Research Article

EXTREME STREAMFLOW FORECASTING USING ARTIFICIAL NEURAL NETWORKS

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ABSTRACT
Forecasting of extreme stream flow is necessary for water resource planning and management at catchment scale. Artificial neural networks(ANN) have been widely used as models for a variety of nonlinear hydrologic processes including that of forecasting runoff over a watershed. In this study, ANN a data driven technique is used for forecasting the extreme streamflow. ANN architecture is optimized by selection of transfer function, training algorithm, hidden neurons, and initial weights. For ANN weights finalization LM algorithm is used. The performance of ANN model is validated using two different performance indices. It was found that the ANN model consistently gives superior predictions without any explicit consideration of different components of the hydrologic cycle during calibration and validation. Based on the results, ANN modeling appears to be a promising technique for forecasting the extreme streamflow in semiarid Saurashtra regions of Gujarat.

INTRODUCTION

Water scarcity, high demand of electricity consumption, water requirement for the irrigation and the drinking purposes are the key factors that compelled researchers to predict streamflow precisely for efficient usage of water resources. Prediction of streamflow plays a key role in economic development of a catchment. Traditionally, streamflow prediction of a river basin is performed using physical and conceptual based models. Hydrological models have been categorized on the basis of their goals and their structures. Data driven models extensively used to model many variables in the field of hydrology, such as prediction of extreme events (e.g. peak and low flows), streamflow or suspended sediment forecasting, reservoir inflow forecasting, precipitation or temperature prediction, evaporation or groundwater or water quality forecasting and rainfall runoff modeling.

In the last few decades, numerous data-driven models for hydrological time series forecasting have been proposed to increase forecasting accuracy. The autoregressive moving average (ARMA) approach, since first being proposed by Box and Jenkins, (1970) and then popularized by Carlson *et al*. (1970) has been one of the most widely-used methods for hydrological forecasting (Khashei and Bijari, 2011; Zhao and Chen, 2015 and Zounemat-Kermani, 2016). The ARMA technique assumes the time series to be stationary and to follow the normal distribution (Box and Jenkins, 1970). However, streamflow time series is usually characterized by features of both nonlinearity and unstableness; thus, linear-related time series forecasting techniques are not sufficient to capture the characteristics of hydrological time series (Wei *et al.*, 2012). In this case, artificial neural networks (ANNs) have been put forward and widely exploited for hydrological forecasting to deal with the nonlinearity and instability of hydrological time series. Hornik *et al*. (1989) have demonstrated that ANN can approximate any measurable function to a certain degree. One of the most obvious advantages of the ANN technique is that one does not need to have a well-defined process for algorithmically converting inputs into outputs (Sudheer *et al.*, 2002). The advantages and disadvantages of ANN in the application of hydrologic research have been discussed in a comprehensive review by Govindaraju (2000).

In this regard, the main objectives of this study is to develop an effective ANN model for forcasting the extreme streamflow events of the study area and verify the models by the global statistics such as coefficient of determination (R^2), Nash-sutcliffe efficiency (NSE), Root Mean Square Error (RMSE) and Mean Absolute Error (MAE) used to evaluate the performance of developed ANN model.

Study area and data used

The Karmal watershed of Bhadar river in Saurashtra region of Gujarat is selected. It is located between 21º 50' to 22º 10' North latitude and 70º 55' to 71 º 20' East longitudes (Fig.1.). The total area of the Karmal watershed is 1196.46 km^2. The average annual rainfall in the study area (Karmal watershed) is 660 mm. As the watershed being situated in tropical and sub-tropical region and dominated with agriculture land, water availability in the region is an important and critical issue. The daily precipitation and streamflow time series data of 30 years (1982-2012) for Kamadhiya rain-runoff gauge stations were collected from the office of State Water Data Centre, Gandhinagar, Gujarat. The daily rainfall-streamflow of Karmal watershed is given in the Fig.2.

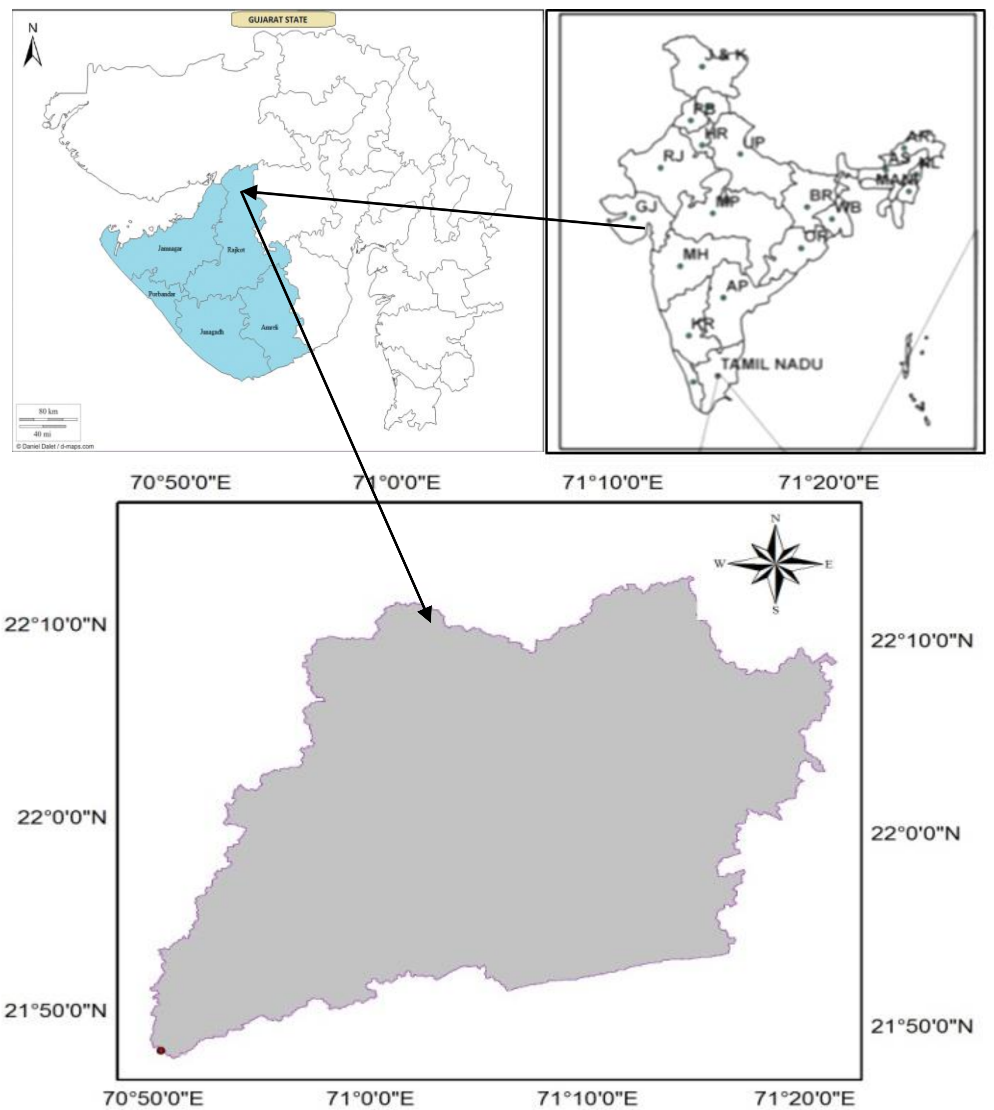

Fig. 1. Location map of Karmal watershed of Bhadar basin

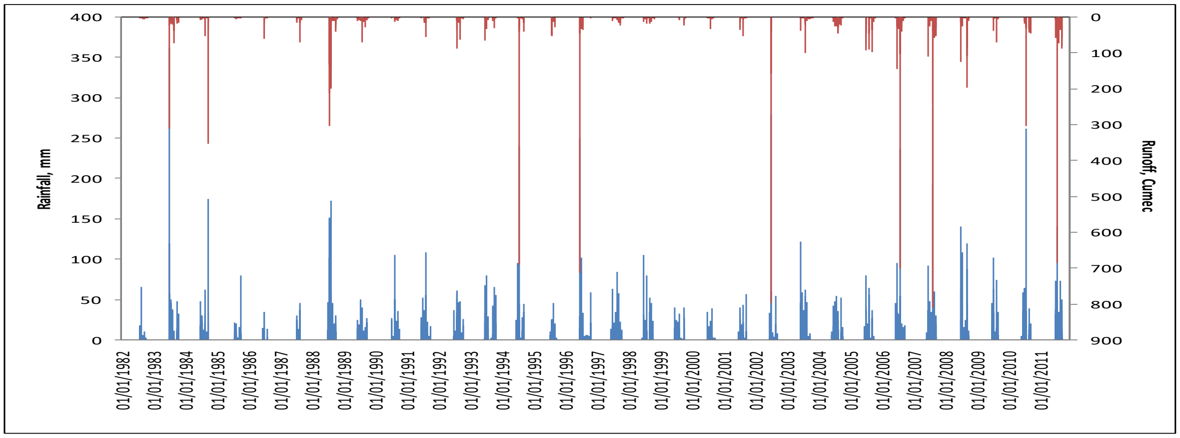

Fig. 2. Daily rainfall-streamflow of Karamal watershed

MATERIALS AND METHODS

Artificial Neural Networks

Artificial neural networks (ANNs) are information processing systems have the capabilities to imitate human neural system by developing a model structure to map complex non-linear relationships and processes that are inherent among several influencing variables. In a simpler term it is a form of a nonlinear regression model that performs an input–output mapping using a set of weights. A feed-forward neural network consists of an input layer, one or more hidden layers of computation nodes, and an output layer of computation nodes. This ANN approach is found to be fast and efficient to model complex relationship among variables even in noisy environments and has been employed to solve several real world problems. With advantages, ANNs have become widely used in numerous real-world applications, such as in time series predictions (Abrahart *et al.*, 2012). An output node of an ANN is presented as

$$y_n = \sum_{j=1}^{J} w_{jk}\,\Psi\left(\sum_{i=1}^{h} w_{ij}\,x_i\right)$$

Where, w_{ij} and w_{jk} are the connections weights, whose values are optimized during training; *y* is generally sigmoidal function; *h* and *j* are the respective number of input and hidden layers, and x_i is the model input variable. The preferred transfer activation functions are generally continuous, bounded, and nonlinear such as the sigmoid and hyperbolic tangent functions (Ozbek and Fidan, 2009).

Model development

ANN models were developed using the dataset for the period 1982-2011. The daily data of rainfall and runoff of the period 1982-1996 were used for the calibration of the model; daily data of years 1997-2001 were used for cross validation of the model, whereas the daily data of years 2002 -2011 were used for validation of the model.

Input determination and selection of optimum model structure are the most important steps in the development of an ANN hydrologic model. After selection of significant input variables, the ANN models were developed by linear and log-transformation of the input variables. In most of the studies a continuous and bounded nonlinear transfer function was usually selected, for that the sigmoid and hyperbolic tangent functions are suited very well (e.g. Haykin, 1998; Govindaraju and Rao, 2000) and therefore in this study, a sigmoid transfer function was used for NN model development. The computational efficiency with accurate results of the training and testing is another important consideration for ANN model development. LM training algorithm for development of robust ANN model 1-20 numbers of hidden neurons are considered. The number of required hidden layer neurons is much more difficult to determine since no general methodology is available for its determination. Thus, the architecture of the network is finalized after a trial-and-error procedure (Hsu *et al.*, 1995).

RESULTS AND DISCUSSION

In this study, the ANN models were tested in daily streamflow forecasting. Only rainfall as a input based on daily streamflow values were selected. Performance of ANN models during calibration and validation using LM training algorithms and hidden neurons are presented in Table 1. The hydrograph and scatter plot between observed and simulated runoff using LM algorithms during calibration and validation are shown in Fig. 3 to 6.

Table 1. ANN model performances during calibration and validation

Training algorithm	Input variable	Particular	Hidden Neurons	R^2	NSE %	RMSE Cumec	MAE Cumec
LM	$Rain_1(t)$	Calibration (1982 -2001)	11	98.4%	94.64	3.83	3.59
		Validation (2002 -2011)	11	98.5%	97.06	4.65	3.81

The NSE and R^2 values for the calibration phase are given in Table 1. The table discloses that, the validation phase's NSE values of were superior than the calibration phase. This is true for R^2 values too. The hydrographs between original and forecasted streamflows by the ANN models are presented in Figs. 3 and 4 for calibration and validation phase respectively. It is also evident from the hydrographs that the predicted streamflow by ANN is in good fit with the original streamflow.

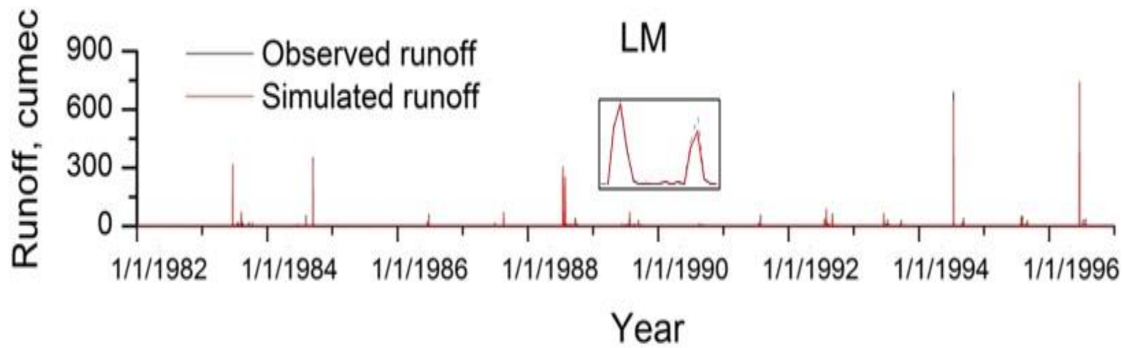

Fig. 3. Hydrograph of observed Vs ANN simulated runoff using LM during calibration

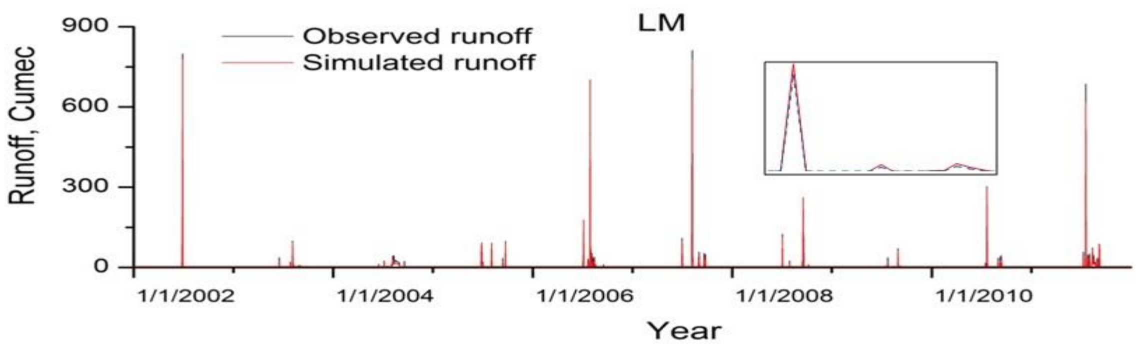

Fig. 4. Hydrograph of observed Vs ANN simulated runoff using LM during validation

The observed and forecasted daily streamflows by the ANN models for the input is shown in Fig. 5 and 6 for calibration and validation phase respectively in the form of scatter plot. The scatter plot of LM algorithm for $Rain_1(t)$ input variables shows highly concurrence between the observed and forecasted extreme streamflow. The points are closes to the 1:1 line and had trained the data very well.

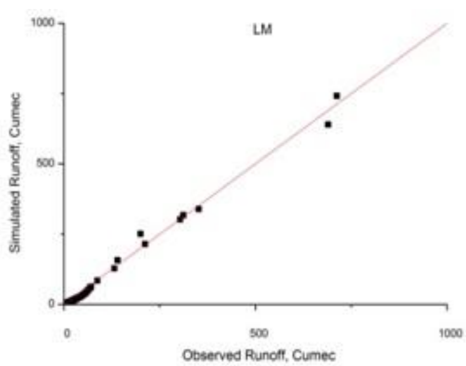

Fig. 5. Scatter plot using LM during calibration

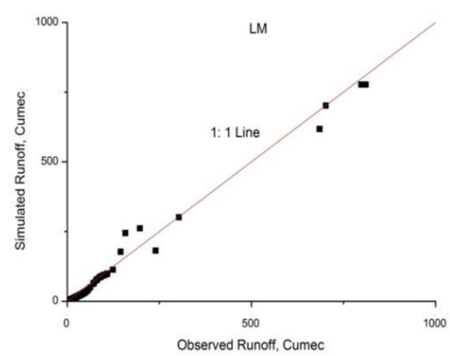

Fig. 6. Scatter plot using LM during validation

CONCLUSIONS

In this study, to check the performance of developed ANN models, different performance indices are used to predict extreme streamflow. The results revealed that scatter plot between observed and predicted is highly concurrence and the NSE was found 94.46% and 97.06% during the calibration and validation period. Thus, ANN model could be successfully used for predicting extreme streamflow in semi-arid Saurashtra region of Gujarat.

REFERENCES

Abrahart, R.J., F. Anctil, P. Coulibaly, C.W. Dawson, N.J. Mount, L.M. See, A.Y. Shamseldin, D.P. Solomatine, E. Toth and R.L. Wilby. 2012. Two Decades of Anarchy? Emerging Themes and Outstanding Challenges for Neural Network River Forecasting. *Progress in Physical Geography*. **36**(4): 480-513.

Box, G.E.P. and G.M. Jenkins. 1970. Time Series Analysis: Forecasting and Control. Wiley: Tokyo, Japan.

Carlson, R.F., A.J.A. MacCormick and D.G. Watts. 1970. Application of Linear Random Models to Four Annual Streamflow Series. *Water Resources Research*. **6**: 1070-1078.

Govindaraju, R.S. 2000. Artificial Neural Networks in Hydrology. II: Hydrologic Applications. *Journal of Hydrologic Enginnering*. **5**: 124-137.

Govindaraju, R.S. and A.R. Rao. 2000. Artificial Neural Networks in Hydrology. Kluwer Academic Publisher, Netherlands. pp: 329.

Haykin, S.S. 1999. Neural Networks: A Comprehensive Foundation. Prentice-Hall, Englewood Cliffs, New Jersey. pp: 823.

Hornik, K., M. Stinchcombe and H. White. 1989. Multilayer Feedforward Networks are Universal Approximators. *Neural Netw.*, **2:**359-366.

Hsu, K.L., H.V. Gupta and S. Sorooshian. 1995. Artificial Neural Network Modeling of Rainfall–Runoff Process. *Water Resources Research*, **31**(10): 2517-2530.

Khashei, M. and M.A. Bijari. 2011. Novel Hybridization of Artificial Neural Networks and ARIMA Models for Time Series Forecasting. *Appl. Soft Comput.*, **11**: 2664-2675.

Ozbek, F.S. and H. Fidan. 2009. Estimation of Pesticides Usage in the Agricultural Sector in Turkey Using Artificial Neural Networks (ANN). *Journal of Animal & Plant Sciences*, **4**(3): 373-378.

Sudheer, K.P., A.K. Gosain and K.S. Ramasastri. 2002. A Data-Driven Algorithm for Constructing Artificial Neural Network Rainfall-Runoff Models. *Hydrological Processes*, **16**(6): 1325-1330.

Wei, S., D. Zuo and J. Song. 2012. Improving Prediction Accuracy of River Discharge Time Series using a Wavelet-NAR Artificial Neural Network. *J. Hydroinform*, **14:** 974-991.

Zhao, X.H. and X. Chen. 2015. Auto Regressive and Ensemble Empirical Mode Decomposition Hybrid Model for Annual Runoff Forecasting. *Water Resource Management*, **29:** 2913-2926.

Zounemat-Kermani, M. 2016. Investigating Chaos and Nonlinear Forecasting in Short Term and Mid-term River Discharge. *Water Resource Management*, **30:** 1851-1865.

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