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A comparison between wavelet based static and dynamic neural network approaches for runoff prediction

Muhammad Shoaib [a,*], Asaad Y. Shamseldin [a], Bruce W. Melville [a], Mudasser Muneer Khan [b]

[a] Department of Civil and Environmental Engineering, The University of Auckland, Private Bag 92019, Auckland, New Zealand
[b] Department of Civil Engineering, Bahauddin Zakariya University, Multan, Pakistan

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SUMMARY

In order to predict runoff accurately from a rainfall event, the multilayer perceptron type of neural network models are commonly used in hydrology. Furthermore, the wavelet coupled multilayer perceptron neural network (MLPNN) models has also been found superior relative to the simple neural network models which are not coupled with wavelet. However, the MLPNN models are considered as static and memory less networks and lack the ability to examine the temporal dimension of data. Recurrent neural network models, on the other hand, have the ability to learn from the preceding conditions of the system and hence considered as dynamic models. This study for the first time explores the potential of wavelet coupled time lagged recurrent neural network (TLRNN) models for runoff prediction using rainfall data. The Discrete Wavelet Transformation (DWT) is employed in this study to decompose the input rainfall data using six of the most commonly used wavelet functions. The performance of the simple and the wavelet coupled static MLPNN models is compared with their counterpart dynamic TLRNN models. The study found that the dynamic wavelet coupled TLRNN models can be considered as alternative to the static wavelet MLPNN models. The study also investigated the effect of memory depth on the performance of static and dynamic neural network models. The memory depth refers to how much past information (lagged data) is required as it is not known a priori. The db8 wavelet function is found to yield the best results with the static MLPNN models and with the TLRNN models having small memory depths. The performance of the wavelet coupled TLRNN models with large memory depths is found insensitive to the selection of the wavelet function as all wavelet functions have similar performance.

1. Introduction

Prediction of runoff produced from a watershed as a result of rainfall event is a key area of research in hydrology. It is considered as one of the most complex hydrological process to be modelled because of the involvement of number of variables in the modelling process and the enormous spatial and temporal variability of watershed characteristics. Since the establishment of rational method in 1850 (Mulvany, 1850) for calculation of the peak discharge, numerous hydrological models have been proposed. These models include two main categories: the theory driven (conceptual and physically-based) models and the data driven (empirical and black-box) models. Conceptual models describe the general sub-processes and the physical mechanisms of the hydrological cycle without taking into consideration the spatial variability and stochastic characteristics of the rainfall–runoff process. Physically based models involve the solution of a system of partial differential equations in order to simulate various constituent processes of the hydrological cycle. Data-driven models consider the hydrological system as a black-box and try to establish a relationship between historical inputs (such as rainfall, evaporation etc.) and outputs (such as runoff).

Among data-driven models, the artificial neural network (ANN) models has emerged as powerful black-box models and received a great attention during last two decades. The idea of ANN is inspired by the operation of the biological neural networks of the central nervous system of human brain. Mathematically, an ANN is a compound nonlinear function with numerous factors that are adjusted in such a way that the ANN output becomes comparable to the observed output. The ANN approach has been successfully used for different modelling problems in various branches of science and engineering. In the field of hydrology, French et al. (1992) were the first to use ANN for forecasting rainfall. Shamseldin (1997)

* Corresponding author.
E-mail addresses: msho127@aucklanduni.ac.nz (M. Shoaib), a.shamseldin@auckland.ac.nz (A.Y. Shamseldin), b.melville@auckland.ac.nz (B.W. Melville), mkha222@aucklanduni.ac.nz (M.M. Khan).

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pioneered the use of ANN in modelling rainfall–runoff relationship. The ANN has been successfully applied in many hydrological studies (e.g. Akiner and Akkoyunlu, 2012; Antar et al., 2006; Arsenault et al., 2015; Aziz et al., 2014; Jain et al., 2004; Lallahem and Mania, 2003; Mekanik et al., 2013; Nourani et al., 2009a; Piotrowski et al., 2015; Senthil Kumar et al., 2005). An extensive review of ANN in hydrological applications can be found in ASCE Task Committee (2000a, 2000b), Abrahart et al. (2012) and Tayfur (2012).

However, Cannas et al. (2006) pointed out that the ANN based models may not be able to deal with non-stationary data until pre-processing of the input and/or output data is performed. Application of wavelet transformation (WT) on time series data has been found effective in addressing this issue of non-stationary data (Nason and Sachs, 1999). The WT decomposes the time series data into its sub-constituents and these sub-constituents are used as external inputs to the ANN. The resulting model is known as the hybrid wavelet model. These hybrid models improve the performance of ANN by capturing the important temporal and the spectral information embedded in the time series data. Various studies used WT in order to improve the results of the ANN based hydrological models (e.g., Wang and Ding, 2003; Cannas et al., 2006; Nourani et al., 2009a, 2009b; Tiwari and Chatterjee, 2010; Adamowski and Sun, 2010; Kisi, 2011; Singh, 2012; Shoaib et al., 2014a, 2014b; Altunkaynak and Nigussie, 2015). Wang and Ding (2003) used a three layered hybrid wavelet feed forward neural network (FFNN) model with back propagation (BP) training algorithm for forecasting shallow groundwater levels and river discharges. Cannas et al. (2006) applied hybrid wavelet MLPNN models for forecasting river flows. Nourani et al. (2009a) presented a hybrid wavelet MLPNN model for prediction of precipitation while Nourani et al. (2009b) utilized a FFNN model with BP training algorithm for modelling rainfall–runoff process. Tiwari and Chatterjee (2010) employed a wavelet coupled MLPNN model for flood forecasting purposes. Wavelet coupled flow forecasting MLPNN model for non-perennial rivers was presented by Adamowski and Sun (2010). Likewise, Singh (2012) presented wavelet-MLPNN conjunction models for prediction of flood events. Hybrid wavelet MLPNN and radial basis function neural network (RBFNN) models were used by Shoaib et al. (2014a) for comparing the performance of various wavelet coupled models.

Most of the ANN models including the simple and the wavelet coupled models used in hydrology are of static nature relying on the MLPNN model to learn the relationship between the observed input and the observed output. MLPNN is a static network as it allows only one-way information flow from the input layer to the output layer. Moreover, it is also considered as memory less network because of absence of any memory or recursion component to store the past information at any given time step. Furthermore, the MLPNN models lack the capability to examine the temporal dimension of data and cannot instinctively learn from the preceding conditions of the system (Saharia and Bhattacharjya, 2012). This is very vital in case of the hydrological systems since the current response of a hydrologic system can be very reliant on their preceding states. An implicit method of encoding temporal characteristics in static ANN is to use a sliding window of input sequences (e.g. Coulibaly et al., 2000a, 2000b; Kisi et al., 2013; Lohani et al., 2012; Tayfur and Guldal, 2006; Tayfur et al., 2014). In this method, a form of static memory is implicitly provided to the MLPNN by selecting an input vector comprising of the fixed number of past events relevant to the current system response. But incapability of this method to encode temporal patterns with randomly selected time intervals makes it unsuited for conditions that require high forecasting efficiency (Saharia and Bhattacharjya, 2012). The concept of signal delays play an imperative role in the biological neural network system of human brain. This concept has prompted the development of dynamic recurrent neural network (RNN) models. RNN models have the capability to learn from the preceding conditions of the system as they facilitate time delay units through feedback connections and thus have attracted much attention recently. The application of RNN can be found in many studies (e.g. Anmala et al., 2000; Assaad et al., 2005; Badjate and Dudul, 2009; Chang et al., 2012; Chiang et al., 2004; Coulibaly and Baldwin, 2005; Coulibaly and Evora, 2007; Güldal and Tongal, 2010; Kale and Dudul, 2009; Kote and Jothiprakash, 2008; Ma et al., 2008; Muluye, 2011; Serpen and Xu, 2003).

It is evident from the literature reviewed and cited in this paper that the use of static MLPNN and dynamic RNN models is increasing in hydrological studies, but most of the hybrid wavelet ANN models are relying only on the static MLPNN models. However, to our present knowledge, no study has yet been conducted to evaluate the potential of wavelet coupled dynamic neural network models. This study, is therefore, conducted to compare the performance of hybrid wavelet static MLPNN models and dynamic time lagged recurrent neural network models for runoff prediction using rainfall data. The performance of hybrid wavelet models is sensitive to the selection of a particular mother wavelet function, the choice of decomposition level and the preference of appropriate input variables. This study will, therefore, investigate effect of various most commonly used wavelet functions, the choice of suitable decomposition level and the selection of suitable delay signal for the hybrid wavelet RNN models. The paper is arranged in the following manner. Section 1 gives the introduction and the review of literature. Section 2 is the methodology section which also describes data used in the study. In this section, the theoretical background of MLPNN, time-lagged neural network (TLNN) recurrent models, the development of simple and the hybrid wavelet static and dynamic models are discussed. Also in this section, the performance indices used to evaluate the developed models are presented. The results of the different developed models are discussed in Section 3. The conclusions of the paper are presented in Section 4.

2. Methodology

2.1. Artificial neural networks (ANN)

2.1.1. Multilayer perceptron neural network (MLPNN)

The MLPNN consists of a number of neurons arranged in a series of consecutive layers. Typically, it consists of an input layer, a hidden layer and an output layer. Each neuron receives an array of inputs and produces a single output. The output of a neuron in the input layer will be input for the neuron in the hidden layer. Similarly, the output of the neuron in the hidden layer will be input for the output layer. Each neuron in all the layers processes its input by a mathematical function known as the neuron transfer function. The neurons in the input layer have connection with the neuron in the hidden layer while neuron in the output layer is only connected to the neuron in the hidden layer. There is no direct connection between the neuron in the input layer with the neurons in the output layer. MLPNN is the most widely used neural network type in various application of hydrology (Dawson et al., 2002; Maier and Dandy, 2000). More theoretical background of ANN and its various applications in water resources engineering can be found in Tayfur (2012).

2.1.2. Time-lagged recurrent neural network (TLNN)

Conventionally, MLPNN, where neurons in one layer are only connected to neurons in the next layer, have been used for prediction and forecasting applications. Nevertheless, recurrent networks, where neurons in one layer can be connected to neurons