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Suspended sediment load simulation by two artificial neural network methods using hydrometeorological data

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Abstract

Estimates of sediment load are required in a wide spectrum of water resources engineering problems. The nonlinear nature of suspended sediment load series necessitates the utilization of nonlinear methods for simulating the suspended sediment load. In this study artificial neural networks (ANNs) are employed to estimate the daily total suspended sediment load on rivers. Two different ANN algorithms, the feed-forward back-propagation (FFBP) method and the radial basis functions (RBF), were used for this purpose. The neural networks are trained using rainfall flow and suspended sediment load data from the Juniata Catchment, USA. The simulations provided satisfactory simulations in terms of the selected performance criteria comparing well with conventional multi-linear regression. Similarly, the simulated sediment load hydrographs obtained by two ANN methods are found closer to the observed ones again compared with multi-linear regression.

Keywords: Suspended sediment load; Rainfall; Feed-forward back-propagation method; Radial basis function; Multi-linear regression

1. Introduction

The prediction of river sediment load is an important issue in hydraulic and sanitary engineering. It is a well-known fact that reservoirs are designed to contain a volume known as dead storage. This accommodates the sediment load that will accumulate over a specified period. The underestimation of sediment load results in insufficient reservoir capacities while the overestimation will lead to over-capacity reservoirs. It is important to determine sediment load accurately; however, in sanitary engineering, the prediction of river sediment load has an additional significance, which needs to consider the pollutants transported by the suspended sediment load. The real time distribution of the sediment load is needed in this case and the sediment load forecast is necessary for controlling the pollution level in rivers and reservoirs.

Classical approach of hydromechanics has not yet succeeded in modelling the complete process of sediment load transport in rivers for reasons that particle movements in turbulent flow as well as the properties of the particles are all random. Many of the available techniques for time series analysis assume linear relationships among variables. In the real world, however, temporal variations in data do not exhibit simple regularities and are difficult to analyse and predict accurately. It seems necessary that nonlinear models such as artificial neural networks (ANNs), which are suited to complex nonlinear models, be used for the analysis of real world temporal data.

There are numerous applications of ANNs in water resources. The rainfall–runoff relationship is successfully modelled by ANNs (Minns and Hall, 1996; Fernando and Jayawardena, 1998; Cigizoglu and Alp, 2004). Tokar and Johnson (1999) and Cigizoglu (2003a,b) employed neural network methodology for river runoff forecasting. ANNs were also considered as a powerful tool to use in various groundwater problems (Ranjithan et al., 1993). Other applications of ANNs include unit hydrograph derivation (Lange, 1998), regional flood frequency analysis (Hall and Minns, 1998), estimation of sanitary flows (Djebbar and Alila, 1998), regional drought analysis (Shin and Salas, 2000), classification of river basins

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(Thandaveswara and Sajikumar, 2000), agricultural vulnerability assessment of rural private wells (Ray and Klindworth, 2000), modelling hydraulic characteristics of severe contraction (Kheir El-Din, 1998), modelling air pollution parameters (Slini et al., in press; Agirre-Basurko et al., in press; Ordieres et al., 2005), and modelling water quality parameters (Onkal-Engin et al., 2005; Newham et al., 2003). In other studies, autoregressive moving average (ARMA) models were incorporated into the training and testing data sets of ANNs (Cigizoglu, 2003a) and neural networks based streamflow data infilling procedures were investigated by Khalil et al. (2001) and Elshorbagy et al. (2002). The application of ANN algorithms to sediment load data started recently (Tawfik et al., 1997; Abrahart and White, 2001; Jain, 2001; Cigizoglu, 2002a,b,c; Nagy et al., 2002; Tayfur, 2002; Alp, 2003; Cigizoglu and Alp, 2003; Merritt et al., 2003; Yitian and Gu, 2003; Cigizoglu, 2004; Kisi, 2004; Agarwal et al., 2005; Cigizoglu and Kisi, in press). In his study, Cigizoglu (2004) investigated the estimation and forecasting of daily total suspended sediment load with feed-forward back-propagation method using the past daily or monthly sediment load and river flow data. However, this study was limited because hydrologic and meteorological data were not considered. In the study of Kisi (2004), sediment estimation by ANNs is done using river flow and past sediment observations as input. In our presented study, however, the past sediment values are not included in input layer considering the comments of one of the reviewers in the previous review. In addition, the presented work also considered the rainfall data as input differing from the work of Kisi (2004). The majority of the ANN applications in water resources engineering involve the employment of conventional feed-forward back-propagation (FFBP) method.

In the majority of these studies, the feed-forward back-propagation (FFBP) method was employed to train the neural networks. The performance of the FFBP was found to be superior to conventional statistical and stochastic methods in continuous flow series prediction (Brikundavyi et al., 2002; Cigizoglu, 2003a,b). Though limited, comparison of this method with other ANN algorithms is also available in the literature (Mason et al., 1996; Cigizoglu, 2005a,b). The FFBP algorithm has some drawbacks such as the local minima problem. In their work, Maier and Dandy (2000) summarized the methods used in the literature to overcome this problem of training a number of networks starting with different initial weights, the online training mode used to help the network to escape local minima, the inclusion of the addition of random noise, and the employment of second order (Newtons algorithm, Levenberg–Marquardt algorithm) or global methods (stochastic gradient algorithms, simulated annealing). In the review study of the ASCE Task Committee (2000a,b) other ANN methods such as conjugate gradient algorithms, the radial basis function, the cascade correlation algorithm and recurrent neural networks were briefly explained. Thirumalaiah and Deo (1998, 2000) used conjugate gradient and cascade correlation algorithms together with FFBPs for different hydrological applications. The Levenberg–Marquardt algorithm was employed in the FFBP applications included in the present study.

This study explores two ANN methods in the accurate prediction of total daily suspended loads and comprises three parts: simulating suspended sediment load data using rainfall measurements as input, simulating suspended sediment load data using only flow as input and simulating suspended sediment load data using both rainfall and flow as input. Two ANN algorithms, feed-forward back-propagation and radial basis function are employed throughout the study. The ANN simulations were compared with conventional multi-linear regression (MLR) in terms of the selected performance criteria, which are found in the testing of the ANN simulations.

2. The structure of the ANNs

2.1. Feed-forward back-propagation algorithm

Given a training set of input–output data, the most common learning rule for multi-layer perceptrons is the back-propagation algorithm (BPA). Back propagation involves two phases: a feed-forward phase in which the external input information at the input nodes is propagated forward to compute the output information signal at the output unit, and a backward phase in which modifications to the connection strengths are made based on the differences between the computed and observed information signals at the output units (Eberhart and Dobbins, 1990). The neural network structure in this study possessed a three-layer learning network consisting of an input layer, a hidden layer and an output layer. In the presented study, the Levenberg–Marquardt optimization technique is employed. This optimization technique is more powerful than the conventional gradient descent techniques (Hagan and Menhaj, 1994; El-Bakyr, 2003; Cigizoglu and Kisi, 2005a). While back propagation with gradient descent technique is a steepest descent algorithm, the Marquardt–Levenberg algorithm is an approximation to Newton's method. Hagan and Menhaj (1994) showed that the Marquardt algorithm is very efficient when training networks which have up to a few hundred weights. Although the computational requirements are much higher for each iteration of the Marquardt algorithm, this is more than made up for by the increased efficiency. This is especially true when high precision is required. It was also found that in many cases the Marquardt algorithm converged when other back-propagation techniques failed to converge (Hagan and Menhaj, 1994).

2.2. The radial basis function-based neural networks (RBF)

RBF networks were introduced into the neural network literature by Broomhead and Lowe (1988). The RBF network model is motivated by the locally tuned response observed in biological neurons. Neurons with a locally tuned response characteristic can be found in several parts of the nervous system, for example, cells in the visual cortex sensitive to bars oriented in a certain direction or other visual features within a small region of the visual field (Poggio and Girosi, 1990). These locally tuned neurons show response characteristics