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Rainfall runoff modelling using generalized neural network and radial basis network

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Abstract: Rainfall runoff study has a wide scope in water resource management. To provide a reliable runoff prediction model is of paramount importance. Runoff prediction is carried out using Generalized Regression neural network and Radial Basis neural network. Daily Rainfall runoff model was developed for Nethravathi river basin located at the west coast of Karnataka, India. The comparative study showed Radial basis neural network performed better than generalized neural network during its evaluation by statistical performances.

Keywords: *Generalized regression neural network, Radial basis neural network, Runoff Modelling.*

1. Introduction

Rainfall runoff modelling helps in well planned water resources management. The study on rainfall runoff relationship also helps in planning and developing distribution policies from the available water resources. Modelling Rainfall runoff with better accuracy and consistency is a difficult task, faced by many researchers. Modelling rainfall runoff is complicated, since it involves many parameters and it is nonlinear in nature. Many modelling methods exist but majorly modelling is classified as physical models and soft computing models. Selection of the inputs for the model is one of the important criteria in the rainfall runoff modelling. A main issue for using the physical model is that they require precise and large number of data set, and it includes more number of parameters also. The soft computing techniques have been suggested as a good alternative for the physical modelling, with minimum constraints. There are many parameters which influence the rainfall runoff modelling, but among them rainfall, temperature, land use land cover and infiltration are significant. In the present study two neural network (NN) models generalized regression neural network (GRNN) and radial basis neural network (RBNN) are used for rainfall runoff modelling. Neural network models have gained lot of interest, due to their adaptive nature and quick learning ability. Ability of RBNN has been used in runoff forecasting with orthogonal least square algorithms [1]. RBNN has many applications and has been used in many studies due to its prediction ability [6]. RBNN was used in simulation of sediment yield [2]. GRNN has good forecasting capability and it has been used in many ungauged predictions [3]. NN models are data driven models they converge at all possible cases. The ability of NN models having short training period and higher prediction accuracy has made it as one of the alternate method for rainfall runoff modelling [4]. It has been observed in the study that GRNN never show any solution which cannot be achieved in reality [5], [6]. GRNN model do not stuck up in local minima like typical NN models. It was found that NN are able determine a use full relationship between antecedent rainfall and runoff [7]. The relationship of antecedent rainfall and runoff also depends on the time of concentration. Rainfall runoff modelling by combing a liner model with neural network has been already achieved in the study [9] and was successful in showing the capability of NN in prediction. NN show good prediction accuracy than other statistical methods for rainfall runoff modelling [10]. NN has also been used in different application, such as determination of Earthquake deformation [11].

RBNN is one of the neural network models having radial basis function as a component and its response depends on distance from centre points. GRNN is also one among neural network models used mainly in pattern recognition. In the present study GRNN and RBNN methods are used for rainfall runoff modelling. In the study neural network tool box in MAT Lab is used for rainfall runoff modelling. The modelling of runoff using antecedent precipitation and runoff for GRNN and RBNN has been attempted in the study, which is not previously carried as per literature. The study objective is to do comparative analysis and suggest a better model for daily runoff prediction among these two models.

2. Research Method

2.1. 2.1. Generalized Regression Neural Network

Specht (1991) proposed generalized regression neural network (GRNN) [11]. Like typical feed forward back propagation neural network, GRNN does not need iterative training procedure for approximation of solutions. GRNN show consistent approximation, if a large number of training set is used then the error move towards zero with smaller constraints on the function. GRNN is based on Nadaraya Watson kernel regression and it is used to estimate the solutions similar to regression techniques. GRNN is a process used in prediction of probability density function of dependent and independent variables. GRNN consists of four layers. First layer is the input layer which depends on number of inputs considered. The first layer is connected to the second layer, which is called as pattern layer. Each neuron in pattern layer passes through training pattern, which is processed as output. The pattern layer is then summed up in third layer, called as summation layer. The fourth layer is the output layer with output neuron. Exponential activation is used at pattern layer and linear activation is used at output layer. GRNN has been used in many

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hydrological applications, modelling etc. The Kernel regression for estimation of functional relationship between response y and independent variable X is given by the equation (1) having x1, x2, x3, x4 and x5 as inputs variables.

$$E[y][X]=\frac{\int_{-\infty}^{\infty} y f(X,y)dy}{\int_{-\infty}^{\infty} f(X,y)dy} \quad (1)$$

E[y][X] = Estimation function, X and y are variables

$f(X,y)$ = probable density function of random variable **X** and scalar variable **y**

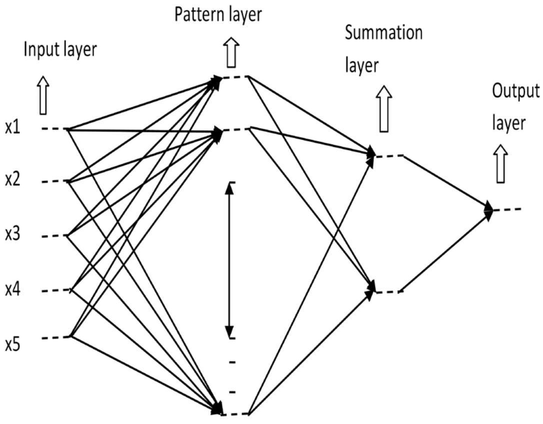

Figure 1. Schematic Representation of Generalized Regression neural network

2.2. Radial Basis Neural Network

Radial basis neural network (RBNN) was developed by Powell (1987) and Broomhead and Lowe (1988). RBNN architecture will have an input layer, single hidden layer and output layer. The network consists of an input layer, hidden layer with Gaussian transfer functions at each neuron and an output layer with linear transfer function. Neurons in the hidden layer have Gaussian transfer function characterized by separate set of mean and standard deviation values. Weights, mean and standard deviation are updated by partial derivation with respect to the corresponding variable [8]. RBNN has been used in many applications such as modelling, prediction and classification. Gaussian function is given by equation 2.

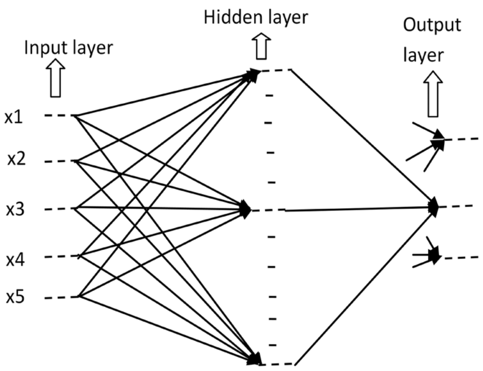

Figure 2. Schematic Representation of Radial basis neural network

$$f(x)=\exp\left[-\frac{\|x-\mu_j\|^2}{2\sigma_j^2}\right] \quad (2)$$

Where μ is the mean and σ is standard deviation.

3. Study Area

Nethravathi River originates in Western Ghats of Karnataka, India and reaches Arabian ocean at Mangalore. It lies between 74o 45l E to 75o 20l E longitude and 12o 30l N to 13o 10l N latitude (Fig. 3). The area of the catchment is 3184 km2. Annual rainfall over the basin varies between 1500 mm and 4500 mm. It receives 70 to 80 percent of rainfall during monsoon months (June to September) and remaining in the other months, the basin is major source of water for Mangalore city, Karnataka. Rain fall runoff model has been developed, using daily rainfall and runoff data for 22 year for the modelling purpose. Average rainfall of the basin was computed from Thiessen method for the rain gauge stations. Since rain fall is the main contributor for runoff. Rainfall and Runoff were selected for modelling purpose. Other parameters were neglected.

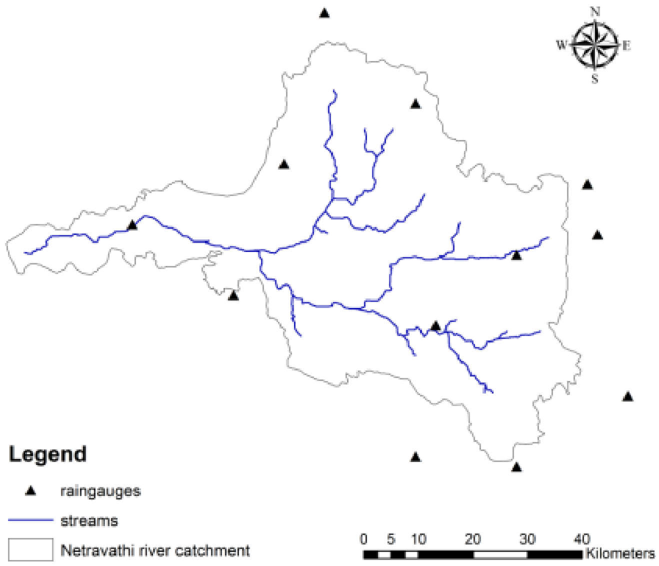

Figure 3. Nethravathi River Basin

4. Results and Discussion

In the present study GRNN having four layers, input layer having five input neurons with exponential activation at pattern layer and linear activation at output layer is adopted, For RBNN five inputs with Gaussian transfer function at hidden layer and linear activation at output is adopted

Rain fall runoff model was developed using GRNN and RBNN. Rainfall runoff modelling was done considering the antecedent runoff and rainfall as the inputs to the model to predict the next day runoff.

The model is $Q_t = f(P_t, P_{t-1}, P_{t-2}, Q_{t-1}, Q_{t-2})$;

Inputs = P_t, P_{t-1}, P_{t-2}, Q_{t-1}, Q_{t-2}; Output = Q_t;

t = current time period; t-1 = lag of 1 day, t-2 = lag of 2 days; output = daily stream flow; Input = daily precipitation, (lags) antecedent precipitations and antecedent stream flow. The inputs to the model was selected by correlation analysis, which showed that previous two day of lags are more prominent for the runoff of today. Nash Sutcliffe efficiency (NS), Coefficient of determination (R2) Mean absolute error (MAE) and Root Mean Square Error (RMSE) were used to check the performances of the models (Table 1).

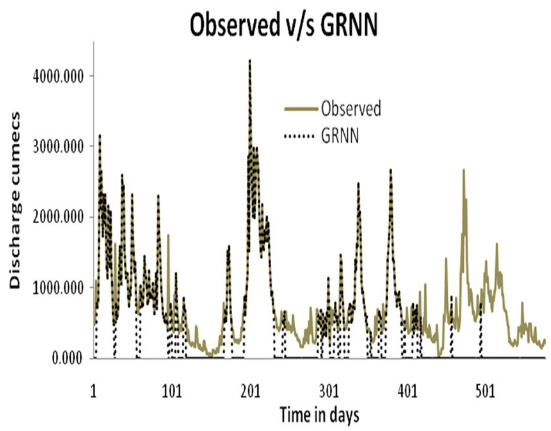

Figure 4. Time series plot of Observed and GRNN predicted flow

Rainfall runoff model for seasonal flow has been done in the study. 70% data was used for training and 30% for testing. RBNN and GRNN both the models show reasonably good R^2 value, but RBNN model shows a better NS value than GRNN during testing cases (Table 1).

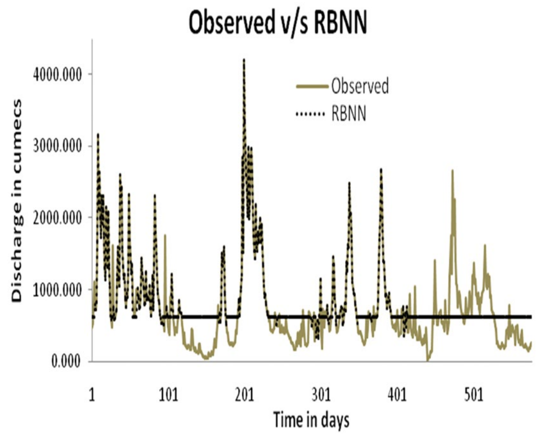

Figure 5. Time series plot of Observed and RBNN predicted flow

The other performance indicators MAE and RMSE of RBNN model are much lower than the GRNN model. GRNN model show a very less value of NS value of 0.359 (Table 1), which shows that the model has failed to capture the nonlinearity of the rainfall runoff model. Fig 4 and Fig. 5 show the time series plot of GRNN and RBNN models. It is observed that the GRNN model captured some of the peaks (Fig. 4), But its most of the points are zeros.

Table 1. Performances of the models during testing

Models	Nash Sutcliffe efficiency	Coefficient of Determination (R^2)	Mean Absolute Error (m^3/s)	Root Mean Square Error (m^3/s)
RBNN	**0.765**	**0.781**	**183**	**294**
GRNN	0.359	0.726	313	486

In Fig.5, it is observed that RBNN model shows good prediction, but its points never fall below 620cumecs. From Fig. 5 it is evident that RBNN model has also captured the peak but it shows a constant value for all the other points where the observed values are less than 620 cumecs. From Table1 it can be noted that even though both models show descent R^2, amongst them RBNN model performing better with higher Nash Sutcliffe efficiency and lower Mean absolute error and RMSE.

5. Conclusion

In the study the applications of NN methods for runoff modelling, adopting GRNN and RBNN is examined. A comparative analysis of RBNN and GRNN is attempted. Using antecedent precipitation and runoff as inputs, rainfall runoff model is established. The performance of RBNN and GRNN models are compared and evaluated from performance indicators such as coefficient of determination, Nash Sutcliffe efficiency, Root mean square error and mean absolute error. From the performances of the GRNN and RBNN model it is observed that, RBNN model perform well when compared with GRNN due to good mean and standard deviation. From the results it is suggested that among these two models RBNN is a good prediction model. So, RBNN can be used for predicting runoff, which results for enhanced water shed management..

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References

[1] D. Achela, K. Fernando,and A. W.Jayawardena, “Runoff forecasting using RBF networks with OLS algorithm,”Journal of hydrologic engineering,vol.3, pp.203-209. July 1998.

[2] Ajai Singh, Mohd. Imtiyaz, R.K. Isaac,and D.M. Denis,“ Assessing the performance and uncertainty analysis of the SWAT and RBNN models for simulation of sediment yield in the Nagwa watershed, India,”hydrological sciences Journal,vol.59, pp.351-364. August 2014.

[3] L. E. Besaw, D. M. Rizzo, P. R. Bierman,and W. R. Hackett,“Advances in ungauged streamflow prediction using artificial neural networks,”Journal of Hydrology,vol.386, pp.27–37, February 2010.

[4] C. Dawson, and R. Wilby, “An Artificial Neural Network Approach to Rainfall – Runoff Modelling,” Hydrological Sciences Journal, vol. 43, pp.47-66, Febraury1998.

[5] Hikmetkaremcigizoglu,“Application of Generalized Regression Neural Networks to Intermittent Flow Forecasting and Estimation,”Journal of hydrologic engineering, vol.10,pp.336-341, August 2005.

[6] HilmiKeremCigizoglu, and Murat Alp,“Rainfall-Runoff Modelling Using Three Neural Network Methods,” International Conference on Artificial Intelligence and Soft Computing, 3070, pp166-171. 2004

[7] A.W. Minns, and M.J. Hall, “Artificial neural networks as rainfall runoff models,” Hydrological Sciences Journal, vol.41, pp.399-417, June 1996.

[8] D.K. Pratihar, Soft Computing, 2nd Ed., New Delhi: Narosa Publishing House Pvt. Ltd. 2008.

[9] M.P. Rajurkar, U.C. Kothyari, and U.C. Chaube, “Modelling of Daily Rainfall runoff relationship with artificial neural networks,” Journal of Hydrology, vol.285, pp.96-113, August 2003.

[10] A. SezinTokar, and A.J. Peggy, “Rainfall-Runoff Modelling Using Artificial Neural Network,” Journal of Hydrologic Engineering, vol.4, pp.232-239, July 1999.

[11] D. F. Specht,“A General Regression Neural Network,”

IEEE Transactions on Neural Networks,vol.2, pp.568-576, November1991.

[12] Tahir ErdemOzturk,"Artificial Neural Networks Approach for Earthquake Deformation Determination of Geosynthetic Reinforced Retaining Walls,"International Journal of Intelligent Systems and Applications in Engineering,vol.2, pp.1-9, 2014.