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Prediction of Discharge with Elman and Cascade Neural Networks

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Abstract

The soft computing techniques have gained popularity for predictions. Stage discharge studies play a crucial role in planning, design or management of any hydraulic system. Over or under estimation of discharge value causes huge loss of investments, structures and lives. Two neural networks have been studied taking stage discharge data of an Indian river named Brahmani. Performance of each network has been summarized. Accuracy of each network model is based on the percentage of successful predictions on the test sets of each data set. Accuracy is measured via the holdout method as well as through cross validation. The present work suggests the suitability of a neural network as a tool for predicting discharge which will be useful in different field of science and engineering.

Keywords: Artificial neural networks, Elman network, Cascade network, stage and discharge.

Introduction

Discharge predictions are always taken into account prior to go for any building of structural component to safe disposal of excess inflows. Fluctuations in velocity change; its stage and difference in pattern of cross section geometry depend much in its prediction. Discharge prediction with statistical analysis by using a rating curve generally in the form of polynomial equation, or regression and auto correlation based methods such as ARIMA models[1] or simply as used by hydrologists with available rating curve or thumb rule are old enough to rely. River engineering, interaction of flow in different mediums, slopes, sediment concentration etc makes the problem more complex in prediction.

Peak flow estimation and effect of consequent flows which affect much for planning, designing or safe disposal of floods is of great importance. Reliable discharge data involving much man power, cost and risk involved in collecting are rarely available. After year 2000 computers helped researchers adoption of function approximation method based models. Naming a few, rating curve predicted by use of Artificial Neural Networks (ANN) with generalized delta rule or back propagation are common in use[2-6]. Several types of ANNs exist in the literature. But till date BPNs are mainly explored in hydrological systems. The current study explores the potential of two new network models namely Elman and Cascade neural network in predicting the discharge using data from two different gauging sites of an Indian river. Several performance parameters for both network models are derived. To measure the accuracy of estimation, hold out as well as cross validation methods are used.

The paper is arranged with a brief overview of neural networks namely Elman and Cascade. Next discussing the data sets used and analysis of performance parameters are made. Lastly with the result and discussions the conclusion of the paper is made.

Material and Methods

Neural Network Models: Artificial Neural Networks are popular in hydrology and water resources study. They represent an inter connection pattern between different neuron layers, then updating of the weights through a learning process and converting neurons weighted input to its output activation[7-9]. In the current study a brief overview of two neural networks namely Elman and Cascade neural networks are presented.

Elman Neural Network (ENN): The Elman neural network also known as partial recurrent network. The outputs of the hidden layer are allowed to feed back onto itself through a buffer, called context layer[8]. This feedback allows the network to learn, recognize and generate temporal patterns as well as spatial patterns. The Elman network mainly consists of four layers: input, hidden, context and output layer. There are adjustable weights connecting each pair of neighboring layers[9]. This network is a special kind of feed forward ANN with short term memory neurons and local feedback. The network is trained using Levenberg- Maruardt (LM) algorithm to minimize the Mean Square Error (MSE).

Cascade Correlation Network (CCN): Cascade correlation networks are self organizing Networks[7-11]. The network begins with only input and output neurons. During the training process, neurons are selected from a pool of candidates and added to the hidden layer. Every input is connected to every output neuron by a connection with an adjustable weight. So each output neuron receives a weighted sum from all of the input neurons including the bias. The output neuron uses different transfer functions to produce the final output.

Data Sampling: Discharge data sets corresponding to its stages were collected for an Indian river Brahmani at two gauging stations namely Panposh and Gomlai. Average monthly Stage-Discharge (1996-2010) along with daily data (2010-2011) for both the stations has been taken into consideration for analysis. For application the data sets were normalized between 0 and 1.

Performance Evaluation: Modeling Performance of different networks has been evaluated on the basis of different statistical parameters. The parameters are average absolute relative error (AARE), Pearson`s correlation coefficient (R) for training and testing, Nash Sutcliff efficiency (E), normalized mean biased error (NMBE), Mean square error (MSE), normalized root mean square error (NRMSE) , mean error estimating peak value (%MF) , persistence coefficient ($E_{per}$). Akaike`s Information Criteria (AIC), Baysian Information Criteria (BIC[10]) .

AARE computes the relative error in prediction with the observed value enabling an unbiased statistic for qualifying the capability of the model. For better performance AARE value should be small. Higher value of R proves the better linear relationship, if not biased with higher or lower values. E proposed by Nash and Sutcliffe certifies the model performance[11]. NMBE positive and negative depicts over or under predictions. NRMSE close to zero value predicts least error in prediction from its mean value. % MF describes the peak values for a safe design criterion to be taken care of. E_{per} Indicates the performance efficiency of the ANN model when observations are related with time.

Results and Discussion

The entire data set is divided into training and testing set. The division is done randomly. From the 365 daily discharge data, 300 are used for training and 65 used for testing. Similarly from 168 monthly average data 160 data were taken for training and eight for testing. Through exhaustive experimentation performance parameters were analyzed. For the monthly average data of Panposh and Gomlai, the calculations of different parameters were calculated. The coefficient of regression (training) in Cascade was found to be less than that of Elman network for Panposh average, daily and Gomlai daily as shown in Performance plots. While in case of regression testing, Cascade performed better for Panposh daily and Gomlai daily. AARE results were minimum for Cascade excepting Gomlai average data sets. Parameters like MSE, NRMSE, E, %MF and $E_{per,}$ Cascade performed better than Elman in all the cases excepting for E_{per} values of Gomlai average and daily data. It was observed as per AIC and BIC, values were better for Cascade than Elman. The calculated results are shown in Tables 1 to 4 respectively for all four data sets.

Performance followed by predicted figures 1 - 4 shows the trend for Panposh average in case of Elman and Cascade network. Predicted trend line is much closer in case of Cascade network.

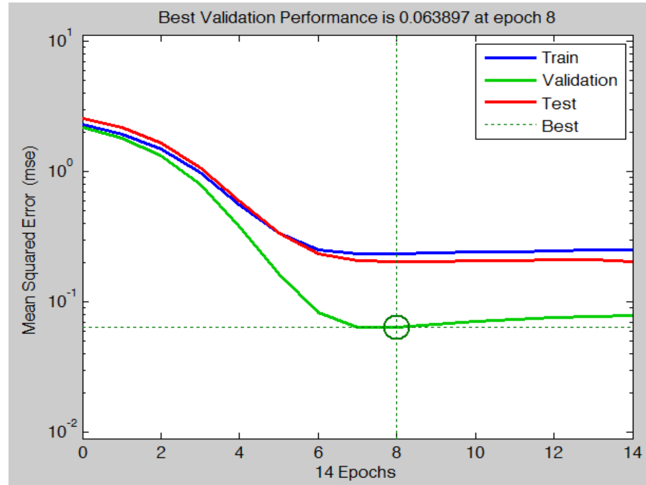

Figure -1
Performance plot of Panposh avg in Elman Network

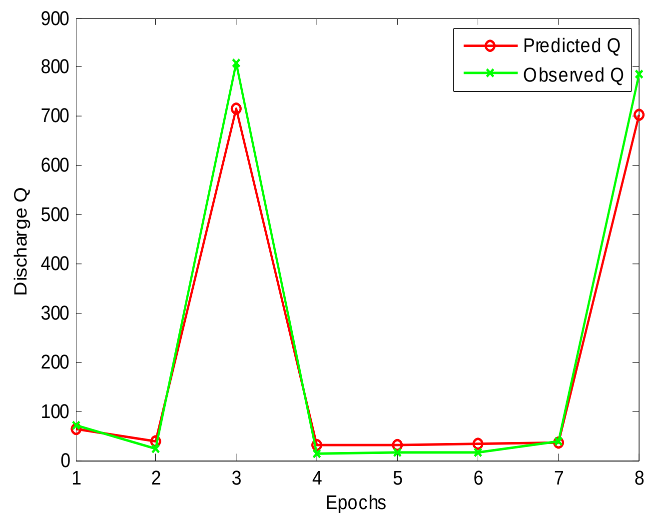

Figure - 2
Panposh avg predicted in Elman network

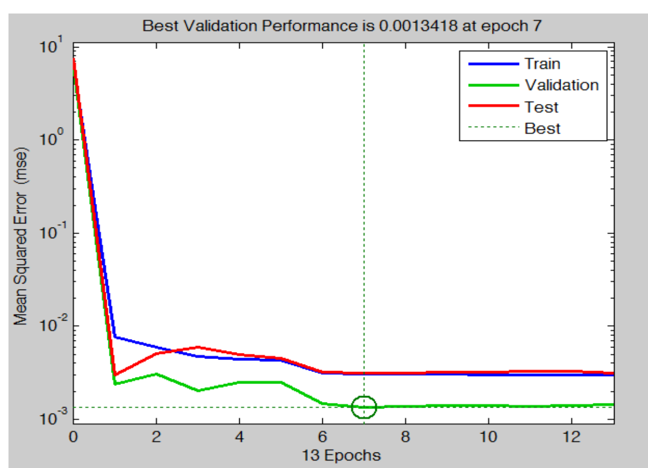

Figure -3
Performance of Panposh avg in Cascade Network

Table-1
Analysis of prediction with panposh average data

Perf para	Elman	Cascade
R Tr	0.9890	0.9920
R Ts	0.9998	0.9656
AARE	51.7941	30.1233
MSE	2218.6000	266.8448
NRMSE	0.0249	0.0092
NMBE(%)	-0.2244	-4.9117
E	0.9824	0.9976
%MF	-11.1754	-0.4381
E_{per}	0.9944	0.9988
AIC	3.5961	2.6763
ΔAIC	1.4921	0.5723
BIC	27.6717	20.3132
ΔBIC	11.9369	4.5784

Table-2
Analysis of prediction with gomlai average data

Perf para	Elman	Cascade
R Tr	0.9964	0.9891
R Ts	0.9950	0.9866
AARE	37.9372	44.7730
MSE	3976.4000	324.5300
NRMSE	0.0413	0.0364
NMBE(%)	0.4173	0.0153
E	0.9485	0.9600
%MF	-14.7156	-0.0592
E_{per}	0.9897	0.9691
AIC	3.8495	2.7613
ΔAIC	1.8181	0.7299
BIC	29.6990	20.9931
ΔBIC	14.5449	5.8390

Table-3
Analysis of prediction with panposh daily

Perf para	Elman	Cascade
R Tr	0.9837	0.9901
R Ts	0.9783	0.9844
AARE	89.1052	36.3823
MSE	723.5810	508.0327
NRMSE	0.3222	0.0043
NMBE(%)	0.0701	-0.0343
E	0.9592	0.9777
%MF	0.4735	-0.00947
E_{per}	0.9570	0.9815
AIC	3.1095	2.9558
ΔAIC	0.1665	0.0128
BIC	23.7790	22.5502
ΔBIC	1.3320	0.1033

Table-4
Analysis of prediction with daily data of gomlai

Perf para	Elman	Cascade
R Tr	0.9757	0.9827
R Ts	0.9786	0.9975
AARE	74.9023	28.7169
MSE	1.24E+03	664.3811
NRMSE	0.3740	0.0042
NMBE(%)	-0.0563	-0.0031
E	0.9544	0.9800
%MF	-17.9579	2.3850
E_{per}	0.9980	0.9883
AIC	3.3421	3.0724
ΔAIC	1.7505	1.4808
BIC	25.6404	23.4824
ΔBIC	14.0046	11.8466

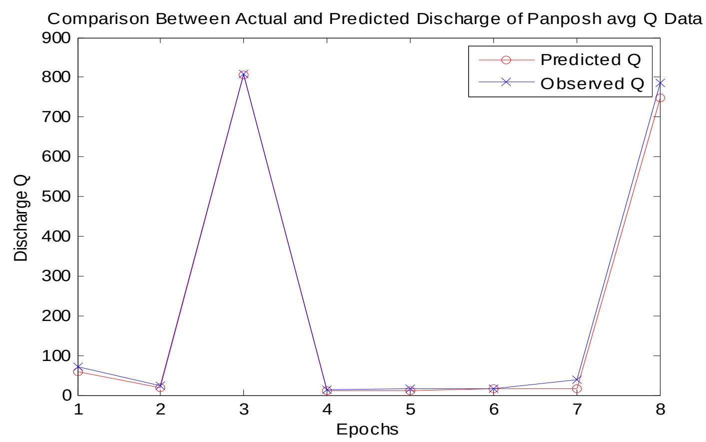

Figure - 4
Panposh average predicted in CCN

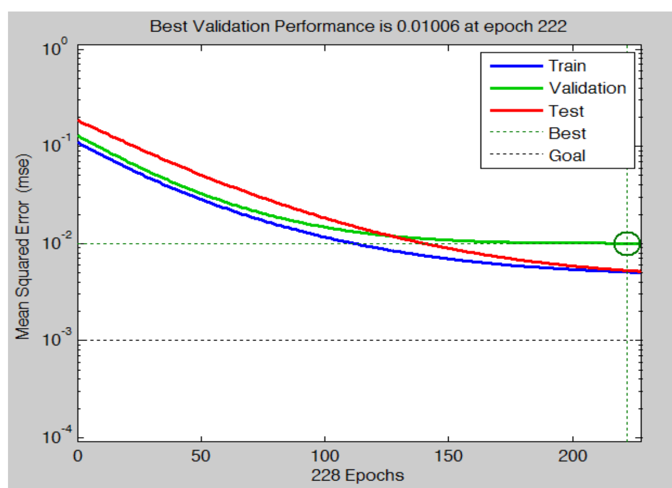

Figure – 5
Performance of Gomlai average in Elman network

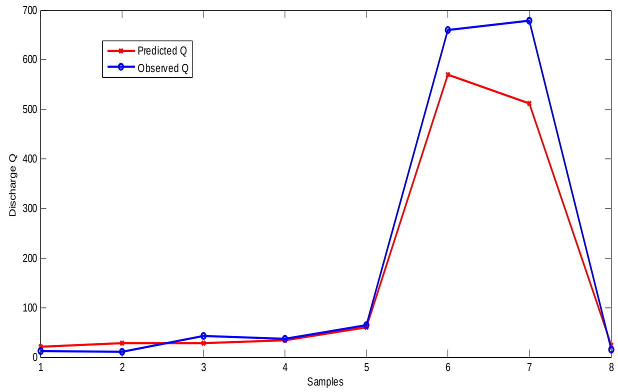

Figure – 6
Gomlai average predicted in Elman network

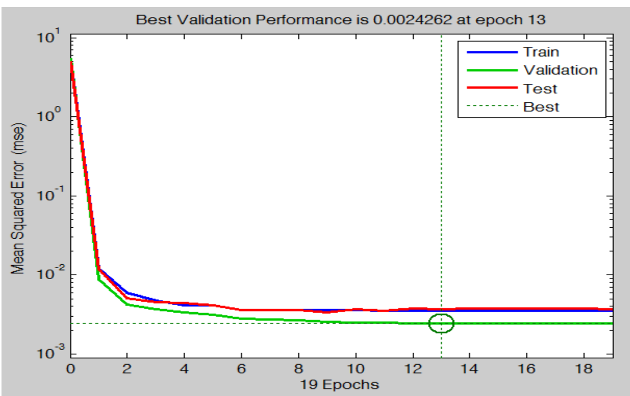

Figure – 7
Performance of Gomlai Avg. in CCN

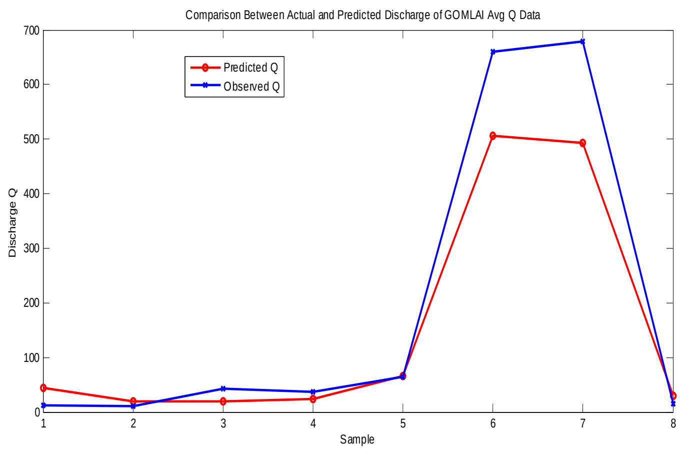

Figure – 8
Gomlai average predicted in CCN

Figures 5 - 8 shows the trend for Gomlai average for Elman and Cascade networks. For each and every parameter the performance is assigned a rank for both the networks. Then the sums of the ranks are determined for individual networks. After summing up it was found that the Cascade predicts better than Elman network for monthly average as well as daily data at both the gauging stations.

While comparing the prediction curves in figure 6 and 8, it is observed that the peak values are estimated more accurately in Cascade than Elman network for Gomlai average data.

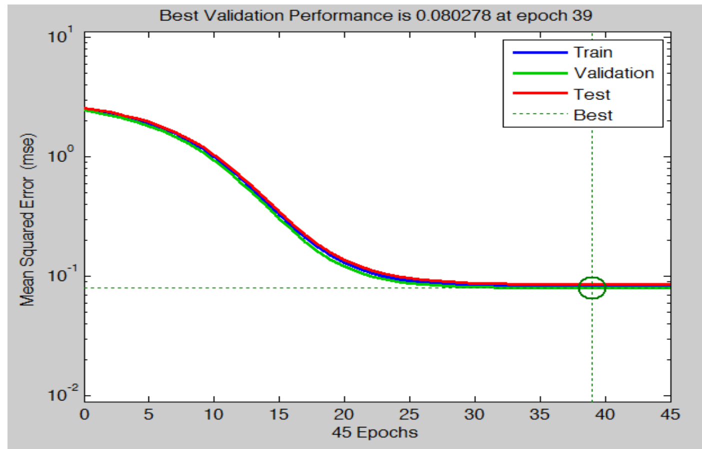

Figure – 9
Performance of Panposh daily in Elman network

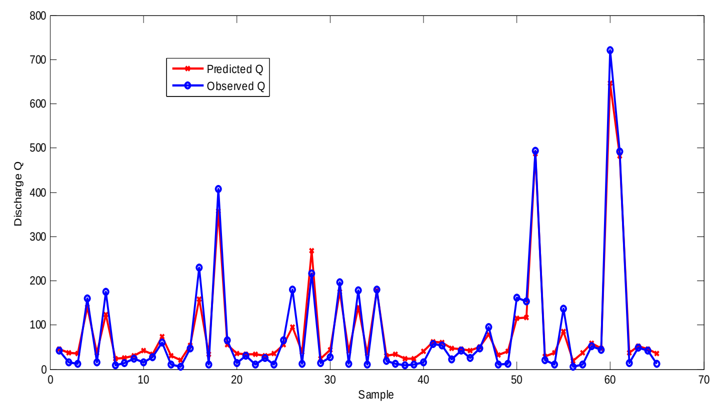

Figure – 10
Panposh daily data predicted in Elman network

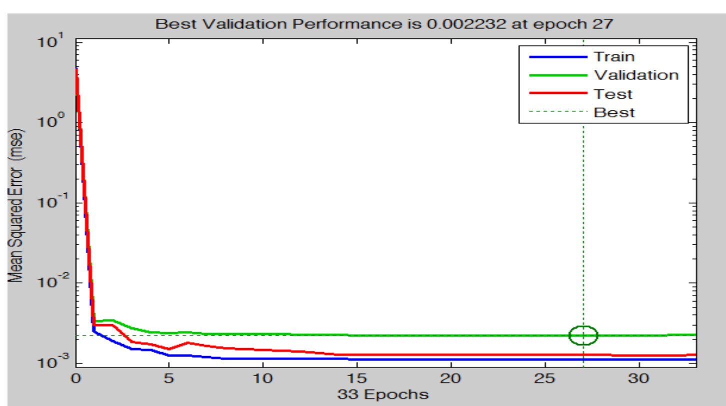

Figure -11
Performance plot of Panposh daily in CCN

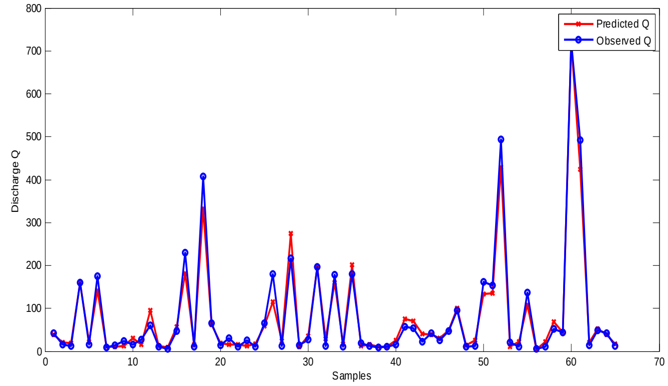

Figure -12
Panposh Daily data predicted in CCN

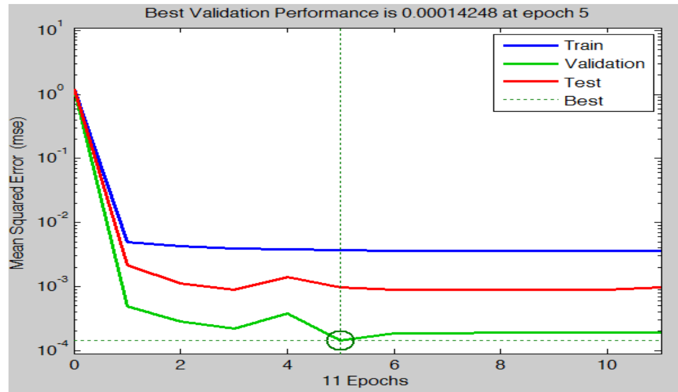

Figure – 15
Performance of Gomlai daily in CCN

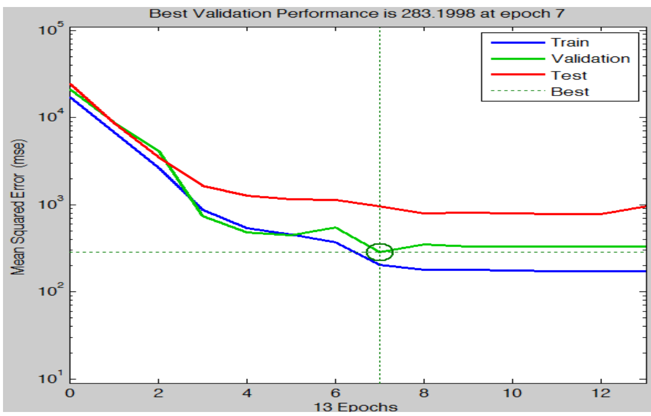

Figure -13
Performance of Gomlai daily in Elman network

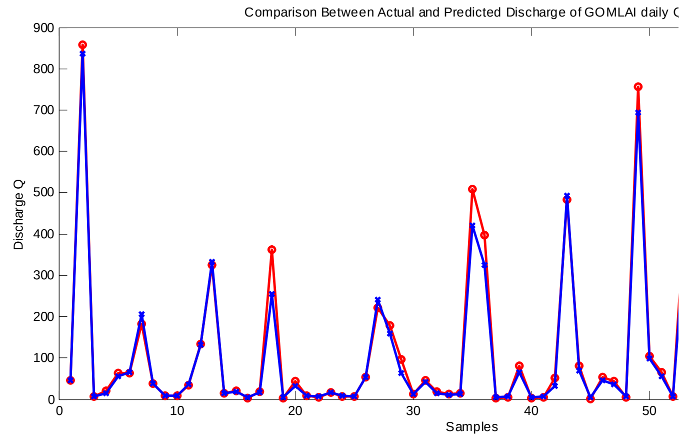

Figure -16
Gomlai daily predicted in CCN

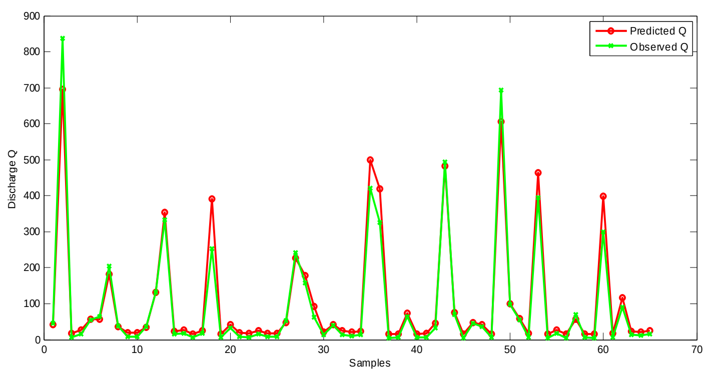

Figure -14
Gomlai daily predicted in Elman network

Prediction for Daily data is shown in figures 9 to 16.

Conclusion

In this paper an attempt has been made to study two artificial neural networks namely; Elman and Cascade and their application in stage discharge prediction.

Efforts were made to develop and analyze the models with single input and single output data. However few global parameters like %MF and E_{per} has been included under this study. The average absolute relative error, NMBE as well as Akaike and Bayesian information criterion are the other performance parameters used for analyzing the prediction capabilities of the ANN tools. The analysis of results reveals that the Cascade network gives better prediction than Elman network in case of monthly average data as well as for daily predictions. Future analysis can be made with multiple input datasets comprising of different dimensionless parameters of the river section to predict with higher accuracy. Models varying with time are of great importance, which has not been covered much under this work and remains an open area for further research.

Acknowledgement

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