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Artificial Neural Networks Modeling in Water Resources Engineering: Infrastructure and Applications

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***Abstract*—**The use of artificial neural network (ANN) modeling for prediction and forecasting variables in water resources engineering are being increasing rapidly. Infrastructural applications of ANN in terms of selection of inputs, architecture of networks, training algorithms, and selection of training parameters in different types of neural networks used in water resources engineering have been reported. ANN modeling conducted for water resources engineering variables (river sediment and discharge) published in high impact journals since 2002 to 2011 have been examined and presented in this review. ANN is a vigorous technique to develop immense relationship between the input and output variables, and able to extract complex behavior between the water resources variables such as river sediment and discharge. It can produce robust prediction results for many of the water resources engineering problems by appropriate learning from a set of examples. It is important to have a good understanding of the input and output variables from a statistical analysis of the data before network modeling, which can facilitate to design an efficient network. An appropriate training based ANN model is able to adopt the physical understanding between the variables and may generate more effective results than conventional prediction techniques.

***Keywords*—**ANN, discharge, modeling, prediction, sediment,

I. Introduction

WATER resources engineering comprises the study of hydraulics, hydrology, environment and some geological related projects. Engineers frequently faced the difficulties while prediction and estimation of water resources parameters (i.e. sediment discharge, water discharge, rainfall, runoff, water quality etc.). The majority of these variables reveal a highly nonlinear behavior because of spatial and temporal variations. Nonlinear and complex exhibition of these variables is because of spatial and temporal variations which are always difficult to estimate accurately owing to these variations and causes uncertainty in the prediction results. However, water resources engineers attempted to respond these problems arising in design and management of different water resources engineering projects.

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Their coherent answer to these crisis has somehow produced an effective solution for planning and design of water resources. The one of the most attractive feature is the ANN modeling which has the ability to learn the exact behavior between the inputs and outputs from the examples without any kind of the physical involvement. Artificial neural networks have a wonderful characteristic that it can extract the exact pattern between the input and output variables without any additional explanation. ANNs has been known as to recognize the fundamental behavior between the variables although the data is noisy and containing some errors. All these qualities recommend the applicability of ANNs for the water resources parameters problems regarding prediction and estimation. In this context, a number of applications of ANNs for prediction, forecasting, modeling and estimation of water resources variables (i.e. water discharge, sediment discharge, rainfall runoff, ground water flow, precipitation and water quality etc.) have been found and related to river discharge and sediment are cited here. However, only the ANN applications for river sediment and discharge published in high impact journals since 2002 to 2011 are examined in this review.

Therefore, the goal of this study is to examine how effectively ANN has been applied to solve problems in water resources engineering particularly in river sediment and discharge. Furthermore, what kind of infrastructure (input selection criterion, selection and division of the data sets, appropriate structure of the network, activation function and algorithms used for training network etc.) has been utilized for proper modeling to find the best solution of the problems.

II. ANN Modeling for Sediment Estimation

River sediment discharge determination is one of the crucial problems in water resources engineering. Several techniques including ANN have been successfully applied for estimation and prediction of suspended sediments around the world [1-33]. However, this study is limited to ANN techniques only. A number of attempts made using ANN to solve problems of sediment prediction since 2002 to 2011 are reported here. The review mainly focused on the infrastructural implementation of ANN for successful prediction.

Nagy et al. [3] predicted sediment load in rivers by using multilayer feed forward neural network with back propagation training algorithm and compared the results with conventional sediment load formulas. They used eight parameters which include tractive shear stress, velocity ratio, suspension parameter, longitudinal slope, Froude number, Reynolds number and stream width ratio as input nodes to predict sediment concentration in output layer. Number of hidden neurons was selected by trial and error approach. For model verification purpose, suspended sediment data from some other rivers was also used to observe the model performance. Nagy et al. [3] found satisfactory prediction results from ANN model. Seven different conventional sediment load formulas were also used to find the sediment load. They compared the ANN model with the results obtained using conventional equations and suggested that ANN model can produce good prediction results as well as conventional equations even in some cases better than from few conventional equations. They concluded that neural network techniques can be successfully applied to predict sediment load when the conventional techniques cannot accomplish because of the vagueness and probabilistic nature of sediment movement.

Tayfur [4] presented feed forward neural network modeling for non-steady state sheet sediment transport and compared the ANN model results with physically-based models. Data on slope and rainfall intensity was used as input neurons to estimate sediment discharge. The number of hidden neurons was determined by trial and error method while sigmoid transfer function was used in hidden layer. Tayfur [4] found satisfactory results of sediment discharge simulated at different slopes using ANN model. He compared the performance of ANN model with some physically based models and suggested that ANN model performed as well as, in some cases better than the physically-based models. Furthermore, he proposed that ANN model could be very powerful tool for sediment transport studies.

Cigizoglu [6] forecasted and estimated suspended sediment data using Multilayer perceptron (MLP) neural network. Cigizoglu forecasted suspended sediment firstly using the past sediment data at downstream and then sediment data from the upstream separately as input for MLP models. He also investigated the relationship for river flow and suspended sediment by using additionally the upstream and downstream flows independently. If the input and output data belongs to the same river station then he used the term forecasting and for different river stations, he used the word estimation. For the study, 29 years of daily suspended sediment and mean flow for two gauging stations was downloaded from the official website of United States Geological Survey (USGS). 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 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. He observed that sediment data had more skewed distribution than the flow data series. Moreover, the autocorrelation between sediment data was also lower than the flow data. The statistical analysis showed the complex nature of the data, autocorrelation and cross correlation helped for the appropriate networking for MLP modeling. Cigizoglu [6] 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. For performance comparison, he used the conventional sediment rating curve, multi linear regression model and stochastic AR model for suspended sediment estimation. He observed 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 [6] proposed 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.

Cigizoglu and Alp [11] predicted river sediment yield by using generalized regression neural network (GRNN) and feed forward back propagation (FFBP) neural networks. They used the daily flow and sediment load data from Juniata River, USA to predict river sediment load using ANN modeling. Training parameters for both ANN models were determined by trial and error approach. They stated that both types of neural networks were able to predict daily sediment load. The coefficient of determination was found little higher in FFBP model than GRNN model. FFBP models generated good prediction results at high and medium sediment loads but it produced some negative values at the low sediment load values. GRNN was able to predict the sediment load at low values as well and did not produce negative values. They suggested that GRNN is faster and can produce accurate results within shorter time than FFBP model. Furthermore, GRNN is also an effective type of neural network which is able to produce satisfactory results even in some cases better than FFBP neural networks.

Alp and Cigizoglu [14] simulated suspended sediment load by using two types of neural networks, radial basis function (RBF) and multilayer perecptron (MLP). The performance of the ANN models was compared with a conventional multi linear regression (MLR) model. Daily rainfall, total flow and suspended sediment load data of Juniata River, USA was used for training (five years data) and testing (nearly one year data) the models. A statistical analysis of the data was done to show the highly skewed distribution with high coefficient of variation of suspended sediment data. The statistical analysis of the data showed the highly complexity for modeling suspended sediment behavior. Autocorrelation and cross correlation analysis was performed between the parameters to examine the correlation between the input variables. However, a number of combinations of the input variables as inputs values were also attempted including (i) only rainfall data, (ii) only flow data and (iii) combination of both rainfall and flow data to find the appropriate selection of input parameters. Similar number of inputs was employed for both types of neural networks. Alike, all three sorts of inputs were also examined for MLR model. Training parameters for both ANN models were decided after the examination of a number of trials. It was observed that at some low flows, all the three models estimated some negative values but MLR model produced many more negative values than RBF and MLP models. Alp and Cigizoglu [14] showed the superiority of ANN models over conventional regression methods. The performance of RBF and MLP models were found very close to each others. However, they concluded that RBF provide some advantage to the user that it provide prediction in a unique simulation while MLP needs many repetitions during training to improve performance. Furthermore, ANN is an efficient tool to solve the problems regarding estimation of suspended sediment load.

Kisi [17] designed neural network model for estimation of suspended sediment concentration of two stations Quebrada Blanca and Rio Valenciano in USA. The stream flow and suspended sediment concentration data from October 1993 to September 1994 (1994 water year) and from October 1994 to September 1995 (1995 water year) was used for training and testing stage of the network respectively. A statistical analysis for preprocessing of the data in terms of autocorrelation, cross correlation and partial autocorrelation analysis was done to get the appropriate number of inputs for the network architecture. Trial and error approach was used to find the number of hidden neurons in the hidden layer. Tangent sigmoid and pure linear transfer functions were used for hidden and output layers respectively. Three different training algorithms conjugate gradient (CG), gradient descent (GD) and levenberg marquardt (LM) was used for training the network. The performance comparison of the training algorithms indicated that LM and CG produced better results from GD training algorithm. Furthermore, they indicated that GD takes unnecessarily higher number of epochs and time than the other two algorithms.

Jothiprakash and Garg [22] estimated sediment deposition in a reservoir by Multilayer percetron neural networks. They also used a conventional regression analysis for estimation of reservoir sedimentation but they did not get promising results from the regression analysis. The annual data of rainfall, inflow and capacity of Gobindsagar Reservoir on the Satluj River, India from 1971 to 2003 (thirty two years) was used for estimation of reservoir sedimentation. 23 year data was used for training and 9 years data for testing stage of the network. Trial and error approach was used to find the number of neurons in the hidden layer and to get the appropriate structure of the network. The results obtained from the network were found good and much better than the conventional regression analysis. They showed in the results that the ANN architecture as 3-5-1 (input-hidden-output neurons) with sigmoid transfer function and resilient propagation learning rule is superior for the estimation of sediment load.

Melesse et al. [32] predicted suspended sediment load of 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). Five years daily and weekly data of precipitation, water discharge and suspended sediment load of three different rivers Mississippi (1971-1975), Missouri (1977-1981) and Rio Grande (1977-1981) from USA were used. Three different types of inputs with different combinations of precipitation, water discharge and suspended sediment load including some antecedent conditions were examined. Three different combinations of training and testing data sets were tried, like 4, 3 and 2 years of training data sets and 1, 2 and 3 years for testing data sets respectively. The model performance was observed higher for 4 years training and 1 year testing data sets for Mississippi River and for 3 years training and 2 years testing for Missouri and Grande Rivers. Prediction results obtained from the daily data were found better than weekly data for all three rivers. Prediction results produced using ANN technique were superior to all other three (MLR, MNLR and ARIMA) modeling techniques.

III. ANN Modeling for Discharge forecasting

Since last two decades, ANN has been broadly applying for discharge forecasting in term of prediction of runoff, flood, streamflows and water level [34-85]. This review reported only the high impact journal publication since 2002 to 2011 for ANN applications in water discharge forecasting.

Sudheer and Jain [75] established stage discharge relationship through modeling rating curves using radial basis function neural network. Three kinds of daily data sets were used for modeling stage discharge relationship (i) 651 pairs of data sets at Narmada River, Jamtara, India (ii) 259 pairs of data set at Kolar River, Satrana, India and (iii) 200 pairs of hypothetical data set. Seven combinations of stage and discharge values with some antecedent conditions defined by Jain and Chalisgaonkar [76] were used as inputs. The input data was normalized ranging from 0 to 1 before training the network. Description length algorithm by Leonardis and Bischof [86] was used to acquire appropriate parameters of RBF network. Comparison of networks among different inputs showed that the model accuracy between all seven models for Satrana and Jamtara does not vary. Whereas while using hypothetical data/ a loop rating curve, three model out of seven performed poor during testing stage. Sudheer and Jain [75] explained the possible reason that this is because of two different discharge values at the same stage value. The network produced the average between these values as network output. However, where the stage has only one discharge values even at rising and falling limb of the curve, the network performance was found good. Sudheer and Jain [75] compared the study with previous work by Jain and Chalisgaonkar [76] and concluded that both RBF and MLP models performance are comparable at Satrana and Jamtara sites but in case of rating curve where the main practice is the trembling state of flow, RBF model performed better than MLP model.

Campolo et al. [37] forecasted flood in the River by using feed forward neural network approach with standard back propagation training algorithm. They used the information of rainfall, hydrometric data and dam operation at the Arno River basin, Italy, to predict the hourly water level variations. They used two years data with some special treatment with as inputs to the network to get better performance of the model. Campolo et al. [37] included the power data of the dam operation as it was assumed that dam release may affect or modify the falling limb of the hydrograph. They performed a cross correlation analysis between power data and water level, and rainfall and water level to incorporate the appropriate lag time in the input data for the model. On the basis of data analysis; to predict water level from time T, they divided the inputs into four categories that include (a) 4-hour cumulative rainfall over the entire basin for time T-20, T-16, T-12, and T-8; (b) average rainfall of each sub-basin from T-7 to T-1; (c) power data from T-9 to T-1; and (d) water level data from T-9 to T-1. Thus, they used 57 numbers of neurons in the input layer while six output neurons (i.e. water level from T to T+5, 6-hour ahead forecasting) in the output layer. Trial and error procedure were adopted to find the appropriate number of neurons in the hidden layer. They tried to reduce the number of inputs by using basin average rainfall from T-7 to T-1 instead of average rainfall of the sub-basin but they found worse results with this input. Campolo et al. [37] stated that the model was able to forecast six hour ahead water level. However, they found that forecasting error increases with the time ahead of forecasting but the increase in error is more prominent in lower levels than the higher levels. They also made another trial for further improvement in the network performance by using the same input structure but with only one output. But they found that the network with multiple outputs performed slightly better as compared to the single output network. They stated that the model performance for 6-hour ahead forecasting authenticate the limitations of forecasting time in advance. Furthermore, they preferred to use the multiple output model over the single output model based on the accuracy of the model significantly at the peak flows.

Cigizoglu and Alp [66] established rainfall runoff modeling using three different types of neural network and compared the results with Multi linear regression (MLR) technique. Feed forward back propagation (FFBP), radial basis function (RBF) and generalized regression neural network (GRNN) types were employed for rainfall runoff relationship. Daily rainfall and runoff data (10496 days, 9000 data for training and 1490 data for testing) from Turkey was used to forecast runoff. After correlation analysis, two different inputs (i) containing current rainfall with four antecedent values and (ii) current rainfall, four antecedent rainfalls and one antecedent flow was used to estimate current flow value. Training parameters for ANN models including number of hidden neurons were selected using trial and error approach. Several simulations were performed to obtain the best performance of the models. The results obtained with (ii) input (antecedent flow) were found significantly better than obtained from (i) input (only rainfall values) in all models. The authors observed some negative flow values at low flow conditions from all models except GRNN model. The authors suggested that all models are capable for flow forecasting and the performance of the models are comparable. However, RBF model produce smallest error among all the models.

Lekkas et al. [35] employed three different types of neural networks for flood forecasting. Half hourly river flow data from two gauging stations of the River Pinios in Greece was used in the study. Authors performed correlation analysis for appropriate selection of antecedent values as input for ANN models. Three ANN models was developed using three types of neural networks which include the traditional feed forward back propagation neural network, Adaptive Linear Neuron Network (ADALINE) and Elman recurrent network. In feed forward back propagation neural network, two hidden layers were used with one hidden neuron in each layer. Log sigmoid and positive linear transfer functions were also examined in the hidden layers. Authors used only hidden layer in ADALINE network and Elman network. In addition with ANN models, the authors used an error prediction method as an updating technique. In this method, they used the error difference between the observed and predicted flow and modeled using ARMA model. They used ARMA model to forecast the error and subsequently added to the flow forecast to so as to correct it. The authors found a significant improvement after using the error prediction method along with ANN models. The comparative analysis of the results obtained using log sigmoid and positive linear functions in feed forward type showed that network perform better with positive linear transfer function. Based on the obtained results, the authors suggested that all the ANN models are capable for flood forecasting and produced comparable results. However, Elman recurrent type of neural network performed better than other models for 7 hour flood forecasting at River Pinios in Greece.

Daliakopoulos et al. [77] forecasted ground water level using three different types of neural networks. These types include (i) Multilayer feed forward neural network (FNN) (ii) Elman or recurrent neural network (RNN) and (iii) Radial basis function neural network. They used three training algorithms (i) Levenberg Marquardt (LM), (ii) Gradient descent with momentum and adaptive learning rate (GDX) and (iii) Bayesian regularization (BR) to train FNN and RNN types of neural networks. Time series data of temperature, rainfall, stream flow and ground water of Messara, Greece from (1988-2002) was used for ANN modeling. Data was divided into three subsets from 1988-1998 for training, 1998-2000 for calibration and from 2000 to 2002 for testing stage of the networks. One present value with four antecedent values of all variables was used as inputs to forecast one step ahead ground water level for all networks. Thus input layer consist 20 numbers of neurons while output layer contain only one neuron. Three hidden neurons for both FNN and RNN were selected by trial and error approach while 25 hidden neurons for RBF. Results were simulated for 1, 6, 12 and 18 months ahead forecasting water level. The performance comparison between the different types of neural networks suggested that multilayer perceptron feed forward type of neural network produce better forecasting in all cases than other types. The performance comparison between training algorithms recommended that Levenberg Marquardt training algorithm performed better in both types (FNN and RNN) than the other training algorithms. The authors proposed that multilayer perceptron feed forward neural network with LM training algorithm and 20-3-1 configuration is best for 18 months ahead forecasting water level. Furthermore, they recommended that neural networks are a useful tool for prediction of variables in ground water hydrology.

Jy et al. [43] conducted a study to forecast watershed runoff and stream flow using multilayer feed forward neural networks. The study was performed on a small watershed in Greensboro North Carolina. Two models were developed, (i) four step ahead or one hour ahead (with 15 min resolution time interval) forecasting of storm water runoff (ANN-WRP) and (ii) flood flows or stream flow forecasting (ANN-SFF) at lead time equal to the time to reach peak flows at an upstream station. On the basis of some preliminary data analysis or correlation analysis; for ANN-WRP model, the authors selected inputs as one current rainfall with seven antecedent rainfall values and one current runoff with three antecedent runoff values to forecast four step (one hour with 15 min resolution) ahead runoff. While, for ANN-SFF model, they used current rainfall and runoff with 23 antecedent values of each variable from the upstream station to forecast one hour ahead runoff at first downstream station and three hour ahead runoff at second downstream station. The authors find the optimal number of hidden neurons equal to the two thirds of the summation of input and output neurons (i.e. 2/3*(number of input neurons + number of output neurons)). The authors stated that the results obtained from the models were encouraging and demonstrate the applicability of ANN for stream flow forecasting and advance forecasting flood at downstream station by using previous/current meteorological and stream flow data at the upstream station. However, it was observed that the model accuracy decrease gradually with the increase of forecasting steps. Thus, one step ahead forecasting results is more accurate than two, three and four step ahead forecasting. Furthermore, the authors suggested that the worth of ANN models to solve multifarious problems particularly for near real time forecasting of stream flow and watershed modeling is effective.

Fernando et al. [78] forecasted combined sewerage overflow using Multilayer Perceptron neural network with standard back propagation training algorithm. Two ANN models with different number of inputs, (i) containing antecedent rainfall and antecedent discharge data and (ii) having only antecedent rainfall data were developed and compared. Cross correlation and series correlation between the input variables were examined for appropriate selection of antecedent conditions for input layer. Hidden nodes were selected as 9 and 6 for both ANN models respectively. The expected forecasted output was only the overflow rate. The authors normalize the data before modeling and suggested that data normalization also have good impact for better model performance. The performance of the both the models was compared and found that the ANN model (i) with rainfall and discharge data performed very well whereas ANN model (ii) having rainfall data only was unable to forecast the overflows. Thus, ANN architecture with rainfall and discharge data including some antecedent conditions was proposed for overflow forecasting.

Sajjad Ahmad and Simonovic [80] estimated shape of runoff hydrograph based on meteorological parameters by using feed forward networks trained with back-percolation [87] training algorithm. Data from Red River in Manitoba, Canada was used for modeling hydrograph. Forty years data was available for the study but seven years data at low flows were eliminated based on the objective of the study to predict hydrograph at high flow. Rest of the thirty three years data was categorized for training, testing and forecasting purposes. The input parameters were selected based on the physical understanding and the study of historic flood data. The input parameters include antecedent precipitation index, melt index, winter and spring precipitations separately, and timing, thus total five input neurons was used. The output parameters expected from ANN model to develop runoff hydrograph were comprised peak flow, time of peak, width of hydrograph at 50% and 75% of peak, base flow, and timing of rising and falling sides of hydrograph. Training was performed using back-percolation algorithm which transforms the error propagation method of the back-propagation algorithm and hypothesizes the errors in the hidden neurons autonomously from error in the output neurons. The overall prediction performance of the model for hydrograph characteristics was found good. The authors stated that ANN technique for estimation of hydrograph is a precious substitute to conceptual watershed techniques, where limited time and topographic data is available and where the inclusive perceptive of the physical processes of watershed is not accessible.

Melesse and Wang [57] used multilayer perceptron with backpropagation algorithm to predict the flood for three time scales of two sub-basins Devils Lake (DL) and Red River at Grand Forks station (RR-GF) in North Dakota, USA. Daily (one year data), weekly (five years data) and monthly (twenty seven years data) data of precipitation, river discharge and air temperature including some antecedent conditions were used for ANN modeling to predict current hydrograph at the DL and RR-GF stations. Three different combinations of variables for inputs to network were examined which include (i) present precipitation with three antecedent values, air temperature and one antecedent river flow, (ii) air temperature and one antecedent river flow and (iii) only one antecedent river flow. All the data was normalized in the range of 0.01 and 0.99. The models produced good prediction results for both DL and RR-GF basins. The use of different kind of inputs showed that prediction results while using inputs type (i) produced better results than the others in all cases of prediction. The comparison of daily, weekly and monthly prediction showed that the daily data sets produced better results than the weekly and the monthly. The authors also showed the problems with ANN that it seems to be deficient for building and tactic to develop proper network architecture. There is no proper established method available for network selection. Furthermore, there is no statistical thoughts occupied in ANN, thus it can only produce point prediction.

Iliadis and Maris [81] estimated the Average Annual Water Supply (AAWS) on annual basis for watershed of Cyprus using application of ANN. Five number of parameters were used as inputs which includes three structural (altitude, slope and area of the watershed) and two dynamic parameters (average annual and monthly rainfall) to determine the AAWS.

Twenty nine years data (1965-1993) collected at 78 stations established in 70 different watersheds of Cyprus was used for training (60 cases) and testing (18 cases) stages of the network. Multilayer perceptron neural network with three hidden layers each containing 15 numbers of hidden neurons was trained with standard backpropagation training algorithm. The authors found good training results with the stated model but it was not able to produce a good generalization when a new set of data was used as testing stage. Thus, the authors examined the performance of ANN model with some other techniques like general regression ANN, learning vector quantization, modular ANN, probabilistic ANN, radial basis function ANN and reinforcement ANN. However, the authors found modular ANN as an appropriate technique for the stated problem and found good prediction results during both training and testing phases. The authors suggested that ANN modeling techniques are able to solve problems related to water resources management. Moreover, the modular ANN model is able to approximate the average annual water flow values at Cyprus and the same configurations can be used for other countries as well.

Feng and Hong [82] investigated on hydrological computation using artificial neural network by illustrating an example of examining peak stage at Shi-Gou station in Sui-Jiang, China. They used three variables as inputs, one peak stage at the upper reach station of Shi-Gou station, one peak stage at the Shi-Gou station measured at the same time as that of the upper reach station and third one is the precipitation of the space interval between the stations. They used 8 numbers of neurons in hidden layer and one neuron in output layer as the output was one peak stage at Shi-Gou station. Thus they defined the ANN architecture as (3, 8, 1). The network was trained using back propagation training algorithm. They emphasis from the example demonstration, that the applications of ANNs for hydrological computation be worthy of appreciation because of its learning ability from the historic data and consequently for future forecasting. They also highlighted many hydrological issues and depicted some logical advises to solve those problems using ANNs. They highly recommended the applicability of ANN's to accomplish hydrological calculations.

Fernando and Shamseldin [79] applied radial basis function neural network for one day ahead flow forecasting. Two RBF networks were trained using daily flow data of two different rivers from different part of the world having different characteristics (i.e. Blue Nile River from Sudan and Brosna River from Ireland). Eight years data were divided into two parts in a ratio 50%, four year for training and testing each. Autocorrelation analysis was examined to select appropriate number of inputs. Present day discharge with two antecedent discharge values were selected to forecast one day ahead discharge in both RBF model architectures. The effect of radial basis functions or hidden neurons in both the models was also investigated. Conjugate gradient descent algorithm was employed to minimize the network error in order to choose the RBF centers, spreads and weights between hidden and output layers. From the inspection of the effect of hidden nodes on outputs, the authors examined that results with hidden node 1 is more dominant at low flow range, hidden node 2 showed dominancy at medium/high flow range and from hidden node 3, the very high zone flow was covered. From this observation, they suggested that RBF model have ability to analytically crumble the flow hydrograph into a number of consequential flow elements in the catchment. Since the authors obtained successful forecasting results of river flow with different flow characteristics, in the mean while they also suggested that RBF network is not completely slanted, but it produce important information about the natural scenario.

Demirel et al. [54] forecasted flow by using two different techniques which include (i) artificial neural network and (ii) soil and water assessment tool (SWAT). Authors used the daily flow data of the Pracana basin in Portugal. Different combinations of rainfall and flow data with some lag periods were examined as input neurons in the input layer. Demirel et al. [54] coded that Jy et al. [43] proposed a thumb rule to determine the number of hidden neurons. According to his thumb rule, optimum hidden neurons could be estimated as two third of the summation of input and output neurons. But Demirel et al. [54] preferred to find the number of hidden neurons by using trial and error method. Sigmoid transfer function was used in the hidden neurons and for training the network, gradient descent with adaptive learning rate was used. One day forecasting flow results found from SWAT model were unable to forecast peaks of flow data but the ANN model promisingly forecasted flow values at the peaks as well. The authors also suggest that the data normalization also help to improve the accuracy of the model. They also recommended the ANN model as a fastest tool for flow forecasting.

Ju et al. [48] used neural network with back propagation training algorithm to simulate division based data of stream flow. They compared the performance of division based back propagation (DBP) model with the ancient back propagation model and Xinanjiang model. The data was divided into two groups, for flood periods and non flood periods separately. Rainfall, stream flow and evaporation data at four different stations on the Luo River, China was used for stream flow simulation. Different combinations of the input parameters with lag time were examined for appropriate selection of input neurons. Training parameters including learning rate, momentum and number of neurons in the hidden layer were selected by using trial and error approach. The output of the models was the one day ahead forecasted stream flow. They used coefficient of efficiency for performance evaluation of the models. For the comparative study of stream flow simulations among the Xinanjiang and ANN models, the authors concluded that the ANN performed well. Furthermore, the grouping particularly on base flow can improve the performance of the ANN model. However, they also observed that the performance for forecasting at the peaks is not sufficient and suggested that ANN model efficiency may be further improved by adding some more information regarding input variables like temperature and humidity or by dividing input data into small groups.

Unal et al. [84] estimated the discharge capacity of compound channels using neural network with Levenberg Marquardt training algorithm and compared with some traditional modeling techniques which includes single channel method (SCM), divided channel method (DCM), coherence method (COHM), exchange discharge method (EDM) and shiono-knight method (SKM). The data was collected during a different study on stage-discharge model performed at university of Birmingham. The data was divided into two data sets one containing 167 data for training stage and second 72 data for testing stage. One hidden layer with 10 numbers of neurons was used. Trial and error approach was used to get the appropriate number of hidden neurons. Prediction results obtained from ANN model were found good and its comparison of performance with all other methods suggested the superiority of the ANN model among the all methods (SCM, DCM, COHM, EDM and SKM).

Kagoda et al. [85] used radial basis function type of neural network for one day ahead forecasting short-term stream flow. Application of RBF neural network for three locations at the Luvuvhu River in South Africa was demonstrated for forecasting stream flows. Daily data of rainfall and stream flow with antecedent conditions were used in the input layer to forecast one day ahead stream flow. Gaussian radial basis function was used during training RBF model. The network training consisted on two stages (i) contain the calibration of Gaussian function parameters and (ii) include the calculation of connection weights. The authors used Self-Organizing Feature Map (SOFM) technique to determine the Gaussian function parameters. While, for calibration of connection weights, Shuffled Complex Algorithm Evolution (SCE-UA) was used. The Performance of the models was evaluated using Nash-Sutcliffe efficiency and root mean square error as statistical measures. Satisfactory results were found at two locations where sufficient data was available, whereas at third location where data was not enough for network training, poor results were observed. Thus, the authors suggested that a good enough length of data is necessary to get satisfactory results from ANN modeling. However, the authors proposed on basis of obtained results that artificial neural networks is promising for forecasting stream flow in South Africa.

IV. Concluding Remarks

Indeed, ANN is a robust 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 showed that appropriate ANN modeling is always beneficial in water resources engineering when compared with conventional modeling techniques. Although, the reviewed papers in this study on ANN modeling for water resources engineering are not comprehensive, but it is explicable that neural networks have done a considerable impact in this vicinity particularly in river sediments and discharge.

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