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Stream Flow Behaviour Studies using Neural Networks

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Abstract: *Flow characteristics of streams are complicated and are influenced by different hydraulic parameters. Although numerical analysis has its own importance, soft computing techniques are becoming popular with availability of high speed computers. Soft computing proves to predict in a better way with sufficient and reliable data sets. Discharge requirement of stream flow is always needed for planning, design and execution of any water resources system. Discharge data of a river at two gauging stations namely Panposh and Gomlai were used for analysis. Four neural networks were used for analysis of data on a common platform and it is assessed that Cascade followed by RBF gave better predictions. Model equations were framed for the stream flow using the network interpretation diagram.*
Keywords*: Neural network, BPN, RBF, Elman, Cascade, NID*

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I. Introduction

Reliable estimate of discharge capacity are essential for the design, operation, maintenance of open channels and to be more precise, for prediction of flood, water level management and flood protection measures. Stage discharge uncertainties are minor due to different physical processes like; turbulent fluctuations, temporal changes of geometry, sediment concentration etc. Whereas it fluctuates much in its prediction mainly due to uncertainty in velocity changes, its stage and change pattern in cross section geometry from time to time depending on the flow received from upper catchment. Discharge prediction is made on statistical analysis; normally a polynomial regression equation is used to represent a rating curve, or regression and auto correlation based methods such as ARIMA models (Goviani) or simply hydrologists follow available rating curve or thumb rule, if a gauging station is located around. Back water plays a crucial role to nullify all estimates done for the prediction.

Most rivers exhibit as a compound channel during flood consisting of a deep main channel flanked by one or two floodplains. All alluvial rivers during their regime of flow take a suitable form depending its banks, flow behavior, ecology, amount, size and type of sediment they carry. Rivers, streams etc while flowing with sediment laden condition with changing geometry and shape gives poor result to all predictions. Similarly river sinuosity, meandering plan and shallow or deep complicates the problem to predict the discharge which are beyond the scope of this study.

However prediction of discharge is always required to know the peak flow and effect of consequent flows which affect much for planning, designing or safe disposal of floods. Measurement of discharge involves much man power, cost, risk in collecting data and above all the data got many times are not reliable (Bhattacharya et. all., 2000).

With advancement in computer technology, function approximation method based models have come up. Naming a few, rating curve (Goel, 2011) predicted by use of Artificial Neural Networks (ANN) with generalized delta rule or back propagation and radial basis function (RBF) method are common in use (Goel, 2012; Bhattacharya et. al., 2003; Bisht et. al., 2010; Jain, 2011). Several types of ANNs exist in the literature. But till date back propagation neural networks (BPN) are only explored in hydrological systems (Tawfik, et. al.,1997; Rees, 2008; Bisht et. al., 2010). Adhikari et. al. 2012 and 2013 have studied separately about the application of Elman and Cascade in discharge prediction followed by RBF and Elman neural networks. BPN is popularly used by many researchers for discharge prediction. (Goel and Pal, 2011).

The current study attempts to compare other networks along with BPN on a common platform. The potential of three network models namely Radial basis function, Elman neural network and Cascade correlation network along with the BPN in predicting the discharge using data from two different gauging sites of the same river is tested. Most work of researchers emphasize on Root Mean Square Error (RMSE) as the main performance criteria, where as multiple performance parameters were used (Srinivasulu et. al.; 2006, Adhikari et.al., 2013) for all the network models to derive and measure the accuracy of estimation, through holdout as well as cross validation method.

The paper is organized as follows: Section two presents a brief overview of neural networks under study. Section three discusses about the data set. The Section four presents derived results and discussions. Next Section five presents the network interpretation diagram. The Section six concludes the paper.

II. Suitability Of Neural Network Models

Commonly known neural network (NN), is a mathematical or computational model inspired by functioning of biological neural networks similar to a human brain. It has capability of solving complex problems of today's requirement in different fields of science and engineering. ANN comprises of 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 (Hajek , 2005; Sumathi et. al., 2006 and Haykin, 2006). Now this is being commonly used for optimization, variable generation and graphical model representation. While learning, the cost function is one of the important aspects of study, to know the approximation of getting the optimal solution. Cost function relates the mismatch between the mapping and the data. Common cost function considered is the Mean Square Error (MSE), which minimizes the average squared error between the input and output. However this tool is used for getting the cost function to get minimized value and in other applications missing data can also be generated through learning from the environment. Various models have been used at different levels of abstraction to model different aspects of neural systems through different cost functions analysis.

The network models under study are BPN, RBF, Cascade and Elman. The basics of these models are available in literature (Hajek, 2005; Haykin, 2006; Xin et. al., 2012; Samek; Mokhiessi et. al. 2011). For implementation of neural network models MATLAB commercial software was used (Sumathi, 2006).

III. Data Collection

To validate different models, stage-discharge data sets were collected for an Indian river Bramhani at two gauging stations namely Panposh and Gomlai. Fig.1 depicts the location map of both the gauging stations. Average monthly Stage-Discharge data over a period of fourteen years (1996-2010) along with daily data for the year 2010-2011 at both the stations have been taken into consideration for analysis. Earlier same data was used by Adhikari et.al., 2012 and 2013.

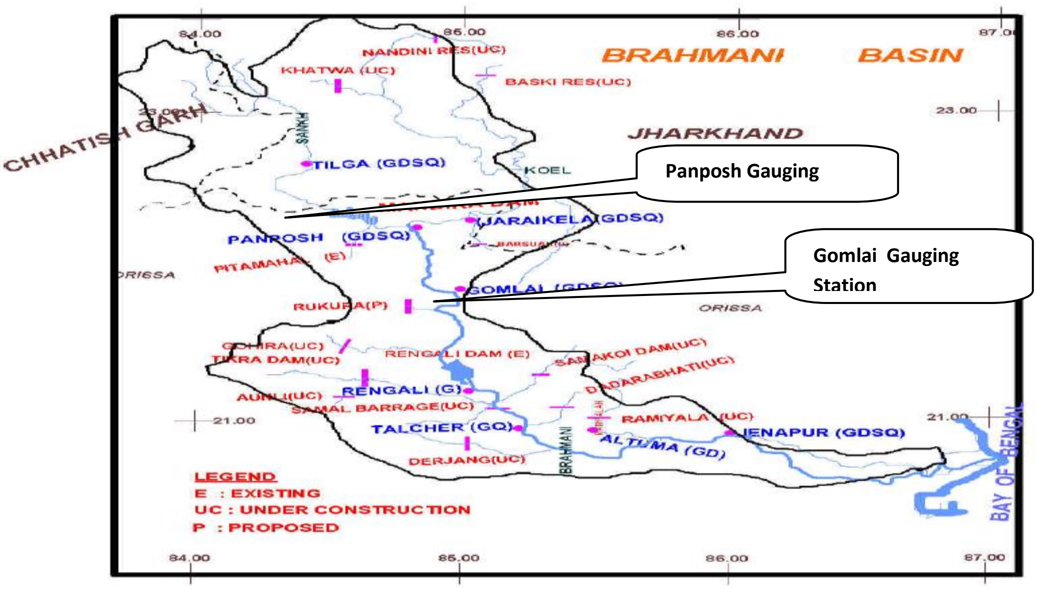

***Fig.1.** Location map of Bramhani River*

In general, the neural networks work better if input and output lie between 0 and 1. For that reason the collected input and output data were normalized.

IV. Performance Evaluation

To study model performance different statistical parameters used are Average Absolute Relative Error (AARE), Pearson`s correlation coefficient (R) for training and testing, Nash Sutcliff efficiency (E), Normalized Mean Bias 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), (Srinivasulu et. al., 2006; Adhikari et.al., 2013).

In case of better model small AARE value is achieved enabling unbiased statistics. Linear relationship is established between the observed and predicted data with higher R value. Nash and Sutcliffe (Zhou et. al. 2006) proposed higher E value as better model performance. Positive and negative values of NMBE shows the over or under predictions. In case of NRMSE, it is assessed from the mean value and better performance is got if close to zero. Peak value is always needed for structural design point of view as depicted by %MF and for better performance it should be close to zero. E_{per} indicates the performance efficiency of the model when observations are related with time and it should be near to one for its better efficiency. AIC and BIC are the criteria which estimates the quality of the model. Minimum value indicates the admissibility of the model.

V. Results And Discussions

Accuracy of each network model is based on the percentage of successful predictions on the test sets of each data set. It is measured via the holdout method as well as through cross validation. The collected data set is partitioned into training and testing randomly. Out of 365 daily discharge data, 300 are used for training and 65 readings were kept for testing. Similarly from 168 monthly average data 160 data were considered for training and remaining were kept for testing. For the network models, the number of layers and the neurons in the hidden layer were fixed through several runs to get minimized mean square error in training and validation phase. Finally Table 1, 2, 3, and 4 were given with different values of performance parameters. It was observed as per AIC for Panposh average BPN gave best result followed by Cascade, RBF and Elman (Table 1). For Gomlai average best results were obtained in case of BPN followed by Cascade, Elman and RBF (Table 2). While analyzing Daily data of Panposh, RBF gave best result followed by Cascade, BPN and Elman (Table 3). Similarly for Gomlai Daily data best results were predicted from BPN followed by Cascade, RBF and Elman as shown in Table 4. It was observed that for average data sets BPN performed best followed by Cascade network. But in case of daily data of Panposh RBF, Cascade and BPN performed well in sequence having close values. For Gomlai daily BPN performed best than other networks.

Considering all the parameters ranking was made to evaluate all four network performances and shown in Tables 5, 6, 7 and 8. In case of Panposh Average data Cascade and BPN scored equal rank. For Gomlai average data Cascade found to be best and Elman remained next to it. Evaluation for daily data resulted RBF best for Panposh followed by Cascade and for Gomlai daily Cascade gave best result followed by BPN. All four data set models were ranked to come to a conclusion for deciding the best network for the study. As shown in Table 9 it is observed that Cascade network performs best for all models followed by RBF, BPN and Elman.

Next the prediction curves of all data sets are presented. Curves are plotted for different stage values chosen at random from testing data set. In case of Panposh average data prediction using all the four network models is shown in Figure 2. Here cascade performed better followed by BPN. The Figure 3 depicts prediction plots of Gomlai average data in all the four networks in which it shows better prediction by cascade network. For daily data of Panposh the related curves are shown in Figure 4. BPN predicted better and was close to Cascade at many points. BPN also predicted better for Gomlai daily data and was very close to the cascade network as shown in Figure 5. It can be seen that the cascade network model predicted best among the other frequently used networks.

Performance of Panposh average was found to be 0.03, 0.002, 0.0013 and 0.063 for BPN, RBF, Cascade and Elman networks respectively. Similarly for Gomlai average data the performance was 0.041, 0.0031, 0.0024 and 0.01 observed in BPN, RBF, Cascade and Elman networks.

Table1. Analysis of prediction with panposh monthly average

PERF PARA	BPN	RBF	ELMAN	CASCADE
R Tr	0.9870	0.9919	0.9890	0.9920
R Ts	0.9939	0.9936	0.9998	0.9656
AARE	19.8415	16.0190	51.7941	30.1233
MSE	71.4431	2380.00	2218.60	266.8448
NRMSE	0.1395	0.217	0.0249	0.0092
NMBE(%)	-0.666	-0.047	-0.224	-4.9117
E	0.980	0.979	0.9824	0.9976
%MF	-8.015	-0.067	-11.175	-0.4381
Eper	0.990	0.989	0.994	0.9988

AIC	2.104	3.626	3.596	2.6763
∆AIC	0.000	1.5226	1.492	0.5723
BIC	15.734	27.915	27.671	20.3132
∆BIC	0.0000	12.1809	11.936	4.5784

Table 2. Analysis of prediction with gomlai average

PERF PARA	BPN	RBF	ELMAN	CASCADE
R Tr	0.9873	0.9887	0.9964	0.9891
R Ts	0.9764	0.9641	0.9950	0.9866
AARE	45.7679	54.5151	37.9372	44.773
MSE	60.4470	7275.2000	3976.4000	324.530
NRMSE	0.3174	0.2669	0.0413	0.0364
NMBE(%)	0.0089	0.1077	0.4173	0.0153
E	0.9525	0.9664	0.9485	0.9600
%MF	-13.6867	-0.0098	-14.7156	-0.059
Eper	0.9634	0.9741	0.9897	0.969
AIC	2.0314	4.1118	3.8495	2.761
∆AIC	0.0000	2.0805	1.8181	0.729
BIC	15.1541	31.7978	29.6990	20.993
∆BIC	0.0000	16.6438	14.5449	5.839

Table 3. Analysis of prediction with panposh daily

PERF PARA	BPN	RBF	ELMAN	CASCADE
R Tr	0.987	0.989	0.983	0.990
R Ts	0.993	0.990	0.978	0.984
AARE	42.449	41.051	89.105	36.382
MSE	616.032	493.155	723.581	508.032
NRMSE	0.248	0.273	0.322	0.004
NMBE(%)	-0.061	-0.071	0.070	-0.034
E	0.975	0.971	0.959	0.977
%MF	-1.968	0.006	0.473	-0.009
Eper	0.999	0.983	0.957	0.981
AIC	3.039	2.943	3.109	2.955
∆AIC	0.096	0.000	0.166	0.012
BIC	23.219	22.447	23.779	22.550
∆BIC	0.773	0.000	1.332	0.103

Table 4. Analysis of prediction with gomlai daily data

PERF PARA	BPN	RBF	ELMAN	CASCADE
R Tr	0.979	0.985	0.975	0.982
R Ts	0.992	0.991	0.978	0.997
AARE	38.671	11.518	74.903	28.716
MSE	21.957	721.089	1.24E+03	664.381
NRMSE	0.233	0.265	0.370	0.004

NMBE(%)	-0.135	-0.052	-0.056	-0.003
E	0.982	0.973	0.954	0.980
%MF	-4.026	-0.558	-17.957	2.385
Eper	0.999	0.987	0.998	0.988
AIC	1.591	3.107	3.342	3.072
ΔAIC	0	1.516	1.750	1.480
BIC	11.635	23.767	25.640	23.482
ΔBIC	0.000	12.131	14.004	11.846

Table 5. Ranking calculation of panposh monthly average

PERF PARA\NW	BPN	RBF	ELMAN	CASCADE
R Tr	1	3	2	4
R Ts	3	2	4	1
AARE	2	1	4	3
MSE	1	4	3	2
NRMSE	3	4	2	1
NMBE(%)	2	4	3	1
E	2	1	3	4
%MF	3	1	4	2
Eper	3	4	2	1
AIC	1	4	3	2
BIC	1	4	3	2
Total	22	32	33	23
	Best			Best

Table 6. Ranking Calculation for Gomlai Monthly Average

PERF PARA\NW	BPN	RBF	ELMAN	CASCADE
R Tr	4	3	1	2
R Ts	4	3	1	2
AARE	3	4	1	2
MSE	1	4	3	2
NRMSE	4	3	1	2
NMBE(%)	1	3	4	2
E	4	1	3	2
%MF	3	1	4	2
Eper	4	2	1	3
AIC	1	4	3	2
BIC	1	4	3	2
Total	30	32	25	23
			Better	Best

Table 7. Ranking calculation of panposh daily

PERF PARA\NW	BPN	RBF	ELMAN	CASCADE
R Tr	3	2	4	1
R Ts	1	2	4	3
AARE	3	2	4	1

MSE	3	1	4	2
NRMSE	2	1	4	3
NMBE(%)	2	1	4	3
E	2	3	4	1
%MF	4	1	3	2
Eper	4	3	1	2
AIC	3	1	4	2
BIC	3	1	4	2
Total	30	18	40	22
		Best		Better

Table 8. Ranking calculation of gomlai daily

PERF PARA\NW	BPN	RBF	ELMAN	CASCADE
R Tr	4	1	3	2
R Ts	2	3	4	1
AARE	3	1	4	2
MSE	1	3	4	2
NRMSE	2	3	4	1
NMBE(%)	4	2	3	1
E	1	3	4	2
%MF	3	1	4	2
Eper	1	4	2	3
AIC	1	3	4	2
BIC	1	3	4	2
Total	23	27	40	20
	Better			Best

Table 9. Ranking Calculation of all four models

Data \ Network	BPN	RBF	Elman	Cascade
Panposh Average	1	2	3	1
Gomlai Average	3	4	2	1
Panposh Daily	3	1	4	2
Gomlai Daily	2	3	4	1
Total	10	9	13	5

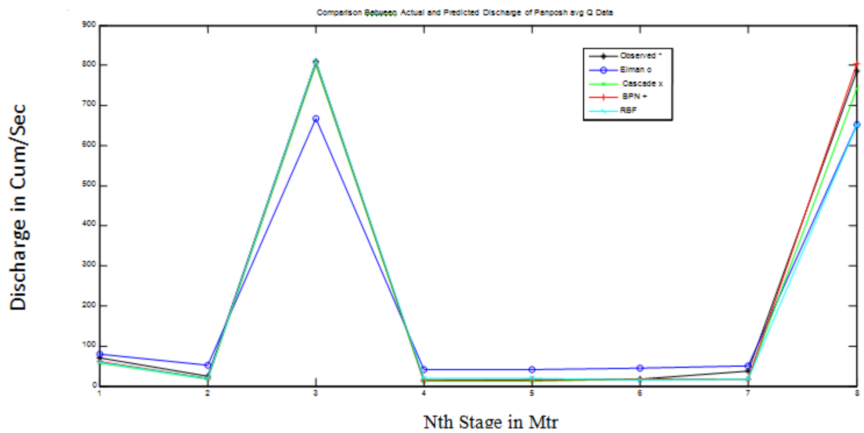

Fig. 2. Performance of panposh avg in Cascade, Elman, BPN and RBF neural network

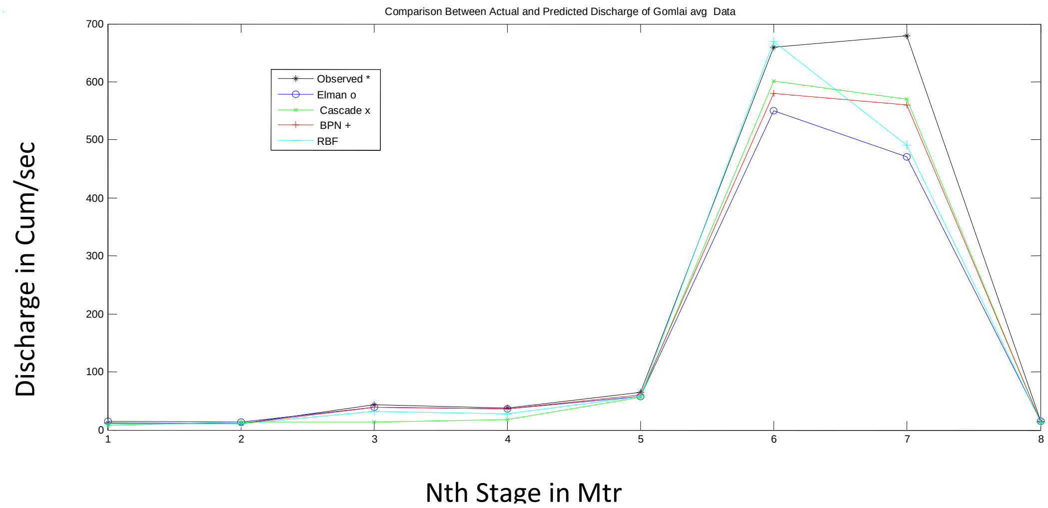

Fig. 3. Gomlai average data predicted in Elman, Cascade, BPN and RBF neural network

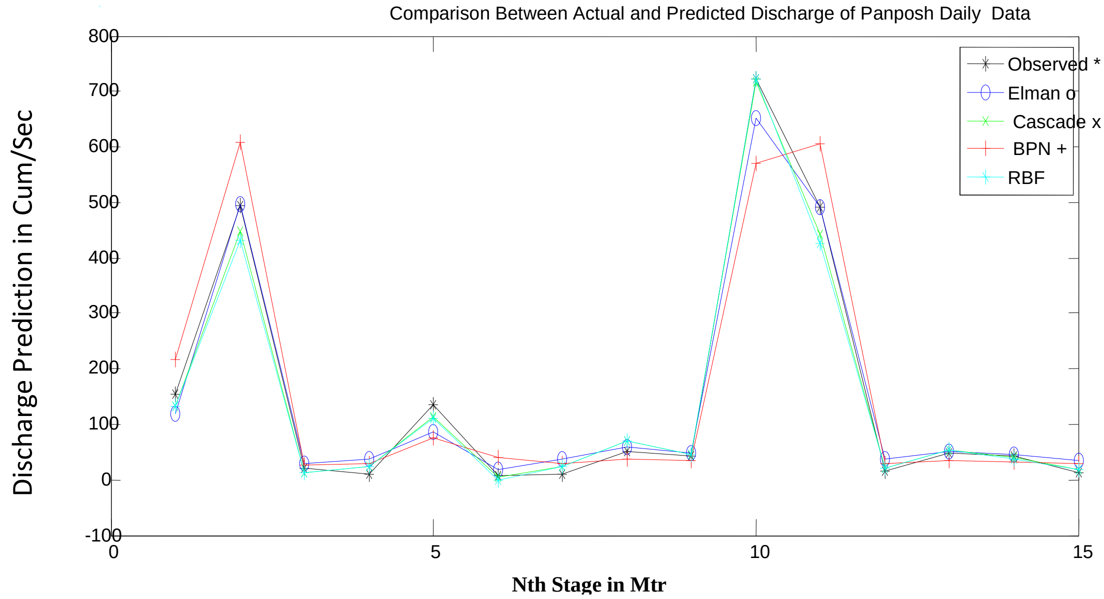

Fig. 4. Panposh daily data predicted in Elman, Cascade, BPN and RBF neural network

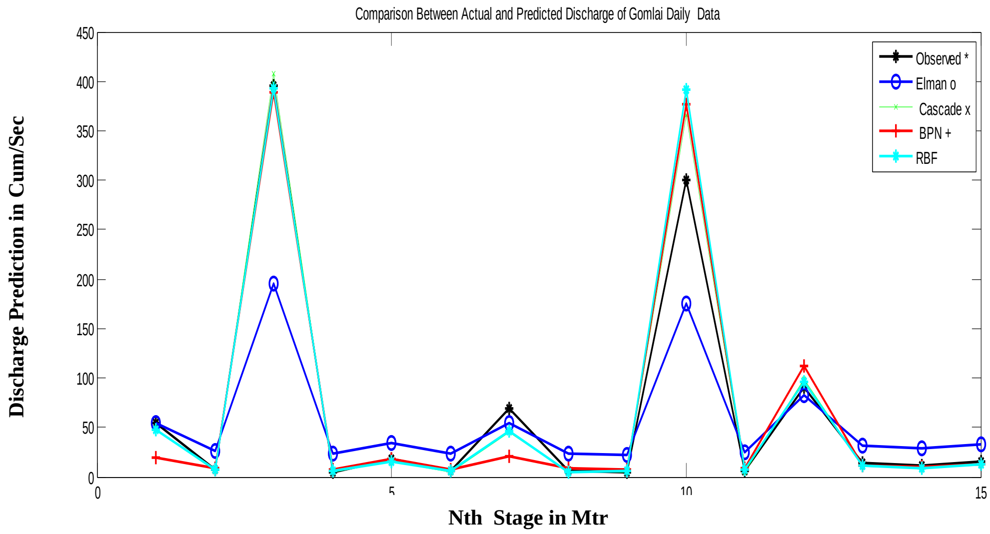

Fig.5. Gomlai daily data predicted in Elman, Cascade, BPN and RBF neural network

VI. Neural Interpretation Diagrams

Neural interpretation diagrams (NID) are a type of visual demonstration of connection weights among the neurons at different layers of the used neural networks. For the present study the weights obtained are tabulated in the next subsections for cascade network only as it secured rank one as shown in Table 9. The lines joining the input-hidden and hidden-output neurons represent the weights. The weights can be positive or negative. The solid lines represent positive weights whereas the dashed lines represent negative ones. The thickness of the lines is proportional to their magnitude. For the current study the dataset collected from two gauging stations namely Panposh and Gomlai consists of one input parameter that is stage and one output parameter that is discharge. Four different neural networks are used to estimate the discharge namely Back propagation, Cascade, Elman and RBF neural network. Efforts have been made to derive model equations for all of these networks. The current work emphasizes only cascade network to restrict the length of the paper. Corresponding weights and NIDs are demonstrated in the following sections with respect to datasets.

6.1 ANN MODEL EQUATIONS FOR φ_r VALUE BASED ON TRAINED NEURAL NETWORKS

The mathematical equation relation to input variable and output can be written as,

$$\phi_{rn} = f_{sig}\left\{b_0 + \sum_{k=1}^{h}\left[w_k \times f_{sig}\left(b_{hk} + \sum_{i=1}^{m} w_{ik} X_i\right)\right]\right\} \quad (1)$$

Where ϕ_{rn} is the normalized ϕ_r value and

b_0 : bias at output layer;

w_k : connection weight between kth neuron of hidden layer and the single output neuron;

b_{hk} : bias at the kth neuron of hidden layer

h : number of neurons in the hidden layer.

w_{ik} : connection weight between ith input variable and kth neuron of hidden layer

X_i : Normalized input variable 'i' in the range [-1, 1] and

f_{sig} : Sigmoid transfer function

Tables 10-13 represent the weights and bias at input and output layers for two stations taking average and daily data. The Table 14 represents four model equations derived basing on the weights and bias obtained using Equation 1. The relationship between stage and discharge obtained in two steps that to direct proportionality when the input variable obtained positive input hidden and positive hidden output weights. Similar proportionality is inferred when variable obtained negative input hidden and negative hidden output. In case of alternate positive and negative variables obtained shows the inverse proportionality of the variables. The network interpretation diagram for cascade network is shown in Fig.14. The inputs to K1 and K2 are positive hence solid lines and that for K3 to K5 are negative and thus dashed lines are used as per vales listed in Table 10. Thickness of the lines corresponds to higher values. Similarly the output lines from node K1 and K2 also have solid and dashed lines corresponding to output weights listed in Table 10.

Table 10: Weight and Bias for Gomlai Average Predicted in Cascade Network

Neurons	Net.iw	Net.lw	Net.b	Net.b
K=1	10.0272	1.6879	-11.0975	1.5191
K=2	3.5272	0.3979	-1.6452	
K=3	-28.2057	-0.0393	0.9992	
K=4	-11.7417	-0.0330	-3.6960	
K=5	-10.1845	0.0451	-8.9142	

Table 11: Weight and Bias for Panposh Average in Cascade Network

Neurons	Net.iw	Net.lw	Net.b	Net.b
K=1	7.169	0.994	-8.196	0.899
K=2	-7.418	-0.086	3.350	
K=3	-6.647	-0.072	1.904	
K=4	-7.395	0.059	-4.143	
K=5	7.09	-0.122	6.431	

Table 12: Weights and Bias for Panposh Daily in Cascade Network

Neurons	Net.iw	Net.lw	Net.b	Net.b
K=1	4.928	-0.097	-6.258	-0.0995
K=2	5.880	0.299	-3.665	
K=3	11.881	0.060	0.029	
K=4	7.902	-0.091	6.722	

Table 13: Weight and Bias for Gomlai Daily in Cascade Network

Neurons	Net.iw	Net.lw	Net.b	Net.b
K=1	-14.356	-0.215	9.779	0.262
K=2	10.598	0.085	-5.155	
K=3	3.538	-0.121	1.139	
K=4	-1.959	0.489	-1.946	

Table 14: Model Equations for Cascade Network for Different Data Sets

PANPOSH AVG	GOMLAI AVG	PANPOSH DAILY	GOMLAI DAILY
A_1= -8.196+7.169 * St	A_1= -11.0975+10.027*St	A_1= -6.2585+4.928 * St	A_1=9.779-14.356*St
A_2= 3.3508-7.418 * St	A_2= -1.6452+3.527*St	A_2= -3.6654+5.880 *St	A_2=-5.155+10.598*St
A_3= 1.904-6.647 *St	A_3= 0.9992-28.205St	A_3= 0.0298+11.881 * St	A_3=1.132+3.538 *St
A_4= -4.143-7.395*St	A_4= -3.6960-11.741*St	A_4=6.7227+7.902 *St	A_4= -1.946-1.9597*St
A_5= 6.4316+7.090 * St	A_5= -8.9141-10.184*St		
B_1= 0.99 X $\frac{e^{A_1}-e^{-A_1}}{e^{A_1}+e^{-A_1}}$	B_1=1.687 X $\frac{e^{A_1}-e^{-A_1}}{e^{A_1}+e^{-A_1}}$	B_1= -0.097 X $\frac{e^{A_1}-e^{-A_1}}{e^{A_1}+e^{-A_1}}$	B_1= -0.215X $\frac{e^{A_1}-e^{-A_1}}{e^{A_1}+e^{-A_1}}$
B_2= -0.086 X $\frac{e^{A_2}-e^{-A_2}}{e^{A_2}+e^{-A_2}}$	B_2=0.397 X $\frac{e^{A_2}-e^{-A_2}}{e^{A_2}+e^{-A_2}}$	B_2=0.299 X $\frac{e^{A_2}-e^{-A_2}}{e^{A_2}+e^{-A_2}}$	B_2= 0.085 X $\frac{e^{A_2}-e^{-A_2}}{e^{A_2}+e^{-A_2}}$
B_3= -0.072 X $\frac{e^{A_3}-e^{-A_3}}{e^{A_3}+e^{-A_3}}$	B_3=-0.039 X $\frac{e^{A_3}-e^{-A_3}}{e^{A_3}+e^{-A_3}}$	B_3= 0.060 X $\frac{e^{A_3}-e^{-A_3}}{e^{A_3}+e^{-A_3}}$	B_3= -0.121 X $\frac{e^{A_3}-e^{-A_3}}{e^{A_3}+e^{-A_3}}$
B_4= 0.059 X $\frac{e^{A_4}-e^{-A_4}}{e^{A_4}+e^{-A_4}}$	B_4=-0.033 X $\frac{e^{A_4}-e^{-A_4}}{e^{A_4}+e^{-A_4}}$	B_4=-0.091 X $\frac{e^{A_4}-e^{-A_4}}{e^{A_4}+e^{-A_4}}$	B_4= 0.489 X $\frac{e^{A_4}-e^{-A_4}}{e^{A_4}+e^{-A_4}}$
B_5= -0.122 X $\frac{e^{A_5}-e^{-A_5}}{e^{A_5}+e^{-A_5}}$	B_5=-0.045 X $\frac{e^{A_5}-e^{-A_5}}{e^{A_5}+e^{-A_5}}$		
C=0.899+B_1+ B_2+ B_3+ B_4+ B_5	C=1.519+B_1+ B_2+ B_3+ B_4+ B_5	C= -0.099+B_1+ B_2+ B_3+ B_4	C= 0.262+B_1+B_2+B_3+B_4

$$\varphi_{rn} = \frac{e^{c}-e^{-c}}{e^{c}+e^{-c}} \qquad (2)$$

The φ_r value is calculated from Equation 2 and the value lies between [-1, 1] . Next the real value is derived by denormalizing using Equation 3.

$$\varphi_r = 0.5(\varphi_{rn} + 1)(\varphi_{rmax} - \varphi_{rmin}) + \varphi_{rmin} \qquad (3)$$

Where φ_{rmax} and φ_{rmin} are the maximum and minimum values of φ_r respectively in the data set.

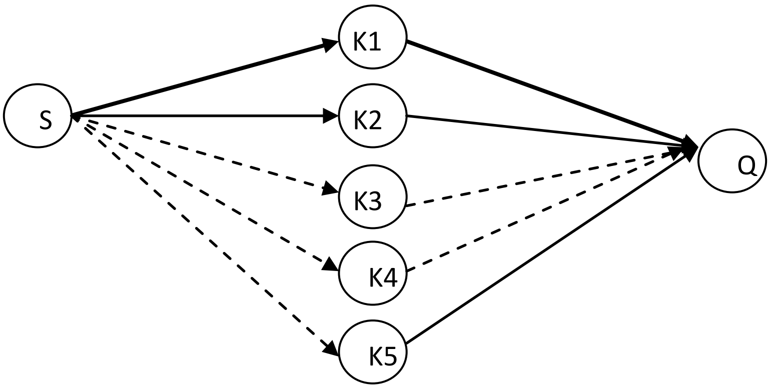

Fig. 6. Network interpretation diagram for prediction of Gomlai Average data in cascade network

VII. Conclusion

In this paper an attempt is made to study few artificial neural networks namely; BPN, RBF, Elman and Cascade. River Bramhani data for two gauging stations Panposh and Gomlai is taken up for study. Analysis of data for two stations, that to taking monthly average and daily discharge data corresponding to stage are considered for the case study. As narrated earlier the flow behavior or the river engineering is complex to study, attempt is made to develop and analyze the models with single input and single output data. Future analysis is made with multiple input datasets comprising of different dimensionless parameters of the river section to predict in more accurate way. Models varying with time are of great importance, which has not been covered much under this work. However few global parameters like *%MF* and E_{perf} is included under this study. Finally the analysis gives better prediction using Cascade Network than other networks taken up for analysis.

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