

Streamflow Simulation In Poorly Gauged Of Pairi Basin Using Artificial Neural Networks

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Abstract

Streamflow simulation in poorly gauged basins is still a major challenge, as a limited quantity of hydrometric observations and the complicated nature of nonlinear processes of rainfall runoffs arises. This research explores the validity and the relative effectiveness of Artificial Neural Network (ANN) models to simulate the streamflow in pairi basin in chhattisgarh. This study presents a comparative analysis of streamflow simulation using two Artificial Neural Network (ANN) approaches Time-Lagged Recurrent Networks (TLRN) and Nonlinear Autoregressive Neural Network with Exogenous Inputs (NARX) for the Pairi Basin of Chhattisgarh. A 30-year time series dataset (1 January 1980 to 31 December 2013) of observed streamflow was used for model development and evaluation. The dataset was divided into training (1980–May 2010), testing (May 2000–November 2008), and cross-validation (November 2008–December 2013) phases to assess learning capability and predictive power. Model performance was evaluated using Mean Squared Error (MSE), correlation coefficient (R), and Nash–Sutcliffe Efficiency (NSE). Results indicate that the NARX model outperformed TLRN, achieving lower MSE and higher R and NSE values during training and testing. The findings demonstrate that NARX provides superior accuracy and generalization for streamflow prediction in the Pairi Basin.

Key words: Artificial Neural Network, poorly gauged, streamflow simulation, stream flow prediction, Pairi basin, Time-Lagged Recurrent Network, NARX.

Introduction

Streamflow measurement in small, poorly gauged basins presents a significant challenge in hydrological science and water resources management, particularly in regions characterized by sparse or absent conventional gauging infrastructure (Georgievová et al., 2023; Madhushani et al., 2024). Accurate streamflow prediction is critical for effective water resource planning, flood assessment, hydropower generation, and early warning systems (Madhushani et al., 2024; Naganna et al., 2023; Wegayehu & Muluneh, 2021). However, the inherent uncertainties and complex behaviors of streamflow and related parameters often complicate these predictions (Madhushani et al., 2024). The problem is further exacerbated in ungauged or poorly gauged basins, where data scarcity makes the calibration and evaluation of hydrological models exceptionally difficult (Alemayehu et al., 2022; Georgievová et al., 2023; Yilmaz et al., 2023).

Physically based, traditional hydrological models, despite being useful in explaining the water-balance process, often face ordeals with complex parameterizations and strong uncertainties especially in areas with limited data availability (Yilmaz et al., 2023). As a way of countering such constraints, the problem of data-driven modelling models especially Artificial Neural Networks (ANNs) has continued to gain increased academic interest (Balacumaresan et al., 2024; Kisi et al., 2024; Madhushani et al., 2024). ANNs are touted to have the ability to obtain highly non-linear input-output relationships behaving off of small observational data sets without having to maintain overt desire toward the underlying physical processes (Madhushani et al., 2024; Poonia & Tiwari, 2020; Pradhan et al., 2020). This property makes ANNs particularly those that could be useful in

hydrological forecasting, where the condition that is rainfallrunoff process is highly non-linear (Ali & Shahbaz, 2020; Poonia & Tiwari, 2020).

Data-driven models provide a flexible and parsimonious alternative by learning complex input-output relationships directly from historical time-series data without explicit representation of physical processes (Huang & Lee, 2025; Özdoğan-Sarıkoç & Dadaser-Celik, 2024). These models have gained significant traction due to their ability to capture the inherent non-linearity and stochastic nature of hydrological data that conventional physical models often struggle with (Tan et al., 2022). Among various data-driven approaches, the Nonlinear Autoregressive model with eXogenous inputs (NARX) has emerged as a powerful tool for streamflow prediction (Balcha et al., 2025; de Mendonça et al., 2023; Shi et al., 2025). NARX models are a type of recurrent neural network architecture specifically designed to capture nonlinear, dynamic, and memory-dependent behaviors inherent in hydrological systems (Shao et al., 2022). The core principle of a NARX model is to predict the current output based on past values of the output and past values of independent, or exogenous, input variables (Zulkeflee et al., 2021). This structure, representing the autoregressive (AR) component from past outputs and the exogenous (X) component from past inputs, enables the model to effectively learn the complex temporal dependencies within streamflow time series. The "N" in NARX signifies its capability to model nonlinear relationships, which are prevalent in hydrological phenomena such as rainfall-runoff processes (Schär et al., 2024).

The implementation of NARX models, particularly using software environments like MATLAB, offers distinct advantages for streamflow simulation. MATLAB's Deep Learning Toolbox and Neural Network Toolbox provide efficient tools for designing, training, and evaluating NARX networks (Tudoroiu et al., 2023). This computational environment facilitates robust streamflow prediction by allowing the integration of rainfall, antecedent flow, and other relevant hydrometeorological variables as inputs (de Mendonça et al., 2023). The advantages of NARX models include their interpretability (via trained weights), built-in workflows for training, validation, and testing, and seamless integration with signal preprocessing techniques like normalization and delay embedding (Nourani et al., 2021). This makes NARX particularly suitable for both operational and research-oriented streamflow modeling, addressing the challenges of predicting river discharge for water resource management, flood mitigation, and drought preparedness (Nourani et al., 2021; Varma & Patel, 2025). Recent studies have successfully applied NARX for various hydrological predictions, including daily runoff (Pishgah Hadiyan et al., 2022), and even water levels in estuaries (Vidyalashmi et al., 2024). The framework is flexible enough to be combined with other advanced techniques, such as Long Short-Term Memory (LSTM) networks for enhanced prediction and error correction (Shi et al., 2025), and Bayesian Optimization for optimizing model parameters (Sun et al., 2024).

Based on the various ANN structures, there are a few structures that have proved to be of value when dealing with streamflow estimations. One of the most common feed-forward networks used in hydrological forecasting is the Multilayer Perceptron (MLP), a structure that has a reputation of having the ability to universally approximate one network (Meshram et al., 2022; Rahman et al., 2022; Wegayehu & Muluneh, 2021). The empirical studies have supported the effectiveness of the MLP in simulating streamflow and reclaiming missing streamflow statistics (Dariane & Borhan, 2024; Wegayehu & Muluneh, 2021). It has been observed that the Generalized Regression Neural Network (GRNN), which is a single-pass memory-based learning architecture, is very robust in the presence of relatively small sample sizes and is very skillful in the smooth approximation of functions, thus making it easy to analyze relationships between rainfall and runoff and forecast discharge (Gomaa et al., 2023; Modaresi et al., 2018). Also, other more dynamic

architectures like the Time-Lagged Recurrent Network (TLRN) or other Recurrent Neural Networks (RNNs) are specifically designed to learn temporal dependencies and hysteresis effects which are essential to rainfall-runoff processes (Shaukat et al., 2022; Shoaib et al., 2016). More sophisticated forms of RNN such as the Long Short-term memory (LSTM) and Gated Recurrent Unit (GRU) networks have been shown to have better results in simulation of stream give the ability to capture long-term memory aspects of sequential data (Farfán-Durán & Cea, 2024; Gomaa et al., 2023; Wegayehu & Muluneh, 2022).

Recent developments have involved the use of ANNs which feature statistical processes and optimization package to optimize streamflow forecasting. As an example, when ANNs are combined with regionalization methods like the Drainage Area Ratio (DAR) and Standardization with Mean (SM), they have been indicated to predict daily streamflow back in ungauged basins (Yilmaz et al., 2023). The use of hybrid paradigms, such as ANNs and optimization based paintings, Particle Swarm Optimization (PSO) and the Firefly Algorithm (FA) has also been considered as a means of improving the predictive accuracy of inflow and sediment-load forecasting (Duan et al., 2020; Gomaa et al., 2023; Katipoğlu et al., 2024; Meshram et al., 2022). In addition, the use of deep-learning systems, which include Convolutional Neural Networks (CNNs) and their hybrid versions, extends further the predictive capability of streamflow models, in particular in smaller basins with short response times (Ali & Shahbaz, 2020; Duan et al., 2020). However, the requirement to increase the interpretability and causal transparency of these machine-learning predictions has remained since better transparency would contribute to improved confidence of users with their predictability (Madhushani et al., 2024).

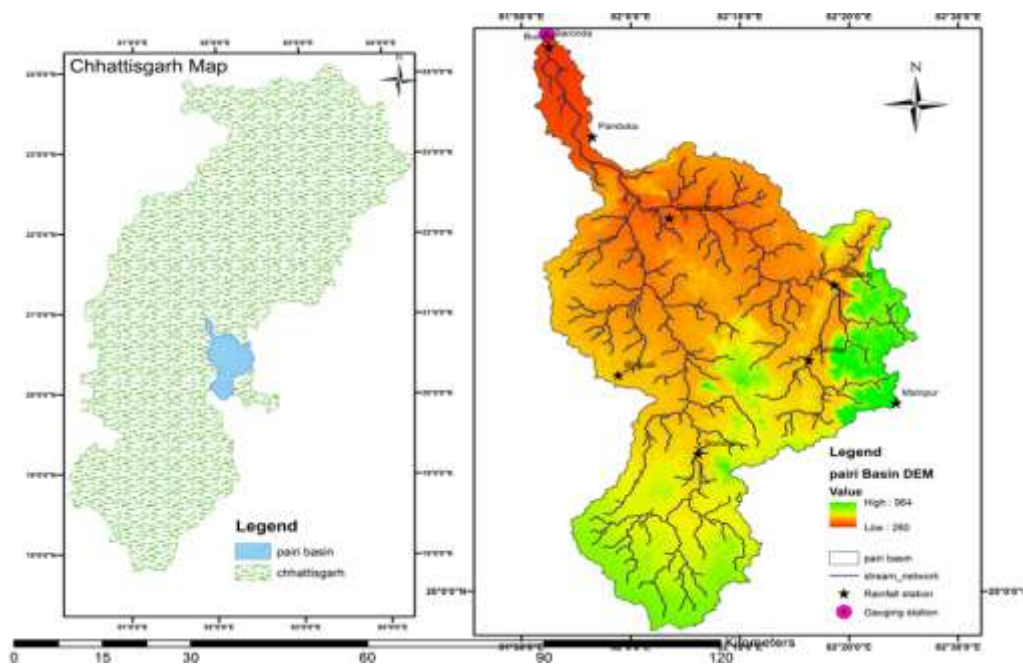
Despite growing the use of Artificial Neural Networks (ANNs) and data driven mode approache the Nonlinear Autoregressive model with eXogenous inputs (NARX) in hydrological studies, there is still a lack of streamflow simulation study in the pairi Basin of Chhattisgarh especially a comparative, multi-model ANN framework. The majority of the past research in Indian river basins has been concentrated in well gauged or large basins and poorly gauged sub-basins such as pairi had little scientific attention. The basin has complex hydro-climatic properties, such as monsoon-controlled rainfall, large inter-annual and anthropogenic consequential creating issues that are inadequately modelled using traditional modelling strategies. It influenced the modeling performances based on the size of the basin of the observational data and spatial resolution. In addition, there has been scanty work done to determine the ability of these models to simulate the day ahead streamflow of the long-term past records. In the recent times, the field of hydrology has adopted the use of Historical rainfall grid based records of precipitation whose high-resolution is $0.25^{\circ} \times 0.25^{\circ}$ by Indian Meteorological department in these to simulate stream flow. To overcome these shortcomings, this paper attempts to create TLRNs ANN models and data driven approaches, the Nonlinear Autoregressive model with eXogenous inputs (NARX) to simulate the daily streamflow to this partially ungauged basin, perform a detailed comparison of the ANN modeling performance (Qobserved) simulation with the India WRIS. This study builds on the research that explores the effectiveness of ANN architectures Time-lagged Recurrent Network (TLRN) and data driven model approaches, the Nonlinear Autoregressive model with eXogenous inputs in the daily simulation of streamflow in a small, sparsely partially gauged basin. This study attempts to develop, train, test, and validate both NARX and artificial neural network (ANN) model to simulate stream flow in a given catchment with the following specific objectives to obtain increased accuracy during estimation and simulation of stream-flow compared to the performances of diverse ANN models , perform a comparative evaluation of the performance of different ANN and data driven models through suitable validation metrics such as Mean Squared Error (MSE), Normalized Mean Squared Error (NMSE), correlation coefficient (R), Nash-

Sutcliffe Efficiency (NSE). Selection of the ideal model over a standard same dataset and also to measure the effects of the input variable selection, network structure (including hidden layers, neurons, and transfer functions). While for NARX Mean Squared Error (MSE), Normalized Mean Squared Error (NMSE), correlation coefficient (R) validation metrics are used for the study. Overall, the research aims at the further spread of ANN, data driven approaches to measuring and simulate stream-flow, recording the benefits and real limitations to its use in practice. Spatially, the study is limited around the chosen catchment in which there is adequate hydrometric and meteorological data. These comparative studies are crucial in promoting scalable, physics-inspired surrogate modelling in the ungauged or partially gauged catchments, thus provide feasible solutions to water-resource management in the data scarcity environment (Guniganti et al., 2024; Mada et al., 2024).

Study Area

The Pairi River originates from the Bhatigarh Hills near Bindranavagarh in Gariaband district, Chhattisgarh, and flows southward to join the Mahanadi River near Rajim before ultimately draining into the Bay of Bengal. The Pairi sub-basin covers a geographical area of about 3194.60 km², lying between 81°51'58.7" to 82°26'16.04" E longitude and 19°55'51.9" to 20°55'6.9" N latitude. Elevation ranges from approximately 250 to 964 m above mean sea level. The basin receives over 85% of its rainfall during the southwest monsoon (June–September). Daily rainfall data (1990–2020) were collected from Baronda, Sikaser, and Sondur stations. The upper catchment is forested, while agriculture dominates the lower region, with the basin extending across parts of Chhattisgarh and Odisha. Pairi basin mainly lies in Chhattisgarh state but a small part of the upper basin comes under Odisha state in Nuapada and Nabarangapur districts. Major portion of the basin lies in two districts e.g. eastern part of Dhamtari and western part of Gariyaband district. Pairi basin stretches over the Dhamtari, Gariyaband districts of Chhattisgarh and Nuapada, Nabarangapur districts of Odisha.

Fig.1 The study area pairi basin Data collecting and processing



Two types of datasets were used Historical rainfall grid based precipitation records with high resolution of $0.25^\circ \times 0.25^\circ$ (Rajput et al., 2025) produced by Indian Meteorological Department (IMD), table 1 shows the Static and dynamic input Data table for each Catchment. streamflow (discharge) at the catchment outlet are collected daily Stream flow from the hydrometric station were used from Indian WRIS. The daily discharge data available from Baronda hydrometric stations were used for this study form the period from 1980 till 2013. The statistical properties table 2 shows the results of the descriptive statistical summary of daily rainfall data for different meteorological stations in the Pairi sub-basin for the study period of the daily rainfall for the gages stations over the period 1980 to 2013. The minimum rainfall at all the stations is zero (zero indicates the dry days) but the maximum amount of rainfall for a day varies considerably in any distribution of hourly rainfall between the various stations, and there is a large variability in extreme rainfall across different stations The mean daily rainfall varies between 2.538 mm (Rajim) and 3.752 mm (Panduka and Sikasar), showing slight spatial variation across the basin. The standard deviation ranges from 11.052 mm to 14.762 mm, which indicates considerable variability in daily rainfall amounts. The coefficient of variation (CV), which measures relative variability, ranges from 3.790 to 4.355. The high CV values (>1) indicate that rainfall in the basin is highly variable and unevenly distributed over time. Rajim station shows the highest variability, while Birgudi shows comparatively lower variability. Overall, the statistical results indicate that rainfall in the Pairi basin is highly fluctuating, with a large number of dry days and concentrated rainfall events during the monsoon season. This high variability highlights the importance of proper hydrological modeling and water resource planning in the basin.

Table 1 Static and dynamic input Data table for each Catchment the dynamic input data time series of precipitation and discharge(Stream Flow)) are available from 1980 till 2013.

Variable	Data	Resolution	Source
DEM(Digital Elevation model)	SRTM	30m x 30m	USGS earth explorer (https://earthexplorer.usgs.gov/)
Precipitation	Daily Station Data(gridded)	$0.25^\circ \times 0.25^\circ$	IMD (http://www.imdpune.gov.in)
Stream flow	Gauge Observation	daily	India WRIS (https://indiawris.gov.in/wris/)

Table 2 Stastical summary of available data (1980-2013)

Station name	Mean (mm)	Standard Deviation (mm)	Coefficient of Variation
Birgudi	3.396	12.870	3.790
Bundeni	2.975	12.356	4.154
Dabnai	2.942	11.949	4.062
Gariaband	3.619	14.749	4.076
Mainpur	3.293	13.050	3.963
Panduka	3.752	14.762	3.934
Sikasar	3.752	14.762	3.934
Sondur	3.594	14.076	3.916
Baronda	2.715	11.380	4.191

Rajim	2.538	11.052	4.355
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Methodology

This study aims to develop data-driven models for streamflow generation using, Artificial Neural Network (ANN) and Nonlinear Autoregressive Network with Exogenous Inputs (NARX). NARX simulates streamflow using Past streamflow values (autoregressive) Past rainfall values (exogenous inputs). Both models are developed using historical time-series data of rainfall and streamflow. ANN approach Time-Lagged Recurrent Networks (TLRNs) has been used in these study. The overall workflow includes data preprocessing, model development, training, validation, testing, and performance evaluation.

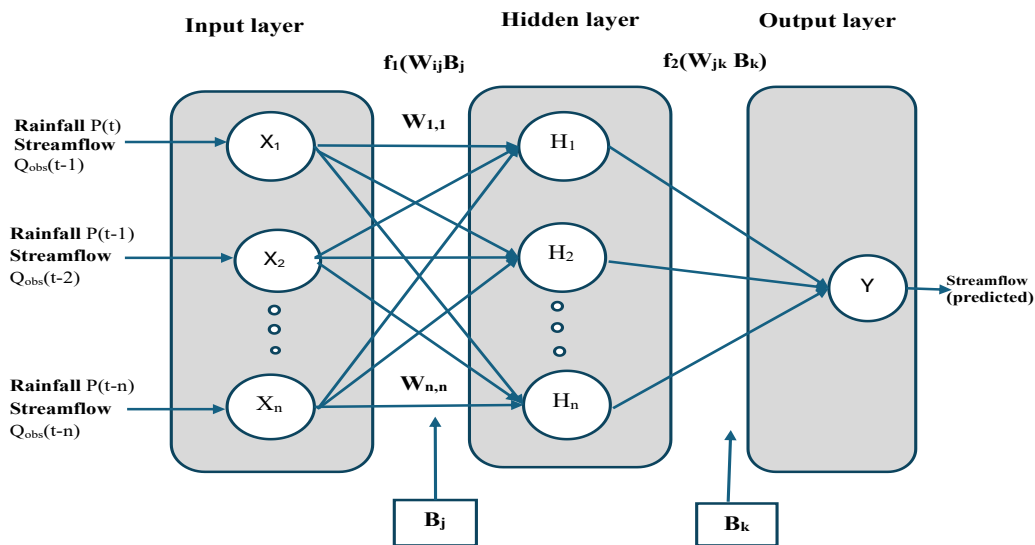
ANN

The ANN is a representative data-driven model proposed by McCulloch and Pitts through modeling the biological neurons (McCulloch & Pitts, 1943). The ANN model solves problems being model learning without the knowledge of physical processes. ANN is having the advantage that it has the ability to detect complicated nonlinear connection between input and output data sets without any physical knowledge. The conceptual diagram of ANN model that consists of input, hidden and output layers is shown in figure 2. Single layer has a limitation of the algorithm to be used in solving non-linear problems (Minsky & Papert, 1969). But to overcome all these limitations, a concept of multi-layer perceptron (MLP) model was devised. The MLP has been developed as an ANN model based on the structure of the brain using the different techniques such as activation function and backpropagation (Khotanzad & Chung, 1998; Kisi & Kerem Cigizoglu, 2007; McClelland et al., n.d.; Poulton, 2001; Rezaeian Zadeh et al., 2010). The ANN comprises of one or more hidden layers between input and output layer, nodes of each layer and weight value for the connection of every node, Eq. 1 formulate the ANN model mathematically as

$$Y = f_2 \left[\sum w_{jk} f_1 \left[\sum w_{ij} x_i + B_j \right] + B_k \right] \quad (1)$$

where x_i represents input data, f_1 and f_2 denotes the activation function for the hidden and output layers, w_{ij} is weight value between of the input and hidden layers, and w_{jk} is weight value between hidden and output layers. B_j and B_k are bias in hidden and output layers.

Fig. 2 Conceptual diagram of ANN



NARX

The present study employs a Nonlinear Autoregressive Neural Network with Exogenous Inputs (NARX) to simulate and predict streamflow using historical rainfall and streamflow time-series data. NARX is a recurrent neural network architecture that explicitly incorporates the effect of past inputs and past outputs, making it highly suitable for modeling nonlinear and dynamic hydrological processes such as rainfall-runoff relationships. The overall methodological framework consists of data collection, preprocessing, NARX model development, training and validation, streamflow simulation, and performance evaluation. The application of Nonlinear Autoregressive Exogenous (NARX) models, particularly within the MATLAB environment, presents a robust methodology for streamflow simulation and prediction, leveraging historical rainfall and streamflow time series data. NARX models are a class of recurrent neural networks that are well-suited for modeling nonlinear dynamic systems, which are characteristic of hydrological processes (Bal & Demir, 2021). This approach allows for the capture of complex, non-linear relationships between antecedent conditions (rainfall, past streamflow) and future streamflow, which is often challenging for traditional linear models (Bal & Demir, 2021).

A basic or general mathematical equation for a NARX model can be expressed in Equation 1

$$y(t)=f(y(t-1),y(t-2),...,y(t-dy),x(t-1),x(t-2),...,x(t-dx)) \quad (1)$$

Where:

$y(t)$ represents the streamflow at time t .

$y(t-1),y(t-2),...,y(t-dy)$ are past values of streamflow (output feedback), with dy being the output delay order.

$x(t-1),x(t-2),...,x(t-dx)$ are past values of exogenous input, typically rainfall in this context, with dx being the input delay order.

$f(\cdot)$ is a nonlinear function approximated by a neural network.

The NARX model's strength lies in its ability to incorporate both past output values (streamflow) and past exogenous inputs (rainfall) to predict future streamflow. This structure enables the model to learn the system's inherent dynamics and the influence of external factors, making it particularly effective for hydrological time series (Bal & Demir, 2021). MATLAB provides a powerful and user-friendly environment for implementing NARX models, especially through its Neural Network Toolbox (often referred to in the context of general neural network functionality, although specifically named "Deep Learning Toolbox" in recent versions). This toolbox offers specific functions and tools for designing, training, and simulating NARX networks. For instance, the `narxnet` function can be used to create a NARX network, defining the input and feedback delays, as well as the number of hidden layers and neurons. The training process involves feeding historical rainfall and streamflow data to the network, allowing it to learn the optimal weights and biases of the neural network through algorithms such as Levenberg-Marquardt or Bayesian Regularization (Bal & Demir, 2021).

The implementation steps in MATLAB typically involve are as follows

Data Preparation: Organizing rainfall and streamflow time series data into appropriate formats for input to the NARX network. This includes normalization and splitting data into training, validation, and test sets (Darabi Cheghabaleki et al., 2024).

Network Design: Defining the architecture of the NARX network, including the number of hidden layers, the number of neurons in each layer, and the input/output delays (dx and dy). These parameters are crucial for the model's performance and often require careful tuning.

Training: Training the network using historical data. During training, the network adjusts its internal parameters to minimize the error between its predictions and the actual observed streamflow values .

Validation and Testing: Evaluating the trained model's performance on unseen data to ensure its generalization capabilities. Common metrics for evaluation in streamflow prediction include Nash-Sutcliffe efficiency (NSE), Root Mean Square Error (RMSE), and correlation coefficients .

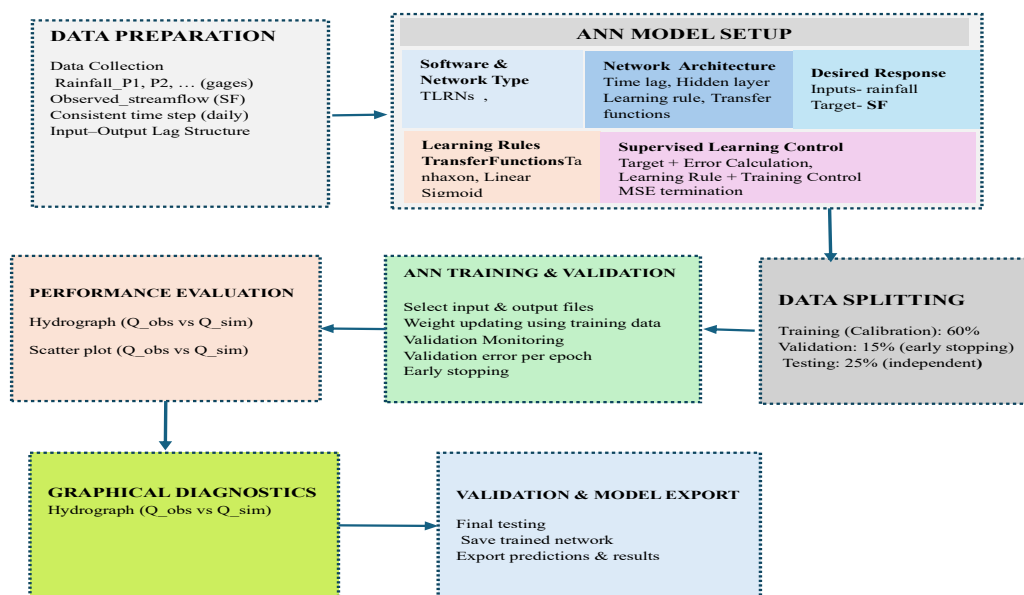
Simulation and Prediction: Once validated, the NARX model can be used to simulate future streamflow based on historical data and forecasted rainfall (Sarigöl et al., 2024).

The use of MATLAB for NARX-based streamflow prediction provides several advantages. Its integrated development environment and extensive library of functions simplify the complex mathematical and computational aspects of neural network modelling(VUKA & PRENGA, 2024). Furthermore, the visualization tools within MATLAB allow for insightful analysis of model performance and the relationships between variables. This makes MATLAB an invaluable tool for researchers and practitioners in hydrology seeking to leverage data-driven approaches for more accurate and reliable streamflow forecasting, particularly in challenging environments such as semi-arid basins where data scarcity or complex hydrological regimes are prevalent (Özdoğan-Sarıkoç & Dadaser-Celik, 2024). The ability of NARX models to capture the temporal dependencies and nonlinearities inherent in streamflow dynamics, coupled with MATLAB's computational power, offers a sophisticated solution for optimizing water resource management and mitigating hydrological risks (Sharma & Goel, 2024).

Application of NeuroSolutions

The NeuroSolutions software is used as it has powerful built-in features that could find the optimal neural network to a problem. These are genetic optimization in network parameters, ability to train neural network multiple times, changing each neural network parameter in a number of implementations. NeuroSolutions are broken down in these study into seven major modules that are used to create and train a network. These modules are presented in Fig. 3 and discussed below.

Fig. 3 Flow diagram for methodology of work with NeuroSolutions software



ANN Models selection for streamflow generation

In these Study Time-Lagged Recurrent Networks (TLRNs) ANN models were used and widely applied Artificial Neural Network (ANN) models for streamflow simulation due to its ability to represent the nonlinear hydrological processes. Figure 4 (Suwal et al., 2025) Schematic illustration of ANN-based process of day-ahead simulation of streamflow, the input of data and the model development along with TLRN and performance evaluation. The Time-Lagged Recurrent Networks (TLRNs) are extensions of feedforward architectures that have explicit temporal dependencies modeled in the form of time-delay units or context layers that have an internal memory of past network states. This recurrent structure, through feedback connections and also time-delay components, allows the network to specify internal temporal dynamics and autocorrelation structures typical of hydrological time series and thus is specially adapted to stream flow forecasting in which antecedent conditions have a strong influence on discharge patterns in the future (Khankhoje & Choudhury, 2024; Mounce, 2013; Saharia & Bhattacharjya, 2012). Unlike static feedforward networks, TLRNs have the ability to represent sequential dependencies by propagating information through time, where the time-delay unit represents the internal mechanism of memory where the historical activation states are stored for further processing steps. Inputs may also contain lagged external variables, but what the TLRN has which makes it naturally suited to sequence modeling is the recurrence of the network. Standard equation (general recurrent hidden update & output). Eq. (2) used here are external inputs rainfall of various station, while Eq. (3) time lagged inputs using TDL block in NeuroSolutions. Eq. (4) describes about the hidden state vector or hidden layer equation in TLRN model. Eq. (5) shows Output Equation used in these model, while Eq. (6) shows the Training (BPTT).

$$x(t) = [x_1(t), x_2(t), \dots, x_n(t)] \quad (2)$$

$$X_d(t) = [x(t), x(t-1), \dots, x(t-d)] \quad (3)$$

$$h(t) = f(W_{xh}X_d(t) + W_{yh}y(t-1) + W_{hh}h(t-1) + b_h) \quad (4)$$

Where

W_{xh} = weights from delayed inputs to hidden units

W_{yh} = recurrent weights from the previous o/p

W_{hh} = recurrent hidden - hidden weights

$f(\cdot)$ = nonlinear activation (sigmoid/tanh)

$$\hat{y}(t) = g(W_{hy}h(t) + b_y) \quad (5)$$

Where

$g(\cdot)$ is usually linear for the regression tasks

W_{hy} = hidden output weights

$$W(t+1) = W(t) - \eta \frac{\partial E}{\partial W}, E = \frac{1}{N} \sum_t (y(t) - \hat{y}(t))^2 \quad (6)$$

NeuroSolutions calculates these gradients at time by using the dynamic learner block. Eq. (7) shows dense dynamical formulation of the TLRN hidden state while output equation is represented in Eq. (8)

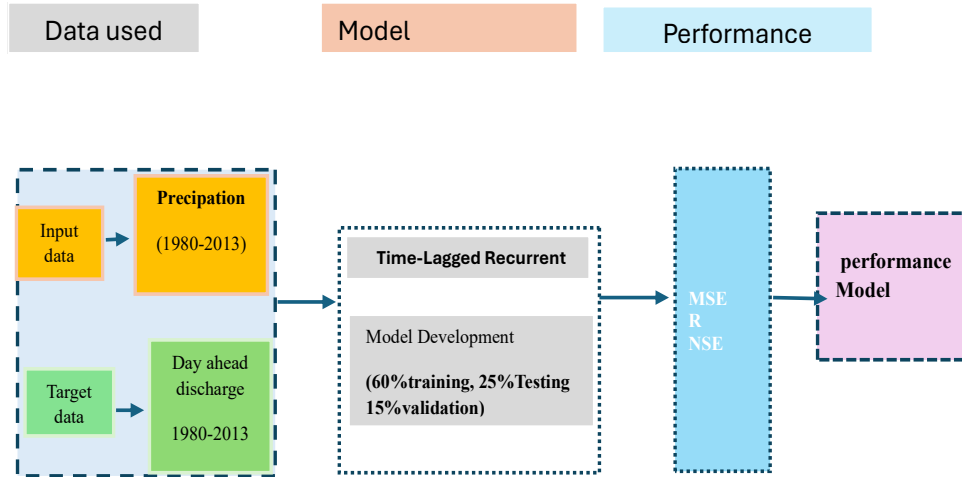
$$h(t) = f(W_{xh}X_d(t) + W_{yh}y(t-1) + W_{hh}h(t-1) + b_h) \quad (7)$$

$$\hat{y}(t) = g(W_{hy}h(t) + b_y) \quad (8)$$

where $X_d(t) = [x(t), x(t-1), \dots, x(t-d)]$ is the tapped-delay input vector (from Time-Delay lines), W_{yh} represents feedback weights from previous outputs (if used), W_{hh} is the hidden recurrence which has a similar form as , $f(\cdot)$ is the hidden activation (sigmoid/tanh) and $g(\cdot)$ is usually linear in case of regression and $y(t)$ represent predicted streamflow. TLRN is a recurrent network architecture, which has a combination of explicit tapped-delay inputs (TDL/context units) and recurrent feedback. For streamflow modeling, the TLRN architecture usually consists of Input axons with TDL

blocks generating the lagged input features Hidden layer N non-linearity neurons (sigmoid/tanh), Output node Linear, Recurrent connections (feedback) from the Output or hidden units to the hidden layer so the network develops an internal state in time. Training is done using Backpropagation Through Time (BPTT) or similar recurrent training algorithms.

Fig. 4 overall methodology flow of the study for ANN Models selection for streamflow generation(Suwal et al., 2025)



Performance Evaluation

Metrics error and statistical measures

Performance of both ANN and NARX model were evaluated with Mean Squared Error (MSE), correlation coefficient (R), Nash-Sutcliffe Efficiency (NSE). There is an evaluation of performance based on a combination of error-based, correlation-based, efficiency-based and information-theoretic measures used to assess all the aspects of accuracy, robustness and model complexity. Table 4 shows the error indices, range and equation of the performance evaluation. The most popular objective function in the training of ANNs is the Mean Squared Error (MSE) (Hydrology, 2000; Mahir et al., 2026), which measures the average squared error in predicted and observed streamflow values, and is very sensitive to large error in forecasting.

Table 3 The performance of the ANN and NARX model was evaluated using statistical indices

Error indices	Range	Equation
Mean Squared Error (MSE),	$0 \leq \text{MSE} < \infty$	$\text{MSE} = \frac{1}{N} \sum_{t=1}^N (Q_{obs}(t) - Q_{sim}(t))^2$
correlation coefficient (R)	$-1 \leq R \leq 1$	$R = \frac{\sum_{t=1}^N (Q_{obs}(t) - \bar{Q}_{obs})(Q_{sim}(t) - \bar{Q}_{sim})}{\sqrt{\sum_{t=1}^N (Q_{obs}(t) - \bar{Q}_{obs})^2} \sqrt{\sum_{t=1}^N (Q_{sim}(t) - \bar{Q}_{sim})^2}}$

Nash-Sutcliffe Efficiency (NSE)	$-\infty \leq \text{NSE} \leq 1$	$\text{NSE} = 1 - \frac{\sum_{t=1}^N (Q_{obs}(t) - Q_{sim}(t))^2}{\sum_{t=1}^N (Q_{obs}(t) - \bar{Q}_{obs})^2}$
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Graphical diagnostics and Validation and Model Export

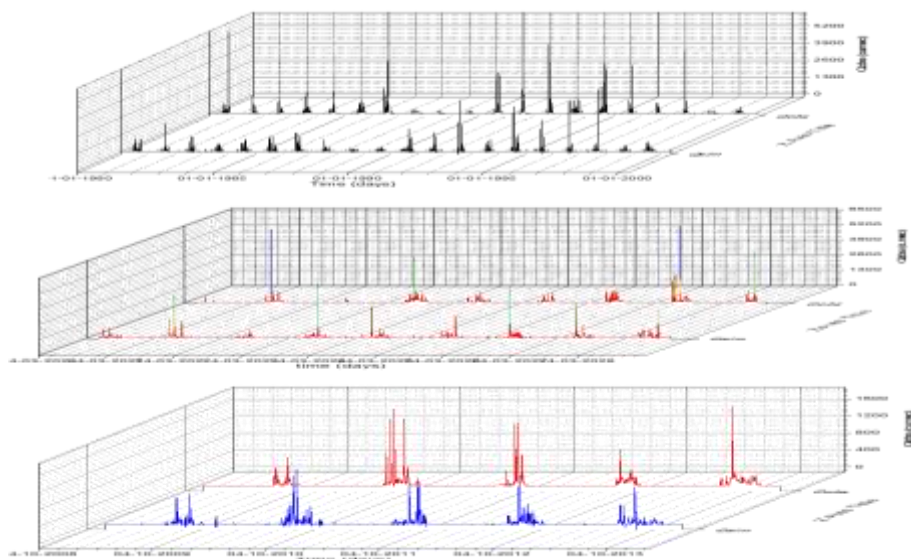
Plot hydrographs time series of observed and simulated flow to verify the performance of ANN models. Plot of Qobs vs Qsim with line assist in visualizing bias. These have been developed to supplement the statistical measures and it is critical to the hydrologic model assessment. When the cost has been calibrated and validated, use the trained model in an independent test period to determine generalization. Record similar values of test data with calibration. Export the trained ANN model (weights, architecture) and simulated flow series to continue working with it as water resources planning, flood forecasting, continuous simulation.

Results and Discussion

Comparison of flow measured with streamflow

The present study was a comparative study of the predicted (Simulated) streamflow by NARX and ANN models approach with Time-Lagged Recurrent Networks (TLRNs) of observed Stream flow over period from 1 January 1980 to 31 December 2013. In Training Phase Period from 01 January 1980 to 25 May 2010 Samples datasets. Sample of data sets for Testing Phase between 25 May 2000 and 25 November 2008. As with Cross-Validation Phase, Time Period 26 November 2008 to 31 December 2013 datasets were illustrated on the study to determine the predictive power of the models. The below graph Figure 5 (a) (b)(c) by giving an exhaustive account of the observed and simulated discharge graphs of training, testing, validation of Baronda stream flow of pairi Basin, the output of the ANN model TLRNs on the basis of the amount of rain and historical streamflow gauging. The graphs compare discharge (Qobs) with ANN-simulated discharge (Qsim) at three different modeling phases namely training, testing and cross-validation. While for NARX error based analysis and performance based analysis were performed.

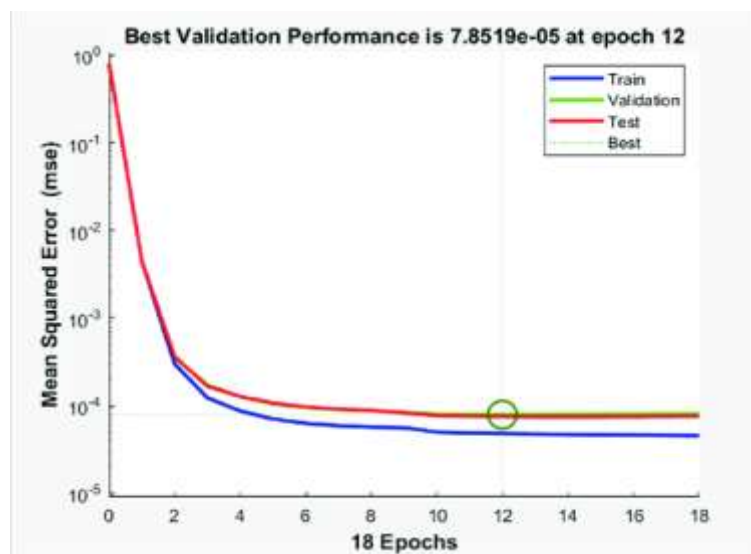
Fig.5 Observed and simulated analysis of TLRN , Training , Testing, cross-validation. NARX model analysis



The present study utilizes a Nonlinear Autoregressive Neural Network with Exogenous Inputs (NARX) to simulate and predict streamflow using historical rainfall and discharge time-series data. NARX, a recurrent neural network, incorporates both lagged rainfall inputs and previous streamflow outputs, making it suitable for modeling nonlinear rainfall-runoff processes. Continuous rainfall data from meteorological stations and corresponding observed streamflow records from gauging stations were used at the same temporal resolution. The dataset was divided into training (70%), validation (15%), and testing (15%) subsets. The model was trained using the Levenberg–Marquardt algorithm in open-loop mode. Model performance was evaluated using R, NSE, MSE, where higher R and NSE and lower mean square error values indicate better predictive accuracy.

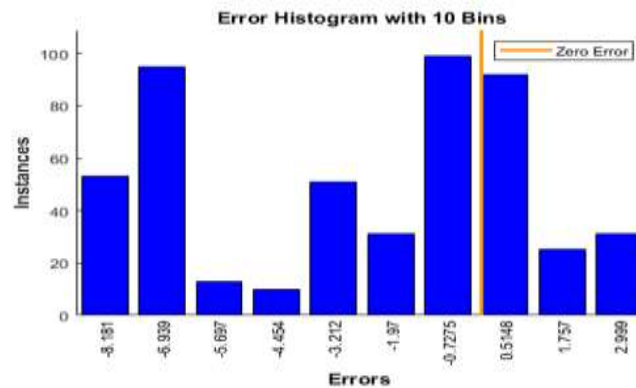
The figure 6 shows the training performance plot of a neural network model, likely developed in MATLAB for streamflow prediction. The graph represents Mean Squared Error (MSE) on a logarithmic scale versus the number of training epochs (0–18). Three curves are displayed: Training (blue), Validation (green), and Testing (red), along with a dotted line marking the best validation performance. The Figure indicates that the best validation performance is 7.8519×10^{-5} at epoch 12, highlighted by a green circle and vertical dashed line. Initially, the error decreases sharply during the first few epochs, showing rapid learning. After epoch 12, the validation error stabilizes and slightly increases, suggesting that further training could lead to overfitting. The close alignment of training, validation, and testing curves indicates good generalization and model stability.

Fig. 6 represent Mean Squared Error (MSE) on a logarithmic scale versus the number of training epochs



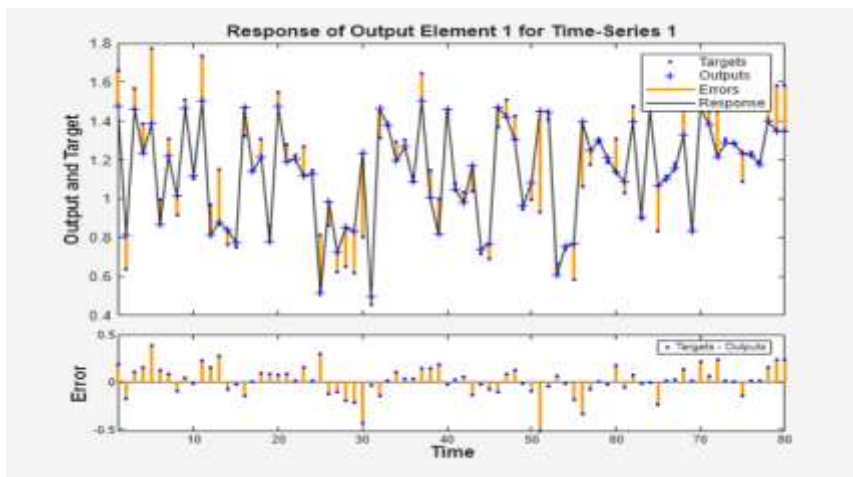
The image figure 7 presents an error histogram with 10 bins showing the distribution of prediction errors from the neural network model. The horizontal axis represents the difference between observed and predicted streamflow, while the vertical axis shows the frequency of errors. The blue bars indicate both negative (underestimation) and positive (overestimation) errors, and the orange vertical line represents zero error. Most errors are clustered around zero, mainly between -1 and $+1$, indicating that the model predictions closely match observed values. The near-symmetric distribution suggests good accuracy with minimal systematic bias.

Fig. 7 represents the distribution of prediction errors generated by the neural network model



The figure 8 shows the response plot of Output Element for Time-Series, typically generated from a neural network model in MATLAB. The upper panel compares targets (observed values) and network outputs (predicted values) over time. The blue markers represent target data, while the black line indicates the model response. The close alignment between targets and outputs suggests good predictive performance. Orange vertical lines represent individual prediction errors at each time step. The lower panel displays the error plot (Targets – Outputs) over time. Most errors fluctuate around zero, indicating minimal bias and good generalization. Although a few larger deviations appear at certain time steps, overall the errors remain small, confirming that the model effectively captures temporal variations in the time-series data.

Fig. 8 the response plot of Output Element for Time-Series



Detailed Description and Interpretation of the Regression Plots

The figure 9 presents four regression plots comparing observed and predicted streamflow for training, validation, testing, and combined datasets. Each plot includes a fitted regression line and a reference line ($Y = T$), representing perfect agreement. The correlation coefficients are 0.72363 (training), 0.77976 (validation), 0.71042 (testing), and 0.74647 (overall), indicating strong positive relationships in all cases. The higher validation R-value suggests good generalization with minimal overfitting. The overall R of 0.74647 implies that nearly 56% of the variance in streamflow is explained by the model.

However, regression slopes less than one indicate slight underestimation of peak flows, a common limitation in data-driven hydrological modeling.

The validation of the ANN model was carried out using test data and evaluated through multiple performance indicators, including Mean Squared Error (MSE), Correlation Coefficient (R), Nash–Sutcliffe Efficiency (NSE), Table 4 presents the statistical and error measures for training, cross-validation, and testing phases of each ANN architecture. The three ANN models were compared based on these metrics to assess learning capability during training, generalization performance during testing, and model robustness and early-stopping behavior during cross-validation. According to the performance metrics of low MSE to make the training and generalization effective, high R and NSE to the performance reporting such approach has been used for statistical analysis.

Fig. 9 represents regression plots generated from developed for streamflow simulation. These plots represent the relationship between observed (target) values and model outputs for the Training, Validation, Testing, and combined.

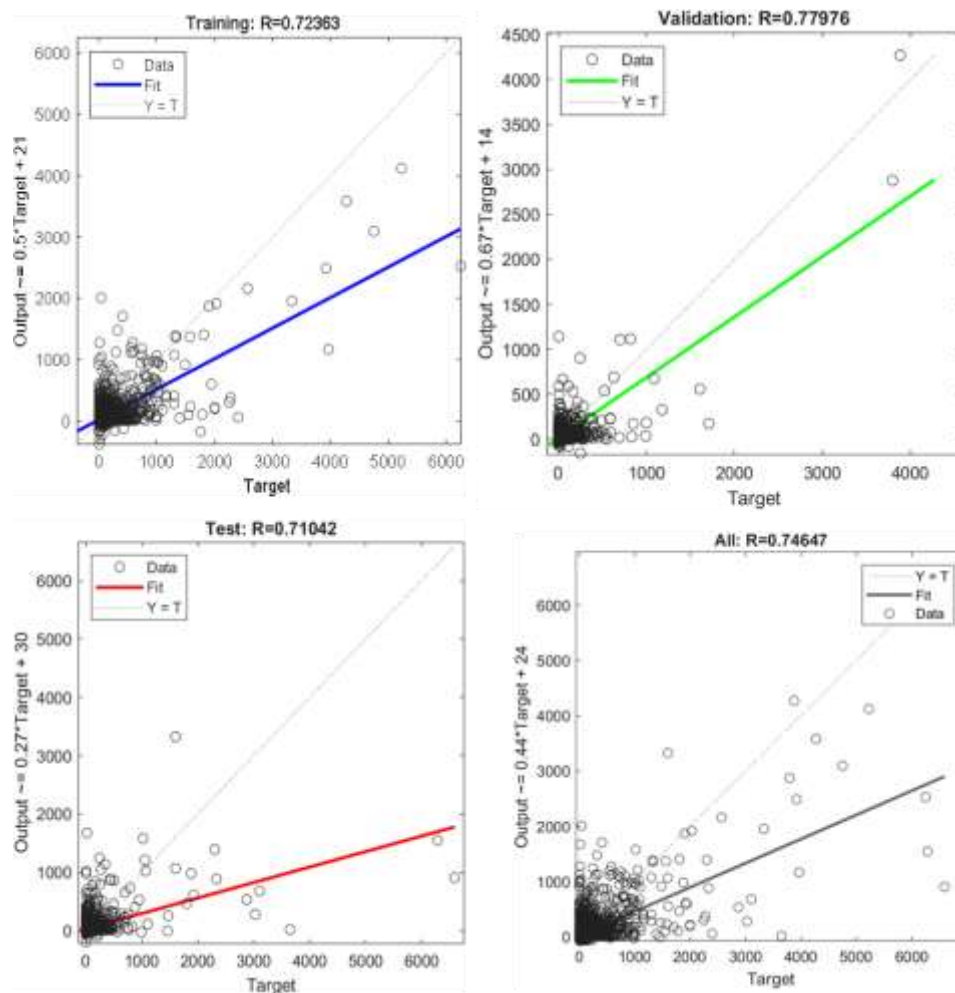


Table 4 Performance of different ANN Models for Training, Testing, cross-validation (Cv)

Metrics	TLRN			NARX		
	Training	Testing	Cv	Training	Testing	Cv

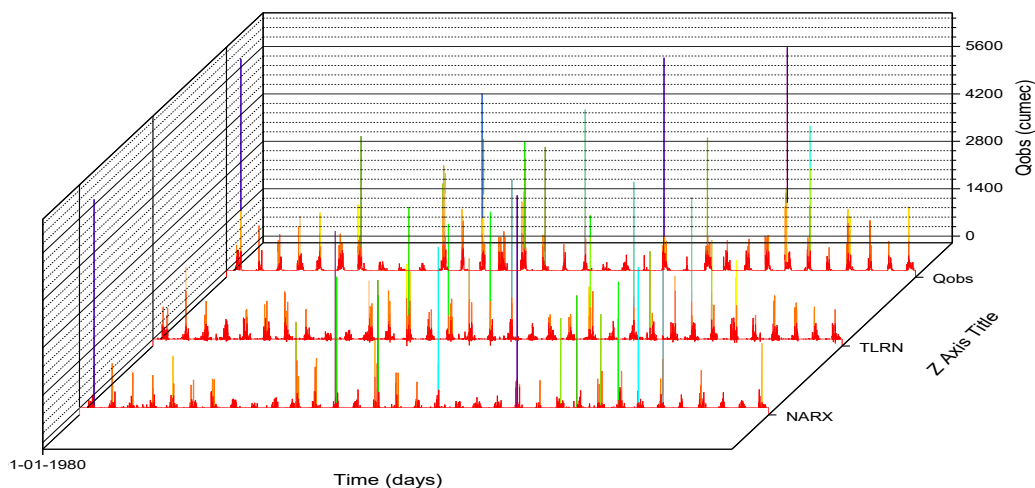
MSE	0.001	0.0097	0.003	0.0007	0.0016	0.011
R	0.711	0.699	0.701	0.723	0.779	0.710
NSE	0.717	0.785	0.711	0.872	0.891	0.812

Comparative Performance Analysis of TLRN and NARX Models. The performance metrics indicate clear differences between the ANN-TLRN and NARX models in simulating streamflow. In terms of Mean Squared Error (MSE), NARX shows lower training (0.0007) and testing (0.0016) errors compared to TLRN (0.001 training; 0.0097 testing), indicating better accuracy and generalization. Although TLRN exhibits a slightly lower CV MSE (0.003), its testing error is considerably higher. For the correlation coefficient (R), NARX achieves higher values in training (0.723) and testing (0.779) compared to TLRN (0.711 and 0.699), demonstrating stronger agreement with observed data. Similarly, Nash-Sutcliffe Efficiency (NSE) values are significantly higher for NARX (0.872 training; 0.891 testing) than TLRN (0.717 training; 0.785 testing), confirming superior predictive skill. Based on the criteria of low MSE and high R and NSE, the NARX model outperforms the TLRN model and is selected as the best-performing approach.

Conclusion

This study presented a comparative evaluation of streamflow simulation using two ANN-based approaches Time-Lagged Recurrent Networks (TLRN) and Nonlinear Autoregressive Neural Network with Exogenous Inputs (NARX) for the Pairi Basin of Chhattisgarh using 30 years of historical data (1980–2013). The models were assessed through training, testing, and cross-validation phases to examine their learning capability, generalization performance, and predictive reliability. The statistical results clearly demonstrate in figure 10 that the NARX model outperformed the TLRN model. NARX produced lower MSE values and higher R and NSE values during training and testing phases, indicating better agreement with observed streamflow and improved prediction accuracy. The higher NSE values (above 0.87 in training and 0.89 in testing) confirm the strong predictive skill of the NARX architecture. Based on the criteria of low error and high efficiency metrics, the NARX model is identified as the most suitable approach for streamflow simulation in the Pairi Basin.

Figure 10 Comparison of observed streamflow with simulated streamflow generated using ANN-Time-Lagged Recurrent Network (TLRN) and NARX neural network model



In presents study a comparative evaluation of streamflow simulation using two artificial neural network models: the ANN based on Time-Lagged Recurrent Networks (TLRN) and the Nonlinear Autoregressive Neural Network with Exogenous Inputs (NARX) implemented in MATLAB. The comparison is made against observed streamflow data using time-series plots that highlight peak and low-flow variations. Visual inspection indicates that while both models capture the general trend of streamflow, the TLRN model slightly smooths and underestimates peak discharges. In contrast, the NARX model shows better alignment with observed peak magnitudes and improved timing accuracy. During low-flow periods, NARX maintains closer agreement with observed values. The improved performance of NARX is attributed to its incorporation of both lagged rainfall inputs and autoregressive streamflow feedback, enabling better representation of basin memory and nonlinear hydrological dynamics.

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