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Implementation of Neuro-Fuzzy and Statistical Technique for Flood Forecasting in Cauvery Basin, India

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Abstract— Prediction and forecasting has been significant area of study in computer science since last decades**.** Out of various approaches, soft computing data driven models are very effective for forecasting. Soft Computing Models are usefully applicable when the relationship between the parameters are very complex to understand. India a disaster prone country which requires such major soft computing based data driven models to handle disasters like flood, drought, landslide etc. Flood has a major impact in many parts of India out of which Cauvery, Godavari and Ganges river basins are the mostly affected regions. The paper attempts to forecast floods by modeling river flow in the area of Cauvery river basin of India which has a complicated topography. In this study, the potential of two data driven techniques namely, Adaptive Neuro Fuzzy Inference System (ANFIS) and Gaussian Process Regression (GPR) were used for forecasting floods by predicting river flow in Cauvery river sub-basin of southern India. The techniques were applied on various models constructed from combinations of various antecedent river flow values from two gauging stations and the results were compared for the best fit models of each technique. To get more accurate assessment of results of the models, three standard statistical quantitative performance assessment parameters, the Mean Squared Error (MSE), the coefficient of correlation (R) and the Nash-Sutcliffe coefficient (NS) were used to analyze the performances of the models developed. A complete comparison of the overall performance indices demonstrated that the ANFIS models performed better than GPR models in flood prediction.

Keywords—Adaptive Neuro Fuzzy Inference System (ANFIS), Gaussian Process Regression (GPR), Mean Squared Error (MSE), the coefficient of correlation (R), Nash-Sutcliffe coefficient (NS)

I. Introduction

Forecasting and prediction problems have been studied by various researchers during the past few decades. Forecast models can be classified into the two main categories, physical statistical models and data driven models. Physically statistical models are complicated and need advanced mathematical and statistical tools, a significant quantity of calibration data and some degree of expertise and experience with those models [1]. On the other hand, data driven models do not furnish any knowledge of the hydrological processes, they are very helpful for forecasting where the underlying relationship between the parameters are very complex to understand and model mathematically [2]. River flow forecasting is very important for flood prediction as they can result in loss of life, destruction of infrastructure, devastation of power generation capacity, scarcity of clean drinking water and increased likelihood of waterborne illness [3].

In the recent past, various data driven techniques that have emerged and became popular in the research community for solving computationally demanding problems are Adaptive Neuro Fuzzy Inference System (ANFIS) and Gaussian Process Regression (GPR). These models provide superiority over conventional modeling by providing the ability to handle noisy and uncertain data in dynamic and nonlinear systems thus providing us the ability to utilize them in analyzing and assessing various phenomenon causing disasters where it is not possible to fully avoid the uncertainty in datasets.

In the past few decades, the focus of research has been shifting from conventional methods of forecasting to data driven Soft Computing methods extensively. A hybrid method combining ANN and Fuzzy Logic called Adaptive Neuro Fuzzy Inference System (ANFIS) has been extensively used in recent years for forecasting disasters. ANFIS technique was employed for landslide susceptibility mapping [4]. The authors present a comparative study of ANFIS and multi-objective evolutionary neural network for predicting floods [5]. ANFIS was used for the purpose of drought prediction in Anatolia, Turkey [6]. The authors apply ANN and ANFIS methodologies and provide a comparative study for river flow forecasting [7]. ANFIS is applied for hydrological modeling and river flow forecasting of river Great Menderes, located in western Turkey [8]. The authors developed an artificial neural network for rainfall prediction [9]. Another research provided classification of data mining techniques for the purpose of weather prediction using machine learning [10].

Gaussian Process Regression (GPR) has also been gaining importance in this field. The GPR was employed for the prediction of stream water temperature of Drava River, Republic of Croatia [11]. The authors employed GPR to perform one month ahead streamflow prediction of river basins in United States of America [12].

The main aim of this study is to analyze the applicability and efficiency of Adaptive Neuro Fuzzy Inference System (ANFIS) and Gaussian Process Regression (GPR) for modeling and forecasting floods in the Cauvery Basin subzone located in Southern India. This paper obtains the results of these two data driven models and compares them to examine their accuracy in modeling the river flow for flood forecasting and evaluate their performance.

The rest of the paper is organized as follows. Section II describes the various methods implemented in this paper. In Section III, the study area is discussed. Section IV describes the dataset and performance criterion used for testing the accuracy of the various techniques. Section V explains the model inputs, configuration and discusses the results. Section VI concludes the paper.

II. METHODOLOGY

Data driven methods have been applied by researchers in the field of disaster management successfully as they aim to exploit tolerance is data for imprecision, uncertainty and partial truth to achieve robustness effective solutions [13]. Although it is not possible to fully avoid the natural disasters due to the uncertainty in datasets related to disasters, but their impact can be minimized by developing an appropriate forecasting system, through application of data driven soft computing techniques for more accurate and successful disaster management activities.

A. Adaptive Neuro Fuzzy Inference System (ANFIS)

Adaptive Neuro Fuzzy Inference System (ANFIS) is a universal approximator and is able to approximate any real continuous function on given dataset set to any degree of precision [14]. ANFIS is functionally analogous to fuzzy inference systems. There are two types of fuzzy inference system in the literature: the Sugeno–Takagi inference system and the Mamdani inference system. In this paper, the first-order Sugeno–Takagi fuzzy model is used for modeling which is detailed as follows.

The first-order Sugeno–Takagi fuzzy model for two inputs x and y and one input z can be expressed as:

Rule 1: If x is A_1 and y is B_1; then $f_1 = p_1x + q_1y + r_1$
Rule 2: If x is A_2 and y is B_2; then $f_2 = p_2x + q_2y + r_2$

where p_1, q_1, r1 and p_2, q_2, r_2 are the parameters in the consequent part of the first-order Sugeno–Takagi fuzzy model. Figure 1 shows the architecture of ANFIS composed of five layers.

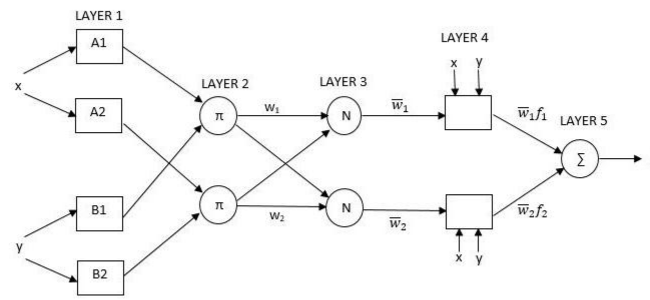

Figure 1: ANFIS architecture for 2 – input first order Sugeno Takagi fuzzy model with 2 rules.

Layer 1: Every node in this layer is an adaptive node with a node function as described below.

$$O_{1,i} = \begin{cases} \mu_{A_i}(x),\ for\ i = 1,2 \\ \mu_{B_{i-2}}(y), for\ i = 3.4 \end{cases} \quad (1)$$

here x and y are input to node i and A_i and B_{i-2} are linguistic label associated with this node. Therefore, $O_{1,i}$ is the membership grade of a fuzzy set A_1, A_2, B_1 or B_2 characterized by shape of membership function such as gaussian, bell, triangular or trapezoidal.

Layer 2: This layer consists of a number of nodes each of which is labelled Prod and produces the product of all the incoming inputs in it as its output.

$$O_{2,i} = \mu_{A_i}(x).\mu_{B_i}(y), for\ i = 1,2 \quad (2)$$

The output from each of these nodes represent the firing strength of the corresponding rule.

Layer 3: Nodes in this layer are fixed nodes labelled Norm and the i^{th} node of this layer calculates the ratio between the i^{th} rule's firing strength and the sum of the firing strengths of all the rules.

$$O_{3,i} = \overline{w_i} = \frac{w_i}{w_1+w_2}, for\ i = 1,2 \quad (3)$$

The outputs of these nodes are referred to as the normalized firing strengths.

Layer 4: The node function of i^{th} node which calculates the contribution of i^{th} rule to the model output in this layer is:

$$O_{4,i} = \overline{w_i} f_i = \overline{w_i}(p_i x + q_i y + r_i) \tag{4}$$

where w_i is the normalized firing strength from layer 3 and $\{p_i, q_i, r_i\}$ is the parameter set of the i^{th} node and is known as consequent parameters.

Layer 5: This single node layer calculates the output of the network by the summation of incoming inputs and is expressed as:

$$O_{5,i} = \sum_i \overline{w_i} f_i = \frac{\sum_i w_i f_i}{\sum_i w_i} \tag{5}$$

The ANFIS is trained using a hybrid learning algorithm composed of least squares and gradient descent methods. The least squares method is used to identify the consequent parameters in layer 4 during forward pass. During the backward pass the errors are propagated backward and the premise parameters are updated using the gradient descent method.

B. Gaussian Process Regression (GPR)

Gaussian Process Regression (GPR) models represent a nonparametric and kernel based probabilistic technique for the purpose of solving nonlinear regression [15]. Consider a training dataset $\{\{x_i, y_i\}; i = 1, 2\ldots n\}$, where $x_i \epsilon R^d$ and $y_i \epsilon R$, are taken from an unknown distribution. A GPR method forecasts the value of an output variable y_* given the new input vector x_* and the training data.

A linear regression model is of the form

$$y = x^t\beta + \epsilon \tag{6}$$

where $\epsilon \sim N(0,\sigma^2)$. The error variance σ^2 and the coefficient β are approximated from the data. A GPR model calculates the output by proposing latent variables, $f(x_i)$, $i = 1, 2\ldots n$, from a gaussian process and basis function h. The covariance of the latent variables represents the smoothness of the output and basis function h project the inputs x into a p-dimensional feature space.

A gaussian process is a set of random variables chosen in such a way that any finite number of them have a gaussian distribution. If $\{f\{x\}, x \epsilon R^d\}$ is a gaussian process, then for $\{x_1,x_2,\ldots,x_n\}$, the distribution of random variables $f(x_1),f(x_2),\ldots,f(x_n)$ is gaussian and $E(f(x)) = m(x)$ and $Cov[f(x),f(x')] = E[\{f(x) - m(x)\}\{f(x') - m(x')\}] = k(x, x')$are the mean and covariance functions of the gaussian process. Now consider the following model:

$$h(x)^T\beta + f(x) \tag{7}$$

where $f(x) \sim GP(0, k(x, y'))$ i.e., f(x) are from a zero mean gaussian process with covariance function k(x, x′). h(x) are a set of basis functions that convert the original input $x \epsilon R^d$ into $h(x) \epsilon R^n$. β is a p X 1 array of basis function coefficients. This model represents a GPR model and an instance of output y can be given as:

$$P(y_i|f(x_i), x_i) \sim N(y_i|h(x_i)^T\beta + f(x_i),\ \sigma^2) \tag{8}$$

III. STUDY AREA

The applicability of the various mentioned techniques as a time series forecasting model is studied in this paper. To demonstrate the ability and validity of these methods for time series forecasting and modeling, the Cauvery River, the biggest in southern India is chosen. The river has been used for irrigation, domestic and industrial use and hydropower generation. The Cauvery river basin is one of the most important agricultural regions in south India. It has a length of 800 km and a drainage area of 81,155 km^2. The annual runoff potential of Cauvery river is 21.36 km^3 [16]. The location of Cauvery River and its drainage basin are shown on Figure 2. There are two river flowing gauge stations, Kodumudi and Musiri equipped with automatic daily flow recorders on the Cauvery river main branch as shown in Figure 3. As can be seen in the figure, the river flow gauging station of Kodumudi is located upstream of Musiri. The data records of both these river gauging stations are used for river flow and flood forecast modeling.

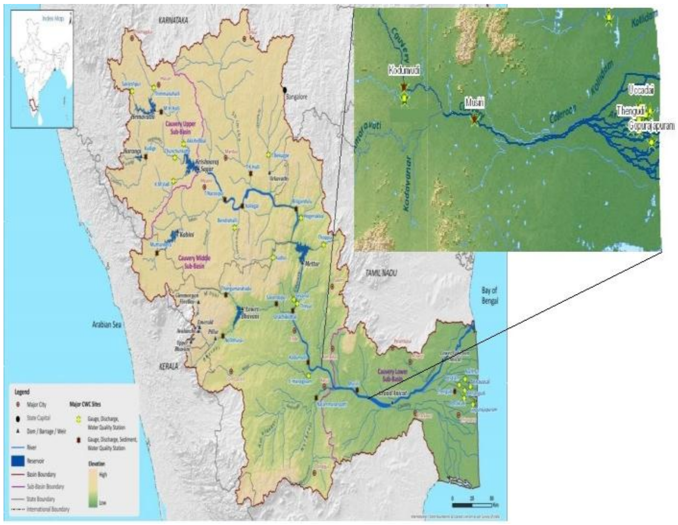

Figure 2: Location of Cauvery River and Gauging Stations.

IV. MODEL DEVELOPMENT

A. Description of Data

In this paper, the performance of ANFIS and GPR were examined on daily flow. To achieve this, 17 year flow data was available from 2000 to 2016 [17]. In total, the number of days for which the flow data was available were 3562. The data were divided into two sets: a training data composed of years 2000-2015 and a testing dataset of year 2016. This paper utilizes whole year dataset was used in training of the models as it allows the incorporation of numerous hydrological conditions that are prevalent throughout different seasons of the year. In this way, the models become more resilient for handling different hydrological conditions that occur in the whole time series [18]. The daily statistical parameters which contain the minimum value M_{min}, maximum value M_{max}, mean M_{mean}, standard deviation M_{stdev} and skewness coefficient M_{ske} of the river flow data are shown on Table 1.

Table1: Statistical Parameters of Dataset

	M_{min}	M_{max}	M_{mean}	M_{stdev}	M_{ske}
Training	0.08	7690.26	323.78	383.05	6.07
Test	1.23	683.86	195.15	164.19	0.29

The number of lags were selected according to the partial auto-correlation function (PCF) of daily flow data of Musiri gauging station which is shown in Figure 3. It is clear from the figure that first two lags have significant effects on M_{t+1}. The cross correlation of the Musiri and Kodumudi gauging stations presented in Figure 4 shows a significant correlation for up to two days lag in the flow data. Thus two previous lags of Musiri and two lags of Kodumudi gauging stations were considered as inputs to the model in this study. The inputs present the previous flow (t-1 and t-2) and the output corresponds to the flow at time t+1. Thus, the structure of the forecasting models are shown in Table 2 where the Musiri gauge flow data is represented as M and Kodumudi gauge flow data is represented as K.

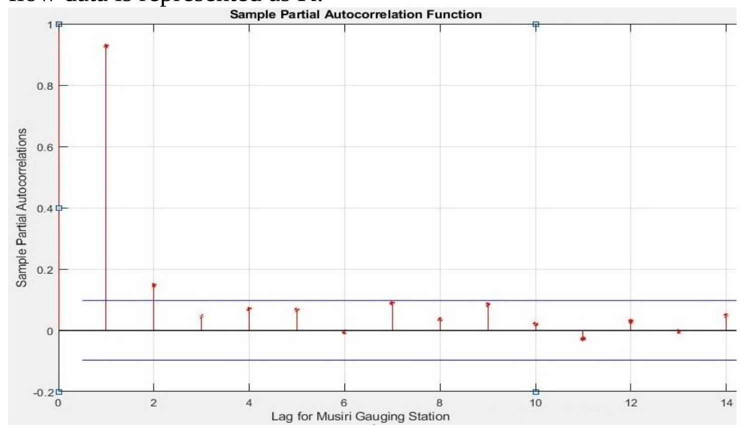

Figure 3: Partial auto-correlation function of daily flow data of Musiri Gauge station.

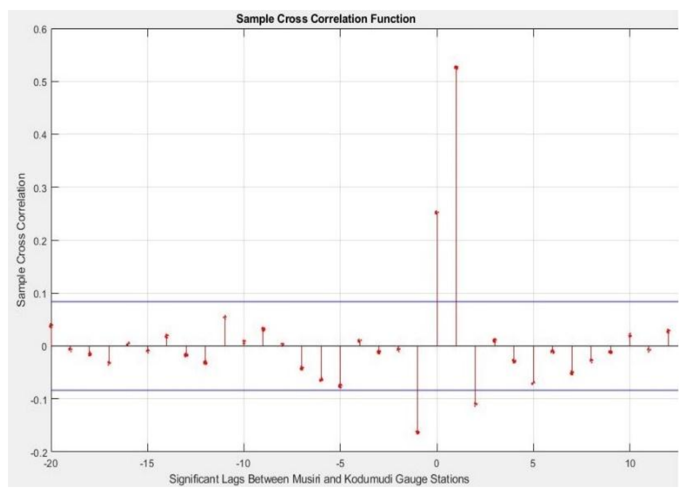

Figure 4: Cross-correlation function of daily flow data of Musiri and Kodumudi Gauge stations.

Table 2: Model Structures for Forecasting

Model No.	Input Structure	No. of Variables	Output
M1	M_{t-1}	1	M_{t+1}
M2	M_{t-1} M_{t-2}	2	M_{t+1}
M3	M_{t-1} K_{t-1}	2	M_{t+1}
M4	M_{t-1} M_{t-2} K_{t-1}	3	M_{t+1}
M5	M_{t-1} K_{t-2}	2	M_{t+1}
M6	M_{t-1} M_{t-2} K_{t-2}	3	M_{t+1}

M7	M_{t-1} M_{t-2} K_{t-1} K_{t-2}	4	M_{t+1}

B. Data preprocessing

For the purpose of obtaining efficient and accurate training of the models, the data are needed to be normalized. It was reported in [19] that models trained on normalized data attain better performance and rapid convergence. In this paper, normalization is performed on all data scaled in the range 0 - 1 independently by employing the following equation:

$$X' = \frac{X - X_{min}}{X_{max} - X_{min}} \quad (9)$$

where X' is the normalized value, X is the sample value, X_{min} is the minimum value and X_{max} is the maximum value.

C. Model Performance Criteria

The performance of the models developed in this paper were evaluated using three standard statistical performance assessment criteria. The statistical measures used were the Mean Squared Error (MSE), coefficient of correlation also known as Regression (R) and Nash–Sutcliffe efficiency coefficient (NS). MSE gives the information about the predictive ability of the model, R measures the degree to which two variables are linearly related and NS gives the predictive power of the models. MSE provides the average squared difference between output of the model and the actual test outputs. It can be calculated as follows:

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(t_i - a_i)^2 \quad (10)$$

where n is the size of dataset, a_i is the output of the model and t_i is the corresponding actual output.

R is defined as the correlation between targets and outputs. When the value of R = 1, it means that there is a close relationship between targets and outputs and is R = 0, it means that there is random relationship between the two. It is calculated by the equation:

$$R = \frac{\sum_{i=1}^{n}(t_i - \bar{t})(a_i - \bar{a})}{\sqrt{\sum_{i=1}^{n}(t_i - \bar{t})^2 \sum_{i=1}^{n}(a_i - \bar{a})^2}} \quad (11)$$

The Nash–Sutcliffe efficiency coefficient (NS) can be measured as:

$$NS = 1 - \frac{\sum_{i=1}^{n}(t_i - a_i)^2}{\sum_{i=1}^{n}(t_i - \bar{t})^2} \quad (12)$$

where n is the size of dataset, a_i is the output of the model and t_i is the corresponding actual output. A model can be claimed to give a perfect prediction if the NS criterion is equal to 1 but a model can considered as accurate if the NS value of larger than 0.8 as shown in [20].

V. RESULTS AND DISCUSSION

In this study ANFIS and GPR methods were applied to the models developed above and the results are described in this section. The implementation and analysis of results of the above mentioned techniques were performed in MATLAB 2017b.

A. Adaptive Neuro Fuzzy Inference System (ANFIS)

The ANFIS technique was applied to all seven models. The number of membership functions was considered 4 or 5 according to the type of model. The type of membership function used for all models was of Trapezoidal-shaped membership function which is function of a vector x and depends on four scalar parameters a, b, c and d and is given by (13). The parameters of the membership functions were adjusted using the back-propagation algorithm. The outputs function of the ANFIS model was considered as a linear type.

$$f(x,a,b,c,d) = \begin{cases} 0, x \le a \\ \frac{x-a}{b-a}, a \le x \le b \\ 1, b \le x \le c \\ \frac{d-x}{d-c}, c \le x \le d \\ 0, d \le x \end{cases} \quad (13)$$

Table 3 illustrates the performance indices from all seven models trained using ANFIS technique. As observed in the table Model 6 composed of both antecedent flow data of Musiri gauging station and the second antecedent flow data of Kodumudi gauging station has the lowest MSE value of 0.00549, highest R value of 0.945 and highest NS value of 0.8937 is the best fit model for ANFIS technique. The comparison between the observed and the ANFIS computed temporal variation of flow obtained during testing of Model 6 is shown in Figure 5.

Table 3: Performance Indices of ANFIS Models

Model	MSE	R	NS
M1	0.01722	0.863	0.6667
M2	0.02938	0.778	0.4320
M3	0.18635	0.437	0.6054
M4	0.18584	0.288	0.5914
M5	0.03503	0.729	0.3230
M6	0.00549	0.945	0.8937
M7	0.23587	0.248	0.5583

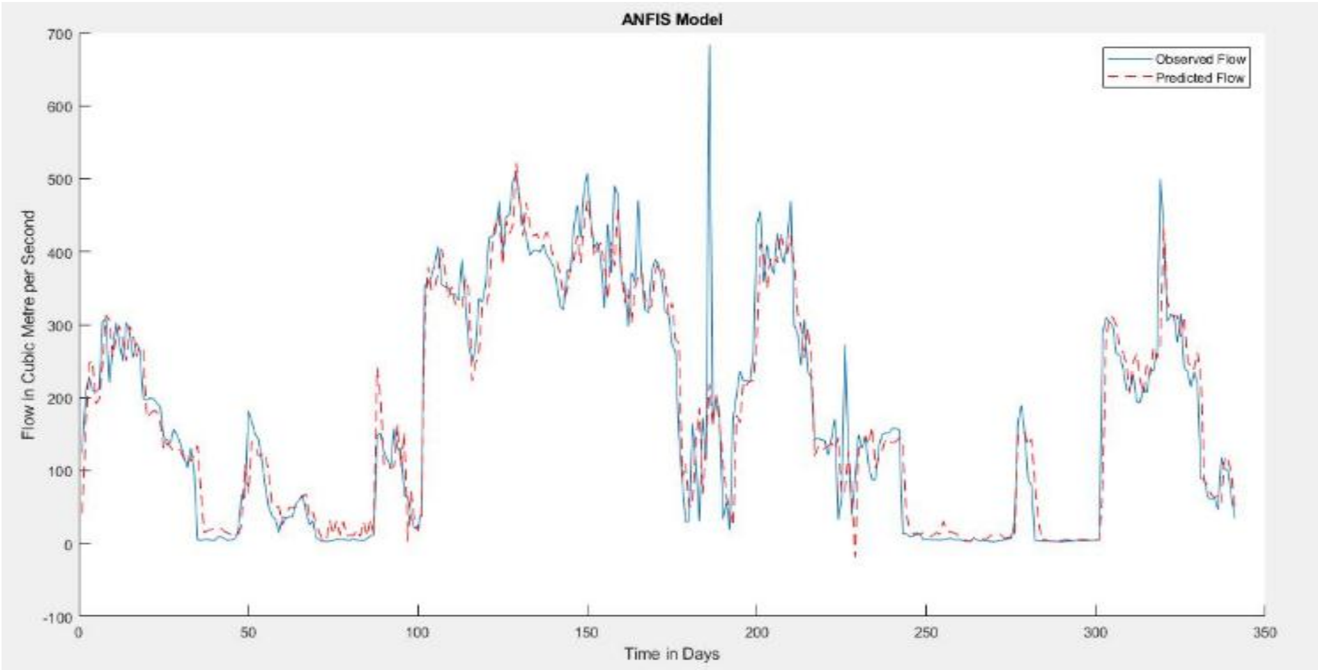

Figure 5: Comparison of observed and ANFIS predicted flow obtained from Model 6 during testing.

B. Gaussian Process Regression (GPR)

Table 4 represents the performance indices of the models obtained after applying GPR technique. As can be observed from Table 4 that the Model 3 which consists of one antecedent flow data of both the gauging stations has the lowest MSE value of 0.04417, the highest R value of 0.684 and NS value of 0.6454 and thus it was selected as the best fit model for GPR in this study. The comparison between the observed and the GPR computed temporal variation of flow obtained during testing of Model 3 is shown in Figure 6.

Table 4: Performance Indices of GPR Models

Model	MSE	R	NS
M1	0.08397	0.301	0.2246
M2	0.04934	0.670	0.0465
M3	0.04417	0.684	0.6454
M4	0.05350	0.591	0.0341
M5	0.06047	0.620	0.1687
M6	0.06906	0.569	0.3346
M7	0.05546	0.500	0.0718

The performances of best fit models of ANFIS and GPR are shown in Table 5. It can be observed from the results that ANFIS model seem to perform better than other models as it has minimum MSE and highest R and NS values. The model of ANFIS showed good prediction for low values of flow but was unable to maintain its accuracy for peak value of flow. The GPR model was not able to predict the flow with high accuracy as is evident from high value of MSE and low values of R and NS.

Table 5: Comparison of Performance Indices of ANFIS and GPR Best Fit Models

Technique	Model	MSE	R	NS
ANFIS	M6	0.00549	0.945	0.8937
GPR	M3	0.04417	0.684	0.6454

Overall, the ANFIS techniques can give good forecasting performance and could be successfully employed to establish prediction models that could provide accurate and reliable flood forecasts. The results show that the ANIFS model was superior to GPR models in flood and river flow forecasting.

VI. Conclusion

In this study, ANFIS and GPR models were developed for forecasting of floods based on antecedent values of river flow data. For attaining the objective, the Musiri and Kodumudi gauging stations located on the Cauvery River in southern India has been selected as case study. The results of ANFIS and GPR models were compared and evaluated based on their testing performance. While comparing the results of these models it was observed that the MSE values of ANFIS model were lower than GPR model. Moreover, the R and NS values of ANFIS model were higher than those of GPR model. Therefore, the ANFIS model could improve the accuracy over the GPR model. The results also demonstrated that ANFIS model showed good forecast accuracy for low values of flow but was unable to maintain its accuracy for peak value of flow. Overall, the analysis done in this study demonstrates that ANFIS method was better to the GPR method in flood forecasting.

Although the results from the study were satisfactory and ANFIS model can be successfully applied for flood prediction but these models underestimate peak values of flood conditions and thus future work is needed to improve the forecast accuracy for higher values of flow by using other hybrid methods or improving model parameters.

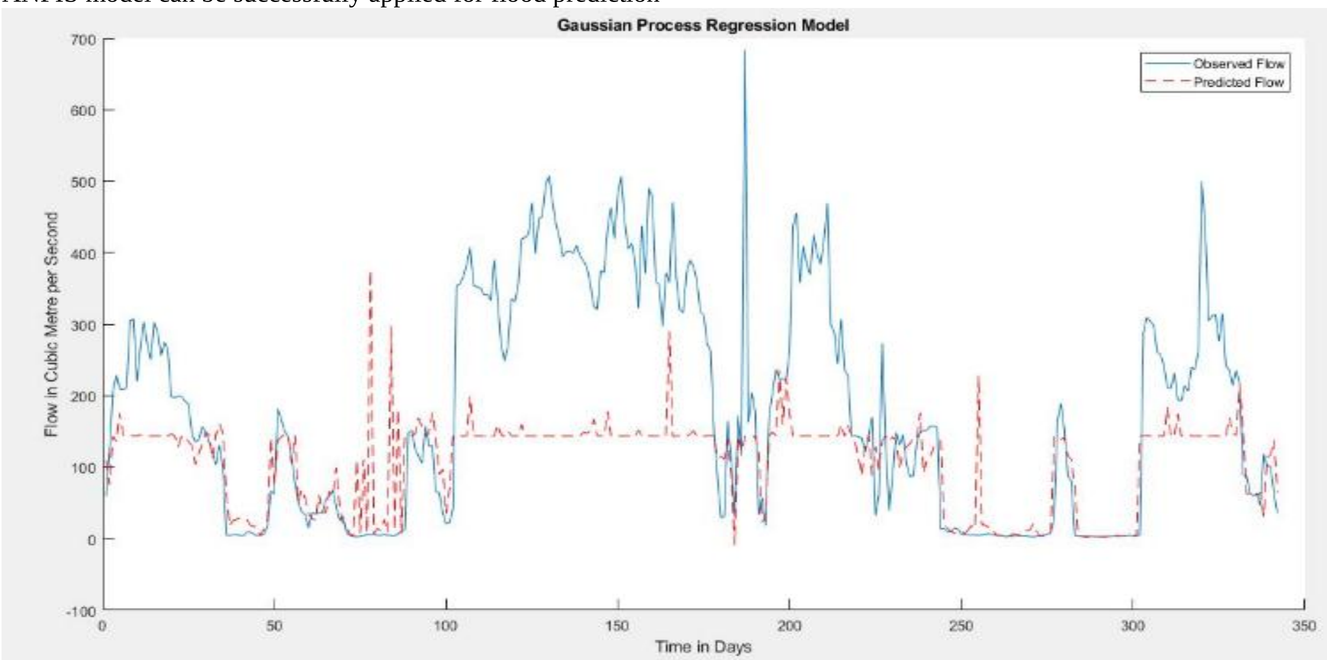

Figure 5: Comparison of observed and GPR predicted flow obtained from Model 3 during testing.

REFERENCES

[1] M. Aqil, I. Kita, A. Yano, S. Nishiyama, Journal of hydrology **337(1-2), 22, 2007**.

[2] Nayak, P. C., K. P. Sudheer, D. M. Rangan, and K. S. Ramasastri. "Short‐term flood forecasting with a Neurofuzzy model." Water Resources Research **41**, no. **4**, **2005**.

[3] Keong, Khoo Chun, Mahfuzah Mustafa, Ahmad Johari Mohammad, Mohd Herwan Sulaiman, and Nor Rul Hasma Abdullah. "Artificial neural network flood prediction for sungai isap residence." In Automatic Control and Intelligent Systems (I2CACIS), IEEE International Conference on, pp**. 236-241**. IEEE, **2016**.

[4] Oh, Hyun-Joo, and Biswajeet Pradhan. "Application of a neuro-fuzzy model to landslide-susceptibility mapping for shallow landslides in a tropical hilly area." Computers & Geosciences **37**, no. **9**, pp. **1264-1276**, **2011**.

[5] S.L. Kant, Amal, Pranmohan K. Suman, Brijesh K. Giri, Mukesh K. Tiwari, Chandranath Chatterjee, Purna C. Nayak, and Sawan Kumar. "Comparison of multi-objective evolutionary neural network, adaptive neuro-fuzzy inference system and bootstrap-based neural network for flood forecasting." Neural Computing and Applications **23**, no. **1**, pp. **231-246**, **2013**.

[6] Bacanli, Ulker Guner, Mahmut Firat, and Fatih Dikbas. "Adaptive neuro-fuzzy inference system for drought forecasting." Stochastic Environmental Research and Risk Assessment **23**, no. **8**, pp. **1143-1154**, **2009**.

[7] Pramanik, Niranjan, and Rabindra Kumar Panda. "Application of neural network and adaptive neuro-fuzzy inference systems for river flow prediction." Hydrological Sciences Journal **54**, no. **2**, pp. **247-260**, **2009.**

[8] Firat, Mahmut, and Mahmud Güngör. "Hydrological time‐series modelling using an adaptive neuro‐fuzzy inference system." Hydrological processes **22**, no. **13**, pp. **2122-2132**, **2008**.

[9] Shaikh, L, and Sawlani, K. "A Rainfall Prediction Model Using Articial Neural Network" International Journal of Scientific Research in Network Security and Communication **Vol. 5, Issue 1, pp. 24 – 28, 2017.**

[10] Jaswant Meena, Ashish Mandloi , "Classification of Data Mining Techniques for Weather Prediction", International Journal of Scientific Research in Computer Science and Engineering, **Vol.4, Issue.1, pp.21-24, 2016.**

[11] Grbić, Ratko, Dino Kurtagić, and Dražen Slišković. "Stream water temperature prediction based on Gaussian process regression." Expert systems with applications **40**, no. **18**, pp. **7407-7414**, **2013**.

[12] Sun, Alexander Y., Dingbao Wang, and Xianli Xu. "Monthly streamflow forecasting using Gaussian process regression." Journal of Hydrology **511**, pp. **72-81**, **2014**.

[13] Pal, Sankar K., and Ashish Ghosh. "Soft computing data mining." pp. **1-3, 2004**.

[14] Jang, Jyh-Shing Roger, Chuen-Tsai Sun, and Eiji Mizutani. "Neuro-fuzzy and soft computing; a computational approach to learning and machine intelligence.", **1997**.

[15] Rasmussen, Carl Edward, and Christopher KI Williams. "Gaussian processes for machine learning. Number **ISBN 0-262-18253-X**." **2006**.

[16] Bhawan, Sewa, and R. K. Puram. "WATERSHED ATLAS OF INDIA.", **2014**.

[17] India-WRIS WebGIS Water Resource Information System of India. Retrieved from http://www.india-wris.nrsc.gov.in/

[18] Kişi, Özgür. "Daily pan evaporation modelling using a neuro-fuzzy computing technique." Journal of hydrology **329**, no. **3-4**, pp. **636-646, 2006**.

[19] Shanker, Murali, Michael Y. Hu, and Ming S. Hung. "Effect of data standardization on neural network training." Omega **24**, no. **4**, pp. **385-397**, **1996**.

[20] Shu, C., and T. B. M. J. Ouarda. "Regional flood frequency analysis at ungauged sites using the adaptive neuro-fuzzy inference system." Journal of Hydrology **349**, no. **1-2**, pp. **31-43**, **2008**.

Authors Profile

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