STREAM FLOW FORECASTING USING ARTIFICIAL NEURAL NETWORK

[1]Mr. Ajay Bansode, [2] Mr. Rushikesh Shinde, [3] Mr. Prathamesh Sarpate.

[1]Asst. Professor, [2]BE Civil (pursuing), [3]BE Civil (pursuing).
[1]Department of Civil Engineering,
[1]Zeal College of Engineering and Research, Pune, India.

Abstract : This paper highlights the use of Artificial Neural Network (ANN) to forecast the stream flow beforehand by exploitation of the previous values of stream flow and precipitation at a location specifically Gaganbawda region in Kolhapur district, in India. Separate Monthly models were developed for monsoon months from June to September. The potential of various ANN algorithms specifically Levenberg-Marquardt (LM), Conjugate Gradient function (CGF) and Quasi-Newton's back propagation (BFG) were investigated through varied models in daily stream flow foretelling and to boost the acute flow prediction. All models performed higher except Gregorian calendar month September model. LM, CGF performed higher in extreme flow prediction as compared to other algorithms.

***Index Terms* – Artificial neural network, stream flow, algorithm, modelling.**

I. INTRODUCTION

Modelling of stream flow method is probably the foremost asked for analysis topic for hydrologists everywhere on the planet, thanks to its importance in style, construction and operation of many prediction model. Since a long time a knowledge driven approach of Artificial Neural Networks (ANN) is employed extensively in modelling water flows by several researchers (ASCE 2000). Historically this can be done by using abstract models. Correct foretelling of stream flow well earlier can facilitate in saving human life and furthermore as preventing property harm. Due to numerous difficulties concerned in these modelling techniques researchers are continuously in search of a stronger modelling approach which can be easier, less time consuming and fairly accurate. Presently, the prediction of stream flow one day beforehand by studying the previous measured values of stream flow and rainfall with Artificial Neural Networks (ANN), at Gaganbawda, in Kolhapur district, India is done. In addition to this, different ANN algorithms particularly Levenberg-Marquardt (LM), Conjugate Gradient function (CGF) and Quasi-Newton's back propagation (BFG) were compared with relation to their accuracy in foretelling the runoff. Successive section describes ANN in short, at the side of a review, its application for stream flow modelling followed by data of concerned study area and types of input data used.

II. ARTIFICIAL NEURAL NETWORKS

ANNs were made as a general form of mathematical model of neurons in human brain. An ANN could be a massive parallel distributed system for processing information that contains performance parameters similar to that of neural networks of the human brain (ASCE 2000). An ANN model consists of variety of nodes that are unit organized as per a specific arrangement. One way of separating neural networks is by the no of layers i.e single, bilayer and multilayer. ANNs can even be classified according to the flow direction of data and process. During a feed-forward network, layer wise the nodes are arranged beginning from input layer and terminating at the output layer. There are many hidden layers, with every layer having single or multiple nodes. The nodes in any specific layer are connected to the nodes in the next layer, however to not those within the same layer. Thus, the resultant of a node in a succeeding layer is simply akin about the input data it acquires from previous layers and therefore the corresponding weights. On the opposite hand, in an exceedingly perennial ANN, information flows through the nodes in each directions, from the input to the output facet and vice versa (ASCE 2000). The last layer consists of numeric values foretold by the network and so represents model output. The no of hidden layers and therefore the variety of nodes in every particular hidden layer are determined by a trial-and-error method. The nodes at intervals neighboring layers of the network are absolutely connected by links. A weight is appointed to every link to resent the relative affiliation strength of 2 nodes at each ends in predicting the input-output relationship. Fig. 1 shows the configuration of a feed forward tri layer ANN. These types of ANNs may be utilized in a large type of issues, such as storing various types of information, recalling variable data, classifying the data patterns, performing general mapping from input to output pattern, clubbing similar patterns, or finding answers to strained improvement issues. In this figure, X is an input vector consisting of variables that affect the behavior of the system, and Y is the output vector generated by the system showing system behavior and consisting of variables.

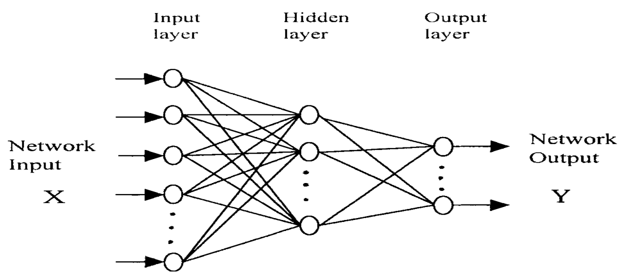

fig 1: schematic diagram of three layer network.

Particularly just in case of stream flow modelling several analysis employees have adopted cause result modelling for predicting runoff within which statistics of motivating variables like precipitation, temperature, also as runoff etc. either separately or together are used to predict stream flow. Three coaching algorithms specifically Levenberg-Marquardt (LM), Conjugate Gradient perform (CGF) and Quasi-Newton's back propagation (BFG) are taken under consideration for the current study. The Neural Network tool provided in MATLAB atmosphere was accustomed, trained and used to check the networks. Details will be found within the ASCE Task Committee (2000), Maier and Dandy (2000), town and Wilby (2001) for rainfall-runoff and stream flow modelling. Though an outsized range of papers on rainfall-runoff modelling on ANN will be seen out there though literature of the current work differs within the proven fact that for coaching the network, the intense event is employed notably to extend the accuracy of the prediction generally and accuracy at peak prediction above all.

III. Study Area And Data

The selected site for the project is Gaganbawda region near Kolhapur. It is located 55 km away from Kolhapur. Gaganbawda is situated on the Western Ghats. It is a non-developed and hilly area of the district. Gaganbawda gets maximum rainfall of 260 mm during rainy season [(IMD report number ESSO/IMD/HS/R.F.REP/02 (2013)/16)]. A total of 36 years of data namely rainfall(R), runoff(Q), temperature(T), evaporation(E) and relative humidity(H) was utilized for the proposed site. The proposed site requires data such as rainfall and runoff for input. Sufficient data is available for a meaningful study in terms of both quantity and quality was obtained from IMD. The India Meteorological Department is an agency of the Ministry of Earth Sciences of the Government of India.

IV. Model Formulation

The data obtained from IMD for last 36 years was carefully segregated and examined for previous data such as, rainfall, runoff, humidity, maximum temperature and evaporation. It is observed that rainfall occurs only during June, July, august and September. Hence data only for these months is considered. Variation was observed in each month therefore separate models for respective months were made. Details are shown in figure 2. All models were trained to use more or less 70% of the data and therefore the 30% of the data that remains was utilised to test the model. The output generated from the model would be the stream flow on the next day. 'Sigmoidal and Linear' were the 2 transfer functions utilized in the primary and secondary layer. The quantity of hidden neurons was determined by trial and error method. Model for every month was then trained for three completely different algorithms specifically Levenberg Marquardt (LM), Conjugate-Gradient function (CGF), Quasi-Newton's back propagation (BFG) and therefore the performance of these models were compared by mean square error and coefficient of correlation. The visual examination was done by plotting the hydrographs of each observed and predicted runoff. Architecture of all models of ANN is different from each other and it has been found by trial and error method.

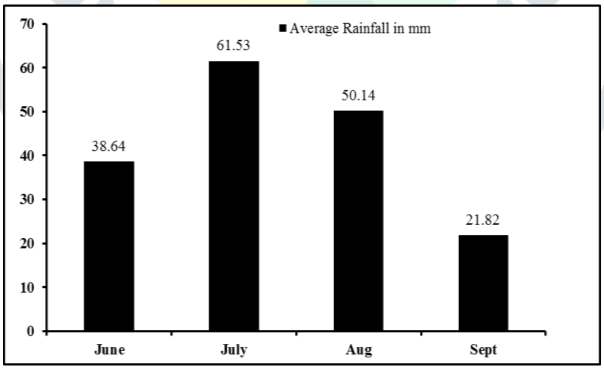

fig 2 : graph showing variation in total rainfall for respective month

V. Model Assessment

Many methods for assessment of the model are available in literature related to application of hydrology. The traditional measures such as coefficient of correlation (r) and mean squared error MSE etc were studied by Mr. McCabe and Mr. Ligates (1999) in their paper, and they suggested that it is not suitable to use only coefficient of correlation as a parameter for model evaluation. Need for more than one model assessment technique is also emphasized by Dawson and Wilby (2001). Mr. Legates and Mr. McCabe (1999) proposed a complete evaluation of model performance should have at least one absolute error measure and a goodness of fit measure or any relative error measure and with additional information. Similarly, bi evaluation criteria is used in the current study to analyze performances in addition to correlation coefficient and scatter plot between the observed and predicted stream flow values are plotted.

VI. RESULTS AND DISCUSSION

The trained models tested with specifically 9 types of inputs performed very well as seen from high values of correlation coefficient and the corresponding scatter plot. The three algorithms were run for each month and the best model for every specific month was identified.

table 1. statistical parameters of runoff (m^3/s) at Gaganbawda.

	June	July	Aug	Sept
Mean	25.02	33.98	27.74	13.43
St.Deviation	27.18	31.24	26.43	18.62
Minimum	0.2	0.11	0.275	0.11
Maximum	212.85	274.45	199.65	138.6

table 2. statistical parameters of rainfall (mm) at Gaganbawda

	June	July	Aug	Sept
Mean	38.64	61.53	50.14	21.82
St.Deviation	49.69	56.97	48.29	34.58
Minimum	0	0	0	0
Maximum	387	499	363	525

table 3. statistical parameters of temperature (celsius) at Gaganbawda

	June	July	Aug	Sept
Mean	29.74	26.83	26.47	28.56
St.Deviation	3.40	2.08	2.05	2.52
Minimum	20.7	20.5	19	19.2
Maximum	40	32.6	31.9	35.7

table 4. statistical parameters of evaporation (mm) at Gaganbawda

	June	July	Aug	Sept
Mean	2.66	2.851	0.92	2.65
St.Deviation	1.30	1.46	2.47	1.70
Minimum	0	0	0	0
Maximum	8.5	19.7	51	21

table 5. statistical parameters of humidity (%) at Gaganbawda

	June	July	Aug	Sept
Mean	74.87	83.99	84.10	75.86
St.Deviation	13.39	10.97	10.01	11.31
Minimum	39	27	57	23
Maximum	100	276	255	100

table 6. model details of Gaganbawda station.

Month	LM	CGF	BFG	Input	Training	Testing
June	9:2:1	9:7:1	9:3:1	$Q_t = f(Q_{t-1}, Q_{t-2}, R_{t-1}, R_{t-2} T_{t-1}, E_{t-1}, E_{t-2} H_{t-1}, H_{t-2})$	713	307
July	9:8:1	9:5:1	9:5:1	$Q_t = f(Q_{t-1}, Q_{t-2}, R_{t-1}, R_{t-2} T_{t-1}, E_{t-1}, E_{t-2} H_{t-1}, H_{t-2})$	735	317
August	9:7:1	9:6:1	9:4:1	$Q_t = f(Q_{t-1}, Q_{t-2}, R_{t-1}, R_{t-2} T_{t-1}, E_{t-1}, E_{t-2} H_{t-1}, H_{t-2})$	732	315
September	9:3:1	9:5:1	9:7:1	$Q_t = f(Q_{t-1}, Q_{t-2}, R_{t-1}, R_{t-2} T_{t-1}, E_{t-1}, E_{t-2} H_{t-1}, H_{t-2})$	705	304

table 7. results at Gaganbawda station

	R			MSE		
Mon./Algo	**LM**	**CGF**	**BFG**	**LM**	**CGF**	**BFG**
June	0.98	0.89	0.89	0.000328	0.0077	0.00762
July	0.99	0.97	0.99	0.000126	0.00312	0.000128
August	0.99	0.99	0.99	0.000236	0.000581	0.000300
September	0.99	0.98	0.99	0.00374	0.00504	0.00376

table 8. details of maximum observed and predicted stream flow at Gaganbawda Station

Model	Observed discharge	Max. predicted discharge (m^3/s)		
		LM	**CGF**	**BFG**
June	212.85	211.77	165.85	177.09
July	161.15	161.43	158.53	161.99
August	199.65	190.23	161.86	196.94
September	138.6	133.63	105.41	133.64

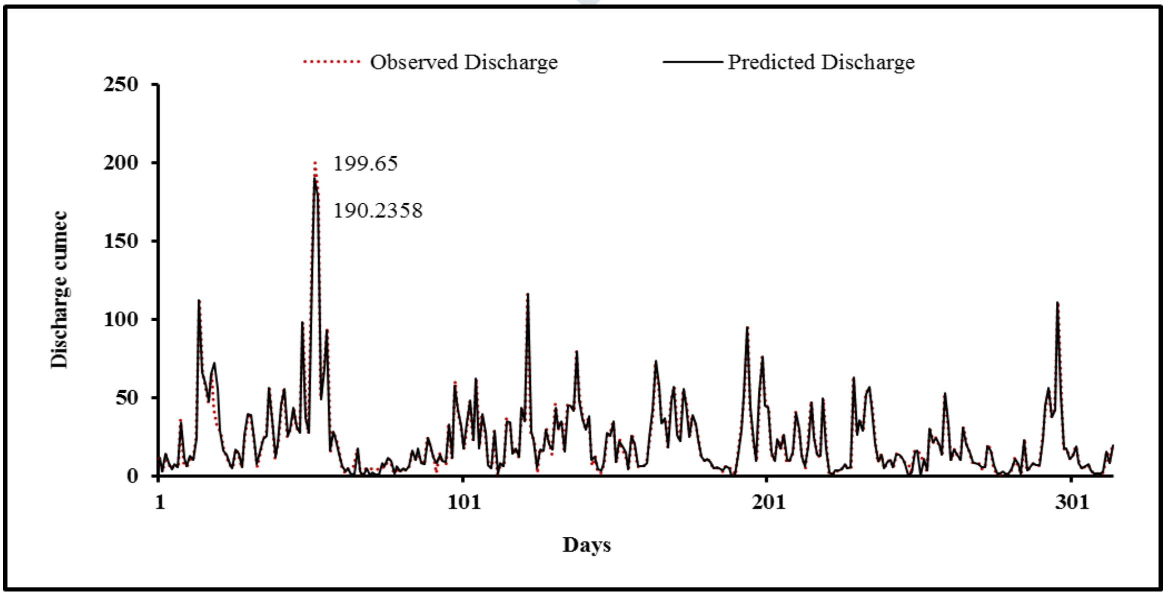

fig 3 : stream flow forecasting one day in advance for LM (August.)

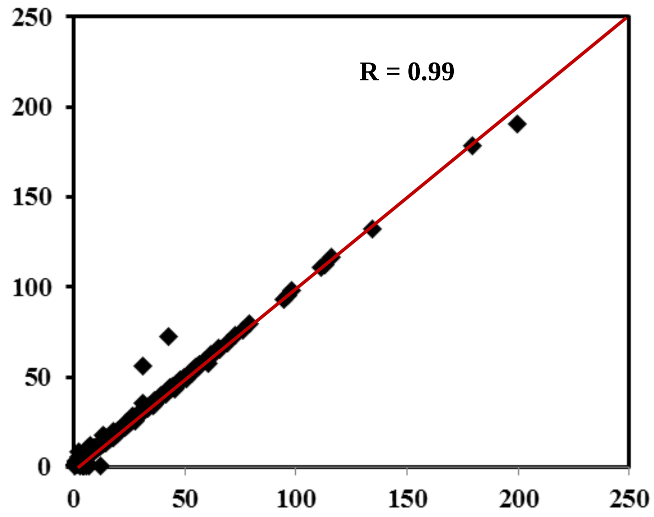

fig 4 : correlation coefficient graph for LM (August).

VII. CONCLUSION

Forecasting of stream flow one day in advance using the previous values of runoff, rainfall, humidity, maximum temperature and evaporation and the soft computing tool of Artificial Neural Networks (ANN), at Gaganbawda, in Kolhapur district of Maharashtra, India was presented in the foregoing sections. Three different ANN algorithms namely Levenberg-Marquardt also known as LM, Conjugate Gradient Function also called CGF, and Quasi-Newton's back propagation known widely as BFG, were tested for each model and compared to identify the best algorithm that was suitable. For the month of June, value of coefficient of correlation for LM was 0.98. The mean square error value of LM was 0.000328 which was lowest observed between the three algorithms. For the month of July, LM and BFG were the best performing algorithms. The mean square error values were marginally different with values being 0.000126 and 0.000128 respectively. The correlation coefficient values were 0.99 for both algorithms. For August model, the value of correlation being 0.99 for each of the algorithm. LM performed marginally well with mean square error value being lowest among the three at 0.000236. In the September model, coefficient of correlation value at 0.99 were observed for both the algorithms. The mean square error value for LM was slightly better at 0.00374. Hence it was observed that for the month of June LM was the best performing algorithm. For July LM and BFG performed better than CGF with LM being the most favorable. For August all the three algorithms performed relatively well with LM being most favorable. Finally for September, LM outperformed all the other algorithms. The peak value in each model was predicted accurately by LM.

VIII. ACKNOWLEDGMENT

We would like to express our sincerest gratitude towards Indian Meteorological Department for providing the relative data which was crucial for the success of this research work. Also, we would like to thank Zeal College of Engineering and Research, Pune and the authors of the research papers used as reference in this project

REFERENCES

[1] ASCE 2001, Artificial neural networks in hydrology. i: preliminary concepts by the asce task committee on application of artificial neural networks in hydrology.
[2] Dawson and Wilby 2001, Hydrological modelling using artificial neural networks
[3] David R. Legates Gregory J. McCabe Jr. 1999, evaluating the use of "goodness-of-fit" measures in Hydrologic and hydro climatic model validation
[4] Graeme C. Dandy , Holger R. Maier 1999, Neural networks for the prediction and forecasting of water resources variables: a review of modelling issues and applications
[5] K. P. Sudheer 2005, Knowledge Extraction from Trained Neural Network River Flow Models , 0.1061/~ASCE!1084-0699~2005!10:4~264
[6] Ms Sonali. B. Maind and Ms Priyanka Wankar 2014, Research Paper on Basic of Artificial Neural Network
[7] Ozgur Kişi 2007, Streamflow Forecasting Using Different Artificial Neural Network Algorithms, 0.1061/_ASCE_1084-0699_2007_12:5_532.