WATER LEVEL PREDICTION BY ARTIFICIAL NEURAL NETWORK IN THE SURMA-KUSHIYARA RIVER SYSTEM OF BANGLADESH

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ABSTRACT

The nonlinear relationship between rainfall and water levels is one of the most complex hydrologic phenomena to figure out due to the involvement of spatial and temporal inconsistent geomorphic and climatic factors. In this study, attempt is made to recognize the water levels pattern in the Surma-Kushiyara River system of Bangladesh by artificial neural network. Only recorded past rainfall and water levels information are utilized. Multilayer perceptron (MLP) and radial basis function network (RBFN) are the two feed forward neural networks which are applied for this envisagement. In MLP, logistic sigmoid activation function with unit steepness parameter is exercised for non-linear transformations in both hidden and output layers. Synaptic weights are adjusted using modified delta rule through error back propagation algorithm. Batch mode of training is adopted for global error minimization. The back propagation algorithm is considered to have converged when the absolute rate of change in averaged square error per epoch approaches to zero. The basis function for the RBFN is Gaussian in form. Numbers of centers which determine the dimension of space nonlinearity in the hidden layer are chosen by k-means clustering. The transformations from input to hidden layer and hidden to output layer are nonlinear and linear respectively. Finally, statistical indicators are used to evaluate the prediction performance of neural network. It is observed that both MLP and RBFN are capable to identify the intricate pattern of water levels in the Surma River. One, two and three day lagged rainfall in conjunction with one day lagged water levels is capable to recognize the water level patterns. With the increase of lead time, the performances of statistical indicators became inferior slightly. Higher water levels are predicted more fairly than the lower water levels. In the case of MLP, single hidden layer with two hidden neurons are found adequate to train the network. Higher numbers of hidden neurons are speeding up the training procedure with unacceptable generalization for application. The learning rate and momentum coefficient equal to 0.10 and 0.50 respectively formulates better results. Higher number of hidden neurons is required for RBFN. In RBFN, the numbers of iterations that are required to produce the acceptable results is lower than multilayer perceptron but better generalization is achieved in multilayer perceptron.

Keywords: multilayer perceptron, error back propagation, modified delta rule, batch mode, radial basis function network.

INTRODUCTION

Prediction of water level in a river system is of great interest for water management and flood control. In Bangladesh, the simulation model 'MIKE11' and a special version of 'MIKE11 FF' conceptual hydrodynamic model are in operation to forecast water levels (FFWC, 2008). It involves runoff calculation, flow routing to the desired downstream location from the upstream observation and conversion of flow to water level by using a rating curve. But difficulties are associated to construct an authenticated rating curve and accurately present spatially distributed heterogeneous geomorphic and climatic factors to the model. The study area is located at the agriculturally and ecologically

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important northeast hydrological region of Bangladesh where flash flood during pre-monsoon (March-May) season is very common and one of the major concerns for the economy. Steep upstream basin topography, short concentration time, sudden excessive rainfall and flashy character of the rivers are the driving components of rapid water level rises and falls with little or no advance warning. The principal river is the Barak which divides into Surma and Kushiyara River at the border of Bangladesh and India. Total catchment areas of Surma and Kushiyara River are approximately 8176 km^2 and 36945 km^2 (BUET, 2008) respectively which are stretched in India and Bangladesh. Surma River is fed by the heavy rainfall of Meghalaya and Assam area. Unfortunately available rainfall information of Indian hilly area is very limited which is a big challenge for water levels prediction in these rivers. Figure 1 shows the Surma and Kushiyara River along with water levels measuring station.

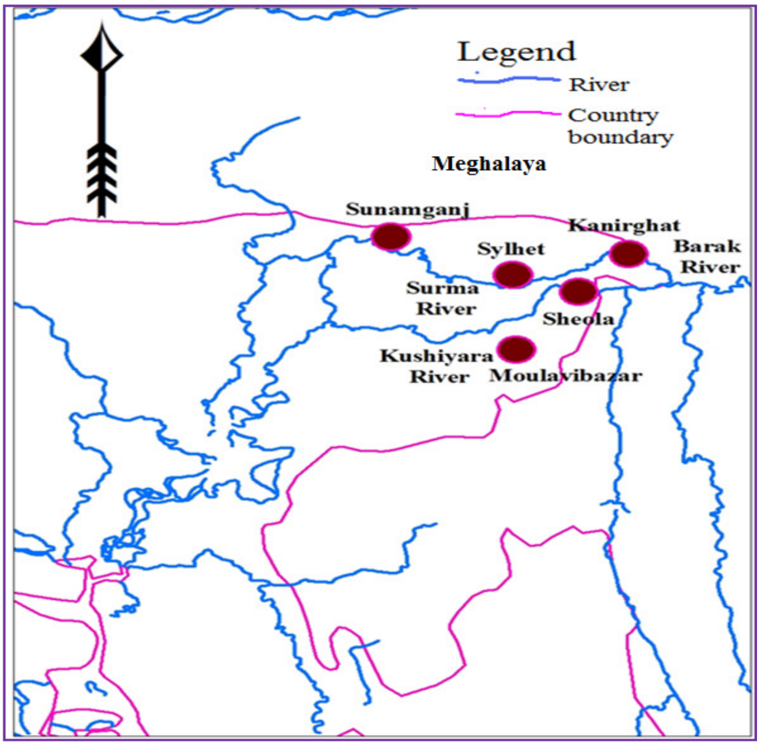

Figure 1: Surma and Kushiyara River with water levels measuring stations

DATA

Daily water levels and rainfall data are collected manually by the Bangladesh Water Development Board (BWDB). Data from 18/8/1980 to 28/8/2008 at Sylhet and Sunamganj gauging stations of river Surma are utilized for training, validating and application by splitting into three equal parts. Table-1 summarizes the data that are used in this study in different phase of simulation.

Table 1: Summary of used data in training, validation and application phases of simulation

Data source	Station	River	Total data range	Training range	Validation range	Application range
BWDB	Sylhet	Surma	18/8/1980 to 28/8/2008	21/8/1980 to 23/12/1989	24/12/1989 to 27/4/1999	28/4/1999 to 28/8/2008
BWDB	Sunamganj	Surma	18/8/1980 to 28/8/2008	21/8/1980 to 23/12/1989	24/12/1989 to 27/4/1999	28/4/1999 to 28/8/2008

THEORY AND METHODOLOGY

The adopted methodology is consisted of correlation analysis, principal component analysis, designing the architecture of MLP and RBFN, finding suitable data normalization range, training the network and generalization for application. Initial combination of rainfall and water levels in an input pattern are selected by autocorrelation, cross-correlation and principal components analyses. Sensitivity analysis is performed to decide an appropriate rainfall and water levels combination in an input pattern, data normalization range, number of hidden neurons in the hidden layer, learning rate parameter and momentum coefficient. These selected parameters are applied for higher lead-time prediction.

The activities of MLP are composed of forward and backward passes. The forward pass starts with the presentation of the input data to the network. These inputs are the stimulus signal of the network. Before presenting the data to the network, the input and desired output data for training, validation and application are normalized using the relationship as delineated below:

$$\text{Normalized Value=Lower bound+}\frac{(\text{Value-Minimum})(\text{Upper bound-Lower bound})}{(\text{Maximum-Minimum})}$$

where ‘Lower bound’ and ‘Upper bound’ are expected minimum and maximum response of the network, ‘Maximum’ and ‘Minimum’ is the highest and lowest value of a data set.

The feed-forward type neural network with sigmoid activation function is adopted in this study because of its simplicity and ability to approximate any continuous function (Flood & Kartam, 1994a). Mathematically, the general form of response function of two-layer perceptron network with single output neuron, I_n number of variables in an input pattern and 'h' number of hidden neurons is expressed in Eq. 1. Figure 2 shows the working principle of MLP.

$$y=f\left(w_0^{(2)}+\sum_{\alpha=1}^{h} w_\alpha^{(2)} f\left(w_{\alpha 0}^{(1)}+\sum_{\beta=1}^{I_n} w_{\alpha\beta}^{(1)} x_\beta\right)\right) \tag{1}$$

where, x_β are the input variables, $f(\cdot)$ is logistic sigmoidal nonlinear activation function, $w_{\alpha\beta}^{(1)}$ and $w_{\alpha 0}^{(1)}$ are input weights and thresholds, $w_\alpha^{(2)}$ and $w_0^{(2)}$ are second layer weight and threshold.

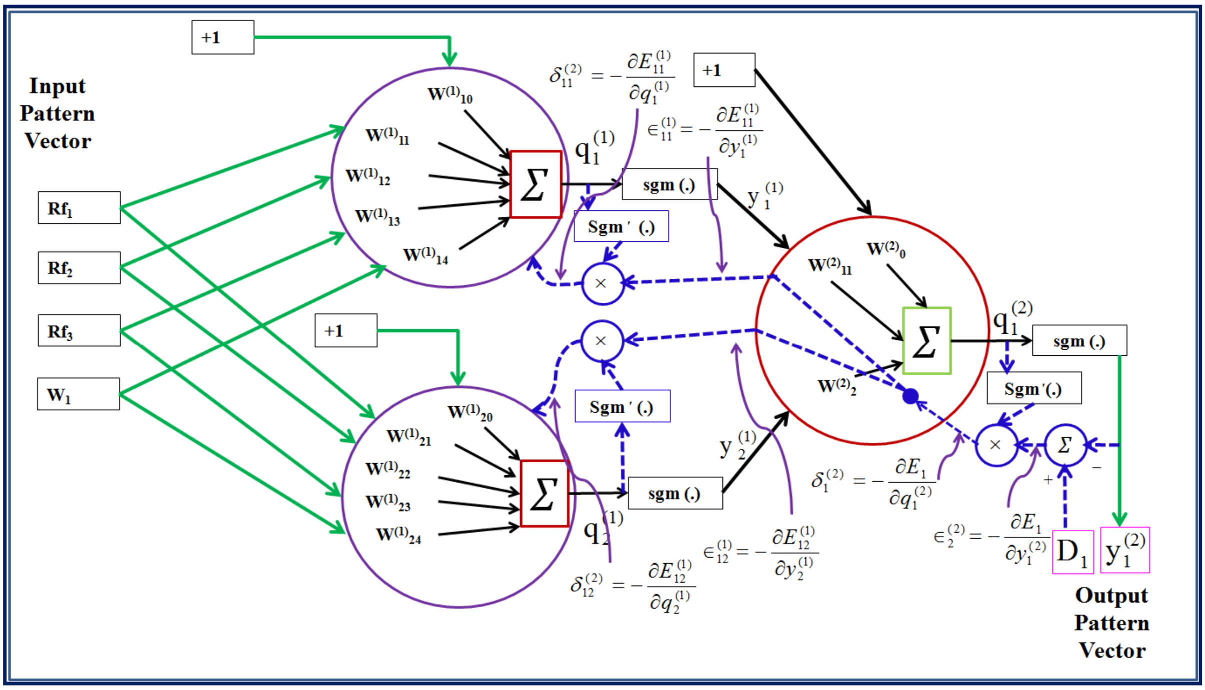

Figure 2: Forward and backward pass details of MLP

Initial weights and biases for both hidden and output layers are chosen randomly. The difference between network output and target output corresponding to the input pattern determines the error. Backward pass starts with the back propagation of the error through the network. The batch mode of training in back propagation learning and weight updating is used because of its capability to accurately estimate the gradient vector (Haykin, 1998). The objective of training is to reconstruct the hyper-surface of input-output mapping by reducing the global error E which is defined by Eq. (2).

$$E=\frac{1}{2N}\sum_{i=1}^{N}\left(y_i-d_i\right)^2 \tag{2}$$

where, N=total number of training pattern, y_i=network output for i^{th} input pattern and d_i= corresponding desired output.

Steepest descent or gradient descent algorithm is involved for the minimization of the global error. The network weights and biases, on which the global error depends, are adjusted by moving a small step in the direction of the negative gradient of the error function after an epoch. The iterations are repeated until the absolute rate of change in averaged square error per epoch approaches zero.

The function defined by Poggio and Girosi (1990) is exercised with the intention of reconstructing the solution surface during the application of radial basis function network. The general mathematical form is given as below:

$$F(x)=\sum_{i=1}^{C} w_i G(x,t_i)$$

$G(x,t_i)$ is the basis function which can be expressed as shown in Eq. 3.

$$G(x;t_i)=\exp\left(-\frac{1}{2\sigma^2}\|x-t_i\|^2\right)=\exp\left[-\frac{1}{2\sigma^2}\sum_{i=1}^{C}\|x-t_i\|^2\right] \tag{3}$$

where, C is the number of center, σ is the common variance, w_i is weight from hidden to output layer, t_i is the selected centers of the data set by k-means clustering, x is an input pattern.

RESULTS AND DISCUSSION

Sensitiveness of rainfall water levels combination: A number of rainfall and water level combinations are used for both stations to select the appropriate rainfall and water levels arrangement to predict the water levels with twenty four hours lead-time. Sensitivity analysis indicates that one, two and three day lagged rainfall along with one day lagged water levels is capable to comprehend the water level pattern splendidly. Concordance between measured and predicted water level pattern along with their linear relationship are shown in Figures 3 and 4 as an example in the form of time series and scatter plotting for the application phase of simulation at Sylhet gauging station.

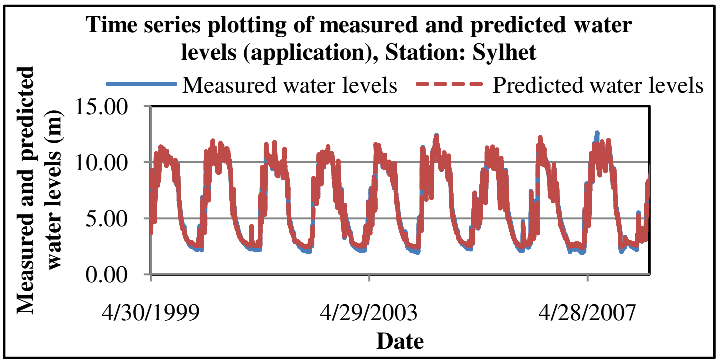

Figure 3: Concordance between measured and predicted water levels

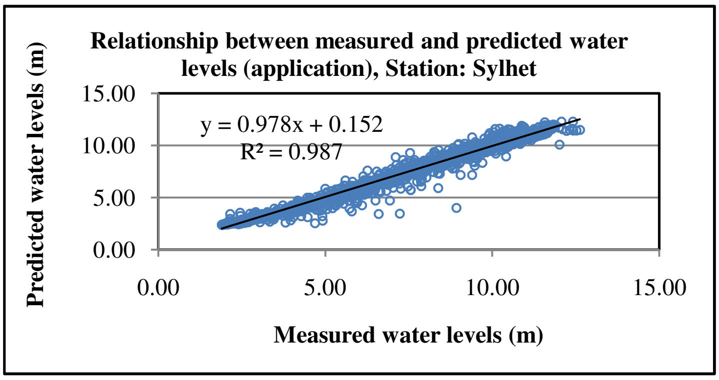

Figure 4: Colinearity of measured and predicted water levels

The value of mean absolute error which measures the closeness of prediction is lowest. The overall spread of predicted water levels with respect to the mean of the observed water levels is also lowest. Nash and Stucliffe's (1970) coefficient of efficiency (EF) measures how well the plot of the observed versus simulated value fits the 1:1 line. In the training, validation and application phases of simulation, the attained value of EF is 0.99 for both stations which is very close to the optimum value. Scattering of the predicted and observed values is measured by taking the ratio of the variance of the observed water levels to the predicted water levels around the mean of the observed water levels. The optimum value is 1.0. The obtained value of this indicator is 1.03 and 1.02 for application phase of simulation at Sylhet and Sunamganj gauging stations respectively. This represents that the measured and predicted water levels follow same straight line.

Influence of learning rate parameter and momentum coefficient: The changing patterns of relative root mean square error per epoch for different values of learning rate parameter (momentum coefficient=0.50) at Sunamganj gauging station are shown in Figure 5. The analysis indicates that for lower momentum coefficient and learning rate parameter, the required numbers of epochs to attain the convergence point are higher than that of the higher value of these parameters. Larger momentum coefficients are able to improve this slowness. But there exists the potential danger of oscillation in the generating error surface. Learning rate constant and momentum coefficient equal to 0.10 and 0.50 respectively gives best generalization.

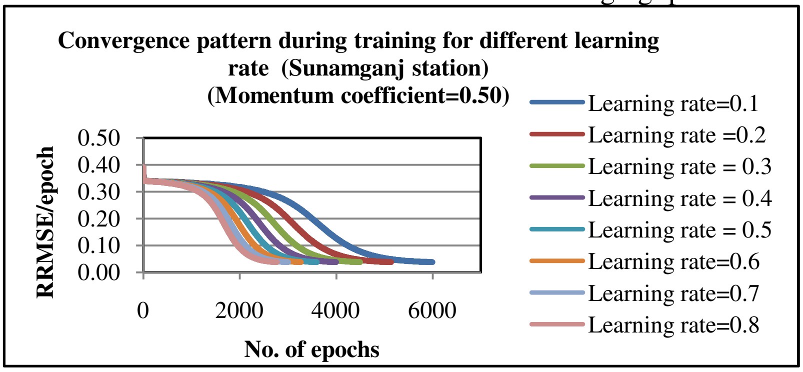

Figure 5: Convergence pattern of RRMSE

Outline of selected parameters of multilayer perceptron: Based on the results of the sensitivity analysis one, two and three day lagged rainfall in conjunction with one day lagged water levels are selected as the variables in an input pattern. The number of hidden layer is one and it is composed of two hidden neurons. The chosen learning rate parameter and momentum coefficient are 0.1 and 0.5 respectively. These values are used in both layers. Using the normalization range (0.20-0.80), synaptic weight of the network is computed.

Application for forecasting with longer lead-time: The parameters which are selected based on sensitivity analysis are applied for prediction of water levels with 48 hours lead-time. Statistical indicators suggested that the performance of prediction is dwindling with the increase of lead-time though these indicators are very close to their optimum value. The value of R^2 is close to 1.0 which signifies a very good linear regression correlation between the measured and predicted values. Mean absolute error is becoming higher in the case of longer lead-time prediction. This indicates that the deviation of predicted values from the measured values is increasing. The agreement between the measured and predicted water levels at Sunamganj gauging station with 48 hours lead-time is shown in Figure 6. The plotting represents good co-linearity between measured and predicted water levels.

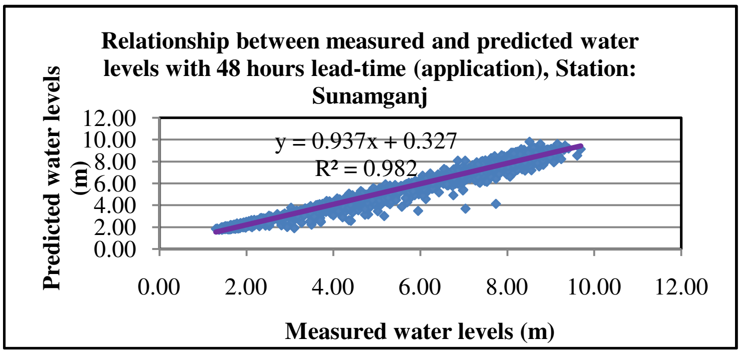

Figure 6: Colinearity between measured and predicted water levels with 48 hours lead-time

Application of RBFN: Application of RBFN indicates that with the increase hidden layer dimension, the performance of the prediction is becoming better for both stations. The colinearity between measured and predicted water levels at Sylhet gauging station in application phases of simulation for number of centers equal to twenty are illustrated in Figures 7. The value of MAE is getting lower with the increase of dimensionality. R^2 is very close to 1.0 which signifies good linear regression relationship between measured and predicted water levels. The performances of relative root mean square error are almost similar in both methods. The value of Nash and Stucliffe coefficient of efficiency (EF) is 0.98 which indicates that most of the predictions are fitted well with the 1:1 line. This is same for Sunamganj station as well. The scatter of the predicted and observed values around the mean of the observation indicates that the variances of predicted and measured water levels are almost same. So RBFN is capable to recognize the water levels pattern.

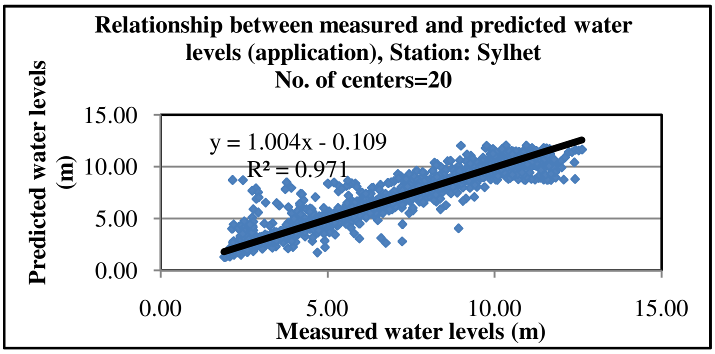

Figure 7: Colinearity of measured and predicted water levels in RBFN

CONCLUSIONS

Both multilayer perceptron and radial basis function networks are capable of predicting the water levels in the Surma river system. Radial basis function network has relatively higher dimensions in hidden layer than that of the multilayer perceptron. Number of iterations required to produce a desirable results in the case of multilayer perceptron with back propagation algorithm is higher than RBFN. One hidden layer consisting of two hidden neurons is adequate to train the network for MLP. Multilayer perceptron is giving better generalization results than radial basis function networks. The performance of forecasting results is receding with longer lead-time.

RECOMMENDATION

Future study should be conducted to reduce of the dimensionality of the radial basis function network by searching optimum number of centers using the statistical properties of the data pattern.

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