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Rainfall-Runoff Modelling using Artificial Neural Network: A Case Study of Banas River Catchment

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ABSTRACT

In the last two decades, Artificial Neural Networks (ANNs) have become one of the most promising tools for modelling complex hydrological processes such as the Rainfall-Runoff interaction. The Artificial Neural Network could be used in cases where the availability of required data is limited. The Rainfall-Runoff model developed in this study was applied to the Banas River catchment of Gujarat, India. The hydrologic data were available for twelve years at CWC, Gandhinagar (such as Meteorological, weather, etc.). The Rainfall-Runoff model was developed by using an ANN technique (Feed-Forward Backpropagation algorithm) and a Multiple Linear Regression (MLR) method. The performance of both models was assessed by correlation coefficient (R), coefficient of determination (R2), and Mean Square Error (MSE). As the ANN gives only a black-box image, the sensitivity analysis was done to find the relative importance of input parameters. For the ANN models, the evaluation shows correlation coefficient (R) was obtained as 0.9318 whereas an MLR model, the correlation coefficient (R) was obtained as 0.8831. The RMSE values for the ANN and MLR models were 0.023535 and 0.15073 respectively. The results and analysis indicate that the ANN model provides better outcomes for datasets scaled between zero and one based on this study. In the comparison of both ANN and MLR models, the Artificial Neural Network technique was more suitable than the Multiple Linear Regression method. Hence the present study suggests that ANN models are an essential tool for predicting the hydrological responses in the Banas River Catchment.

Keywords**--** Rainfall-Runoff Modelling, Artificial Neural Network, Multiple Linear Regression, Water Balance Equation, Runoff Prediction, Banas River Catchment, Gujarat

I. INTRODUCTION

Rainfall-Runoff models are widely used in hydrology for a range of applications and play an important role in the optimal planning and management of water resources in the river basin. Managing risk in the short term is one of the most important applications of R-R modelling. A rainfall-runoff model is, by definition, a simplification of a complex, non-linear, time and space varying hydrological process reality. Such a model contains parameters that cannot often be measured directly but can only be estimated by calibration against a historical record of measured data. The system input and output data are often contaminated by measurement errors. The system input data such as rainfall, temperature, etc. and output are often contaminated by measured errors. Consequently, predictions made by such a rainfall-runoff model are far from perfect, in other words, there always exists a distinction between the model prediction and the corresponding observed data, no matter how precise the model is and how perfectly the model is calibrated. Thus, the model errors which are the mismatch between the observed and the simulated system behaviour are unavoidable in rainfall-runoff modelling. There has been extensive research on the rainfall-runoff relationship with different models that can be classified into three main groups, namely fully distributed physically-based models, lumped conceptual models, and black-box models. Empirical models contain no physically based transfer function to relate input to output: in other words, no consideration of the physical processes is involved. Such models usually depend upon establishing a relationship between input and output, calibrated from existing hydrometeorological records. In this study empirical model has been used.

The terminology of artificial neural networks has developed from a biological model of the brain. A neural network consists of a set of connected cells and neurons. ANNs have been in existence since McCulloch and Pitts (1943) introduced the concept of the artificial neuron. The ultimate goal of this project was to prove that ANN models are capable to accurate modelling the relation between runoff and rainfall in a catchment. An existing software tool in the MATLAB R2018a environment was selected for testing and design ANN for the available data set. A special algorithm (feed forward backpropagation) is programmed and employed in this tool. This algorithm was expected to ease of trial and error for obtained an optimal network architecture. In the present study, Multiple linear regression was also

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employed for the same data set. Later the comparison between ANN and MLR was done and the best model was sought from both techniques. The analysis and model performance were tested in form of R2, Root mean square error. The models were validated by plotting predicted discharge vs Actual discharge (Normalized values) for the years 2012 to 2018.

II. STUDY AREA

The present study was carried out in the Banas River catchment, Gujarat, India. The study area lies in two states of India, the catchment area originates from Rajasthan state and the outlet of the catchment of this study is in Gujarat. The total study area is 2862 km2. The study area catchment lies between 24° 20' 17" to 24° 52' 57.4248" North latitude and 72° 20' 20" to 72° 51' 32.0184" East longitude.

Figure 1: BANAS River catchment Map Up to Dantiwada Dam (Source: ArcGIS)

III. DATA COLLECTION

The study area consists of seven rain gauge stations, to monitor rainfall. These rain gauge stations; six rain gauge stations are located upstream side of the Dantiwada Dam. Out of seven three stations measure discharge also. Moreover, other climatic variables such as temperature, relative humidity, and wind velocity, are also measured at some of these stations in particular time intervals. All the stations are operated by Central Water Commission, whose characteristics are given in Table. The precipitation data from the year 2004 to 2018 (2009 to 2011 was missing due to some reasons) is available for this study. For the present study, the monsoon storm data (Precipitation, weather data, and inflow are available) are adequate for the development of the model and other seasons (winter and summer) data were in a dequate to fit the model. Total 1836 no. of data pairs was used, but due to inadequacy of inflow data row here only 357 data pairs were considered for model development.

IV. METHODOLOGY

The methodology is one of the significant parts of research work. The whole computation is done in MATLAB R2018a software. The ANN techniques with Feedforward Backpropagation algorithm was used. The training data sets are used to adjust connection weight according to its error. Validation is used to measure network generalization. The testing does not affect training and so provides an independent measure of network performance during and after training. Precipitation, gauge inflow, wind velocity, humidity, temperature was being used to predict the runoff of the catchment area. The target and input data forms are divided into three parts; training (70%), validation (15%), and testing (15%).

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The artificial neural network with one input layer, one hidden layer, and one output layer is taken into consideration. For the selection of the best network architecture with an optimum number of hidden layer neurons, many trials have to be carried out. Different training algorithm such as Levenberg Marquardt (LM), and Scaled Conjugate Gradient has been used to train the model. In the network architecture, many trials have been done with changes number of neurons in the hidden layer. The performance of the model can be evaluated in the terms of accuracy refers to the ability of the model to reduce calibration error consistency is used for representing the characteristics of the model whereby the level of accuracy and estimation of the parameter's values persist through a different sample of data. The various statistics indices were used (R^2, RMSE, etc.) to measure the performance of the trained network. A versatile model is defined as a model which is accurate and consistent when used for different applications.

V. RESULTS AND ANALYSIS

5.1 ANN Result

As earlier decided that the best model with training, testing, and validation data distributed 70%, 15%, and 15% respectively for both different algorithm LM and SCG using feedforward Backpropagation Neural network obtained from the MATLAB software. The Transfer function sigmoid in the hidden layer and the Transfer function purelin in the output layer, only the hidden neuron was changed and the best ANN architecture was selected based on high regression value of testing and low mean square error. The architecture M1- 18-10-1 containing training (70%), testing (15%), and validation (15%) possessed the best result in this study. The coefficient of correlation (R) and RMSE for the ANN model is 0.9318 and 0.0005539 respectively.

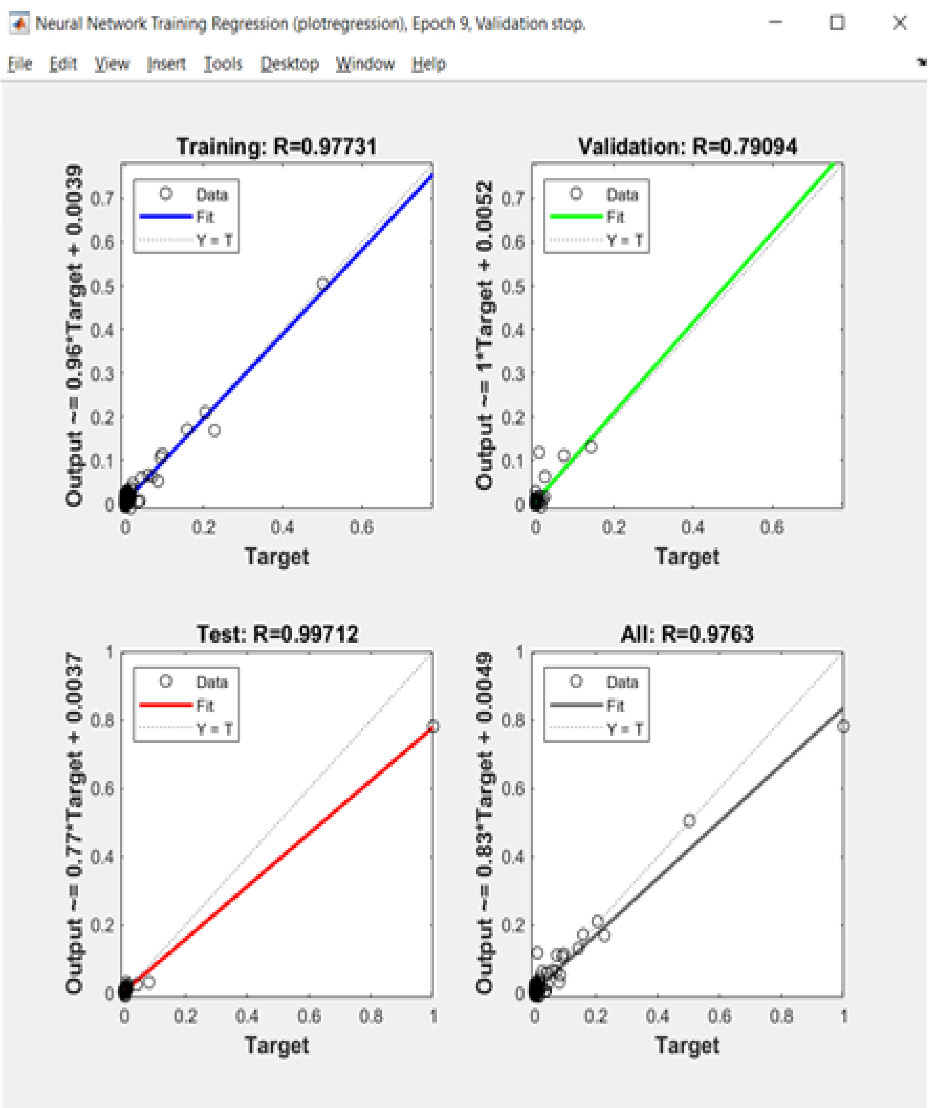

Figure 2: Training, validation and testing regression for the Levenberg-Marquardt algorithm

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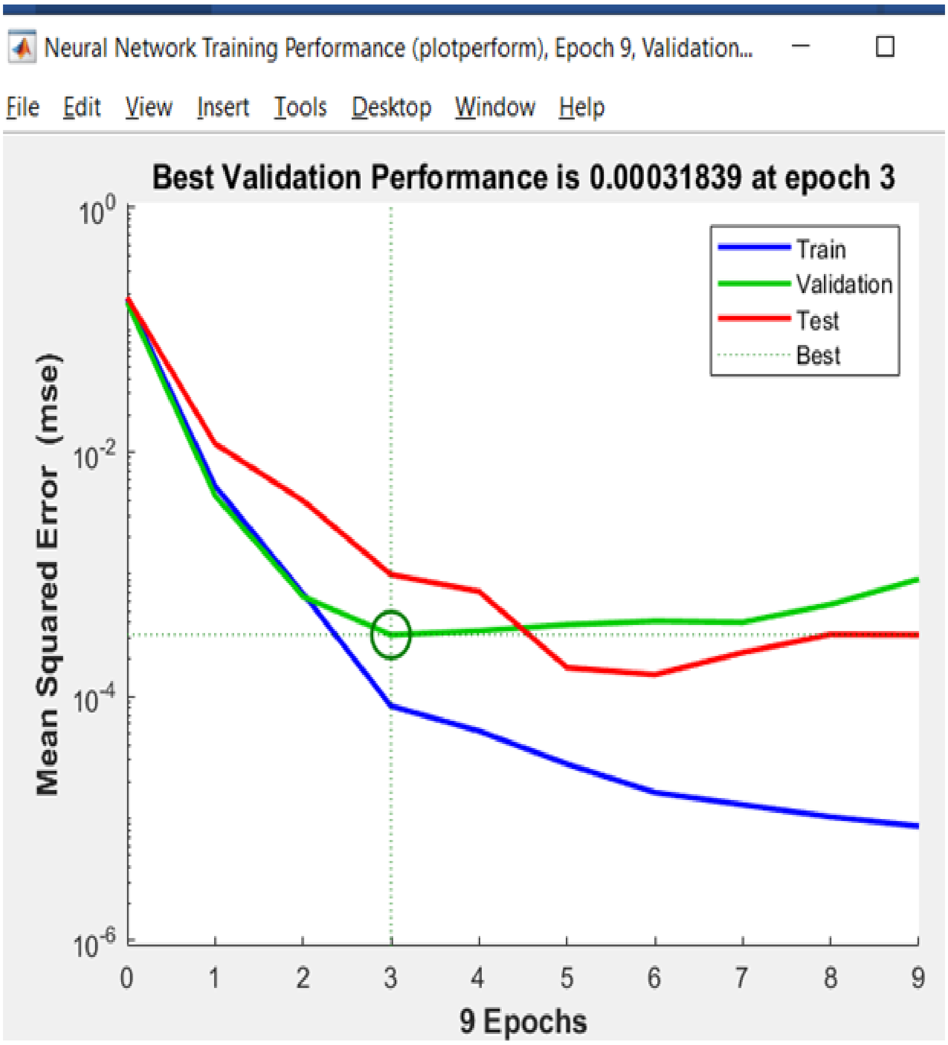

Figure 3: MSE for training, validation and testing using LM algorithm

5.2 Comparison of ANN and MLR results

Table 1: Comparison of R and RMSE values of both models

ANN model	MLR model
R=0.9318	R=0.8831
RMSE=0.00055	RMSE = 0.15073

The Statistical value of the above Table shows the comparison of the ANN and MLR model. From the table, it is distinguished that the ANN model gives reliable results than and MLR model. The best ANN model is sought with a 0.9318 value of R (coefficient of correlation) and a corresponding MSE value of 0.0005539, whereas the MLR models' R and MSE values is obtained 0.8831 and 0.02272 respectively. The number of hidden neurons in ANN was taken differently to obtain a good result of the model in which increases in neurons number lead to more training time and a greater number of epochs, later the decreased number of neurons and selected the best model architect to fit for this study.

At the end of training phase, the model architecture 18-10-1 is selected as the best fit model. From the above result, it is clear that both the ANN and MLR model were able to predict the catchment runoff with adequate accuracy. The ANN and MLR models result demonstrate that the ANN model is the best fit for the prediction of catchment runoff for the present study. Moreover, the Model1, which has 18 inputs parameters ANN model provides a slightly better result with

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Levenberg Marquardt algorithm than the ANN model with a Scaled conjugate gradient algorithm. The Statistical value of the above Table shows the comparison of the ANN and MLR model. From the table, it is distinguished that the ANN model gives reliable results than and MLR model. The best ANN model is sought with a 0.9318 value of R (coefficient of correlation) and a corresponding MSE value of 0.0005539, whereas the MLR models' R and MSE values is obtained 0.8831 and 0.02272 respectively. The number of hidden neurons in ANN was taken differently to obtain a good result of the model in which increases in neurons number lead to more training time and a greater number of epochs, later the decreased number of neurons and selected the best model architect to fit for this study. At the end of training phase, the model architecture 18-10-1 is selected as the best fit model. From the above result, it is clear that both the ANN and MLR model were able to predict the catchment runoff with adequate accuracy. The ANN and MLR models result demonstrate that the ANN model is the best fit for the prediction of catchment runoff for the present study. Moreover, the Model1, which has 18 inputs parameters ANN model provides a slightly better result with Levenberg Marquardt algorithm than the ANN model with a Scaled conjugate gradient algorithm.

5.3 Sensitivity Analysis

ANN gives the black box image so it can be removed by finding the relative importance of the variables. The relative importance of input parameters is obtained by the portioning of weights (Garson algorithm,1991). For the sensitivity analysis, keep all the variables at their mean value except one variable, and find the relative change in the output concerning change in that variable from mean up to half the value of standard deviation. Repeat the procedure for all parameters.

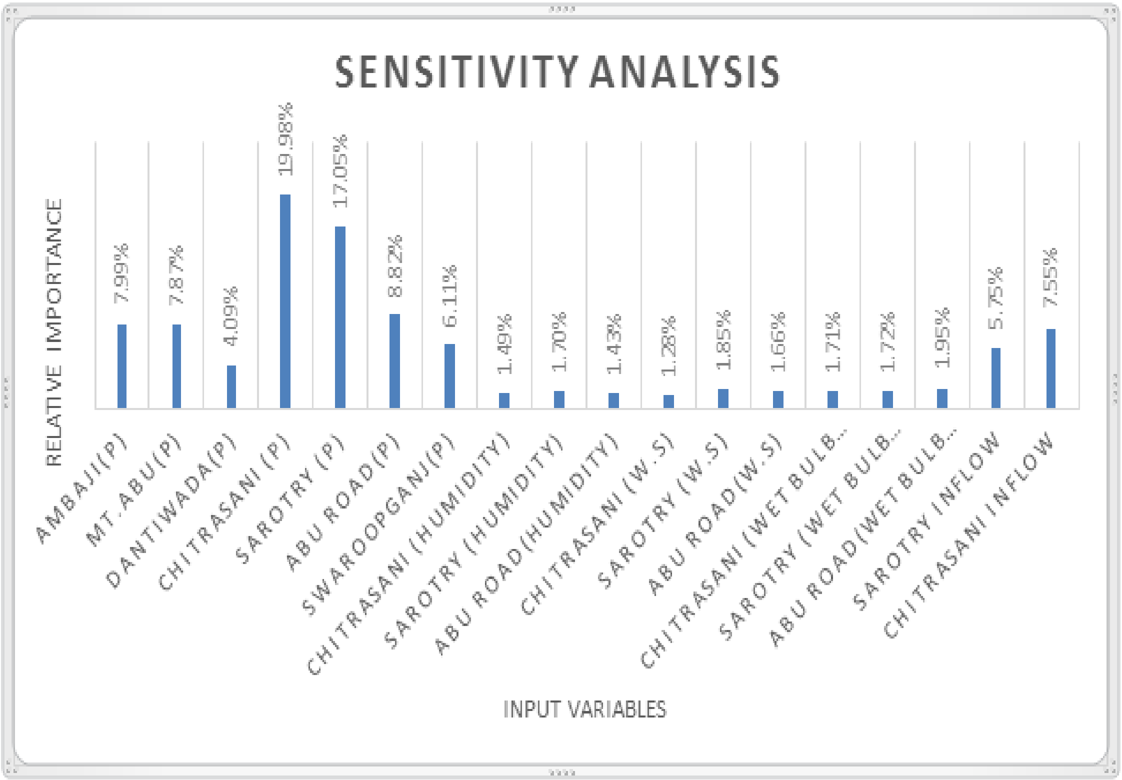

Figure 4: Relative importance of input parameters

The above figure shows that the precipitation of Chitrasani, Sarotry, Abu Road have a much importance on runoff generation, but also Ambaji, mt. Abu, Dantiwada, and Swaroopganj has a good impact on runoff. Meanwhile other weather data such as wind velocity, temperature, and humidity does not show a better importance on generation of runoff in the Banas River Catchment. From the above analysis, rain gauge/ gauge stations Chitrasani and Sarotry contribute 19.98% and 17.05% precipitation and 7.55% and 5.75% of inflow to generating runoff in the Banas River catchment, Gujarat, India.

5.4 Comparison of actual output vs predicted output

The Scattered graph has been plotted for comparison of ANN model predicted catchment runoff with actual runoff (normalized value).

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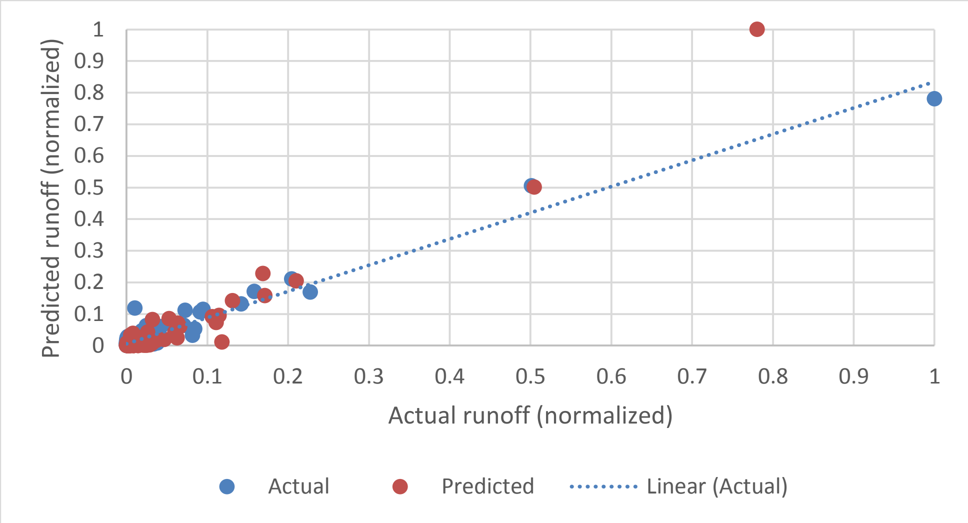

Figure 5: Scatter plot of actual vs predicted values (Normalized)

VI. CONCLUSIONS

The ANN hydrological model with Feed-Forward Back Propagation network is developed in the present study for Banas River catchment, Gujarat, India. The performance of the developed models was evaluated by statistical indices, such as correlation coefficient (R), Mean Square Error (MSE), and Root Mean Square Error (RMSE). For the ANN models, the evaluation shows correlation coefficient (R) was obtained as 0.9318 whereas an MLR model, the correlation coefficient (R) was obtained as 0.8831. The RMSE values for the ANN and MLR models were 0.023535 and 0.15073 respectively. The architect 18-10-1 ANN model was the best model among all of the models developed for this study.

From the sensitivity Analysis, prediction of catchment runoff, the precipitation of Chitrasani, Sarotry, Mt. Abu, Abu Road, and Ambaji rain gauge stations has a significant role, furthermore the Chitrasani and Sarotry inflow has a greater impact on runoff for Banas River Catchment. The results indicate that the ANN model had a good ability to capture the relationship between input/output i.e., Rainfall/Runoff better than an MLR model. The result concluded that ANN can capture the nonlinearity of rainfall-runoff modelling very well.

REFERENCES

[1] S. Raid, J. Mania, L. Bouchaou, Y. Najjar, Rainfall-runoff model using artificial neural network approach (2003), Journal of Science Direct, Elsevier.

[2] Ashu Jain, KV Prasad Indurthy, Comparative analysis of event-based rainfall-runoff modelling techniques - deterministic, statical, and Artificial Neural Networks (2003), Journal of hydrologic engineering, ASCE.

[3] A. R. Senthil Kumar, K. P. Sudheer, S. K. Jain, P. K. Agarwal, Rainfall-runoff modelling using artificial neural networks: comparison of network types (2005), Wiley InterScience

[4] Ajay B Patel, Geeta S Joshi, modelling of rainfall-runoff correlations using artificial neural network (2017), Civil Engineering Journal.

[5] Lateef Ahmed Dar, Rainfall-runoff modelling using artificial neural network technique (2017), International Research Journal of Engineering and Technology.

[6] Anant Patel, Rainfall-runoff modelling and simulating using remote sensing and Hydrological model (2020), springer.

[7] Vikas Poonia, Hari Lal Tiwari, Rainfall-runoff modeling for the Hoshangabad Basin of Narmada River using artificial neural network (2020), Saudi Society for Geosciences, Springer.

[8] A. M. Kalteh, Rainfall-runoff modelling using artificial neural networks (ANNs): modelling and understanding (2008), Caspian Journal of Environmental Sciences, Research Gate.

[9] Samir Mitra, Rashmi Nigam, An approach to utilize artificial neural network for runoff prediction: River perspective, Emerging Trends in Materials Science, Technology and Engineering, Elsevier. (2021)

[10] Jy S. Wu, P.E., M. ASCE, Jun Han, Shastri Annambhotla, and Scott Bryant, Artificial Neural Networks for Forecasting Watershed

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Runoff and Stream Flows, Journal of Hydrologic Engineering, ASCE (2005)

[11] ASCE Task Committee on Application of Artificial Neural Networks in Hydrology, Artificial Neural Networks in Hydrology: Hydrologic Applications, Journal of Hydrologic Engineering, ASCE (2000)

[12] Rajurkar, M.P., Kothyari, U.C., and Chaube, U.C. Modeling of the daily rainfall-ruuoff relationship with artificial neural network. Journal of Hydrology, ASCE (2004)

[13] Maurya, N. K., & Tanwar, P. S. (2021). Estimation of Temporal R-factor Based on MonthlyPrecipitation Data. Journal of Physics: Conference Series, 2070 (2021) 012210. doi:10.1088/1742-6596/2070/1/012210