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Hourly runoff forecasting for flood risk management: Application of various computational intelligence models

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SUMMARY

Reliable river flow forecasts play a key role in flood risk mitigation. Among different approaches of river flow forecasting, data driven approaches have become increasingly popular in recent years due to their minimum information requirements and ability to simulate nonlinear and non-stationary characteristics of hydrological processes. In this study, attempts are made to apply four different types of data driven approaches, namely traditional artificial neural networks (ANN), adaptive neuro-fuzzy inference systems (ANFIS), wavelet neural networks (WNN), and, hybrid ANFIS with multi resolution analysis using wavelets (WNF). Developed models applied for real time flood forecasting at Casino station on Richmond River, Australia which is highly prone to flooding. Hourly rainfall and runoff data were used to drive the models which have been used for forecasting with 1, 6, 12, 24, 36 and 48 h lead-time. The performance of models further improved by adding an upstream river flow data (Wiangaree station), as another effective input. All models perform satisfactorily up to 12 h lead-time. However, the hybrid wavelet-based models significantly outperforming the ANFIS and ANN models in the longer lead-time forecasting. The results confirm the robustness of the proposed structure of the hybrid models for real time runoff forecasting in the study area.

1. Introduction

Water, despite being essential for all forms of life can also at times be destructive. Floods, landslides, and debris flow are all triggered by excess water. Many regions in the world are vulnerable to water related disasters and the damage as well as the resulting casualties are on the increase (Bates et al., 2008). Of the different types of water-related disasters, flood disasters take the lead in terms of the resulting number of casualties and the extent of damage. It is also important to note that not only the numbers of disasters are increasing, but also the number of people affected too because of migration of people into areas with better economic prospects.

Flood disaster mitigation can be achieved by structural means and non-structural means. The former is capital intensive and not affordable in developing countries which often face flood disasters. The latter, of which providing early warning systems is one approach, is favored in developing countries and practiced in developed countries as well. An essential component of an early warning system is an appropriate mathematical model which transforms the input rainfall data to corresponding river discharge.

There are several types of mathematical models that can be used in an early warning system. Broadly, they can be classified as physics based models, conceptual models and data driven models with each type having its own pros and cons. For example, physics based models have the potential to understand the underlying mechanisms of rainfall-runoff transformation, but require high resolution data as well as complex mathematical formulation (Garcia-Pintado et al., 2015). Conceptual models are relatively easy to formulate but require assumptions, such as linearity which sometimes may not be realistic. Data driven models, on the other hand do not require a detailed description of the processes in the hydrological cycle. In data driven models, only variation of a hydrological variable with time and input–output transformation is considered as in the case of stochastic models (time series models). These methods can be categorized in two main types of classical and computational intelligence approaches. There are various forms of computational intelligence (CI) methods such as artificial neural networks, fuzzy logic systems, adaptive neuro-fuzzy systems, support vector machines, dynamical systems approach and genetic programming. The focus of this study is on artificial neural networks and adaptive neuro-fuzzy systems.

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The application of artificial neural networks in hydrology started perhaps in the early 90's when Daniell (1991) listed ten potential applications of ANN in hydrological modeling. Since then, there has been an proliferation of related research including the use of radial basis function type artificial neural networks (Fernando and Jayawardena, 1998; Jayawardena et al., 2006), evolutionary product unit based neural networks for hydrological time series analysis (Karunasingha et al., 2011), water level prediction using artificial neural networks (Biswas and Jayawardena, 2014), and, river flow forecasting (Tawfik et al., 1997; Abrahart and See, 2000; Imrie et al., 2000; Birikundavyi et al., 2002; Cigizoglu, 2003; Moradkhani et al., 2004; Machado et al., 2011), among others. During the last decade or so, fuzzy logic approach has been used in hydrological applications (e.g. Liong et al., 2000; Şen and Altunkaynak, 2006; Firat et al., 2009; Turan and Yurdusev, 2014; Jayawardena et al., 2014). More recently, adaptive neuro-fuzzy system, or ANFIS (Jang, 1993) which has the advantages of both neural networks and fuzzy reasoning techniques has found applications in hydrology including river flow forecasting (Chiang et al., 2004; Vernieuwe et al., 2005; Chang and Chang, 2006; Aqil et al., 2007; Firat et al., 2009; Keskin et al., 2006; Nayak et al., 2005; Talei et al., 2010; Sanikhani and Kisi, 2012; Badrzadeh et al., 2014).

River flow time series is very complex and contains a wide range of frequency components. One of the recent developments for improving the accuracy of the forecasting is applying the wavelet multi-resolution analysis on the river flow time series. In the last decade, some researchers developed hybrid models by combining wavelet and a forecasting model. The most popular hybrid wavelet model for river flow forecasting is wavelet neural networks method (Kim and Valdes, 2003; Wang and Ding, 2003; Cannas et al., 2006; Kisi, 2009; Adamowski and Sun, 2010; Krishna et al., 2012; Nourani et al., 2013). The application of combining the wavelet analysis and neuro-fuzzy technique for hydrological forecasting has been investigated in a very few studies (Partal and Kişi, 2007; Kisi and Shiri, 2012; Badrzadeh et al., 2013). The application of hybrid wavelet-base model for river flow forecasting needs more investigation for different area with different characteristics.

In this study, the authors attempt to carry out a comparative study of four different types of data driven techniques. First, a feed-forward multi-layer perceptron type artificial neural network is developed followed by a hybrid wavelet neural network using discrete wavelet decomposition, an adaptive fuzzy neural network with grid partitioning and finally a hybrid adaptive fuzzy neural network with multi-resolution wavelet decomposition. They are then applied to forecast 1, 6, 12, 24, 36, and 48 h ahead river discharges at the Casino station across Richmond River in New South Wales, Australia. Root mean square error (RMSE) and Nash–Sutcliffe coefficient of efficiency (NSE) are considered as the main models' performance criteria. The results are satisfactory with the hybrid models performing better than the standard models as indicated by the performance indicators as well as event simulation and peak flow forecasting.

2. Methodology

2.1. Feed forward artificial neural networks

Artificial neural networks are general computational models that have been inspired by the operations of biological neural system. ANN has flexible structures that are capable of simulating the complex nonlinear relationships between model's input and output. Trained networks can be used to forecast future output for given inputs (the past observations). Artificial neural networks was first introduced by McCulloch and Pitts (1943). There are different classifications for ANN based on their type, topology, activation functions, learning paradigms and training algorithms. ANN can be designed in feed-forward or recurrent form. Recurrent neural networks are mainly used when there are temporal patterns in the data. Feed-forward neural networks are the most common neural networks in use (Mehrotra et al., 1997). There are different type of feed-forward neural networks such as multilayer perceptron (MLP) and the radial basis function (RBF). The most popular neural network paradigm in hydrology is the multilayer feed-forward backpropagation neural networks (Jayawardena and Fernando, 1998; ASCE task committee, 2000; Dawson and Wilby, 2001; Kumar et al., 2005; Firat, 2008; Weilin et al., 2011), which is also a used in this study.

The backpropagation training algorithm was first introduced in 1986 (Rumelhart et al., 1986). In multilayer backpropagation neural networks, the connections between neurons are in one direction, from the input layer, through hidden layers to the output layer. The numbers of neurons in the input and output layers depend on the problem and the number of hidden layers and the number of neurons in each hidden layer should be specified. In practice, a single hidden layer with sufficient neurons is capable of approximating arbitrarily well any continuous mapping from one finite-dimensional space to another (Lippmann, 1987; Cybenko, 1989). Having a large number of hidden neurons, gives the network flexibility to solve complex problems, but may cause overfitting problem. Different approaches, including trial and error, have been used to reach an optimum number of neurons. The general relationship between input (x) and output (Y) vectors in feed forward ANN can be defined as follows;

$$Y = f_o\left[\sum_j W_{kj} \cdot f_h\left(\sum_i W_{ji}x_i + b_j\right) + b_k\right] \tag{1}$$

where W_{ji} is the connection weight from the ith node in the input layer to the jth node in the hidden layer; b_j is the threshold value or bias of jth hidden neuron; W_{kj} is the connection weight form the jth node in the hidden layer to the kth neuron in the output layer; b_k is bias of kth output neuron and f_h and f_o are the activation function for hidden and output neurons, respectively. Activation functions could be sigmoid (logistic), hyperbolic tangent (tan-sigmoid), inverse tangent, threshold, radial basis and linear, while the first two are the most commonly used in the hydrological modeling (Dawson and Wilby, 2001). Backpropagation algorithm (BP) is a supervised learning algorithm which adjusts the connection weights and biases using a gradient descent. In order to find the optimal weight (W) and bias (b), training or learning processes must be employed to minimize the error. A number of algorithms have been developed to train back propagation learning. Among all, Levenberg-Marqurdt algorithm (LM) has the fastest convergence and it is also able to obtain the lowest mean square error in many cases (Cigizoglu and Kisi, 2005; Beale et al., 2012; Lam et al., 2012). LM is a combination of steepest descent and the Gauss–Newton method. The one step weight updating equation uses Newton's method. In this study tan-sigmoid transfer function and LM algorithm are used in training the network.

2.2. Adaptive Neuro-fuzzy inference system

The concept of fuzzy logic was originally proposed by Zadeh (1965), in which linguistic variables are often used rather than numerical values in order to facilitate the expression of rules and facts. The most important modeling tool based on fuzzy set theory is fuzzy inference systems (FIS). FIS is a knowledge base system in which the information of input and output data is converted into the fuzzy if-then rules. The basic structure of FIS consists of three conceptual steps of fuzzification, rule-based fuzzy inference pro-