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FLOOD RISK ASSESSMENT OF SUBARNAREKHA RIVER USING ADAPTIVE NEURAL-BASED FUZZY INFERENCE SYSTEM (ANFIS)

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Abstract

Flood risks are among the many water-related concerns that have the potential to cause the most damage. Urban flooding and the risk it poses are growing issues with global significance, but they are especially serious in developing nations like India, where the risk is typically understudied and little understood. Consequently, it is crucial to develop a stage-discharge model that would aid in flood prediction. In comparison to the past, floods in mountainous areas are increasingly more frequent, and this trend is expected to continue owing to global warming. The study presents the adaptive neural-based fuzzy inference system (ANFIS) approach to estimate the flood risk for the Subarnarekha River at the Rajghat Gauge site. Techniques for assessing the risk of flooding are based on a variety of factors, including socioeconomic, geometric hydraulic surfaces, and meteorological data. Characterizing the environment, figuring out the type and severity of hazards, and estimating susceptibility and risk are the four key steps in assessing flood risk. The current study uses independent parameters such as water elevation, precipitation, average temperature, soil moisture, and relative humidity. Various error statistics have been used to analyze the model's efficiency. The results show an expected improvement over past studies with improved R- squared values. The MAE, MAPE, RMSE, and R^2 were used to assess the models' performances with 20.96, 0.187, 284.28, and 0.97 values, respectively. Flood catastrophe management may benefit significantly from the strengthening of community resilience through socioeconomic empowerment and increased adaptive ability.

Keywords: *Flood risk; ANFIS; Statistical; Stage-discharge; Hydraulic; Urban flooding*

1. Introduction

Floods are common hydrologic events that lead to substantial environmental and property damages also loss of life on a global scale. In sensitive places such as fields with steep slopes and insufficient vegetative cover, heavy rainfalls can result in flooding conditions. In developing nations like Iran, where there are insufficient data on soil moisture, soil storage, percolation rates, snow covering, etc., for thorough hydrologic modeling, this issue can also become a priority. According to official sources, catastrophic floods, particularly in Iran's southwest, caused a large number of fatalities among humans, animals, and agricultural products (Sabziparvar et al.,2010; Rezaeianzadeh et al., 2014). Flooding is a tricky task that differs from place to place. Excessive high precipitation intensity, especially in the form of downpours, is one of the physical causes of flood occurrence.

The relevance of floods has increased the need for cutting-edge hydrologic models and mathematical methods to simulate streamflow. Streamflow forecasting has recently paid a lot of attention to adaptive neuro-fuzzy inference systems (ANFIS) and other artificial intelligence-based computational techniques. The ANFIS is a neuro-fuzzy system that employs a feed-forward network to find fuzzy decision rules that perform well on a given task. ANFIS generates a fuzzy inference system based on a given feedback data set, with membership function variables modified using a back-propagation algorithm alone or in conjunction with a least mean squares (LMS) method (hybrid learning) (Folorunsho et al., 2012). This enables fuzzy systems to learn from the data being modeled. Mitra and Hayashi (2000) provide a method for the fuzzy modeling procedure to learn information from the data set, followed by the creation of the membership function variables that perform the given task the best.

ANFIS is well adapted for dealing with poorly and uncertain systems because it finds implementation in imaging, statistical phenomena, watershed, control, and soft-computing such as hyper-spectral image, groundwater vulnerability, rainfall, system identification, control design, genetic algorithms, fault diagnosis, and rough sets (Qiu, 2008; Mu’azu, 2006; Dixon, 2000; Mitra and Hayashi, 2000; Folorunsho et al., 2012). The effectiveness of the ANFIS model was compared to observation in the training and testing sets and was also assessed. The outcomes show that the ANFIS model can be successfully deployed and offers excellent accuracy and reliability for estimating river flow. For the purpose of forecasting the intake to an electric power plant, Valenca and Ludermir (2000) created a fuzzy-neural network model. The findings indicated that the ANFIS model is a useful tool in this area. Pahlavani et al. (2017) modelled the flood hydrograph flowing to the Shirindarreh Reservoir dam in the northern Khorasan Province of Iran in their research to show how an adaptive neuro-fuzzy inference system (ANFIS) is applied to flood hydrograph modelling.

This research aims to capture the behavior of ANFIS techniques with various types of input data sets. In fact, the goal of this research is to evaluate the use of ANFIS for peak discharge prediction using various hydro-meteorological inputs to the networks.

2. Methodology

2.1 Study Area and Data Source

The research area Subarnarekha River originates near Nagri village in the Ranchi district of Jharkhand. Subarnarekha is one of the longest east-flowing interstate rivers. The Subarnarekha River flows through three states (Jharkhand, West Bengal, and Odisha) before meeting in the Bay of Bengal. The boundaries of Subarnarekha basin fall within the geographical coordinates of north latitude between 21°33' to 23°32' and east longitudes between 85°09' to 87°27' in the North-East corner of peninsular India with a total drainage area of 18,951 sq. km. The Rajghat gauge station in Balasore District, Odisha, located across the Subarnarekha River at 21°46'03" latitude and 87°09'44" longitude, has been selected for this investigation and the basin map of the Rajghat in the Subarnarekha basin is shown in Fig.1.

Figure 1. Basin Map of Subarnarekha River

The data has been collected from CWC, State Government, and India Meteorological Department, Bhubaneswar and NASA Power website. The daily stage and discharge data for the monsoon period of the year (2019-2020) are collected from Water Year Book, while precipitation data, temperature data, soil moisture data, and relative humidity data are collected from the NASA Power website. The range of the independent parameters is shown in Table 1. site.

Table 1 Range of input variables considered in the model

Sl no.	Input Variables	Range
1	Water Elevation(m)	3.4-8.47
2	Precipitation(mm/day)	0-86.15
3	Average Temperature(°C)	11.415-31.83
4	Soil moisture	0.54-95.81
5	Relative Humidity	69.12-95.81

2.2. Adaptive Neural-based Fuzzy Interference System

Jang (1993) first described the adaptive neuro-fuzzy inference system as a universal approximator that could approximate any real continuous function on a compact set with any level of precision (Jang and Sun 1997). ANFIS and a fuzzy inference system are functionally identical. The MATLAB toolbox is used for Adaptive Neural-based Fuzzy Inference Systems (ANFIS). The Adaptive Neuro-Fuzzy Inference System (ANFIS) was used to forecast the discharge of the Subarnarekha River at the Rajghat gauging site using water elevation level, precipitation, average temperature, soil moisture, and relative humidity from July – December 2019 as the input variables. There are 184 daily data sets altogether, of which 130 data are used for training, and 54 data are utilized for testing. The data sets include measurements of soil moisture, relative humidity, precipitation, average temperature, and water elevation. The criteria for developing the ANFIS model, as shown in Table 2: -

Table 2 Modelling criterion based on ANFIS

SLNO.	CUSTOM ANFIS	VARIABLES
1	Membership function type	Generalized bell membership function
2	Number of membership functions	Five (5)
3	Learning algorithm	Hybrid learning algorithms
4	Epoch size	Thirty (30)
5	Output type	Linear

The modelling criterion used is to effectively adjust the membership functions so that the output error measure is minimised and the performance index is maximised (Jang, 1993; Folorunsho et al., 2012). This neural- based system is a fuzzy Sugeno by an interlinking network structure. Typically, these models are created and integrated into the neural network model to enable adaptation (Jang, 1993). The membership function with a generalized bell-shaped shape in this study is employed. As can be seen in Figure 2, each node in this layer represents a fuzzy set, and every node's output correlates to the membership level of any input variable in this fuzzy set.

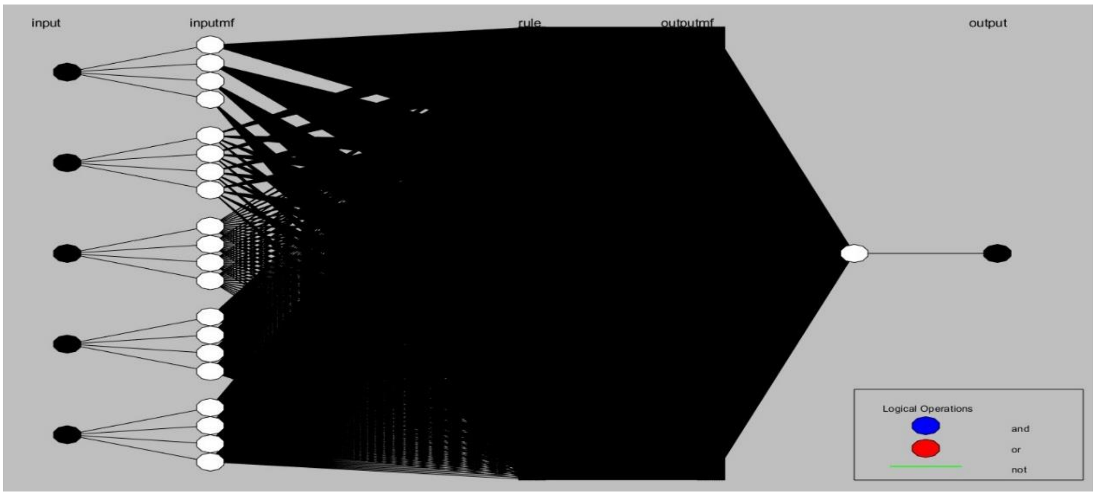

Figure 2. Generalized Structure of the model

2.3 Performance evaluation of the ANFIS model

The potential of the ANFIS model was examined in terms of its ability to model the discharge values. The excellent performance indicators were based on the R^2, MAE, and RMSE values for the model assessment. Error analysis in terms of the mean absolute error (MAE) mean absolute percentage error (MAPE), and root-mean-squared error (%) (RMSE) have been carried out, which are calculated by applying the Eqs. (1)- (3).

$$MAE = \frac{1}{n}\sum |Q_{predicted} - Q_{observed}| \tag{1}$$

$$MAPE = \frac{1}{n}\sum \frac{|Q_{predicted} - Q_{observed}|}{Q_{observed}} \tag{2}$$

$$RMSE = \sqrt{\frac{1}{n}\sum \left(\frac{Q_{predicted} - Q_{observed}}{Q_{observed}}\right)^2} \tag{3}$$

3. Results and Discussion

The ANFIS-based network is generated by importing the training data sets and testing data sets from MATLAB into the ANFIS Editor graphical user interface (GUI) workspace. The input and output data for this study have been taken from the CWC, the state government, and the India Meteorological Department in Bhubaneswar. For the neuro-fuzzy model, the data was split into two groups i.e., training data and testing data. 184 daily data sets of water elevation, precipitation, average temperature, soil moisture, and relative humidity were employed, of which 130 datasets were used for training and 54 datasets for testing. This is the result of the massive amount of data used in neural-fuzzy system. The predicted discharge well matches with the observed discharge. This is proved from the plot Fig. 3 because the R^2 value is found to be 0.97. So, the present model can successfully use to predict the flow of Subarnarekha River.

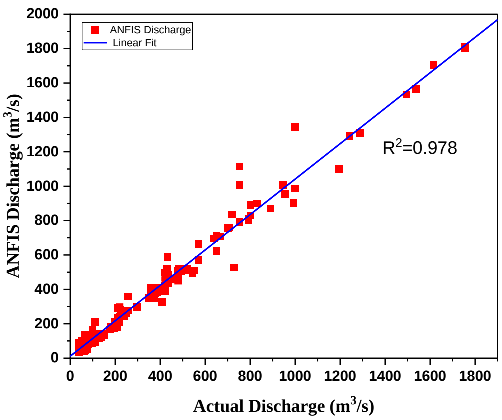

Figure 3. Predicted and observed values of discharge(m3/s) for Subarnarekha River

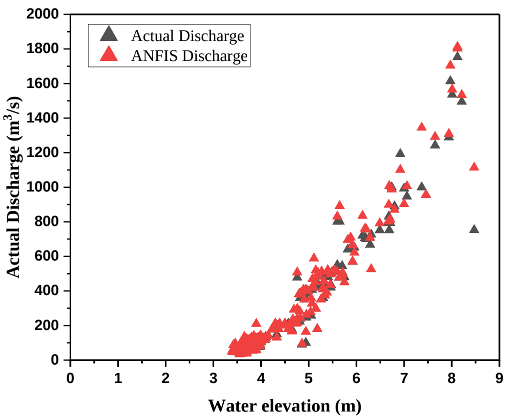

Figure 4. Actual vs. Predicted discharge with water elevation level of Subarnarekha River

Fig. 4 shows that the observed values and predicted values are showing nearly equal values. The model-predicted output almost shows an excellent fit with the observed values as per the plot between the observed and model output. With the above conclusion, one can easily rely on the ANFIS model as it is showing excellent prediction capability and the performance of the ANFIS model for the training and testing stages is shown in fig 5. However, the improvement may still require adding a few more parameters that were actually directly related to stage-discharge of a natural river. The datasets used for this research include the daily precipitation data, temperature data, soil moisture data, relative humidity data for the Rajghat gauge station, and the stage-discharge data for the studied river. These variables are stochastic, non-linear, and uncertain by nature. For the analysis of the ANFIS-based model, three types of estimating errors—the mean absolute error, mean absolute percentage error, and root mean square error were used to compare actual discharge and predicted discharge. For the stage-discharge relationship, the values of MAE, RMSE, and MAPE are 20.96, 284.28, and 0.187, respectively.

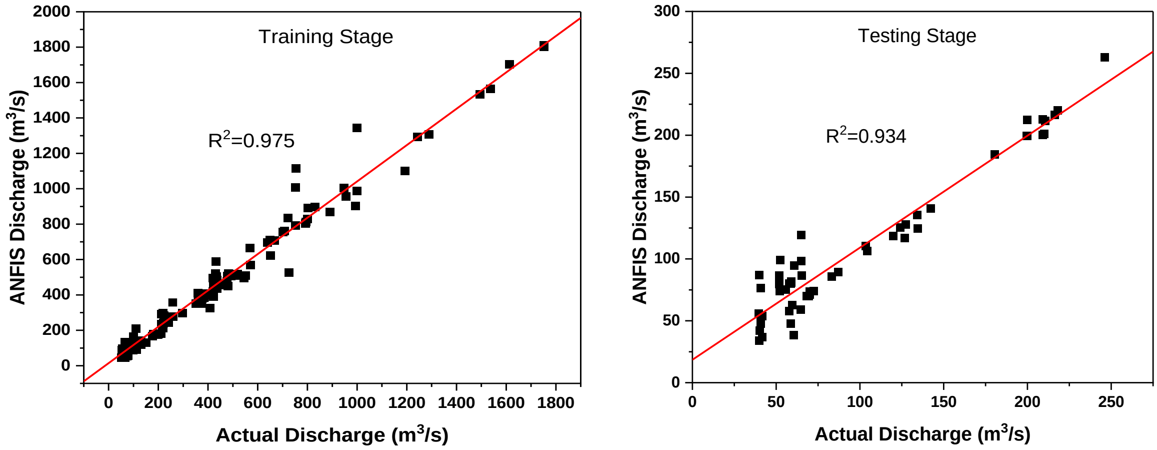

Figure 5. The performance of the ANFIS model for training and testing stages

4. Conclusions

The ability of the ANFIS model to predict maximum daily flow is evaluated in this study. As model inputs, different types of input variables were considered. The findings indicate that the input variables to the models have a significant impact on prediction performance. This study created an ANFIS-based model to predict the River Subarnarekha's discharge based on available factors (water elevation level, precipitation, temperature, soil moisture and relative humidity). Daily discharge data of Subarnarekha River have been successfully predicted using the ANFIS approach, with an average performance of testing of nearly 98%. Due to the high correlation coefficient the ANFIS-based model demonstrated, it can be inferred from the results of this study that it is a better modelling tool for estimating river discharge which suggests that the model can be used in other rivers as long as the input data are accessible, especially for policymakers in hydrological modelling, development, and administration. The research was created for long-term planning and safeguards the local government's personnel and other resources against flood risk.

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