

Neural network models for river flow forecasting

Nguyen Tan Danh, Huynh Ngoc Phien* and Ashim Das Gupta

Asian Institute of Technology, PO Box 4, KlongLuang 12120, Pathumthani, Thailand

Abstract

In this study, back propagation neural network (BPNN) models were used to forecast daily river flows in two basins, namely the Da Nhim and La Nga basins, in the Central Highlands of Vietnam for comparison with the Tank Model. It was found that the developed BPNN models provided satisfactory forecast discharges for both basins. Moreover, the discharges were also forecast from individual data of different stations within the La Nga Basin which were input directly and separately to the considered model. In this case, however, the model took a longer time to run and the corresponding forecast discharges were not as accurate as those obtained when mean areal values of rainfall and evaporation were used instead.

Introduction

Forecasting of daily discharges has been one of the important problems for hydrologists, reservoir operators and for flood protection engineers. In this connection, the relationship between rainfall and runoff has been widely exploited in many conceptual rainfall-runoff models, of which the Tank Model of Sugawara (1961; 1979) appears to be a well-known example (Phien and Pradhan, 1983; Phien and Danh, 1997). Besides these conceptual models, several black-box models (having little or no physical considerations) have also been used. These models include the time-series approach using Box-Jenkins ARIMA models, multiple regression models (Phien et al., 1990) etc. Recently, back propagation neural networks (BPNNs), a particular type of neural network, have been developed and successfully used in many fields (Gorr et al., 1994; Lachtermacher and Fuller, 1995; Maier and Dandy, 1996).

In this study, BPNNs were used to develop models for forecasting daily discharges (with lead time equal to one day) in two catchments, namely the Da Nhim and La Nga Basins in the Central Highlands of Vietnam (Phien and Danh, 1997). Besides daily rainfall and evaporation data, the input to these models may include past values of the discharge itself, thanks to the structure of BPNNs. As a consequence of this flexibility in input data, the effect of the different combinations of input data was also investigated.

Back propagation neural networks

Neural networks are mathematical models of theorised mind and brain activities which attempt to exploit the massively parallel local processing and distributed storage architecture of the human brain. The basic building block of the brain and nervous system is the neuron, that sends/receives information to/from various parts of the body. Each neuron collects inputs from a single or multiple sources and produces a single output in accordance with a certain predetermined non-linear function. A neural network model is created by interconnecting many of these simple neuron models in a known configuration.

* To whom all correspondence should be addressed.

☎ (66-2) 524-5701; fax (66-2) 524-5721; e-mail hnp@cs.ait.ac.th
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Among the different neural network structures, BPNNs introduced by Rumelhart et al. (1986) are most popular because of their applicability in many different areas (see, for example, Wasserman, 1989; Gershenfield and Weigend, 1993; Phien and Siang, 1993; Shamseldin, 1997). For forecasting purposes, a typical BPNN model consists of an input layer, one or two hidden layers and an output layer that has only one node. Shown in Fig. 1 is a typical simple structure which is most commonly used in forecasting. In this case, the input layer has several nodes, each representing an input variable. The hidden layer also has several nodes and represents the non-linearity of the network system. The output layer has only one node which represents the forecast value corresponding to each set of input values. In principle, a BPNN may have several hidden layers, but in practice, only one or two layers are used. The number of nodes in the hidden layer is determined mainly by trial and error. Several attempts have been made to arrive at some kind of optimal structure of a BPNN model (Fahlman and Lebiere, 1990; Lim and Hong, 1993).

The back propagation method

Back propagation is a systematic method for training (calibrating) multilayer neural networks. It uses a set of pairs of input and output values (called patterns). An input pattern is fed into the network to produce an output, which is then compared with the actual output pattern. If there is no difference between the network output and the actual output, then no learning is needed. Otherwise, the weights - which express the contribution of the input nodes to the hidden nodes, and the hidden nodes to the output - are changed (backward from the output layer through the hidden layer(s) to the input layer). Since the training makes use of the actual output, the back propagation method is referred to as a *supervised training* method.

Notation

The following notation system is used:

- $W_{j,i,m}$ weight of the effect received by j^{th} unit in layer m caused by i^{th} unit in layer $(m-1)$ at n^{th} iteration.
- $O_{j,m}$ output of the j^{th} element in layer m ($m = 1, 2, \dots, L$)
- I_i i^{th} element of the input.
- t_j j^{th} element of the desired output (target)
- n_m number of units in the m^{th} layer.