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Neural Network–Based Modeling and Prediction of Reservoir Inflow Dynamics in Real Time

Akram Salim Pathan, Alka K. Pardeshi, Sunil D. Shinde, Fatima Ansari, Kiphaytulla Mohd.Ismail Sayyad

Abstract: *A neural network modeling approach is used to construct a real time catchment flow prediction model for river basin. The present study aims towards introducing the use of ANN technique to model and predict the monthly inflow of Jayakwadi Reservoir. The data pertaining to the years 1927-1971 have been explored to develop the predictive model with Tanh Axon nonlinearity and Levenberg Marquardt as a training algorithm. The Jayakwadi reservoir, one of the largest irrigation projects in Maharashtra with catchment area of 21,750 km2, is selected as the study area. ANN model was developed based on the historical inflow data of the Jayakwadi Reservoir and successfully predicted inflow with less errors. In this study six forecasting model approach are used, which are multilayer Perceptron (MLP), feed forward (FF), modular neural network (MNN), Jordan/Elman network, time-lag recurrent (TLRNN), CANFIS network method for the natural inflow at Jayakwadi utilizing the inflow data of the monitoring stations. Inflow data collected over the last 45 years is used to develop the model and examine its performance. 70% of data is used to develop the model and rest of data is utilized to test the models. Except CANFIS method in all five methods i.e. MLP, GFFNN, MNN, J/ENN, TLRNN results shows that coefficient of correlations are above 90% and in CANFIS method coefficient of correlation is 89%. The result of this study showed that ANN technique is capable with small computational effort and high accuracy of predicting the monthly inflow.*

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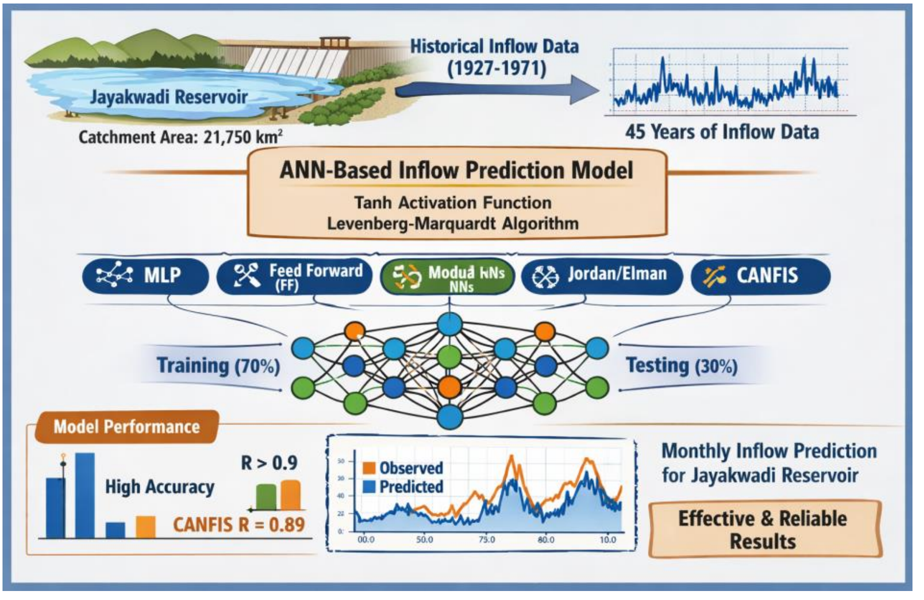


Graphical Abstract

Paper Highlights

- Developed a real-time ANN-based catchment flow prediction model for monthly inflow forecasting of the Jayakwadi Reservoir.
- Utilized 45 years of historical inflow data (1927–1971) for model development and performance evaluation.
- Implemented Tanh activation function with Levenberg–Marquardt training algorithm to enhance prediction accuracy.
- Evaluated six neural network forecasting approaches: MLP, Feed Forward, Modular NN, Jordan/Elman, Time-Lag Recurrent NN, and CANFIS.
- Adopted a 70%–30% data split for training and testing of all models.
- Achieved high prediction accuracy (R > 0.90) for MLP, FF, MNN, Jordan/Elman, and TLRNN models.
- CANFIS model also showed reliable performance with a correlation coefficient of 0.89.
- Results confirm that ANN techniques provide high accuracy with low computational effort for monthly reservoir inflow prediction.

Introduction

The management of the water resources is of crucial importance since it directly affects the design and operation of many water resources structures. Conventional procedures for design and analysis are basically trial-and-error procedures. In these methods the aim is to predict the monthly inflow of reservoir (Pathan, A.S. et al (2020). At the stage of the planning of the reservoir size this is a very important subject. Here the monthly total inflow of the reservoir is the main data series. It is better to have a data record length as long as possible. Regarding water engineering field, several researchers have incorporated ANN technique in hydrology, groundwater and hydraulics and reservoir operation to simulate their problems. Due to rapid growth of population and economy in the world, water is becoming a precious and scares resource as a result of growing demands from various purposes, such as irrigation, hydropower, municipal and industrial water supply, navigation, etc. (Jain et al 2009).

Artificial neural networks (ANN) are black box models that are used for forecasting and estimating purposes in so many different areas of the science and engineering. The accurate predictions of short- and long-term inflow of Jayakwadi reservoir are important for dam safety (Pathan, A.S. et al (2022).

Neural network technology have provided many promising results in modeling complex nonlinear systems, and successful applications of this artificial intelligence in the field of hydrology and water resources modeling have been widely reported, such as for stream flow and river flow prediction (Sharifi et al. 2005; Aquil et al. 2007, Sankarasubramanian et al. 2007; Kim 2004; Haddad et al. 2005; Ahmed et al. 2007; Raju et al. 2004; Gopakumar et al. 2007; Jian et al. 2006; Lin et al.), and inflow prediction (kote 2010; Coulibaly et al. 2000; Wang et al. 2009; Ismail et al. 2005; Kolen et al. 2000; Shafie et al. 2009), groundwater modeling (Coulibaly et al. 2002001; Sohail al. 2007; Agrawal et al.2004; Nauraniet al. 2009;), rainfall–runoff simulation (Jain et al. 2004; Sminia et al. 2003).

Artificial Neural Networks

A neural network is a method that is inspired by the studies of the brain and nerve systems in biological organisms. Neural networks have the capability of self-learning and automatic abstracting. Artificial neural networks are important alternatives to the traditional methods of data analysis and modeling.

2.1 Multilayer Perceptron

Multilayer Perceptron (MLP) are the most commonly used ANN in hydrological predictions. The multilayer perception neural network is built up of several layers by the addition of more hidden layers. In these method neurons within the same layer connected to the neurons in the next layers.

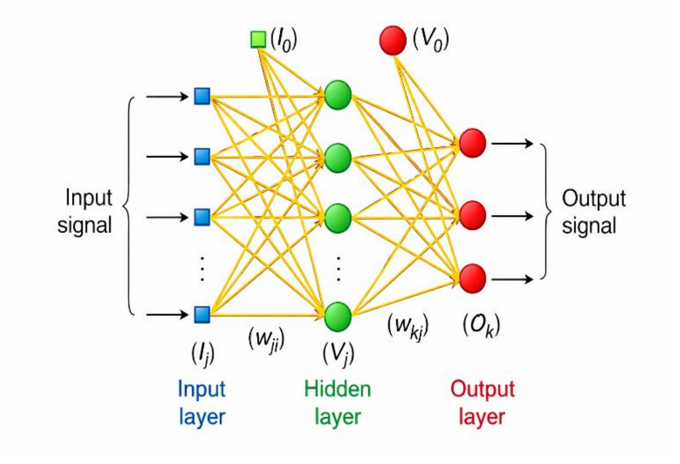


Figure 2.1: Typical Multilayer Perceptron Network

The connections are forward and the layers are cascaded together to form the MLP network. Each MLP is consists of a minimum of three layers these are: an input layer, one or more hidden layers and an output layer. A typical three-layer network is shown in figure 2.1. Only three-layer MLPs will be considered in this work.

2.2 Feed Forward Neural Network

FFNN has parallel layers or subgroups made up of processing elements. Each layer of processing elements makes independent calculations on data that it receives and forwards the results to next layer. The next layer again passes the results to yet further layer.

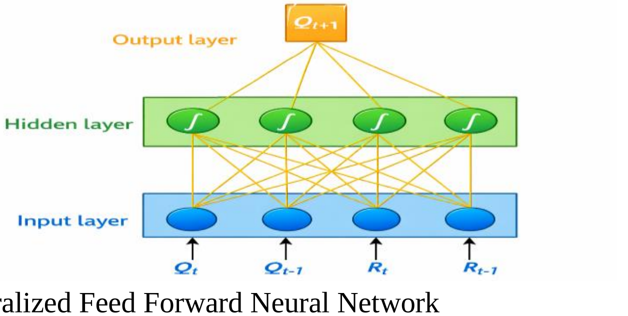


Figure 2.2: Generalized Feed Forward Neural Network

Finally a last layer determines the output from this network system. Basically output of neural network is a weighted sum of its input but threshold function is sometimes used to qualify the output of a neuron in the output layer. In general, it is composed of three or more layers: an input layer, which is used to present data to the network; an output layer, which is used to generate an appropriate output; and one or more intermediate layers or subgroups, which are used to act as a supplier of results to the next layer. The network-layered structure consists of a set of nodes (neurons) connected by links from one layer to its next layer. Following figure 2.2 shows the structure of FFNN. The main advantage of the feed forward architecture is that it requires relatively less of computing time during training.

2.3 Modular Neural Network

In a modular neural network there are combinations of two or more neural networks in one network by providing appropriate connections between layers of one subnetwork to layers of others.

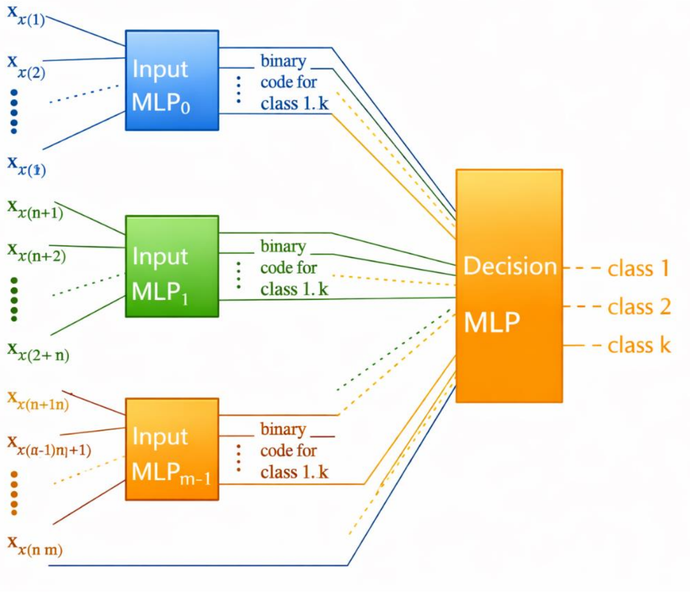


Figure 2.3: Modular Neural Network Architecture

Each independent neural network acts as a module and operates on separate inputs to complete some subtask to achieve the task of network as shown in figure 2.3. The mediator takes the outputs from each module and processes them to generate the output of the network. The mediator only accepts the modules outputs it does not respond to it. The modules do not interact with each other. One of the major benefits of a modular neural network is the ability to reduce a large, unwieldy neural network to smaller, more manageable components.

2.4 Jordan / Elman Neural Network

In Elman neural network the input layer is divided into two parts: the true input units and the context units. The network generated its output signals from the hidden layer to train the network. The connections are all feed forward, and the weights from the context units can be trained exactly as the back propagation methods. In Jordan neural network the network determines its output signals from the output layer to train the network. Its output signals are fed back to the input layer via context units as shown in figure 2.4. Again, the weights from the context units can be trained in exactly the same manner as those of ordinary type ERN.

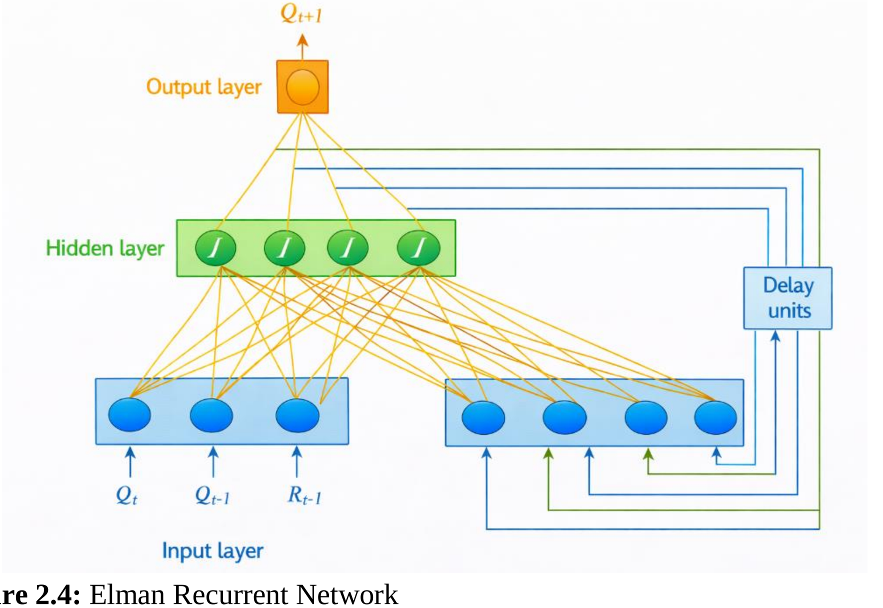


Figure 2.4: Elman Recurrent Network

2.5 Time Lag Recurrent Network

Time lagged recurrent networks (TLRNs) are MLPs comprehensive with short term memory structures and local recurring connections. The input layer used the inputs delayed by multiple time points before presented to the network. The network general architecture has three layers and the feedback connection connected from the hidden layer to the input layer as shown in figure 2.5.

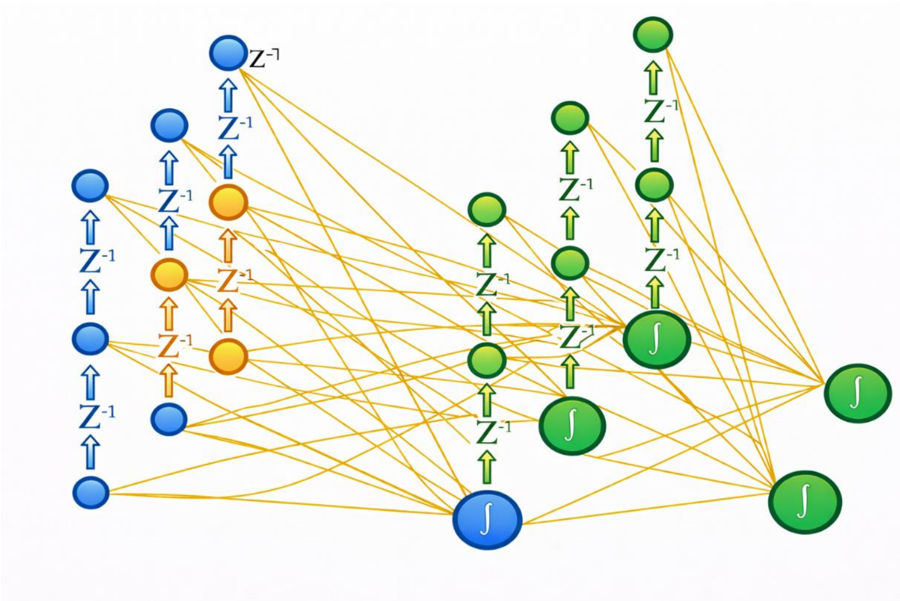


Figure 2.5: Time Lag Recurrent Network

2.6 CANFIS Network (Fuzzy Logic)

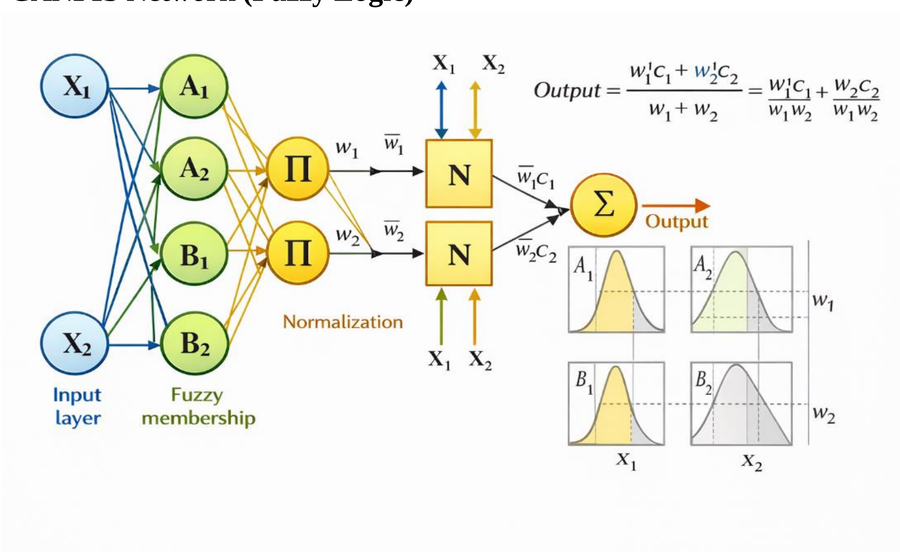


Figure 2.6: CANFIS Architecture

CANFIS is a generalized form of ANFIS has the benefit of non-linear rule formations. CANFIS method can obtain more than one outputs. The CANFIS model integrates fuzzy inputs with a modular neural network to quickly solve poorly defined problems. The output of a fuzzy axon is calculated by the formula as shown in figure 2.6.

2.7 Levenberg Marquardt Backpropagation Training

In this study the LMBP (Levenberg-Marquardt Back Propagation) algorithm method for ANN training is used. (Muhammad Aqil et al. 2007) The LMBP, one of the second-order nonlinear optimization techniques, is usually faster and reliable (Majid Heydari 2011). The LMBP uses the approximate Hessian matrix that can be approximated as follows

$$H=JTJ \tag{2.1}$$

Where J is the Jacobian matrix with first derivatives of the ANN errors with respect to weights and biases.

Model Developments

3.1 Description of Study Area

Jayakwadi project is one of the largest irrigation projects at Paithan in Aurangabad District of Maharashtra State. It is a multipurpose project. Jayakwadi is one of the largest earthen dams in Asia. Its catchment area is 21,750 km^2. Total submergence area due to the reservoir is approximately 35,000 ha. Its height is approx. 41.30 m and length of 9998 m (10 km approximate) Nath Sagar is the name of the reservoir formed due to Jayakwadi Dam. Total area of reservoir is approx 350 km2. Its total storage capacity is approx 2.909 km^3 and effective live storage capacity is 2.17 km^3. The length of left bank canal is 208 km and the length of right bank canal is 132 km. It irrigates cultivable area of 237,452 ha in the Districts of Aurangabad, Jalna, Beed and Parbhani.

The reservoir with latitude 190 29’ 8.7” N and longitude 750 22’ 12” E is located on Godavari river. The hydrological data used in this study included monthly inflow data.

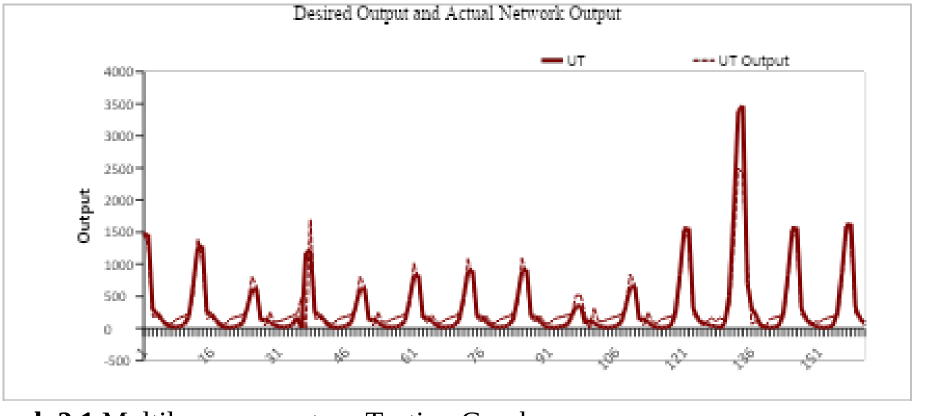
3.2 Model Structure

Accurate prediction of reservoir inflow has been predictable as an important measure for effective flood-risk management strategy (Shelke, M et al.2023). A neural network modeling approach is used to construct a real time reservoir inflow prediction model for a river basin. Six types of neural network architecture i.e. MLP, GFFNN, MNN, J/EN, TLRNN, CANFIS Network and Levenberg-Marquardt training algorithm, with adaptive learning examined in this study. (Vasheghani et al. 2025)

Artificial Neural Network models have developed by using Neuro Solution Software. Six models are developed depending one lag of previous one month using data from 1927-1971. It is very important to make sure that the validation data should not have been used as part of the training process. (P. Coulibaly et al.2000)

Model 1 of MLP

Graph 3.1 shows the graph of desired output and the graph of actual network output result for 2-20-1 model developed in Neuro solutions. With two input nodes U(t-1), U(t-2), one hidden layers with 20 processing elements and one output node U(t).



Graph 3.1 Multilayer perceptron Testing Graph

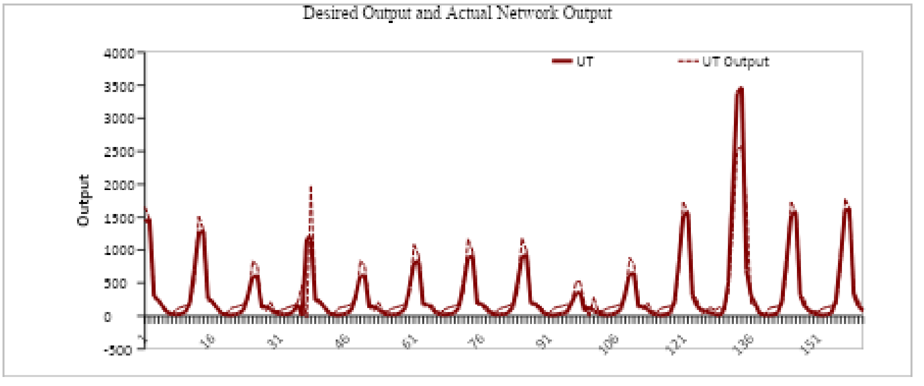
Table 3.1: Result Summary of MLP Model

Performance	Ut
MSE	38373.71651
NMSE	0.129848209
MAE	128.4363943
Min Abs Error	5.37409643
Max Abs Error	1177.047649
r	0.940817632

The monthly inflow data of 45 years was taken in model, out of which 70% was used for training and 30% for testing. The network build is Multilayer Perceptron with learning algorithm, Levenberg Marquardt. The TanhAxon transfer function has used. The correlation factor r is 0.9408 and Normalized Mean Square Error (NMSE) is 0.1298 as shown in Table 3.1.

Model 2 of GFFNN

Graph 3.2 show the graph of desired output and the graph of actual network output result for 2-25-1 model developed in Neuro solutions. With two input nodes U(t-1), U(t-2), one hidden layers with 25 processing elements and one output node U(t). The monthly inflow data of 45 years was taken in model, 70% was used for training and 30% for testing. The TanhAxon transfer function has used. (Yu-Min Wang et al. 2009) The correlation factor r is 0.9296 and Normalized Mean Square Error (NMSE) is 0.1419 as shown in Table 3.2.



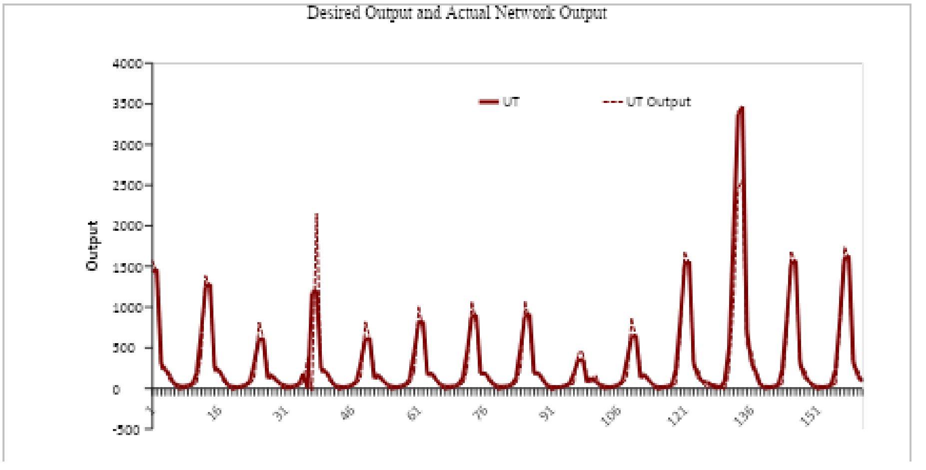
Graph 3.2: Generalized Feed Forward Testing Graph

Table 3.2: Result Summary of GFFNN Model

Performance	**Ut**
MSE	41954.75529
NMSE	0.141965656
MAE	115.2845047
Min Abs Error	0.059851748
Max Abs Error	1199.446658
r	0.929627666

Model 3 of MNN

Graph 3.3 shows the result for 2-6-4-1 model developed in Neuro solutions. With two input nodes U(t-1), U(t-2), two hidden layers with upper and lower PEs 6 and 4. In both hidden layer upper and lower transfer function is TanhAxon and in output layer sigmoid Axon transfer function has been used with one output node U(t).



Graph 3.3: Modular Neural Network Testing Graph

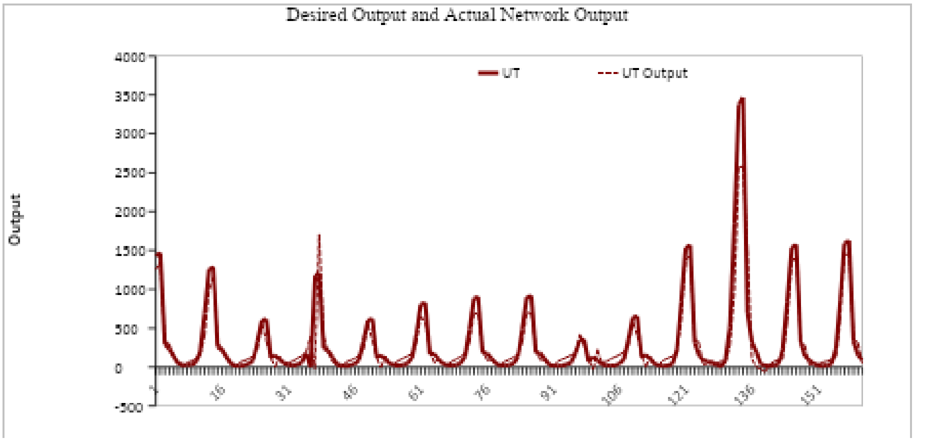
Table 3.3: Result Summary of MNN Model

Performance	UT
MSE	37710.10661
NMSE	0.127602699
MAE	90.39697836
Min Abs Error	2.242450689
Max Abs Error	1201.326289
r	0.936429223

The monthly inflow data of 45 years was taken in model. The correlation factor r is 0.9364 and Normalized Mean Square Error (NMSE) is 0.1276 as shown in Table 3.3.

Model 4 of J/ENN

Graph 3.4 shows the graph of desired output and the graph of actual network output result for 2-12-1 model developed in Neuro solutions. With two input nodes U(t-1), U(t-2), one hidden layers with 12 processing elements and one output node U(t).



Graph 3.4 Jordan / Elman Network Testing Graph

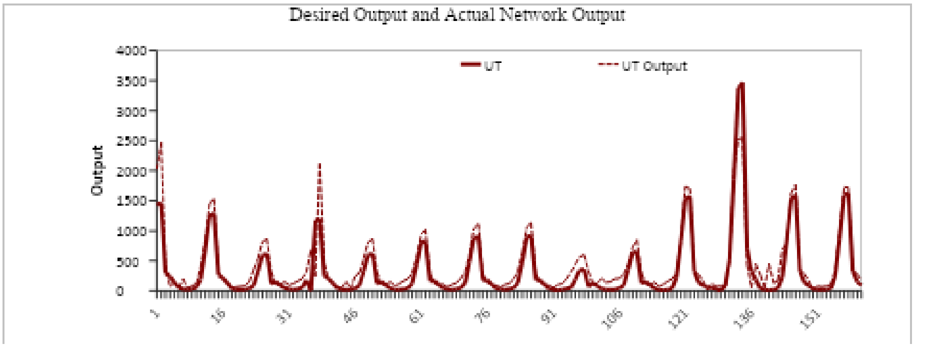
Table 3.4: Result Summary of J/ENN Model

Performance	**UT**
MSE	40834.65052
NMSE	0.138175468
MAE	115.0383927
Min Abs Error	0.088124269
Max Abs Error	1192.850927
r	0.9388224

The monthly inflow data of 45 years was taken in model, out of which 70% was used for training and 30% for testing. The network build is Jordan/Elman Network with learning algorithm, Levenberg Marquardt. The TanhAxon transfer function has been used in hidden layer and SigmoidAxon transfer function has been used in output layer. The correlation factor r is 0.9388 and Normalized Mean Square Error (NMSE) is 0.1381as shown in Table 3.4

Model 5 of TLRNN

Graph 3.5 shows the result for 2-15-1 model developed in Neuro solutions. With two input nodes U(t-1), U(t-2), one hidden layers with 15 processing elements and one output node U(t). The monthly inflow data of 45 years was taken in model, out of which 70% was used for training and 30% for testing.



Graph 3.5: Time Lag Recurrent Network Testing Graph

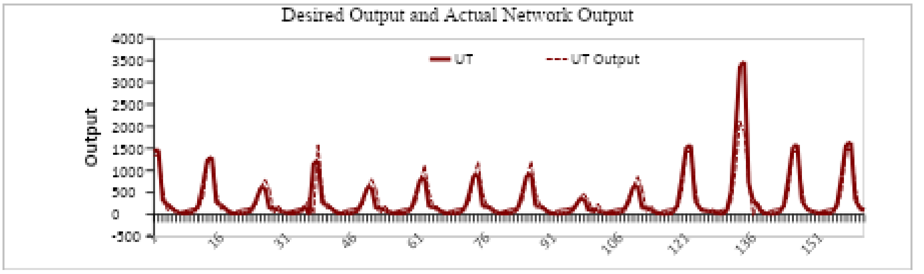
Table 3.5: Result Summary of TLRNN Model

Performance	UT
MSE	51472.08936
NMSE	0.174170219
MAE	149.1692248
Min Abs Error	0.350832829
Max Abs Error	1002.121712
r	0.929158665

The network build is Time Lag Recurrent Network with learning algorithm, Levenberg Marquardt Focused on Gamma Axon. The TanhAxon transfer function has used. The correlation factor r is 0.9291 and Normalized Mean Square Error (NMSE) is 0.1741 as shown in Table 3.5.

Model 6 of CANFIS Network

Graph 3.6 the result for 2-0-1 model developed in Neuro solutions. With two input nodes U(t-1), U(t-2), one hidden layers with zero processing elements and one output node U(t). The network build is CANFIS Network with learning rule, Momentum. The correlation factor r is 0.8998 and Normalized Mean Square Error (NMSE) is 0.2048 as shown in Table 3.6.



Graph 3.6: CANFIS Network Testing Graph

Table 3.6: Result Summary of CANFIS Model

Performance	**UT**
MSE	60540.27553
NMSE	0.204854965
MAE	136.2111536
Min Abs Error	1.805163592
Max Abs Error	1595.529907
r	0.899828108

Table 3.7 Result Summary of ANN Models

Model	**% Training & Testing**	**Network & Transfer function**	**Learning algorithm**	**Epochs**	**Testing result**		
					NMSE	**MAE**	**r**
ANN (2-20-1)	70:30	MLP (TA-TA)	LM	25	0.129	128.436	0.94
ANN (2-25-1)	70:30	GFFNN (TA-TA)	LM	27	0.141	115.284	0.92
ANN (2-6-4-1)	70:30	MNN (TA-SA)	LM	37	0.127	90.3969	0.93
ANN (2-12-1)	70:30	J/ENN (TA-SA)	LM	18	0.138	115.038	0.93
ANN (2-15-1)	70:30	TLRN (TA-TA)	LM	27	0.174	149.169	0.92

ANN (2-0-1)	70:30	CANFIS	LM	481	0.204	136.211	0.89

3.2 Justification for Error

The methods were used to predict inflow in Jayakwadi river basin at paithan, the model results indicate that reasonable prediction accuracy was achieved for most of models for one month ahead forecast with correlation > 0.91. However, the model accuracy deteriorates as the lead time increases. When compare, a 2-20-1 multilayer Perceptron and 2-25-1 generalized feed forward network, has produced better performances on indicators related to average goodness of prediction for the one month ahead river inflow compared to CANFIS model based on fuzzy logic. Thus the result of the study show that MLP, GFFNN, MNN, J/ENN and TLRNN trained with Levenberg-Marquardt are able to forecast the reservoir inflow up to one month in advance with reasonable prediction accuracy. It means one lag is sufficient for predicting better inflows. ANN predicts much better that is magnitude of each and every error term leads to higher accuracy than CANFIS method based on fuzzy logic. Table 3.7 shows result summary of ANN models.

Conclusions

Artificial neural networks, one of the artificial intelligence tools which capture the pattern between input and output is found to be suitable in predicting inflows. Even though the conventional models show that the future value could be predicted well, researchers are seeking for better model to predict the future inflows with better accuracy in terms of high flows and low flows.The results shows that MLP, GFFNN, MNN, J/ENN and TLRNN trained with Levenberg-Marquardt are able to forecast the reservoir inflow up to one month in advance with reasonable prediction accuracy, it means one lag is sufficient for predicting better inflows.

In Model 1 of MLP ANN shown best result with maximum correlation coefficient (r) as 0.94 and minimum value of Normalized Mean Square Error (NMSE). In all ANNs model accuracy is so significant that all error measures were improved by using correlation. The result of a given case study shown that ANN has some significant advantages for short and long term prediction of inflow in hydrology.

The ANN methodology has been reported to provide reasonably good solution for circumstances where there are complex systems that may be poorly defined or understood using mathematical equations.

Artificial Neural Networks are considered as a promising tool for reservoir inflow prediction when detailed time series of hydrological metrological data are available. When trying to decide the input parameters of the neural network a correlation coefficient analysis of the parameters can give hints of which parameters are important and should be included.

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