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A Review on Artificial Neural Networks Modeling for Suspended Sediment Estimation

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Absctract: *Nowadays, the application of Artificial Neural Networks is not hidden to anyone. The use of Artificial Neural Networks has been significantly increased in past years. One of the most important applications of Artificial Neural Networks is in water resource engineering field. Modeling and predicting the rate of suspended sediment is extremely important for planning and managing the water resource projects. Therefore, Artificial Neural Networks are one of the most advanced methods serving water resource engineering.*
Keywords: *Suspended Sediment, Artificial Neural Network, Multi-Layer Perceptron, Feed-forward neural networks (FNN).*

I. Introduction

1.1. The Importance of the Sediment Estimation

Accurate sediment yield estimation is very significant in water-related projects. Sedimentation in dam reservoirs and reducing their useful volume, avulsion of the river due to channel sedimentation, deducting in the water transmission capacity of water installations and quality degradation of drinking and agricultural water are some problems of water projects. There are two different ways for estimating suspended sediment yield of rivers. The first method is to use the mathematical models in which they are concentrated on physical concepts and hydrodynamic and flow-field equations that should be solved. These models usually require various data such as material gradation, specific weight and viscosity, temperature of water, river profile, flow velocity, the kind of materials in the sides of channel and river slope. In most cases such data are not available but the most available ones include the water and sediment discharges. The second approach is to prepare sediment rating curves on water and sediment discharge data. The most frequent way is fitting a power curve with the form of $Q_s=a.Q_w$ b in which Q_s is sediment discharge, Q_w is water discharge and a, b are constant coefficients (Montazer et al., 2003). Maier and Dandy, 2003, made a detailed review of the ANN applications to forecast and to predict several hydrological variables, but in the water resources literature the use of ANN technique to model the suspended sediment is quite new.

1.2. Artificial Neural Networks (ANN)

An ANN is the information processing sample inspired by the way human brain processes information. The two major structural components of a brain are synapse and neurons. Synapses are elementary structural and functional units that mediate the interaction between neurons and neurons are the information processing units; in a human brain, there are approximately sixty trillion synapses and ten billion neurons, which are massively interconnected, making it an extremely efficient information processor (Haykin, 1999). Haykin had further defined artificial neural networks as parallel distributed processors made of simple processing units, which are able to acquire and store the empirical knowledge and making it accessible for use.

Artificial Neural Networks have so far been successful in dealing with issues such as function approximation, system identification, optimization and anticipating the results. Artificial Neural Network system based on data flexibility having various weights to the neural connections establishment throughout the learning process is able to recognition complex and ambiguous issues that are not easily explained in mathematical relationships.

Using Artificial Neural Network (ANN) modeling to predict and forecast the variables in water resource engineering is being grown quickly. Infrastructural applications of artificial neural network in terms of inputs selection, the architecture of the networks, training algorithms, and selecting the parameters of training in different types of neural networks applied in water resources engineering have been reported. In other words, ANN is a robust technique for development of enormous relationship between the input and output variables, and able to draw out complex behavior between the water resources variables such as river sediment and river discharge. It can generate sturdy prediction results for huge numbers of water resources engineering problems by appropriate learning from a set of examples. It is necessary to have an enough understanding of the input and output variables from a statistical analysis of the data before modeling of the network, which can simplify to design an spectacular network. A convenient training based ANN model is able to pursue the physical understanding between the variables and may produce more beneficial results than conventional prediction techniques.

II. ANN Serves Water Resource Engineering

Water resource engineering contains the study of hydraulics, hydrology, environment and some geological related projects. Engineers have often faced the difficulties while estimation and prediction and of water resources parameters such as runoff, rainfall, water quality, water discharge, sediment discharge, and etc. due to temporal and spatial fluctuations, most of these variables indicate a highly non-linear behavior. Non-linear and complex exhibition of these variables is because of temporal and spatial fluctuations which are always difficult to estimate accurately owing to these variations and brings dubiety in the prediction results. However, water resource engineers have attempted to response these problems appearing in design and management of different water resource engineering projects.

Engineer's coherent response to these crises has somehow generated a beneficial solution for water resources planning and designing. One of the most interesting features is the artificial neural network modeling which is capable of learning the complete behavior between the inputs and outputs from the examples without any type of the physical involvement. Artificial Neural Networks have a exceptional characteristic that it is able to elicit the exact pattern between the input and output variables without any additional explanation. ANNs have been known as to identify the basic behavior between the variables though there is noisy data consisting of some errors. All these qualities recommend the ANNs applicability for the water resources parameters related to estimation and prediction.

One of the important aspects in water resources engineering is the sediment discharge determination of the river. Several techniques involving ANN have been successfully applied to predict and to estimate the suspended sediments across the world. (Jain. S. K., 2001, Mustafa. M. R et al, 2011).

Sedimentation and erosion are the most complex problems in hydrodynamic which are very crucial in water-related projects. Therefore, the presence of the suitable methods for the accurate estimation of suspended sediment load in rivers is very precious. The solution of the hydrodynamic equations in relation to these phenomenon and access to a mathematical-conceptual model is very hardship and in most cases, fundamental data for these models are not accessible. Then again, most of the widely used experimental methods are not accurate enough. Using the hidden knowledge in the data; effort to elicit intrinsic relations between data; and generalizing them to other conditions are the principles of wise method. Artificial Neural Network (ANN) is one of the most important methods of artificial intelligence which is inspired from the human brain model while performing training process, data related information are kept into weights of network.

III. Multilayer Perceptron (MLP)

Nowadays, Multilayer Perceptron (MLP) is the most known sort of employed neural networks. In MLP structure, the neurons are arranged into layers. The first and the last layers are called as input layer and output layer respectively, since they demonstrate inputs and outputs of the overall network. The relict layers are called as hidden layers or middle layers. Usually, one MLP consists of one input layer, one or more hidden layers, and one output layer.

Montazer et al., 2003, estimated the sediment yield of Bazoft River in Iran, using artificial neural network. They applied two kinds of neural networks including Multi-layer perceptron neural network and counter propagation of Grassberg. The result was accurate mapping but not necessarily an ascending one. Hence, due to the fact that sediment rating curve is usually an ascending one, this kind of neural network is not suitable. Despite of counter propagation of Grassberg network, multi-layer perceptron network produces ascending mapping which with sigmoid function in the first hidden layer and linear function in the second hidden and output layers, is able to do better estimation of high sediment discharges and can be used in sediment rating curve preparation. Meanwhile they considered the effect of mean monthly air temperature on their research and concluded that this parameter does not have a considerable effect on improvement of the model.

Ghodsian and Zaker Moshfegh, 2003, have examined the MLP neural network application on hydraulic parameters of side sluice gates. They employed two different approaches for selecting the MLP layers function to find out which approach executes appropriate. Once they used the hyperbolic tangent function for hidden layer and linear function for output layer, then they create a MLP network with the structure using a hyperbolic tangent function for all layers. They detected that the network having hyperbolic tangent activation function for hidden layer and linear function for output layer runs better than network having hyperbolic tangent function for all layers.

Memarian Khalilabad. H et al., 2009, investigated at Bar river in Ariyeh hydrometric station placed in Khorasan province, Iran. They have utilized MLP (Multi- Layer Perceptron) neural network to obtain the sediment rating curve. After importing the input patterns into the network and definition of a neuron for input and a neuron for output layers and performance of repeated trial and error, optimum architecture (topology) of MLP network was characterized as a network with five neurons in hidden layers and hyperbolic tangent activation function for the first and second hidden layers and Linear function for the third hidden layer.

Kumorjain, 2001, had estimated the suspended sediment yield of Mississippi river by ANN model. Applying the continuous data set of water-level, water discharge and sediment discharge, the concentration of the sediment has been calculated in each time step as a function of water level and water discharge of that time step and previous time step. Although the results indicated optimum operation of multilayer perceptron neural network, but this model is not applicable when a continuous series of water discharge and sediment concentration are not accessible. In another research which has been done on water discharge and sediment discharge of Jajrood River located at Iran, the results obtained from MLP neural network have been reported to be satisfactory (Avarideh et al., 2001).

Kisi, 2008, had designed a neural network model for estimating the suspended sediment concentration of two stations named Quebrada Blanca and Rio Valenciano in USA. Data related to the stream flow and suspended sediment concentration data since October 1993 to September 1994 (1994 water year) and also since October 1994 to September 1995 (1995 water year) was applied to train and to test the network respectively. To acquire the suitable number of inputs for the network structure, a statistical analysis for data preprocessing in terms of cross correlation, autocorrelation, and partial autocorrelation analysis was done. Trial and error methods were used to determine the number of hidden neurons in the hidden layer. For hidden and output layers, they have employed tangent sigmoid and pure linear activation functions respectively. To train the network, three different training algorithms have been used which consist of Levenberg Marquardt (LM), Conjugate Gradient (CG), and Gradient Descent (GD). Then, he noticed that LM and CG have generated better results than GD training algorithm by comparing the training algorithms performance. Besides he stated that GD takes unnecessarily higher number of epochs and time than the other two algorithms.

Multilayer Perceptron (MLP) neural network has been used to estimate and to forecast the suspended sediment by Cigizoglu in the year 2004. For this purpose, suspended sediment forecasting has firstly done using the past sediment data at downstream and then sediment data from the upstream separately as input for MLP models. He also studied the relationship for river flow and suspended sediment with the help of additionally the upstream and downstream flows independently. If the input and output data belongs to the different river stations then he used the term estimation and for same river station, he used the word forecasting. For the study, he downloaded 29 years of daily suspended sediment and mean flow for two gauging stations from the official website of United States Geological Survey (USGS). To examine the complexity within the data, to analyze the variability and nature of the data, and to investigate the correlated elements between the flow and suspended sediment variables, an extensive statistical analysis including autocorrelation, cross correlation, mean, standard deviation, coefficient of variation, skewness coefficient, overall minimum and maximum of the data was performed. He noticed that sediment data had more skewed distribution than the flow data series. In addition, the autocorrelation between sediment data was also lower than the flow data. The statistical analysis indicated the complex nature of the data, autocorrelation and cross correlation helped for the appropriate networking for MLP modeling. Cigizoglu forecasted one day ahead suspended sediment in four different modes, (i) using four antecedent sediment values at downstream data only as input, (ii) using upstream data of current sediment with 9 antecedent sediment data to forecast current sediment at downstream station, (iii) using downstream current flow and five antecedent flow data to estimate downstream current sediment and (iv) using upstream current flow and nine antecedent flow data to estimate current downstream sediment value. In order to compare, he applied the multi linear regression model, the conventional sediment rating curve, and stochastic AR model for suspended sediment estimation. He noticed that the downstream sediment forecasting by using upstream sediment data as inputs produced much better results compared to use past downstream data as input. While comparing the performance of MLP models with conventional models, Cigizoglu suggested that MLP produced superior results than all other conventional methods. On these basis, he stated that MLP has the ability to capture non linear, highly dynamic behavior of the data and able to generalize the structure of whole data.

Mustafa et al., 2012, have examined how effectively artificial neural network has been applied to solve issues in water resources engineering especially in river sediment and discharge. Moreover, to find the best solution of the problems, what kind of infrastructure (input selection criterion, selection and division of the data sets, appropriate network structure, activation function and algorithms used for training network etc.) has been utilized for proper modeling. They figured out that ANN is a sturdy technique for modeling water resources engineering parameters. But its effectiveness highly depends on the understanding of the behavior between the variables as well as the extensive knowledge about the appropriate operation of neural network. Statistical analysis of data before modeling network is important to know variations between variables and behavior of data. This kind of statistical analysis may facilitate to get more efficient model. Furthermore, autocorrelation and cross correlation analysis of variables are useful for selecting the input variables for ANN model.

Additionally, testing of a number of training algorithms in MLP neural networks and radial basis functions in RBF neural networks are always advantageous to get more vigorous results. The study also indicated that appropriate ANN modeling is always effective in water resources engineering as compared with conventional modeling techniques.

Kisi, 2004, has applied different types of ANN methods to predict the suspended sediment density. The fastest MLP training algorithm, that is the Levenberg-Marquardt algorithm, is used for optimization of the network weights for data from two stations on the Tongue River in Montana, USA. The first part of the study deals with prediction and estimation of upstream and downstream station sediment data, separately, and the second part focuses on the estimation of downstream suspended sediment data by using data from both stations. In each case, the MLP test results are compared to those of generalized regression neural networks (GRNN), radial basis function (RBF) and multi-linear regression (MLR) for the best-input combinations. Based on the comparisons, it was found that the MLP generally gives better suspended sediment concentration estimates than the other neural network techniques and the conventional statistical method (MLR).

Kisi, 2004, utilized different ANN techniques to predict and to estimate the daily suspended sediment concentration. He showed that multi-layer perceptron could show better performance than the other algorithms of ANN technique. A multi-layer perceptrons artificial neural network (MLPs) in daily suspended sediment estimation and forecasting is applied by Cigizoglu, 2004. It was shown that MLPs capture the complex nonlinear behavior of the sediment series relatively better than the conventional models.

IV. Feed-Forward Neural Networks (FNN)

Feed-forward neural networks (FNN) are one of the popular structures among artificial neural networks. These efficient networks are widely used to solve complex problems by modeling complex input-output relationships. They adopt trials-and-errors to seek possible values of parameters for convergence of the global optimum. The learning process of an FNN cannot guarantee the global optimum, sometimes trapping the network into the local optimum. The Back-Propagation Learning Algorithm (BPLA) is a widely used method for FNN learning in many applications. It has the great advantage of simple implementation.

Sediment load prediction in rivers has done by Nagy et al. 2002, using multilayer feed forward neural network with back propagation training algorithm. They compared the results with conventional sediment load formulas. Eight parameters including tractive shear stress, velocity ratio, suspension parameter, longitudinal slope, Froude number, Reynolds number and stream width ratio had been used as input nodes for predicting sediment concentration in output layer. Number of hidden neurons was taken by trial and error approach. Suspended sediment data from some other rivers was also applied to observe the model performance, for the purpose of model verification. Nagy et al. found adequate prediction results from ANN model. They have also used seven different conventional sediment load formulas to gain the sediment load. They compared the ANN model with the results obtained using conventional equations and proposed that ANN model can produce acceptable prediction results as well as conventional equations even in some cases better than from few conventional equations. They concluded that neural network techniques are successfully able to predict sediment load when the conventional techniques cannot accomplish due to the vagueness and probabilistic nature of sediment movement.

Tayfur and Guldal, 2006, have carried out feed forward neural network modeling for non-steady state sheet sediment transport and compared the results of ANN model with physically-based models. Slope and rainfall intensity data was utilized as input neurons for sediment discharge estimation. The number of hidden neurons was determined by trial and error method while sigmoid transfer function was used in hidden layer. Tayfur reached competent results of sediment discharge simulated at different slopes using ANN model. He compared the ANN model performance with some physically based models and recommended that ANN model performed as well as, in some cases better than the physically-based models. Furthermore, he suggested that ANN model could be very powerful tool for sediment transport studies.

River sediment yield prediction using generalized regression neural network (GRNN) and feed forward back propagation (FFBP) neural networks has been investigated by Cigizoglu and Alp in 2006. To predict river sediment load with the help of ANN modeling, they used the daily flow and sediment load data from Juniata River, USA. For both ANN models, training parameters were examined by trial and error approach. They assigned that both kinds of neural networks could be able to predict daily sediment load. The determination coefficient has been found little higher in FFBP model than GRNN model. Satisfactory prediction results procreated by FFBP models at high and medium sediment loads but some negative values could be generated at low sediment load values. The sediment load prediction at low values without producing negative values could be done by GRNN. They proposed that GRNN is able to generate accurate results within shorter time rather than FFBP model, then it can be stated that GRNN model is faster. Besides, GRNN model could generate adequate results in some cases better than FFBP model; hence, it is an effective type of neural network.

Sarangi and Bhattacharya, 2005, have developed two ANN models, one geomorphology- based (GANN) and another non- geomorphology- based (NGANN) to predict the sediment yield and validity with the help of hydrographs and silt load data. A Comparison between the results of GANN and NGANN models and those predicted by an earlier developed regression model for the same watershed, demonstrated that the feed- forward ANN model with back propagation algorithm works well for the GANN with highest coefficient of determination R^2 as compared to NGANN.

Raveendra, K. R and Mathu, B.S, 2008, developed a back propagation feed forward artificial neural network (ANN) model to compute the event-based temporal variation of sediment yield from the watersheds. They used the gradient descent algorithm with automated Bayesian regularization to train the network and different ANN structures were tested with different input patterns. Their model was expanded from the storm event data (i.e. rainfall intensity, runoff and sediment flow) recorded over the two small watersheds and the responses were computed in terms of runoff hydrographs and sedimentographs. Selecting the input variables was done by employment of the autocorrelation and cross-correlation analysis of the data as well as by applying the concept of travel time of the watershed. They have computed error in total sediment yield (ESY) for the storm events to evaluate the models. They observed that ANN based model results present better agreement than the linear transfer function model to compute the run- off hydrographs and sedimentographs for both the watersheds.

Agarwal et al., 2006, used artificial neural networks to simulate the runoff and sediment yield as daily, weekly, ten-daily, and monthly monsoon runoff and sediment yield from an Indian catchment with back propagation artificial neural network (BPANN) technique, they found out that ANN model provides quite reliable results by the way of comparing the results with observed values obtained from using single- and multi-input linear transfer function models.

V. Conclustion

The neural networks approach has been employed to many divergences of science. This approach is growing towards a strong tool for providing civil and environmental engineers with adequate details for the purposes of designing and management practices. According to successful applications in modelling nonlinear system behaviour in an extensive range of fields, ANNs have been applied in hydrology and hydraulics. To model the rainfall- runoff, flow predictions, flow/ pollution simulation, to identify the parameters, and to model the nonlinear/ input- output time series, ANNs have been applied to achieve the best results. (ASCE Task Committee, 2000).

Artificial Neural Network application is studied by many researchers in critical and fundamental topics of hydrology and hydraulics such as sediment load prediction, rainfall-runoff modeling, prediction of flow and etc. Briefly, ANN technique is one of the most popular soft computing methods.

Hence, the present study will try to adopt and elaborate an appropriate method of yield sedimentation, based on observed data, generated

In recent years, a great interest has occurred to investigate the possibility of using Artificial Neural Network systems. Neural networks are powerful computational tool in organizing and establishing the relationship between the different intelligence capabilities. The use of the mapping capabilities of these systems in a multi dimensional spaces and the analysis of the issues without resorting to the relations sophisticated mathematical difficulty can be useful in engineering.

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