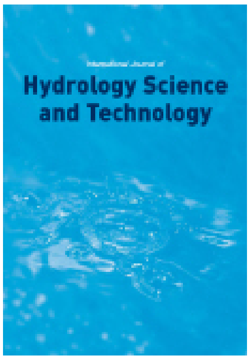

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Mohammad Zakwan, Shaik A. Qadeer, Mohammed Yousuf Khan

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Application of deep learning algorithm in hydrometry

Mohammad Zakwan*

Department of Civil Engineering,
Polytechnic Hyderabad,
Manuu, Hyderabad-50032, India
Email: zakwancivil@gmail.com
*Corresponding author

Shaik A. Qadeer

Department of Electrical Engineering,
Muffakham Jah College of Engineering and Technology,
Hyderabad-50032, India
Email: haqbei@gmail.com

Mohammed Yousuf Khan

Maulana Azad National Urdu University,
Hyderabad – 500032, India
Email: dryousufkhanmanuu@gmail.com

Abstract: Estimation of discharge in a river is an integral part of water resource engineering. In this regard, various artificial intelligence (AI) techniques have been employed to model the discharge ratings. The present work compares the performance of two neural networks namely, back propagation neural network (BPNN) and radial basis neural network (RBNN), to model the discharge rating. The estimated discharge was also compared with the discharge estimated using conventional method. Published data of two gauging station was used for the comparative analysis. It was observed that application of neural networks greatly improved the estimates of discharge as compared to conventional method. Application of artificial neural network (ANN) reduced the sum of square of error (SSE) by about 90% on an average. Maximum absolute error was reduced from 51.36 and 141.21 to 5.04 and 7.68 respectively for the two stations for RBNN when compared to conventional method during validation. Calibration results reveal that among the BPNN and RBNN, RBNN could model the ratings at both the stations, better than BPNN.

Keywords: hydrometry; discharge; river; ratings; neural networks; back propagation neural network; BPNN; radial basis neural network; RBNN; artificial neural network; ANN; sum of square of error; SSE.

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Biographical notes: Mohammad Zakwan is an Assistant Professor in the Civil Engineering Department, Maulana Azad National Urdu University; a central university in India. He has over five years of teaching and research experience.

He has published several research papers and is actively involved in review process of several journals. His research interest include, modelling of infiltration, sediment, stage discharge curves, computation of effective discharge and dominant discharge, climate change, trend analysis in hydrology, river engineering, hydraulics and hydrology of rivers.

Shaik A. Qadeer is working as a Professor in the MJ College of Engineering and Technology, Hyderabad; he completed his MTech followed by PhD from the Jawahar Lal Nehru Technological University Hyderabad. He published nine international journals and nine international conferences. Most of the research work is executed with the association of prime universities like Indian Institute of Technology Hyderabad and International Institute of Information Technology Hyderabad. The publications include foreign conferences conducted in the countries like the USA (ISA2016), Denmark (EUSIPCO 2010), and Turkey (ICC 2006). Out of 18 publications, six publications are there in IEEE explorer, eight sponsored projects are successfully completed which is funded by MJCET. An Indian patent is published by Official Journal of the Patent Office on 17-8-2018 with number 201741035875. Four book chapters are published in Springer series-Lecture notes in Electrical Engineering.

Mohammed Yousuf Khan is working as a Principal in the Maulana Azad National Urdu University, Polytechnic Hyderabad since 2009. He has secured 1st rank in Bachelor of Engineering (BE), in Instrumentation Engineering from the Osmania University, Hyderabad. He completed his Masters and PhD from the Jawaharlal Lal Nehru Technological University, Hyderabad. He published 21 papers in national and international journals, one chapter in Springer Nature, Singapore Pte Ltd. and two patents (Indian and Australian). His area of research is signal processing in communication, sensor networks and artificial intelligence.

1 Introduction

A mathematical relationship between two physically related processes is called the rating curve. Stage discharge relationship at a river section is the most commonly used rating curve in water resource engineering (Nawaz et al., 2020). Discharge in a river although depend on a number of factors apart from stage but continuous measurement of all the factors affecting discharge is impractical therefore, discharge is represented as a function of stage alone (Sharief and Zakwan, 2021; Aiyelokun et al., 2021; Umar et al., 2021). Continuous record of stages at a section can be maintained easily without involvement of much labour and capital (Niazkar and Zakwan, 2021). Rating curves relating discharge to stage are called simple rating curve while the rating curve relating discharge to other factors such as rate of change of stage, index velocity and turbine pressure differential in addition to stage are called complex rating curves. A simple rating curve may consist of three segments of low, medium and high rating which makes it a compound curve.

Discharge measurement is made by indirect method which depends on establishing a relationship between stage and discharge. Stage discharge relationship is the epitome of all the characteristics of a reach of stream. This relationship is determined by correlating measurement of discharge with the corresponding observation of stage; the correlation may be achieved manually by various combinations of graphical and mathematical means or directly by using computational techniques such as artificial neural network (ANN).

Discharge measurement in river is an integral part of Hydrometry (Ara and Zakwan, 2018; Pandey et al., 2020). Several attempts were made to enhance estimates of discharge by utilising computational techniques. Tawfik et al. (1997) induced the concept of application of neural network for monitoring discharge in river. Thereafter, various computational techniques such as fuzzy logic (Lohani et al., 2007); support vector machine (Sivapragasam and Muttil, 2005); gene expression programming (Guven and Aytek, 2009; Azamathulla et al., 2011), model tree, genetic algorithm (Zakwan et al., 2017a); generalised reduced gradient (Muzzammil et al., 2015, 2018; Zakwan et al., 2017a), pattern search (Zakwan et al., 2018); Levenberg-Marquardt algorithm (Zakwan et al., 2018), piecewise continuous splines (Fenton, 2018), evolutionary algorithm (Niazkar and Zakwan, 2021) and multiple gene genetic programming (Niazkar and Zakwan, 2021) have been proposed to model the discharge ratings. Umar et al. (2021) proposed the application of excel solver for developing the rating curves. Abdolvandi et al. (2021) proposed a new method for estimating average velocity and discharge in the river. A comprehensive literature on the application of data driven techniques is available in Zakwan et al. (2017b). The present article compares the performance of RBNN and BPNN with the conventional method to model the rating curves.

2 Materials and methods

Published data of stage and discharge has been used to model the rating curves. Data sets used in the present study were obtained from Zakwan et al. (2018). Data sets pertain to Walton station on Choctawhatchee River and Philadelphia station on Schuylkill River. Around 75% of the data was used for training and the remaining data was used to test the results. The description of various methods used in the present articles is as follows.

3 Conventional method

Commonly, discharge in river is estimated using equation (1) (Zakwan et al., 2018):

$$Q = C(h-a)^n \tag{1}$$

where Q is the discharge in river; h is the water level (stage); a corresponds to water level at zero discharge; C and n are the rating curve parameters.

For determining 'a' straight line regression fitting is used on log Q versus log(h – a) curve. The curve plotting is carried out by trial-and-error procedure based on assum ed values of a. Now, the modified logarithmic form of equation (1) becomes:

$$\log Q = n\log(h-a) + \log C \tag{2}$$

Assuming Y = log$Q$, A = n, X = log (h – a) and B = log C, equation (2) transforms to $Y = AX + B$.

Based on conventional regression, the estimates of A and B can be calculated through equation (3) and equation (4), respectively. Using these equations, the values of K and n in equation (1) can be determined.

$$A = \frac{N\left(\sum XY\right) - \left(\sum X\right)\left(\sum Y\right)}{N\left(\sum X^2\right) - \left(\sum X\right)^2} \tag{3}$$

$$B = \frac{\sum Y - A\left(\sum X\right)}{N} \tag{4}$$

where N is the total number of observations.

Description of back propagation neural network (BPNN): neural networks are based on the human brain structure (also known as biological neuron) and its function. The network of biological neurons can be made intelligent with the help of finely formatted datasets. In this case the each output of neuron is compared with a desired label, and the error is fed-back (or propagated back) to the input side until a desired least mean squared error is achieved.

Algorithm:

1 Apply 'X' inputs to the provided network interface.

2 Initially the dynamic network parameter, (i.e., the weights) is made randomly initialised.

3 The output for all neuron is computed in forward direction.

4 Then the error in the outputs layer is computed.

5 Then perform the back propagation operation to reach our goal: 'to adjust the weights such that the error is decreased'.

Repeat the steps (3 through 5) until the convergence occur.

Here in our case NNTOOL of MATLAB is used with the following specification to train the network.

1 Network: 2 layer neural network with 20 neuron at hidden and one at output layer as shown in Figure 1.

2 Network parameters:

 2.1 Network type: 'feed-forward backprop'.

 2.2 Training function: 'TRAINLM'.

 2.3 Adaption learning function: 'LEARNGDM'.

 2.4 Performance function: 'MSE'.

 2.5 Number of layers: '2'.

 2.6 Properties of neurons:

  2.6.1 Layer1: number of neuron is '20' and transfer function is 'TRANSIG'.

  2.6.2 Layer2: transfer function is 'PURELIN'.

Description of radial basis functions neural networks (RBNN): RBNN networks main purpose is to perform linear separable operation. Like the other network (artificial) it is also consist of three layers (input-hidden-output layer). However its hidden layer count is always fixed to one. It is called as feature vector. Gaussian functions are generally used (as radial basis function) for RBNN as activation functions. This network has many uses, like 'function approximation, time series prediction, classification, and system control'. Basic three step procedure to construct RBNN is as follows

1 Calculate number of radial basis functions in the hidden layer.

2 Calculate centres and width of hidden layer.

3 Determine the weights of output layer.

Here in our case NNTOOL of MATLAB is used with the following specification to train the network:

1 Network: two layer neural network with 176 neuron at hidden (the activation function at this layer is radial basis) and one at output layer as shown in Figure 2.

2 Network parameters:

  2.1 Network type: radial basis

  2.2 Performance function: MSE.

Figure 1 Two layer BPNN (see online version for colours)

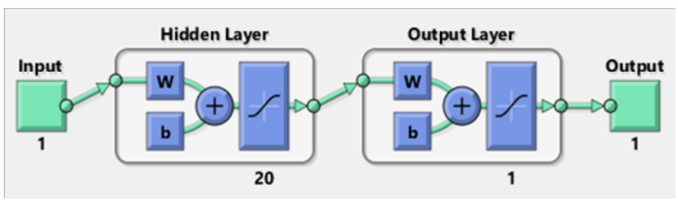
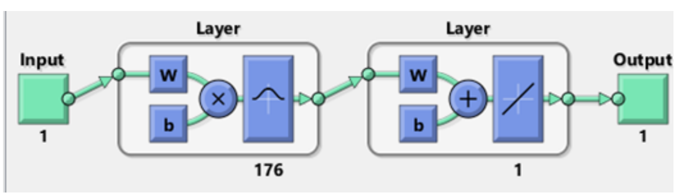


Figure 2 Two layer RBNN (see online version for colours)



4 Results and discussion

In this paper the rating curve was developed for two stations (Walton and Philadelphia) using conventional as well as deep-learning methods. To determine the performance of these methods the following cost functions are used shown from (5) through (7) (Zakwan, 2019; Zakwan and Niazkar, 2021):

1 Sum of square error (SSE)

$$\text{SSE} = \sqrt{\sum\nolimits_{i=1}^{n} (Q_{o_i} - Q_{e_i})} \tag{5}$$

2 Maximum absolute relative error (MXARE)

$$\text{MXARE} = \sum_{i=1}^{N} \frac{Q_{e_i} - Q_{o_i}}{Q_{o_i}} \times 100 \quad (6)$$

3 Mean absolute relative error (MARE)

$$\text{MARE} = \frac{1}{N} \sum_{i=1}^{N} \frac{Q_{e_i} - Q_{o_i}}{Q_{o_i}} \times 100 \quad (7)$$

where Q_o is observed discharge and Q_e is estimated discharge

The estimation method with lowest errors will surely be the better estimation model.

The performance indices for both the stations for calibration and validation are presented in Table 1 and Table 2.

Table 1 Performance of models during calibration

Method	*Station 1(Walton)*			*Station 2 (Philadelphia)*		
	SSE	*MARE*	*MXARE*	*SSE*	*MARE*	*MXARE*
Conventional	19,621.34	3.66	93.85	85,158.21	10.22	150.76
BPNN	362.57	0.96	7.26	469.5739	1.06	9.43
RBNN	416.11	1.04	9.01	463.83	1.09	7.19

Table 2 Performance of models during validation

Method	*Station 1*			*Station 2*		
	SSE	*MARE*	*MXARE*	*SSE*	*MARE*	*MXARE*
Conventional	3,741.22	3.31	51.36	315,83.36	10.45	141.21
BPNN	1,094.22	3.26	46.43	548.93	1.73	16.09
RBNN	119.71	1.05	5.04	213.65	1.25	7.68

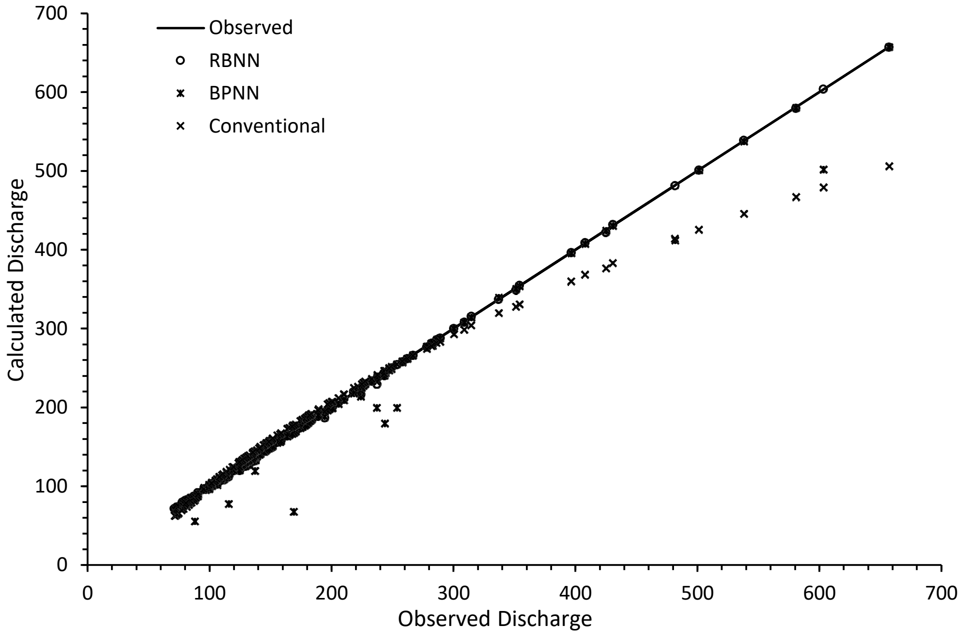
The data is divided into two parts as calibration (75%) and validation (25%). Table 1 and Table 2 reveal that the efficiency of deep learning models was superior to that of the conventional method. The reduction in errors with deep-learning methods as compared to conventional method for the two stations is listed in Table 3 and Table 4 for calibration and Validation data respectively.

Table 3 Reduction in error of models during calibration in comparison with conventional method

Method	*Station 1*			*Station 2*		
	SSE	*MARE*	*MXARE*	*SSE*	*MARE*	*MXARE*
BPNN	98%	74%	91%	99%	89%	93%
RBNN	97%	71%	90%	99%	89%	95%

It may be noted from Table 3 and Table 4 that both of the deep learning methods outperform the conventional method. However, one of the deep learning method (BPNN) for station 1 leads only to slight improvement during validation, it may be due to overtraining, i.e., high variance effect; while the other (RBNN) consistently performing well for both stations data as well as in both the phases of testing.

Figure 3 Observed discharge and estimated discharge at Walton and Philadelphia station



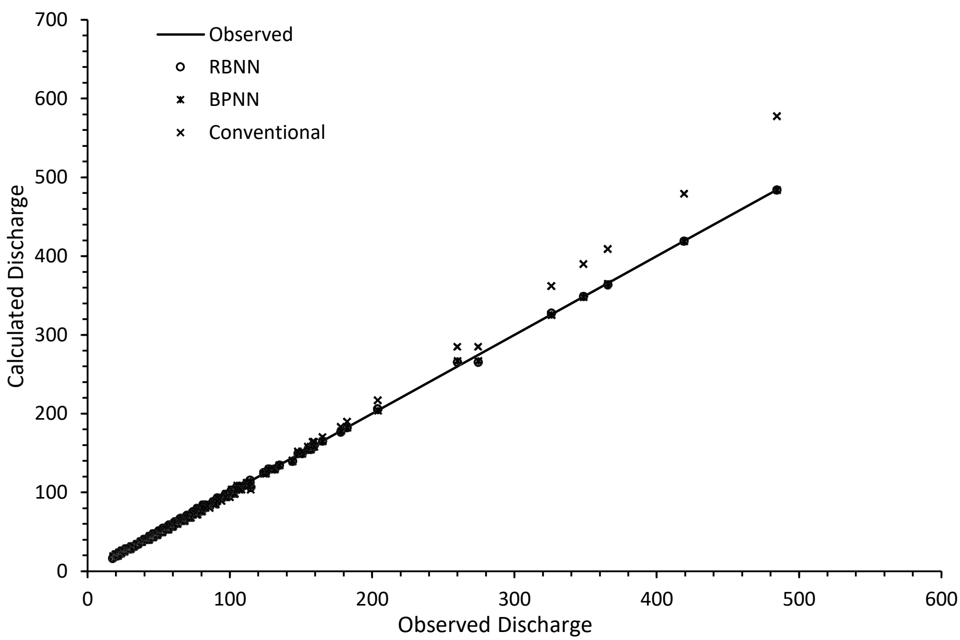


Figure 4 Observed and estimated discharge ratings at Walton and Philadelphia station

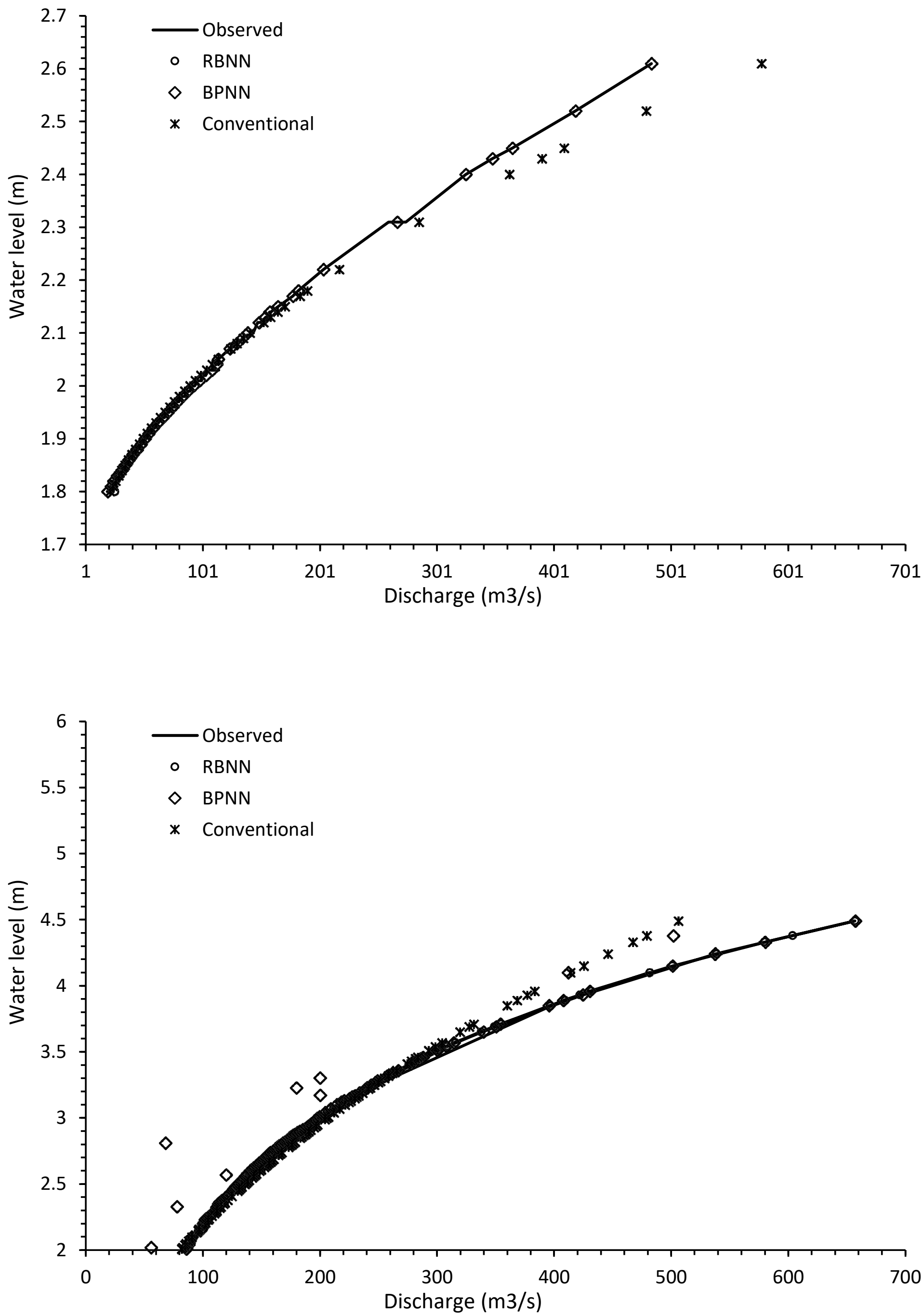


Table 4 Reduction in error of models during validation in comparison with conventional method

Method	*Station 1*			*Station 2*		
	SSE	*MARE*	*MXARE*	*SSE*	*MARE*	*MXARE*
BPNN	69%	2%	10%	98%	83%	88%
RBNN	97%	68%	90%	99%	88%	94%

Figure 3 shows the qualitative results of estimated discharge. Discharge estimated by conventional method deviates from observed discharge at both the stations as shown in Figure 3. At Walton conventional method underestimates the higher discharges while at Philadelphia it overestimates the discharge. The performance of BPNN and RBNN appears to very similar at Philadelphia but at Walton, BPNN appears to underestimate the observed discharges. Figure 4 represent the observed and estimated discharge ratings at the two gauging stations, it may be observed that particularly for higher discharges conventional ratings poorly estimates the discharge. Higher discharges are specifically of interest to the hydrologists and hydraulicians for the design of hydraulic structures and therefore, relying on conventional ratings may lead to improper design.

Neural networks are highly nonlinear in nature which makes them suitable for modelling complex phenomenon. On the other hand conventional method is based on trail and error and linear regression approach and as such has limited capability to model complex relationships. However, conventional model reveals the functional relationship of the ratings, unlike neural networks which have black box nature. Further, modelling through neural networks requires number of trails to select the best fit model. ANN can be very helpful to the hydrometric stations in terms of accurately predicting the river discharges and planning of various projects.

5 Conclusions

Discharge ratings were derived at two stations utilising conventional method and deep learning models, namely BPNN and RBNN. The performance indices of discharge during calibration and validation demonstrate the superiority of deep learning models over the conventional method in particular the RBNN. It is observed from the results that RBNN is the best solution for this problem as it performs best not only for both stations data but also in both phases of training and testing. Based on the present study it is suggested that ANN can be very helpful to the hydrometric stations in terms of accurately predicting the river discharges and planning of various projects. However, ANN are black box models and therefore, functional form of relationship will not be obtained.

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