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An implementation of Artificial Neural Reservoir Computing Technique for Inflow Forecasting of Nagarjuna Sagar dam

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***Abstract:**All over India flash flood or recurring flood is one of the major natural disaster causing life and economic threats. Several times a year, some or the other state disaster management in India have to face this. Forecasting system for inflow of any dam plays a key role in this disaster and its recovery. Current forecasting systems follow conventional, graphical metrological procedures and limited Artificial Neural Network models.This work provides novel model for forecasting inflow of a dam. Proposed model uses Neural Reservoir Computing for forecasting inflow. Forecasts are based on standard dam parameters like inflow. Most importantly, forecasts done are several days ahead of time. This would help disaster management systems to be prepared well in advance to save lives. Proposed system is demonstrated over data from two major dams in Andhra Pradesh. Results are compared with statistical forecasting models like AR, MA, & ARIMA and Artificial Neural Networks (ANN) model. Comparison prove proposed neural reservoir computing model to be better than existing systems.*

***Keywords:** Artificial Neural Reservoir Computing; ARIMA; Inflow forecasting; Nagarjunasagar dam;*

I. INTRODUCTION

Water inflow is major factor driving any dam dynamics. Knowledge about near future inflow amount enables effective and efficient dam operations and management. It also enables flood forecasting, drought control, irrigation management, hydropower generation and effective daily usage. So, an accurate model for forecasting inflow values is necessary. Classical rainfall and runoff models exist, such as empirical, conceptual, physically, and data-driven [1,2]. Promising results are obtained using Data-driven models in different fields of water resources with [3,4,5]. At the same time, researchers have realized complex nature of relationship between rainfall and runoff so various complex models are introduced like fuzzy logic [6], support vector regression [7], and artificial neural networks (NNs) [2].

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Human decision making model is inspiration behind current neural network models. Neural networks have been widely applied as an effective method for modeling highly nonlinear phenomenon in hydrological processes [8]. Reservoir computing is an improved artificial intelligence paradigm that requires significantly less computations than existing ANN models for training the datasets.
It is due to the fact that training is limited only to the output layer all other layers need not be trained [9]. A reservoir is a dynamic system capable of modeling complex patterns in a time series input sequence. Artificial Neural Network (ANN) model is successful in various fields forpredictions. Even in hydrological predictions it has shown success but with few limitations in cases of non-stationary data[10,11]. A non-stationary time series data has a variable variance and mean that does not remain constant or same to their long – run mean over time. On the other hand, stationary time series data reverts around a constant long-term mean exhibits a constant variance independent of time.Daily flow time series data are often nonlinear and non-stationary [12]. Non stationary behavior of a time series is due to variations in seasons and trends. This significantly affects predictability of classical models for forecasting. Various researchers have applied hybrid models of neural networks or complex pre-processing or their combinations to improve prediction performance with limited success.Now, Reservoir computing has emerged as an effective tool to simplify the non-stationary in the dataset and has been widely applied by coupling with neural networks for rainfall runoff modeling. Reservoir computing has shown its steady performance on time series forecasting problems of various domains like wind power, finance, weather [12, 13].

II. STUDY AREA

Nagarjuna sagar dam catchment, a part of the Krishna river basin extends over Andhra Pradesh, maharastra and Karnataka having the total area 2,58,948 sq.km which is nearly 8% of the total geographical area of India. The area lies between 73°17' to 81°09' east longitudes and 13°10' to 19°22' north latitude with an elevation 1337 meters above mean sea level.The catchment falls within sub tropical climate, and daily mean relative humidity varies from 17 to 92% with alternating dry and wet periods.The total length of the river from origin to it’s out fall into bay of Bengal is 1400 km.

There are two major canals from this dam one going to right and other to left side. Comparison of these two canals for various parameters is presented using figure 2. Here length of the main canal is described in unit (10^2 km), max bed width is in unit (10mt), depth of flow is in unit (mt), max discharge is in unit of (10^2 cum/s), head regulator still level unit is (10^2 mt), length of branches and channels is in unit (10^3 km), and finally localized ayacut is measured in unit (lakh ha). Both canals have strength in different parameters.

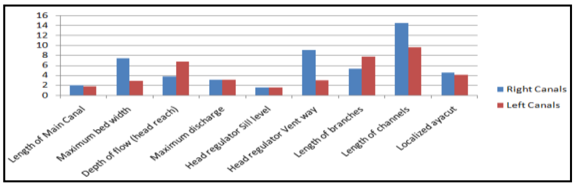

Fig 2. Canal Statistics for Nagarjuna Sagar Dam

Additionally,the study area comprises with agricultural land accounting to 75.86% of total area and 4.07% covered by water bodies. Krishna catchment consists of 7 reservoirs namely konya,Tungabhadra, srisailam, nagajunasagar, almatti, narayanapur , Bhadra with intention of hydropower generation ,water supply for irrigation, industrial and domestic uses and flood control.

Data set used in the study

Daily inflow data is collected for 15 years (from 2003-2017). Data has an entry of inflow record per day for all these years. Missing values and extreme values are treated with standard procedures. After this basic processing,data is used for forecasting. Sample inflow values for Nagarjuana Sagar Dam are shown in Table 1. Table 2 shows statistics for inflow data of same dam.It is very clear that in past this dam has received very high inflow of more than 1 million in a single day.

Date	Inflow	Date	Inflow	Date	Inflow
01-01-2017	8921	11-01-2017	3174	21-01-2017	12620
02-01-2017	6511	12-01-2017	5425	22-01-2017	10116
03-01-2017	5333	13-01-2017	2849	23-01-2017	8276
04-01-2017	12415	14-01-2017	3784	24-01-2017	7365
05-01-2017	17363	15-01-2017	36	25-01-2017	2220
06-01-2017	15662	16-01-2017	1992	26-01-2017	2261
07-01-2017	13307	17-01-2017	7606	27-01-2017	790
08-01-2017	20849	18-01-2017	6972	28-01-2017	1908
09-01-2017	2600	19-01-2017	11986	29-01-2017	2172
10-01-2017	6388	20-01-2017	13621	30-01-2017	4355

Table 1: Sample Data of Inflow values from Nagarjuna Sagar Dam

	Nagarjuana Sagar
Mean	21585.08925
Mode	0
Median	5016
Standard Deviation	64210.37905
Minimum	0
Maximum	1173690

Table 2: Statistical Details of Nagarjuna Sagar Dam inflow Data for 15 years (2003-2017)

Figure 3 and 4 shows exploratory data analysis of inflow data collected. Fig 3ashows pattern of monthly average for all fifteen year inflow data. Clearly,August is having highest peak followed by September or October peaks. Minimum peaks are observed in May and June.Other figure, fig 3b shows great peaks in 2005, 2006 and 2009 highlighting floods in Andhra Pradesh. Figure 4a makes it clear that floods occurred in August for 2005 and 2006 but in November for 2009. Another highlight of this analysis is, 2003, 2012 and 2015 were least inflow years in Nagarjuana Sagar dam.

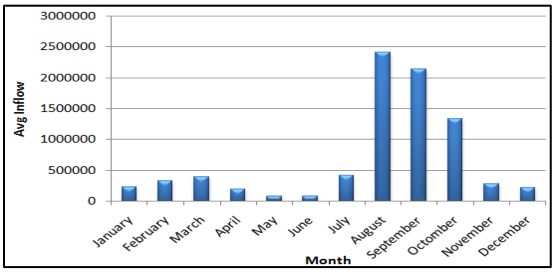

Fig 3: Average Inflow a) per month

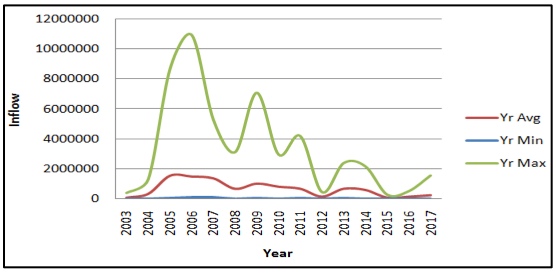

Fig 3: Average Inflowb) per year

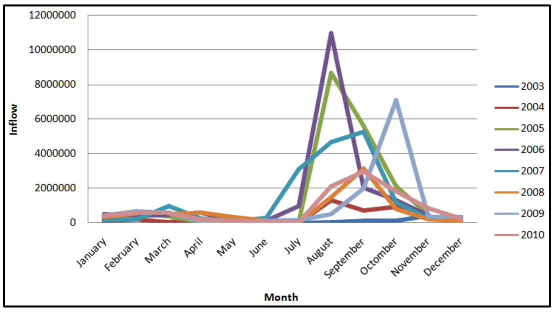

Fig 4: Inflow graph for every year a) between 2003 to 2010

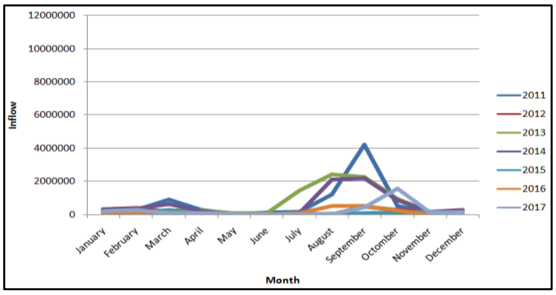

Fig 4: Inflow graph for every year b) 2011 to 2017

III.DAM INFLOW MONITORING FOR FLOOD FORECASTING

1. Statistical Methods:

Traditionally statistical methods are used for forecasting in various domains. Domains like flood predictions, finance, share market, soil quality, and predictive maintenance are just some examples for their application. Models like ARIMA, AR, and MA are popularly used statistical models. Also, models like Halts winter, spline interpolation, and regression analysis are used regularly.

a. Auto Regression (AR):

This is one of the classical statistical techniques for time series predictions. Here variable to be predicted is related with its own history. This model assumes a linear relation between historical values and current value of the input variable.This relation is used for future value prediction for the variable. A particular variable may be related to itself for multiple historical values. So, auto regression is performed for previous ‘p’ values. It can be stated in details for equation 1.

$$AR(x, p) = f(x_{-1}, x_{-2}, \ldots, x_{-p}) \quad - \text{eq (1)}$$

Here, equation 1 depicts the current value ‘x’ is dependent on its ‘p’ historical values, x_{-1} , x_{-2} , … , $x_{-p.}$ Function ‘*f*’ is linear function which detects the statistical pattern of historical values and maps it to current value.This model may suffer from non-stationary issues.
This model is being applied in various domains like finance, flood routing, predictive maintenance and Medicare. Another variant of this model is used in medical domain. Here auto-regression is applied varying with time. General additive method is combined with auto regression for better results, especially in psychological dynamics[14].

b. Moving Average (MA)

A simple modification of averaging technique for time series analysis is known as moving average or simple moving average. In time series absolute mean or average value over all samples is not very relevant as data keeps on changing with time [14]. To find relevant patterns in current data, moving average is taken.
Here, a fixed window of size ‘q’ is used. All values in this window are averaged. This window keeps on sliding one step at a time. So, at each time‘t’, there is a separate window and moving average value.

$$MA(x,q) = \frac{\sum_{i=1}^{q} x_{-i}}{q} \qquad \text{-eq(2)}$$

c. Auto Regression Integration and Moving Average (ARIMA)

This is one of the most powerful statistical models used in forecasting. It comprises of three parts, Auto Regression (AR), Moving Average (MA) and Integration (I).AR & MA components are as discussed earlier. Another part, Integration,works by differencing provided series to itself.Degree of differencing is represented by ‘d’ value. Such differencing helps in better pattern modeling. So, together all these three parts can handle even very complex time series models.

$$ARIMA(p,d,q) = f(AR(p), I(d), MA(q)) \quad \text{- eq(3)}$$

2. Artificial Neural Network Based Methods

In recent times Artificial Neural Network (ANN) based models are flooding various application domains. In field of forecasting also, they have achieved enormous results[10].Here, multiple layers of neurons doprocess input, extract features with various weights, and finally leading to output. These networks can be modeled for numeric forecast or categorical forecast as well.
In application field of non stationary time series forecasting, normal ANN architectures are not efficient.Special architecture of ANN called reservoir computing has proved significant than other models here[11].

1. Reservoir Computing in ANN

It is a dynamic system modeling based on reservoir of neurons. Here, there are three major components, namely input layer, output layer and set of neurons called reservoir.An example of reservoir computing neural network architecture is shown in figure 1. Input and output layer are as per the standard neural network definition [15].

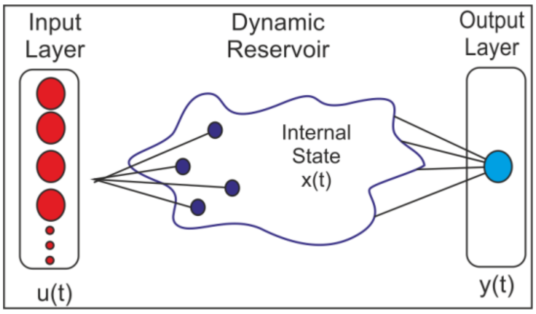

Fig 5: Architecture of Reservoir Computing Neural Network

Input is directly given to input layer. Input can vary in size and number of variables. In time series forecasting generally there are two types, single variable time series and multivariate time series. In addition, same input with along with its several historical instances can act as input. So input *I* can be defined as,

$$I = (i_0, i_{-1}, i_{-2}, \ldots i_{-p}) \quad \ldots \text{eq (4)}$$

Here, *I*is set of input values with its ‘p’ historical instances. For example, ‘i_0’ is current instance of input and ‘i_{-1}’ is historical instance of one unit time.
Output layer provides numeric output for time series forecasting problems.

This number is treated as output forecast valueof inflow ‘In_{pred}’. In training phase, if there is differencein actual inflow ‘In_{actual}’ and predictedinflow ‘In_{pred}’, then erroris back propagated only to output layer. Error can be calculated using Mean Absolute Error (eq 5) or Mean Squared Error (eq 6) or Root Mean Squared Error formula as given by eq 7. Mean Absoluter Percentage Error (MAPE) is another popular error major for time series analysis. It is given in eq 8. Here in following equations ‘n’ is number of total predicted samples.

$$MAE = \frac{\sum_{i=0}^{n} |In_{pred} - In_{actual}|}{n} \quad \dots \text{eq (5)}$$

$$MSE = \frac{\sum_{i=0}^{n} (In_{pred} - In_{actual})^2}{n} \dots \text{eq (6)}$$

$$RMSE = \sqrt{\frac{\sum_{i=0}^{n} (In_{pred} - In_{actual})^2}{n}} \dots \text{eq (7)}$$

$$MAPE = \frac{100}{n} \sum_{i=0}^{n} \frac{|In_{pred} - In_{actual}|}{In_{actual}} \quad \dots \text{eq (8)}$$

2. Concept of Neural Reservoir

A Reservoir is network of neurons which are sparsely connected to each other. Also, there can beself loops amongst themselves. Neuron based reservoir is unaffected and is not modified on back propagation of error[15]. Only input and output layers get affected by error back propagation. So, there is no problem of vanishing gradient here. Also, such architecture of reservoir represents dynamic system. Another limitation is, at each neuron only limited modification to the input is possible. Difference between Output and Input of a neuron in reservoir is between 0 and 1. This limitation reduces the gradient explosion problem [16].

Let ‘ I_r’ be input to a neuron in reservoir and ‘ O_r ’ be output from that neuron. Then relation between input and output is given by equation

$$\| O_r - I_r \| \leq \delta \quad \dots \text{where } 0 \leq \delta \leq 1 \dots \text{eq (9)}$$

3. Approach for Implementing Reservoir Computing Model

Here, reservoir computing model is proposed for inflow forecasting. So, first input and output layers are defined. Number of neurons in input layer depends on number of inputs. Here past six values of inflow are taken as input to predict inflow. On the other hand output layer has only single neuron as this is a regression task. Next, capacity of reservoir in terms of ‘x’ number of neurons is set. Also, ‘δ’ is defined for better performance of the reservoir.

Sl. No	Type of Dataset	Date Range
1	Training Dataset	01/01/2003 to 01/09/2017 (5357 samples)
2	Test Dataset	02/09/2017 to 31/12/2017 (121 samples)

Table 3. Training and Testing Dataset Details

In training phase input of all training samples is provided. Then model is trained using one of the error MAE, MSE or RSME. Error is back-propagated only to the output and input layer. Output layer, also known as read out layer, weights are adjusted to give best output. Training is carried out in multiple epochs on the same data. Training and testing dataset details are given in table 3. Next, for testing the performance predictions are made on testing data. On these predictions MAE, MSE and RMSE is calculated to check optimal performance of the model. For further optimization of the model, reservoir parameters like number of neurons ‘x’ or ‘δ’ are adjusted. Then training is done again and further optimized model is obtained.

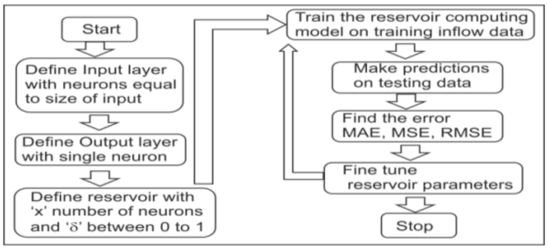

Fig 6. Approach for Implementing Reservoir Computing Model

IV. RESULTS AND DISCUSSION

Experiment is conducted to compare various methods for inflow forecasting. For this purpose Nagarjuna Sagar Dam data is used. Data is taken from project management system, Government of Andhra pradesh, India website [17,18,19]. Here proposed Reservoir Computing (RC) method is compared with statistical method ARIMA and Artificial Neural Networks (ANN). Each model is made to forecast on test data. Figure 7 shows the predicted values graph of ARIMA, ANN and RC along with actual values for those days. Predictions of ARIMA can be concluded to be general predictions. It predicts a pattern that inflow will be consistently increasing. But it clearly fails to catch pattern in future inflow values. Another prediction curve is of ANN, which seems to follow the inflow pattern. But after careful observation it is very clear that ANN is following the pattern and not predicting it. So, for example in case there is change in pattern on day 30 then it will change its pattern for day 31. And same thing continues for the entire predicted pattern. This clearly indicates model is poor to lead the predictions. Additionally it has missed the major peaks in predictions leading to large errors. On other hand proposed reservoir computing model has captured the pattern of inflow time series. It has presented a dynamic predictions and it’s not just following the inflow pattern. Reservoir computing predictions have better captured the peaks leading to less error.

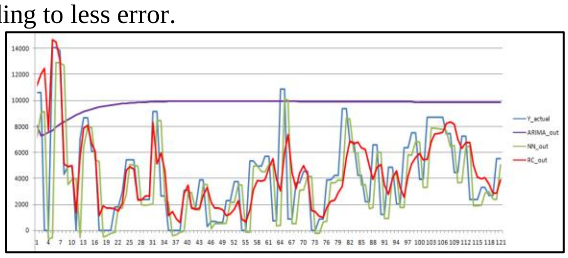

Fig 7: Result comparison for ARIMA, ANN and Reservoir Computing

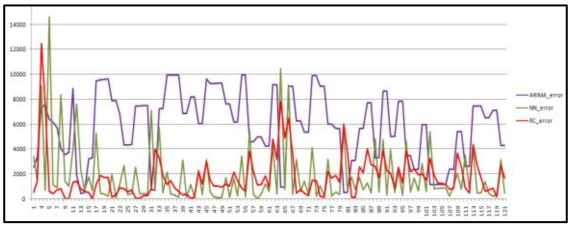

Fig 8: AbsoluteError curve comparison for ARIMA, ANN and Reservoir Computing

Figure 8 presents absolute error curve comparison between ARIMA, ANN and RC. ARIMA has high error nearly for all the samples. ANN has major error when it has missed the peaks.Finally, proposed reservoir computing model has missed some peaks but at many places it has achieved reasonable predictions.

	ARIMA	ANN	RC
MAE (10^3)	41.95	14.14	**10.5**
MSE (10^8)	50.72	6.63	**6.24**
RMSE (10^3)	6.79	2.45	**2.38**
MAPE	111.66	24.7	**11.18**

Table 4: Statistical Comparison of Inflow Predictions

Table 4 clearly demonstrates better performance of Reservoir computing over ANN and ARIMA over MAE, MSE, RMSE and MAPE.

V. CONCLUSION

Flood forecasting is an important task in India for disaster management. Here a neural reservoir computing approach is presented for flood forecasting using inflow prediction. This method has given promising results over other existing methods.

Here in this work, flood forecasting task is done using Nagarjuna Sagar Dam inflow Data for 15 years (2003-2017).Data analysis shows dynamic patterns in inflow data. Existing inflow forecasting methods ARIMA and ANN have limitation to handle such non-stationary time series data. Proposed neural reservoir computing method has captured the pattern well and has given minimal error in predictions. These models are evaluated based on Mean Absolute Error, Mean Squared Error, Root Mean Squared Error and Mean Absolute Percentage Error measures. On all measures proposed neural reservoir computing method is proved to be better than other existing models.

Results depicted to potential of Artificial neural reservoir computing in forecasting task. So, this model can be further applied on various civil domains like predictive maintenance of reservoirs, seepage forecasting in Earthen Dams and soil moisture level prediction.

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