Journal of Applied Hydrology (2) (2) (2015) 73 - 79

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Journal of Applied Hydrology

Applying Artificial Neural Network algorithms to estimate suspended sediment load (Case study: Kasilian catchment, Iran)

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Article history: *Received: 09 March 2015* *Revised: 04 Apr. 2015* *Accepted: 28 Apr. 2015*

Abstract

Estimate of sediment load is required in a wide spectrum of water resources engineering problems. The nonlinear nature of suspended sediment load series necessitates the utilization of nonlinear methods to simulate the suspended sediment load. In this study Artificial Neural Networks (ANNs) are employed to estimate daily suspended sediment load. Two different ANN algorithms, Multi-Layer Perceptron (MLP) and Radial Basis Functions (RBF) were used for this purpose. The neural networks are trained using water discharge and suspended sediment discharge data from the Kasilian Catchment, which is located in north of Iran. In this research, daily water discharge and suspended sediment load data was collected for 41 years (1964-2005) period which includes 509 experimental data in total. From this set of data, 70% were used in the training phase, 20% for testing and remaining 10% were used in validation phase. The results showed that the RBF algorithm provided slightly better results than the MLP algorithm to estimate suspended sediment load.

Keywords: ANN, Kasilian, MLP, RBF, Suspended Sediment

1. Introduction

Information on suspended sediment load is crucial for water management and environmental protection (Melesse *et al.*, 2011). Installing sediment monitoring instruments on rivers is a costly operation. The available methods in literature for sediment concentration estimation can be grouped in four categories: (a) regression methods which use a regression relationship between concentration and discharge to estimate unobserved concentration data; (b) averaging estimators which are based on a selection of available data; (c) ratio estimators constructed by multiplying the averaging estimator by a ratio; and (d) planning level load estimators that are used for ungauged basins (Cimen 2008).

Artificial neural networks have been applied to many kinds of hydrologic data within the last two decades (Yiridim and Cigizoglu, 2002). In the hydrological forecasting context, recent papers have reported that ANNs have capability to apply for rainfall-runoff modeling (Suhaimi and Bustami, 2009); stream flow prediction(Asati and Rathore, 2012); reservoir inflow forecasting (Sattari *et al.*, 2012); prediction of water quality parameters (Khalil *et al.*, 2011); estimation and forecasting reference evapotranspiration (Huo *et al.*, 2012).

The nonlinear nature of the neural network processing elements provides the system with lots of flexibility to achieve any desired response (Msiza *et al*., 2007; Basri *et al*., 2007). Alp and Cigizoglu, (2007) showed the superiority of ANN models (including RBF and MLP) over conventional regression methods. They concluded that RBF has some advantage to provide prediction in a unique simulation while MLP needs many repetitions during training to improve performance. Jayawardena *et al*. (1998) estimated sediment deposition in a reservoir by MLP and conventional regression. They concluded that the ANN architecture as 3-5-1 (input-hidden-output neurons) with sigmoid transfer function and resilient propagation learning rule is better to estimate sediment load. Mar and Naing, (2008) predicted suspended sediment load in river systems using neural network with back propagation training algorithms and compared the model performance with three other techniques named as Multiple Linear Regressions (MLR), Multiple Non-linear Regression (MNLR) and Autoregressive Integrated Moving Average (ARIMA). Prediction results produced using ANN technique was superior in compare to all other three techniques. Msiza *et al*. (2007) used MLP and RBF for water demand forecasting. They observed that the RBF converges to a solution faster than the MLP. The main goal of the current study is applying MLP and RBF techniques and their comparison to estimate suspended sediment load in Kasilian catchment, located in north of Iran.

2. Material and Methods

2.1. Study area

Kasilian catchment (53º18´ - 54 º 30´E, 35º 58´30´´-36º 07´N) is a part of the great basin of Talar River, and the area of the catchment is approximately 68 km^2, located in southeast of Mazandaran Province, North of Iran (Fig. 1). The relief of the study area decreases from 3163m (mountain) in southeast to 1087m (river bed) in central part. The climate changes from humid to cold humid, with 809 mm annual rainfall. More than 70% of the catchment is occupied by forest and the main soil type is Brownish with Acidic PH (Zia Abadi and Ahmadi, 2009).

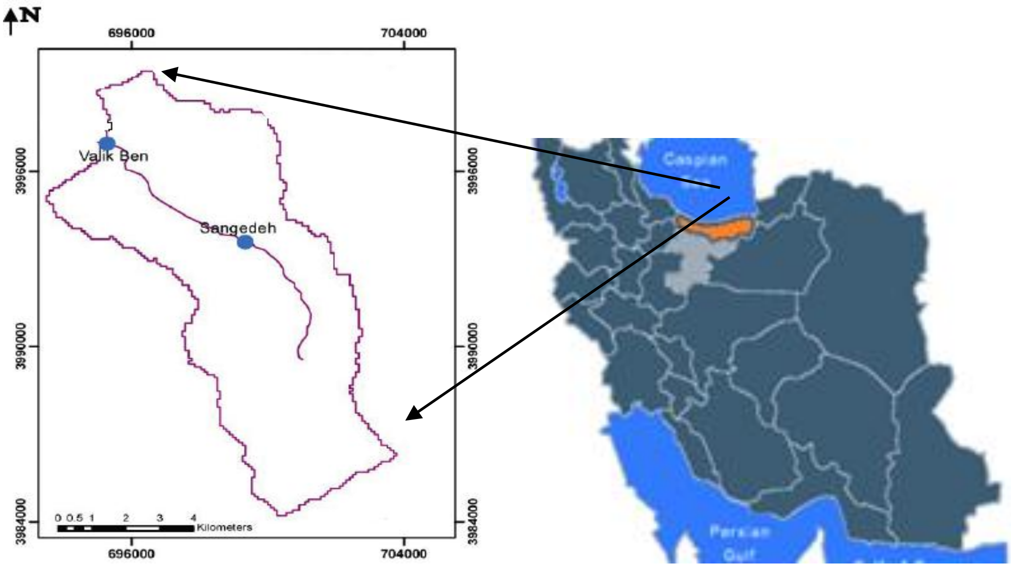

Fig.1. The location of Kasilian Catchment in Iran

2.2. Methodology

Two different neural network algorithms namely Multi-Layer Peceptron (MLP) and Radial Basis Function (RBF) have been examined in this study.

The MLP network can be used to create a model that correctly maps the input to the output using historical data, so that the model can predict the unknown output [Bar et al., 2010]. Various algorithms are available for training of the MLP and this algorithm is especially capable of solving predictive problems (Haykin 1994).

The RBF network offers a viable alternative to the two-layer neural network in many applications of signal processing. A common learning algorithm for such networks is based on first choosing randomly some data points as radial basis function centers and then using singular-value decomposition to solve for the weights of the network (Chen 1991).

In this research, data set on daily river discharge and suspended sediment load were collected for 41 years period (1964-2005). In this study, all data divided into three parts: 70% of data used in training phase, 20% was for testing step, and the remaining 10% used in validation phase. All the samples were normalized in the range of [-1, +1]. Then these data transferred to SPSS software for calculations.

2.2.1. Multi-Layer Perceptron (MLP)

The network architecture of the MLP is shown in (Fig. 2). It contains three layers: input, hidden and output. Each layer consists of one or more neurons and there are two types of them. First, there are passive neurons that consider the input and output data. Another type is active neurons that compute data input using Activation Transfer Function (ATF) and produces an output (El-shafie et al., 2012).

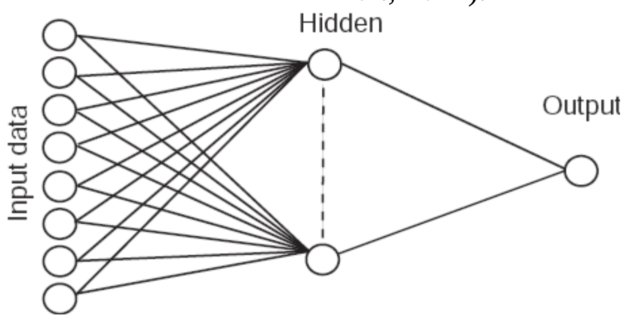

Fig. 2: Schematic diagram of MLP (Gil and Johnsson, 2010)

2.2.2. Radial Basis Function (RBF)

Radial Basis Function (RBF) networks were originally introduced by Broomhead and Lowe in 1988. This RBF algorithm has been successfully applied to many issues (Chang and Chen, 2003) particularly in various fields of water resources engineering including runoff simulation (Jayawardena *et al.*, 1998); rainfall-runoff modeling (Suhaimi and Bustami, 2009), water quality model calibration (Ma *et al.*, 2008) due to its powerful properties in classification and functional approximation. An RBF, which is multilayer and feed-forward, is often used for strict interpolation in multi-dimensional space. The term ‘feed-forward’ means that the neurons are organized in the form of layers in a layered neural network (Haykin 1994). The basic architecture of a three-layered neural network presented in (Fig. 3). An RBF has three layers including input layer, hidden layer and output layer. The input layer is composed of input data. The hidden layer transforms the data from the input space to the hidden space using a non-linear function. The output layer, which is linear, yields the response of the network (Lin and Chen, 2004).

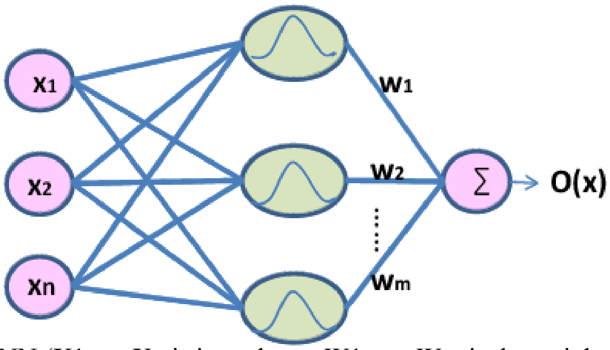

Fig. 3: The structure of RBFNN (X1,…, Xn is input layer, W1, …, Wm is the weight from the hidden node to the output layer and O(X) is output layer) (Fukami *et al*., 2012).

2.3. Data Normalization

According to Hoffer *et al*. (2002) data normalization is the process of decomposing relations with anomalies to produce smaller and well-structured relations.

Before applying the MLP and RBF methods, data were normalized to fall in the range [1, -1] using the following formula:

$$Xp = 2 * \frac{(xp - xmin)}{(xmax - xmin)} - 1 \qquad (1)$$

Where Xp is the normalized value and xp is the original value while $xmin$ and $xmax$ are the minimum and maximum values in the data, respectively. After training and testing results are achieved, the output values were denormalized by multiplying with the corresponding normalization factor to get the output in the original scale of the data.

2.4. Model performance criteria

The Root Mean Square Error (RMSE) is one of the most commonly used performance index in hydrological modeling (Mar and Naing, 2008) to measure the difference between values predicted by a model and the values actually observed from the environment that is being modeled. The difference at one point in time is called the residual, and RMSE serves to aggregate the residuals into a single measure of predictive power (Agnew 2012). RMSE formula is given as follows:

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n} (Qo - Qe)^2}{n}} \qquad (2)$$

Where $Q_o$is observed discharge, $Q_e$is the estimated discharge and n is the number of data, respectively.

3. Results and discussion

In this research, two different types of neural networks (RBF and MLP) have been used to predict suspended sediments in Kasilian catchment. According to RBF's network, it is shown that two hidden layers (H (1), H (2)) used to it (Fig. 4).

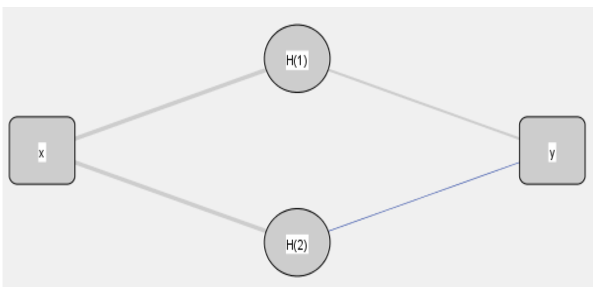

Fig. 4: Schematic diagram of RBF network architecture (X=input layer, H (1), H (2) = hidden layer and Y=output layer)

A comparative analysis using RMSE index during training and testing stages of both RBF and MLP models are summarized in (Table 1).

Table 1: RMSE values for RBF and MLP models

	RBF	MLP
Training	0.032	0.024
Testing	0.005	0.14

As presented in Table 1, in RBF model the RMSE value from training data to testing reduces gradually. The performance of the MLP model in prediction of suspended sediment load increases from training data to testing. During testing stage, RBF model produced less error and better efficiency (RMSE=0.005) than MLP model (RMSE=0.14). Similar trend was found during training stage, where RBF model also performed slightly better (RMSE=0.024) than MLP model (RMSE=0.032).

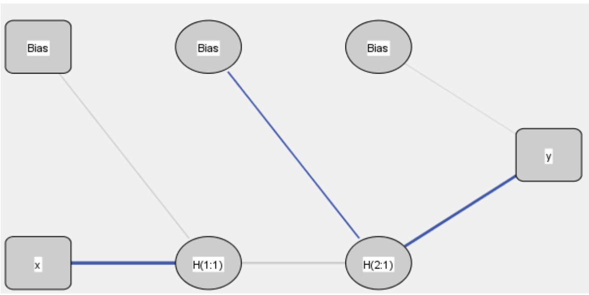

Figure 5: Schematic diagram of MLP network architecture

Accurate suspended sediment prediction is an integral component of sustainable water resources and environmental systems (Rajaee *et al*., 2011). Some endeavors have been made to study the effect of the number of hidden layers on network efficiency in addition to the aforesaid parameters. Thus the hidden layers have been increased to 2 or 3 layers to re-execute the networks (Nazmara *et al*., 2009). As stressed by (Chau 2006), it is necessary to determine the optimal choice between available environmental parameters, in opposition to using them all. In this study the best RMSE performance gained when two hidden neurons were used in both RBF and MLP architecture.

Also, in studies of the models based on RBF networks to simulate runoff (Jayawardena et al., 1998; Msiza et al., 2007; Suhaimi and Bustuami, 2009), rainfall-runoff model can predict with the accuracy comparable to that with the MLP approach. In this research RBF choice was based on achieving a minimum RMSE for the testing phase.

4. Conclusions

The main conclusions of this research can be summarized as follows:

- In general the RBF method performs better than the MLP.

- After the normalization of data in the range [-1, +1], better results obtained from RBF and MLP networks.

- The study also showed that both RBF and MLP networks can be used for prediction of suspended sediment discharge using only flow discharge data.

- The data which was used in this study obtained from only one area and to have a strong conclusion it is better to do further studies with data from various areas.

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