through trials and performance comparison. The format of the rule set contains an output $o_{i,j,k}$ for a combination of category i of input variable x, category j of input y, and category k of input variable z, respectively.