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Forecasting of Flood Flow of Panam River Basin using Adaptive Neuro-Fuzzy Inference System (ANFIS) and ANN with Comparative Study

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ABSTRACT

Flood forecasting is one of the most important issues in the hydrology due to its indispensable contribution in lowering monetary and life losses. In recent years reliability of flood forecasting using various modelling tools has improved to a great extent due to hydrologic modelling, development in expertise and knowledge, and advancement in the collection of data and algorithms for evaluation. The current study presents the use of the Adaptive Neuro Fussy Inference System (ANFIS) in forecasting floods for the Panam River basin system. ANFIS combines neural network algorithms and fuzzy reasoning to map an input space to an output space. This paper includes the development of ANFIS models using various membership function and their comparison for forecasting the inflow rate into the Panam dam, which creates flooding conditions on the downstream side. The different evaluation parameters like Root Mean Square Error (RMSE), Correlation Coefficient (R), Coefficient of Determination (R^2) and Discrepancy Ratio (D) are used to evaluate the results of each model. From all the developed ANFIS models, the best ANFIS model is selected, having RMSE as 271.91, R as 0.98, R^2 as 0.96, and D as 1.00 for training the model, and RMSE as 2000.74, R as 0.95, R^2 as 0.90 and D as 1.12 for validating the model. Artificial Neural Network (ANN) model has also been developed for forecasting flood. In the Neural network there are total 3 types of transfer function in each layer i.e., LOGSIG, TANSIG and PURELIN. All the developed is evaluated with the coefficient of correlation (R) and Mean Squared Error (MSE). In the end, future headings for innovative research work are discussed.

1. Introduction

According to a report by UNISDR, floods have affected 56% of the world's population in the last couple of decades, with India accounting for twenty percent of global flood-related deaths. The Panam River and nearby villages have been frequent victims of flooding in the downstream area of the dam. Overcrowding around water sources is a major cause of this problem, leading to damage to

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infrastructure and loss of human life. Climate change is also exacerbating the situation, as rainfall patterns shift every year. When individuals reside near bodies of water, it is crucial to implement sufficient safety measures and conservation practices to minimize any adverse impacts and prevent loss of life. Employing real-time flood monitoring can be a difficult but valuable technique that integrates multiple efforts, such as identifying high-risk areas, modelling flood-prone regions, calculating probabilities and thresholds for flooding, and establishing warning protocols. While scientists struggle to achieve perfect flood forecasts due to uncertainties and cost factors arising from construction flaws, incorporating estimated uncertainties into prediction schemes can lead to effective alert systems.

Given the increased urbanization and its potential to expose human populations to natural disasters such as flooding, it is crucial to perform accurate and reliable flood forecasting. In this regard, hydrological models have played a significant role by simulating natural hydrological processes using physical and empirical laws. These models have greatly contributed to modern flood forecasting.

1.1 Flood Forecasting

Flood forecasting is the technique of predicting the occurrence and severity of floods in a particular area. It involves the collection of data on rainfall, water levels, river flow, and other factors that could contribute to flooding, which is then analysed to create flood forecasts. These forecasts are essential for emergency management officials, as they provide advanced warning of potential flooding, allowing them to take pre-emptive measures to protect people and property. Flood forecasting also helps in the effective deployment of resources, such as sandbags, rescue boats, and emergency personnel. There are several methods used for flood forecasting, including statistical models, hydrological models, and data-driven models that use artificial intelligence and machine learning techniques. While these methods can help predict flooding with varying degrees of accuracy, it is important to note that they are not perfect and can be affected by unforeseen events or changes in weather patterns. Overall, flood forecasting is an essential tool in mitigating the impact of floods, reducing property damage, and ensuring the safety of people living in flood-prone areas.

In India, the Central Water Commission (CWC) is responsible for flood forecasting. The CWC operates a network of flood monitoring stations across the country to collect real-time data on rainfall, water levels, and other hydrological parameters. The data collected from these stations is used to develop flood models that can forecast floods for various river basins. flood forecasting is an essential aspect of disaster management in India. The Central Water Commission plays a vital role in collecting and analysing data and providing timely forecasts to the concerned authorities. With continuous improvements in the system, it is hoped that the damage caused by floods can be minimized in the future.

1.2 Adaptive Neuro Fussy Inference System (ANFIS)

The ANFIS toolbox is designed to generate a fuzzy inference system from input/output observations. It achieves this by utilizing either a backpropagation algorithm or a least squares method to dynamically adjust the adaptive working boundaries. The ANFIS architecture consists of a fuzzy layer, inference mechanism, defuzzied layer, and total as the final output layer. Its main objective is to leverage a learning algorithm and input data sets to obtain optimal values for the fuzzy inference system's parameters. During the training process, the boundary improvement is performed in a way that minimizes the error between the target and actual output. To optimize the parameters, a hybrid algorithm is employed that blends the techniques of gradient descent and least square estimation. In Figure 1 architecture of ANFIS is shown.

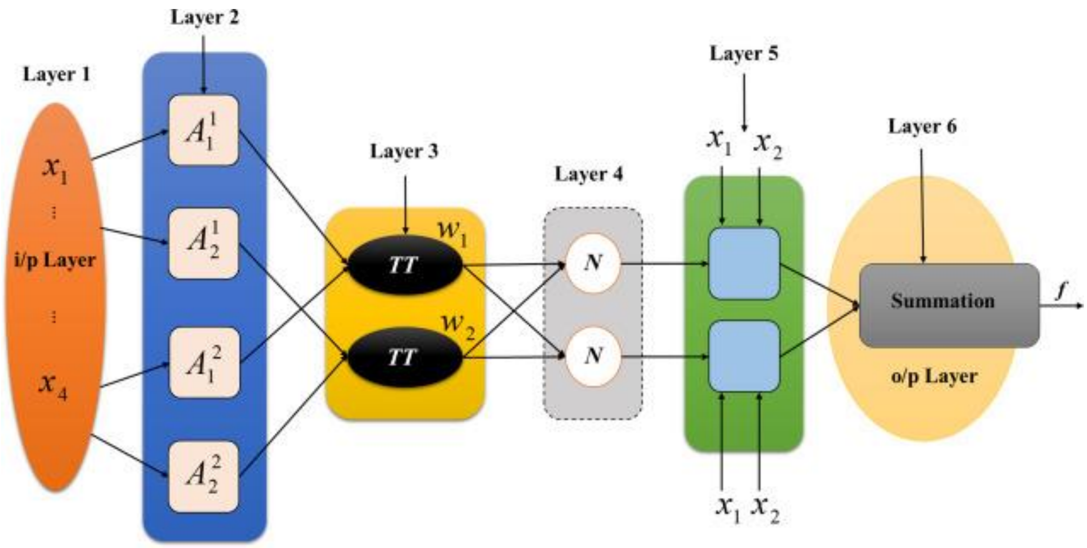

Fig. 1. Typical Architecture of ANFIS

1.3 Artificial Neural Network (ANN)

An Artificial Neural Network (ANN) is a form of artificial intelligence designed to emulate the functions of the human brain. ANNs are composed of processing units that have inputs and outputs, and their structure is based on computational components that utilize predefined activation functions to obtain inputs and outputs. By mimicking the network of neurons in the human brain, ANNs enable robots to understand and make decisions in a manner similar to humans. Unlike regular machines, which are programmed to operate in a linear manner, ANNs build connections between brain cells to create a computational model that consists of multiple processing elements. For receiving inputs and generating outputs based on their predetermined activation functions, the processing elements are responsible. Figure 2 provides a general representation of the ANN model and its processing.

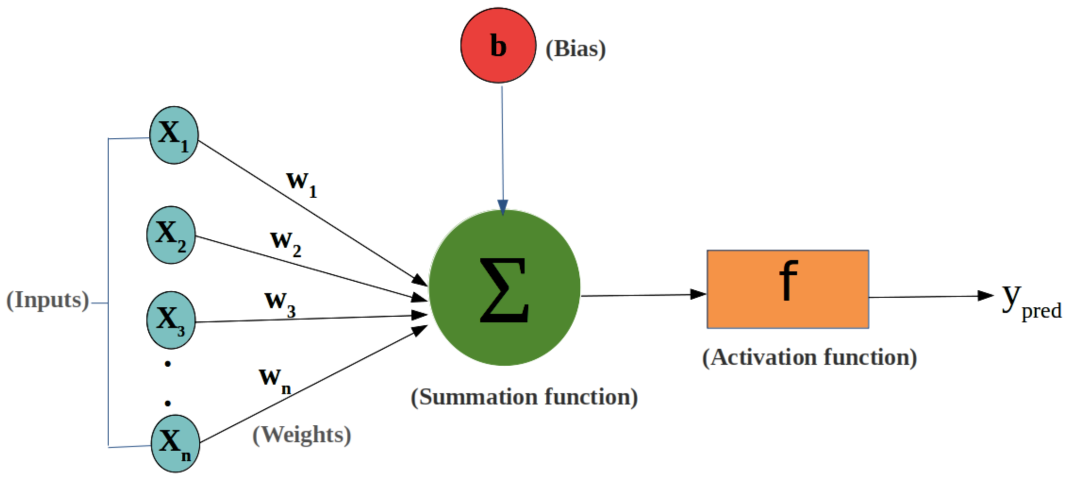

Fig. 2. Model structure of ANN

For the above general model of artificial neural network, the net input can be calculated as follows −

$y_{in} = x_1.w_1+x_2.w_2+x_3.w_3...x_m.w_m$

i.e., Net input $y_{in}=\sum m_i x_i.w_i$

The output can be calculated by applying the activation function over the net input.

$Y=F(y_{in})$

Output = function calculated.

2. Literature Review

Some of the recent literature is summarized in context with flood forecasting using soft computing techniques. Sandeep Samantaray *et al.,* shows that in order to forecast flood water levels accurately in the Mahanadi River basin during the monsoon season in India, two hybrid models were developed. These models combined the adaptive neuro-fuzzy inference system (ANFIS) with two optimization algorithms: the whale optimization algorithm (WOA) and the fruit-fly optimization algorithm (FOA). The performance of these hybrid models was evaluated using several statistical indices, including the determination coefficient (R2), root mean squared error (RMSE), mean absolute error (MAE), and Nash-Sutcliffe coefficient (ENS). The accuracy of the hybrid models was compared to that of a standalone ANFIS model. The results indicated that the ANFIS-WOA hybrid model provided more accurate predictions compared to the ANFIS-FOA and standalone ANFIS models during the training phase [1]. Ankita Agnihotri *et al.,* exhibited the capacity of hybrid optimization algorithm in further developing accuracy of typical ANFIS for flood forecasting. Capability of mixture flood estimating model is contrasted and independent ANFIS in view of quantitative factual lists like coefficient of assurance (R2), Mean Outright Mistake (MAE) and Root Mean Square Blunder (RMSE) [2]. Parag Ghorpade *et al.,* has shown that how machine learning algorithms have recently improved flood forecasting. The authors went over some well-known flood forecasting algorithms that can be used by professionals to create their own solutions [3]. Hongfei Zhu *et al.,* presented that to assess the improved artificial neural network (ANN), four actual flood events were utilized for validation purposes, comparing its performance against an existing model. The introduction of a new training dataset yielded substantial enhancements. Specifically, the rooted mean square error (RMSE) of the model decreased by 10% for the testing dataset and 16% for the real flood events, indicating improved accuracy and precision. The findings of the study highlight the improved accuracy and effectiveness of the enhanced ANN, rendering it a valuable tool for predicting and analysing flood events [4]. Agrawal *et al.,* explores the comparisons and distinctions between the two models MIMO-1 and MIMO-2 by evaluating their performance through rigorous statistical analysis. The validation process includes measuring key statistical criteria, such as the root-mean-square error, where the model's error is within 10% of the observed mean. Additionally, the coefficient of efficiency is assessed, requiring a value above 0.90. Various other statistical parameters are also considered to ensure a comprehensive evaluation. the comparative analysis of the models and their performance validation using diverse statistical criteria provide robust evidence of their potential in real-time scenarios. The paper underscores their applicability while ensuring adherence to the continuity norm, reinforcing their reliability and usefulness in practical settings [5]. Tabbussum and Qayoom carried out an analysis of the Jhelum River which is alluvial river in the area of the Indian Himalayas and various models were assessed and verified. To achieve this, several neural network functions were developed, including LVN network, SCGN network, Bayesian regularization artificial neural network, CGN network and resilient backpropagation [6]. Samantaray and Sahoo show that in order to forecast streamflow, four conventional statistical models - General extreme value method, Gumbel maximum distribution, Normal distribution method, and Log Pearson-III methods were utilized for 10, 20, 30, 35, 40, 50, 60, 70, 75, 100, and 150-year periods. The Gumbel max system was found to outperform the Standard, Log Pearson-III methods, and General extreme value method in terms of flow discharge for all four-gauge stations [7]. Francis Yongwa-Dtissibe *et al.,* utilized the multi-facet perceptron to plan a flood determining model and involved release as info yield factors. The planned model has been tried upon concentrated tests and the outcomes showed the viability of our proposition with a decent estimating limit [8]. Ogras and Fevzi presented that in order to carry out research studies on the effects of river bridges and hydraulic structures, such aqueduct, regulators, on cross-sections and water surface profiles, it is crucial to accurately identify and quantify these changes. To facilitate this process, several software packages have been developed for the measurement and analysis of water surface profiles. One such software is HEC-RAS. In the case of the Tigris River, a 1-Dimensional floodplain analysis was performed using HEC-RAS [9]. Nghiem Van Tinh shows that a study was conducted to assess the predictive capability of a neural network model in comparison to a multiple regression analysis. According to the study findings, the neural network model exhibited excellent performance in terms of prediction accuracy. It achieved an accuracy rate exceeding 96% within the range of +/-100 cubic feet per minute. Furthermore, the average error in the model's predictions was relatively minimal, measuring less than 16 cubic feet per minute. The average error of the predictions was also relatively low, at less than 16 cubic feet per minute. Additionally, the neural network model outperformed the multiple regression analysis in all measurement criteria, indicating that it may be a more effective tool for predicting outcomes in this context. However, without further information on the specifics of the study design and methodology, it is difficult to draw firm conclusions about the efficacy of the neural network model or its suitability for other applications [10]. Sanubari *et al.,* presented that Two key indicators that can be used to predict floods are water levels and rainfall data in a river. In order to explore the predictive capabilities of artificial neural networks for floods, a system has been proposed which uses a Radial Basis Function architecture. This architecture consists of three layers: an input layer, a hidden layer, and an output layer [11]. Mosavi *et al.,* show that various models developed by Machine learning (ML) have made significant contributions to the development of prediction systems in recent periods by the simulation of methods of dynamic statistics of natural flood processes, resulting in improved results and economic solutions. The use of ML has increased among hydrologists due to its variety of advantages and capabilities. Researchers aim to discover more dependable and impactful forecasting models by involving new machine learning approaches and hybridizing various approaches, leading to the development of optimized long-term and short-term flood prediction models [12]. Paul and Das presented that a Flood Prediction Model (FPM) that uses an Artificial Neural Network approach to forecast floods in rivers. This model uses rainfall and current river water level data to forecast river water levels. Changes in water level are caused by a variety of causes, but only two of them are taken into account. The flood prediction problem is a nonlinear problem, and the ANN technique is used to solve it. The Feed Forward (FF) and Back Propagation (BP) algorithms of the Multi Linear Perceptron (MLP) based ANN are utilized to do flood forecasting [13]. Sulafa Hag Elsafi has developed an ANN model for simulating flows at a specific location within a river reach, using the flow data from upstream locations. The study demonstrated that the ANN model was a dependable approach for detecting flood hazards in the river Nile [14].

3. Study Area

The Panam River Basin has been selected as the study area for this research. The Panam River Basin is part of the Mahi River Basin. Panam River is one of the tributaries of the Mahi River. It runs from the Dahod district's Devgadh Baria Taluka. The Mahi River is a significant west-flowing river in the area and has its source in the Vindhya mountains. It meets in the Gulf of Khambhat. The Mahi basin extents in the Madhya Pradesh state, Rajasthan, and Gujarat, with a total area of 34,842 square kilometres. The upper and lower basins are the two subbasins that make up the Mahi basin. (source:https://indiawris.gov.in/). There is a total of 92 rain-gauge stations in the Mahi River basin.

The Panam Dam is constructed on the Panam River in India, can be found in the Santrampur Taluka of the Mahisagar district in Gujarat. The Panam River is a Mahi River tributary originating from the Devgadh Baria Taluka in Dahod. The Panam Dam is located about 25 kilometres upstream from the confluence of the Panam and Mahi rivers. The stretch of the Panam River from the Panam Dam to the Mahi River is approximately 21.77 kilometres in length.

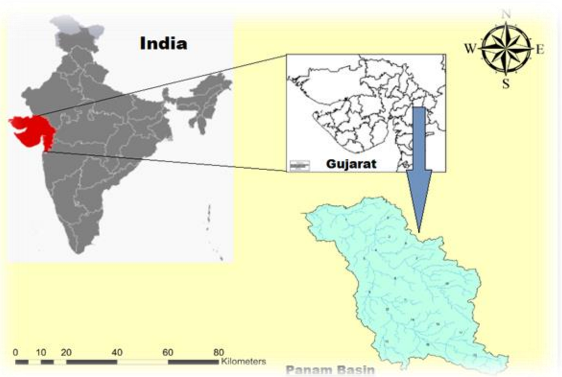

Fig. 3. Map of Panam River Basin

Fig. 4. Google Map of Panam Dam and Reservoir

4. Methodology

4.1 ANFIS Model

For the development of the ANFIS model, the total data set is divided into 2 parts, 70% data are used in the training of the model, and the remaining 30% data are used in validation. In the development of the ANFIS model, one input, i.e., rainfall, and one output, i.e., peak inflow discharge, are used. In the current study, hybrid optimization method is used with 100 epoch value. Many numbers of trials have been done using various numbers of membership functions like 2, 4, 6, 8, 10 and different membership functions like trim, trap me, belief, Gaussmf, Gauss2mf, etc., for the development of the ANFIS model. Then all the developed models are evaluated using different evaluation parameters like Root Mean Square Error (RMSE), Correlation Coefficient (R), Coefficient of Determination (R^2), and Discrepancy Ratio (D), which has concluded the best-suited ANFIS model for the Panam River basin.

Training of Adaptive Neuro-Fuzzy Inference Systems has been done in the following steps:

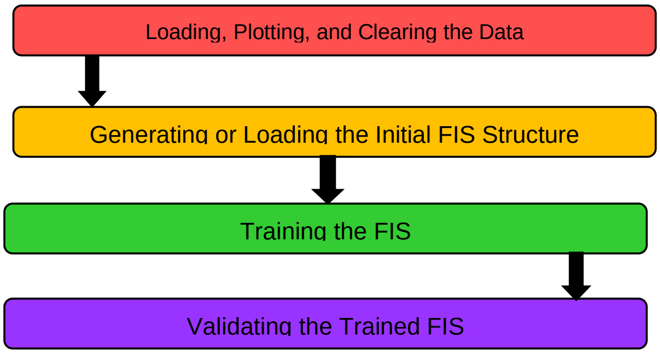

Fig. 5. Workflow of GUI of ANFIS

4.2 Artificial Neural Network Models

Artificial neural networks (ANNs) are computing systems that are inspired by the structure and function of biological neural networks. They consist of interconnected nodes, or artificial neurons, which process information and transmit it to other neurons in the network. ANNs are capable of learning from data and adjusting their internal parameters, or weights, to improve their performance on a given task. This process is known as training, and it typically involves feeding the network a large dataset with known input-output pairs and adjusting the weights to minimize the difference between the network's output and the true output. ANNs are particularly useful for solving problems that are difficult to model using traditional analytical methods, such as those involving complex nonlinear relationships or large amounts of data. They have been successfully applied to a wide range of applications, including image and speech recognition, natural language processing, prediction and forecasting, optimization, and control systems. However, ANNs also have some limitations, such as the difficulty of interpreting their internal workings and the potential for overfitting to the training data. Therefore, they should be used with caution and in conjunction with other analytical methods to ensure the validity and reliability of their results.

For making ANN models, three different training algorithms have been used. They are Levenberg-Marquardt, Bayesian Regularization and Scaled Conjugate Gradient. The all the network has been formed with 2 numbers of hidden layer with 5 neurons. In order to simulate a neuron, a simple calculation is performed by each individual neuron. The neuron receives signals from its input connections and utilizes these values to compute the activation level or output for the neuron. This resultant value is then transmitted to other neurons via its output connections. In the Neural network there are total 3 types of transfer function in each layer i.e., LOGSIG, TANSIG and PURELIN. So, each combination of function has tried for both the hidden layers. So total 270 network models have been formed by using all 3 algorithms with 9 combinations of 3 types of transfer function and 2 network types i.e., Feed forward and backpropagation and Cascade-forward backpropagation. All the developed is evaluated with the coefficient of correlation (R) and Mean Squared Error (MSE).

Following are the basic steps of ANN used in MATLAB:

i. Collection of input-output dataset
ii. Pre-processing of input-output dataset
iii. Neural network design and training
iv. Performance evaluation of the neural network.

The network diagram of Feed forward Back propagation is shown in Figure 6 and of Cascade forward Back propagation is shown in Figure 7.

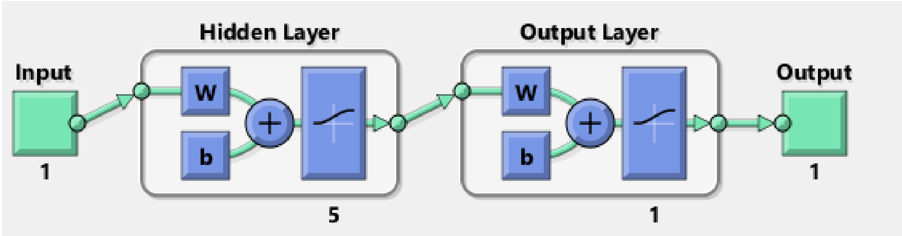

Fig. 6. Two layers feed forward back propagation network

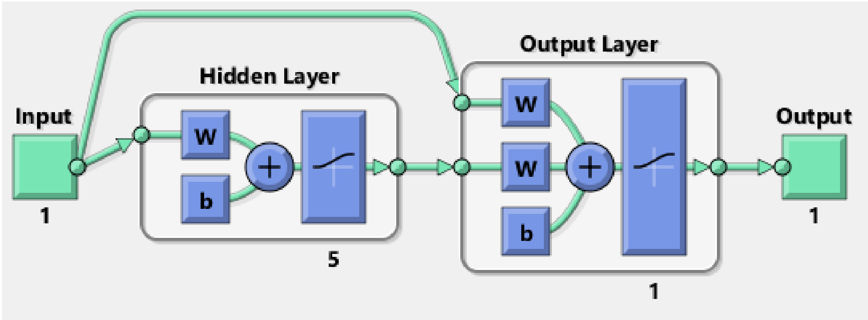

Fig. 7. Two layers cascade forward back propagation network

5. Result and Discussion

5.1 ANFIS Results

Discussing about the results of ANFIS, it is important to provide a comprehensive analysis that covers various aspects, showcasing both the strengths and limitations of the approach and demonstrating its practical utility in various applications.

ANFIS allows for rule extraction, which means it can provide interpretable fuzzy rules based on the learned model. This is particularly useful in domains where interpretability is essential. You can discuss the extracted rules and their implications, highlighting the comprehensibility and transparency of ANFIS compared to other black-box models.

Results and discussion about ANFIS typically involve an analysis of the model's performance, its accuracy, generalization capabilities, rule extraction, and a comparison with other models.

Performance Evaluation is carried out to evaluate ANFIS, such as accuracy of RMSE, R, R^2 etc. A detailed comparison of ANFIS's performance on the training dataset and also highlighting its ability to fit the data accurately is mentioned. The model's performance on a separate validation dataset is also carried out to assess its generalization capabilities.

The performance of different ANFIS models is presented in Table 1 with Root Mean Square Error (RMSE), Correlation Coefficient (R), Coefficient of determination (R^2), and Discrepancy Ratio (D).

Table 1
Performance evaluation parameters in training and validation of the ANFIS Model

Type of Mfs	No.of Mfs		ANFIS Error	RMSE	R	R^2
Gbellmf	6	Training	622.62	622.62	0.88	0.77
		Validation	3529.81	3529.81	0.99	0.98
	8	Training	516.69	516.69	0.92	0.85
		Validation	1140.98	1140.98	0.99	0.98
	10	Training	268.72	268.72	0.97	0.94
		Validation	237305.28	237305.28	0.98	0.96
Gaussmf	6	Training	634.08	634.08	0.88	0.77
		Validation	2119.91	2119.91	0.98	0.96
	8	Training	559.43	559.43	0.90	0.81
		Validation	2784.99	2784.99	0.99	0.98
	10	Training	277.07	277.07	0.98	0.96
		Validation	280176.2	280176.2	0.99	0.98
Gauss2mf	6	Training	666.59	666.59	0.87	0.76
		Validation	5809.66	5809.66	0.67	0.45
	8	Training	321.89	321.89	0.97	0.94
		Validation	19141	19141	0.99	0.98
	10	Training	271.91	271.91	0.98	0.96
		Validation	2000.74	2000.74	0.95	0.90
Pimf	6	Training	671.3	671.29	0.87	0.76
		Validation	5963	5962.76	0.71	0.50
	8	Training	869.59	869.59	0.76	0.58
		Validation	6089.11	6089.11	0.21	0.04

From the table, it has been observed that 10 numbers of Gauss2 type membership function perform best from all the developed ANFIS models as it has minimum RMSE and Correlation Coefficient (R) nearer to 1. The comparative graphs for observed and predicted discharge are plotted for training and validation of the ANFIS model, as shown in Figures 8 and 9, respectively.

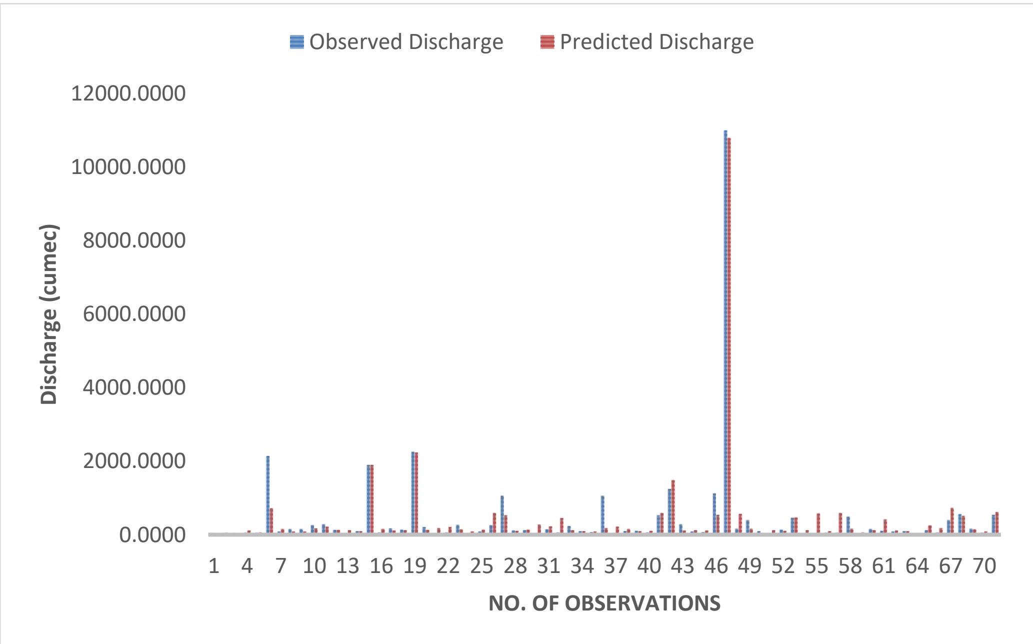

Fig. 8. Comparative graph of observed & predicted peak discharge for Training using ANFIS for 10 number of Gauss2 membership function

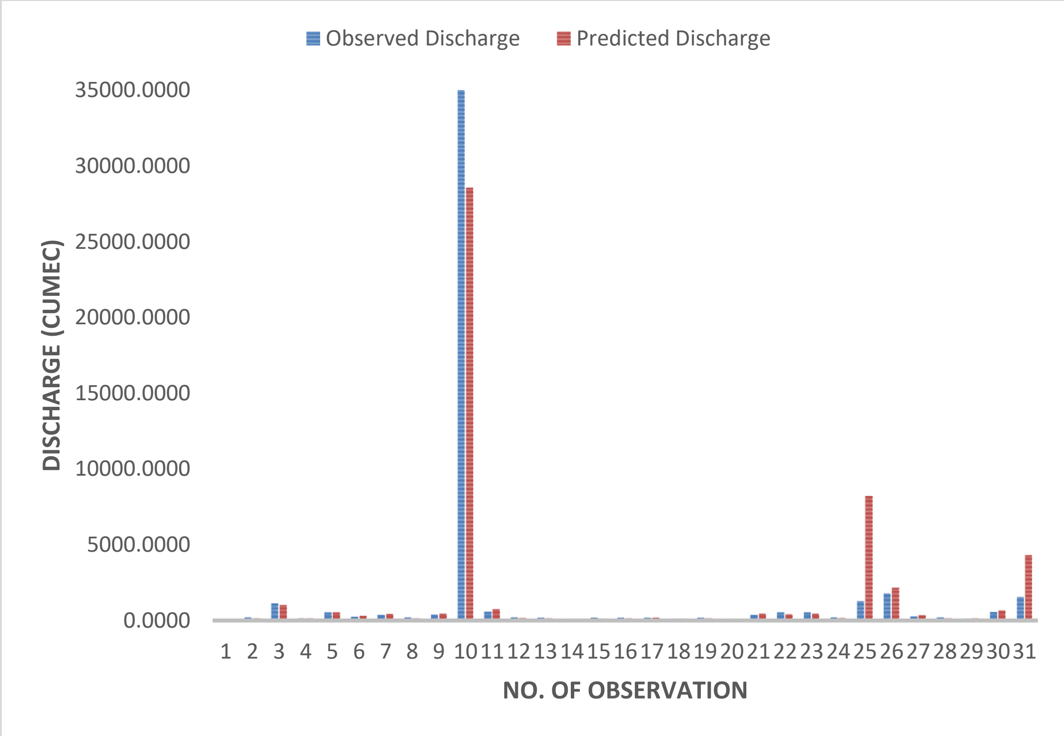

Fig. 9. Comparative graph of observed & predicted peak discharge for Validation using ANFIS for 10 number of Gauss2 membership function

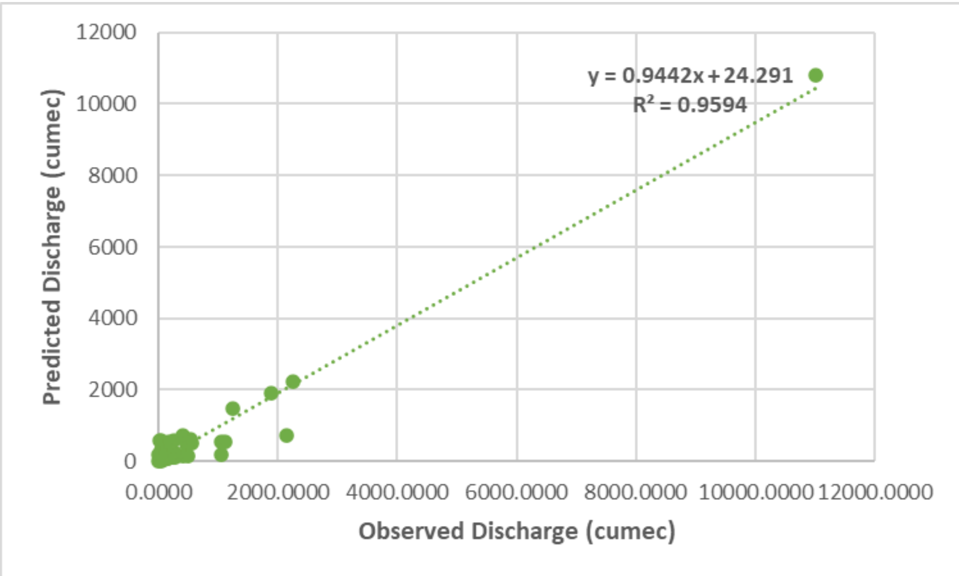

Fig. 10. Regression Curve between predicted discharge and observed discharge in the Training stage of the ANFIS model

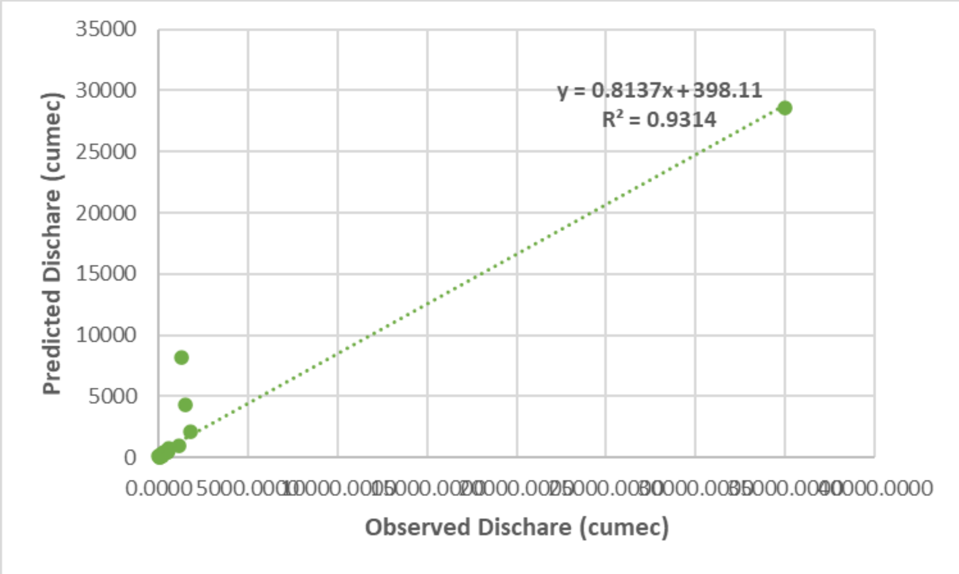

Fig. 11. Regression Curve between predicted discharge and observed discharge in the Validation stage of ANFIS model

Comparing the performance of ANFIS with other existing models or algorithms used for the same problem domain highlights the advantages of ANFIS, such as its ability to handle uncertainty, learn from data, and capture complex relationships.

5.2 ANN results

Results and discussion about Artificial Neural Networks (ANNs) typically involve analysing the model's performance, accuracy, training process, architecture, generalization capabilities, comparison with other models, and potential applications.

For all the developed ANN models corelation coefficient (R) and Mean Squared Error (MSE) are determined in nntool, Matlab. Some of the good results are listed in the Table 2 below.

Table 2
ANN model performance for Levenberg-Marquardt Algorithm

Feed Forward Back Proporgation						
Transfer Function		Values of Corelation Coefficient R				
Layer 1	Layer 2	Training	Validation	Testing	Overall	MSE
LOGSIG	PURELIN	0.71	0.97	0.03	0.71	38362.8
PURELIN	TANSIG	0.67	0.91	0.93	0.67	39985.83
TANSIG	PURELIN	0.72	0.96	0.79	0.71	86769.89
Cascade Forward Back Proporgation						
LOGSIG	PURELIN	0.7	0.63	0.98	0.69	350432.7
PURELIN	PURELIN	0.99	0.71	0.38	0.98	23253.71
TANSIG	TANSIG	0.68	0.9	0.38	0.68	80292.33

Table 3
ANN model performance for Bayesian Regularization Algorithm

Feed Forward Back Proporgation						
Transfer Function		Values of Corelation Coefficient R				
Layer 1	Layer 2	Training	Validation	Testing	Overall	MSE
LOGSIG	TANSIG	0.47	95	-0.12	0.44	49803.87
PURELIN	TANSIG	0.67	0.96	0.51	0.67	14794.56
TANSIG	TANSIG	0.72	0.3	0.64	0.72	75927.02
Cascade Forward Back Proporgation						
LOGSIG	TANSIG	0.99	0.86	0.45	0.99	16140

Table 4
ANN model performance for Scaled Conjugate Gradient Algorithm

Feed Forward Back Proporgation						
Transfer Function		Values of Corelation Coefficient R				
Layer 1	Layer 2	Training	Validation	Testing	Overall	MSE
LOGSIG	PURELIN	0.89	0.86	0.88	0.67	9630.66
TANSIG	PURELIN	0.77	0.63	0.7	0.48	18793.43
Cascade Forward Back Proporgation						
LOGSIG	PURELIN	0.7	0.63	0.98	0.69	350432.7
PURELIN	PURELIN	0.7	0.98	0.66	0.69	23346.45

The results of flood forecasting have various practical uses and applications in mitigating the impacts of floods and improving emergency response. Here are some key uses of the results of flood forecasting:

i. Early Warning Systems: The results of flood forecasting provide critical information for the development and implementation of early warning systems. They enable authorities and emergency management agencies to issue timely warnings to at-risk communities, allowing for evacuation and preparation measures to be implemented in advance.
ii. Emergency Response Planning: Flood forecasting results help in formulating effective emergency response plans by providing insights into the potential extent, severity, and timing of flood events. Authorities can allocate resources, such as personnel, equipment, and supplies, based on the forecasted flood scenarios to ensure an efficient and targeted response.
iii. Infrastructure Design and Management: The results of flood forecasting contribute to the design, construction, and management of infrastructure in flood-prone areas. They aid in determining the appropriate elevations, capacities, and locations of flood protection structures, such as levees, dams, and flood walls. The data can also inform the maintenance and operation of existing infrastructure, ensuring its resilience against flood events.
iv. Land Use Planning and Development: Flood forecasting results play a crucial role in land use planning and development decisions, particularly in floodplain areas. They provide valuable information for zoning regulations, building codes, and development guidelines to mitigate the risk of flooding. Authorities can identify areas prone to flooding and implement measures to limit development or promote flood-resilient construction practices.
v. Insurance and Risk Assessment: The results of flood forecasting are instrumental in assessing and managing flood-related risks for insurance purposes. Insurance companies can utilize the forecasted flood scenarios to determine premiums, coverage, and

underwriting policies. The data also aid in estimating potential losses and damages, supporting risk assessment and modelling activities.

vi. Water Resource Management: Flood forecasting results contribute to effective water resource management, particularly in river basins and reservoir operations. They assist in optimizing water releases, flood control measures, and water allocation strategies during flood events. The data also support decision-making related to hydropower generation, irrigation systems, and water supply management.

vii. Climate Change Adaptation: The results of flood forecasting are crucial for climate change adaptation strategies, helping communities and authorities to anticipate and prepare for the potential increase in flood frequency and intensity. They support the development of adaptive measures, such as flood-resilient infrastructure, improved drainage systems, and land use planning considering future climate scenarios.

viii. Research and Scientific Understanding: The results of flood forecasting contribute to scientific research and the understanding of flood dynamics, hydrological processes, and forecasting methodologies. Researchers can analyse the accuracy and performance of forecasting models, evaluate the effectiveness of different approaches, and identify areas for improvement.

By utilizing the results of flood forecasting in these practical applications, communities, authorities, and stakeholders can make informed decisions, implement appropriate measures, and reduce the impacts of floods on human lives, infrastructure, and the environment.

6. Conclusion

The results clearly illustrated that ANFIS with ten number of Gauss2 type of membership function performed very well in prediction of flood as the RMSE is 271.91 in training and 2000.74 in validation, the coefficient of correlation for Training and validation is 0.98 and 0.95 respectively. Coefficient of determination (R^2) of observed peak discharge and predicted peak discharge for Training is 0.96, and for validation is 0.90.

The ANFIS model that has been developed can be applied in various ways, such as implementing effective measures to control flood risks, reducing flood hazards, evacuating people from areas prone to flooding, establishing appropriate insurance premiums, and managing water resources and environmental systems.

From the results of ANN, it is seen that Scaled Congugate Algorithm with Feed forward and Back Propagation network and LOGSIG and PURELIN transfer function for layer1 and layer 2 respectively gives good results with 9630 MSE and the coefficient of correlation for Training and validation is 0.89 and 0.86 respectively.

So, from the results of ANFIS Model and ANN model it is concluded that ANFIS model performs best in the forecasting of flood of Panam river basin.

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