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Soft Computing For Hydrological Modelling: A Proportional Reading Of ANN And MLR Regarding Runoff Prediction

Seema Avinash Jagtap[1], Ninad Khandare[2], shivamanth Angadi[3], Rutuja Shinde[4], Ashwini Shanbhag[5], Sanjeev Chaudhari[6]
[1]Professor,Thakur College of Engineering & Technology, Kandivali, Mumbai- 400101
[2]Assistant Professor, Thakur College of Engineering & Technology, Kandivali, Mumbai- 400101
[3]Associate Professor, Department of Civil Engineering, KLS GIT, Belagavi-590006, INDIA (Email id: ssangadi@git.edu)
[4]Assistant Professor, Thakur College of Engineering & Technology, Kandivali, Mumbai- 400101
[5]Assistant Professor, Thakur College of Engineering & Technology, Kandivali, Mumbai- 400101
[6]Professor, Thakur College of Engineering & Technology, Kandivali, Mumbai- 400101

ABSTRACT: *Hydrological modelling is essential for water resource management, particularly in forecasting runoff to mitigate flood and drought risks. This study applies Artificial Neural Networks (ANN) and Multi-Linear Regression (MLR) to predict a day advance excess rainfall in the Krishna Catchment, focusing on the Hiranyakeshi, Ghataprabha, and Tambraparni watersheds in Maharashtra, India. The study developed hydrological models using daily rainfall, antecedent rainfall, runoff, antecedent runoff with one to three-day time lags, and daily evaporation as inputs. A Multilayer Perceptron (MLP) ANN with a feed-forward backpropagation network is employed, and model performance is assessed using statistical indicators. The results show that ANN models significantly outperform MLR in predicting runoff, particularly in capturing peak flows. The Rainfall-Runoff Model demonstrates the highest predictive accuracy, achieving an R-value above 0.90, while the best MLR model achieves approximately 0.85. ANN models exhibit lower Mean Square Error (MSE) and Root Mean Square Error (RMSE) values, confirming their superior predictive capabilities, though minor prediction of peak flows is noted, remaining within 20% of observed values. MLR models provide reasonable estimates but struggle with nonlinearity, limiting their accuracy in extreme conditions. The findings highlight ANN's effectiveness in handling complex hydrological processes, making it a suitable tool for real-time runoff forecasting and flood risk management. Future research should explore additional hydrological parameters like soil moisture and temperature variations to enhance prediction accuracy and consider integrating ANN with optimization. The study establishes a data-driven approach for improved runoff forecasting, offering a framework applicable to other river basins for efficient water resource planning and disaster management.*

Keywords: *Artificial Neural Network, Multi-Layer Perceptron, Runoff Prediction, Rainfall-Runoff Modeling, Watershed Management, Hydrological Forecasting*

I. INTRODUCTION

Water and land resources play a crucial role in sustainable development, necessitating efficient watershed management strategies. Hydrological modeling is essential for predicting runoff, assessing water availability, and mitigating flood risks (Nearing et al., 2024). Traditional deterministic and stochastic models have been widely used in hydrological studies; however, their predictive capabilities are often limited by complex nonlinear interactions within watersheds (Nevo et al., 2022). Recent advancements in soft computing techniques, particularly Artificial Neural Networks (ANN), have demonstrated significant improvements in streamflow forecasting and watershed modeling (Gauch et al., 2021). ANNs, inspired by biological neural networks, have played major role in hydrology due to model nonlinear relationships between rainfall, runoff, and other environmental parameters (Ghimire & Reddy, 2020). These models are particularly effective in predicting flood events, optimizing water resource allocation, and improving early warning systems (Díaz et al., 2018). Unlike traditional regression-based approaches, ANNs can acquire patterns from past hydrological records and generalize them to novel conditions, making them a valuable tool in real-time decision support systems (Homayoun et al., 2018). Hydrological applications of ANNs have been extensively studied in recent years. Peres et al. (2015) demonstrated the effectiveness of ANN-based models for predicting significant wave heights, highlighting their adaptability in various hydrological contexts. Similarly, Chang et al. (2014) applied ANN techniques for flood inundation nowcasting, proving their capability in handling large-scale, complex hydrological datasets. In addition to ANNs, hybrid models that integrate multiple machine learning techniques have also shown promise in improving predictive accuracy (Sarkar & Kumar, 2012).

One of the primary advantages of ANN-based watershed modeling is its ability to handle noisy and incomplete datasets. Unlike conventional models that require precise parameterization, ANNs can extract meaningful patterns even in data-scarce environments (Hung et al., 2009). Furthermore, the integration of deep learning techniques has enabled the development of more robust and scalable hydrological models capable of long-term predictions (Jain & Srinivasulu, 2004). However, despite these advantages, ANN models are not without limitations. They often require large datasets for training, and their performance heavily depends on the selection of input parameters and network architecture (Solomatine & Siek, 2004). Additionally, ANN models are opaque boxes, with challenge to comprehend model formation method (Hsu et al., 1997). To address this, researchers have explored the explainable AI techniques and fusion modeling tactics that trust ANN with physical models (Ghosh & Reilly, 1994). Recent studies have also emphasized the importance of real-time hydrological forecasting using ANN-based frameworks. For instance, Yoshioka & Hamazaki (2019) proposed an ANN-based approach has implications for improving hydrological predictions under changing climate conditions. Similarly, Nearing et al. (2024) highlighted the prospective of AI subset models in predicting extreme flood events in ungauged watersheds, underscoring the growing reliance on AI-driven hydrological simulations.
This study aims to develop and evaluate ANN-based watershed models for predicting one-day-ahead runoff in the Ghataprabha basin. This research seeks to identify the most effective approach for hydrological forecasting as well as comparison of ANN and Multi-Linear Regression (MLR) models performance. The findings will contribute for development of more accurate and reliable watershed management tools, ultimately enhancing flood mitigation and water resource planning efforts.

II. LITERATURE REVIEW, SCOPE AND STUDY AREA

A. Literature Review

Numerous studies have explored the application of ANN and MLR in hydrological modelling. Forecasting of runoff is useful in many water resources applications such as water supply, hydropower generation, and flood control and drought management. Runoff models are also used in design of hydraulic structures. Different types of rainfall runoff transformation models are proposed in the past have been presented in this section.
Nearing et al. (2024) present a global predictive model for extreme floods in ungauged watersheds using machine learning techniques. The study emphasizes the challenge of forecasting floods in regions where hydrological data is scarce or unavailable. By integrating large-scale climate and hydrological datasets, the authors develop a predictive framework that enhances flood risk assessment in data-deficient areas. The results demonstrate that AI-based models outperform traditional statistical methods, providing more accurate and timely predictions. The paper portrays the importance of machine learning in global flood forecasting and its potential to improve disaster preparedness and water resource management. **Nevo et al. (2022)** sightsee through their research the application of machine learning models for flood forecasting within an operational framework. The study integrates real-time hydrological and meteorological data to for accurate prediction of flood. By comparing traditional statistical approaches with advanced AI techniques, the researchers demonstrate that machine learning models provide improved forecasting capabilities, particularly in complex and data-scarce environments. The study also highlights the challenges of implementing AI-driven flood forecasting in operational settings, including data reliability and computational requirements. The findings emphasize the potential of machine learning for real-time flood risk management and early warning systems. **Gauch et al. (2021)** predicted the influence of limited training records on streamflow using machine learning models, particularly within the CAMELS dataset. The study highlights how data scarcity affects the generalization ability of AI-based hydrological models. The authors compare different training strategies and assess how machine learning models can be optimized to perform well with limited observations. Their findings emphasize the need for careful data pre-processing and augmentation techniques to improve prediction accuracy. The study provides valuable insights for applying AI in real-world hydrological forecasting, especially in data-scarce regions. **Ghimire and Reddy (2020)** investigate the solicitation of Artificial Neural Networks (ANN) for hydrological modeling in the Bagmati River Basin, Nepal. The study aims to improve runoff prediction accuracy using ANN models trained with historical hydrological data. The authors compare ANN models with conventional statistical approaches and find that ANNs outperform traditional models in capturing nonlinear rainfall-runoff relationships. The study highlights the significance of selecting appropriate input variables, such as antecedent rainfall and evaporation, to enhance prediction performance. The outcomes

prove that ANN-based models serve as effective decision-support tools for flood predicting. **Peres et al. (2015)** explore the Artificial Neural Networks (ANN) combined with exploration wind data to range significant wave height records. The study aims to improve ocean wave predictions by utilizing ANN models trained on historical wave height and meteorological data. The research demonstrates that ANN-based models outperform conventional statistical methods in reconstructing missing wave height records and predicting future trends. The integration of reanalysis wind data enhances model accuracy, making it a valuable tool for coastal engineering and marine navigation. The study highlights the potential of AI-driven approaches in improving ocean wave forecasting and climate modeling. **M. Rezaeianzadeh et. al. (2013)**, incorporated artificial neural networks (ANN), adaptive neuro-fuzzy inference systems (ANFIS), multiple linear regression(MLR) and multiple nonlinear regression(MNLR) for predicting extreme day-to-day flow at the exit of the Khosrow shirin watershed, to track in the Fars Province of Iran. **Archana Sarkar et. al. (2012),** studied approach of the Artificial Neural Network (ANN) approach for hydrological process for catchment of Ajay river basin. The outcomes prove that ANN models can forecast the extent of the peak discharge with precision. **Hung et al. (2009):** Hung et al. introduced an integrated ANN framework for flood prediction in urban catchments. Their study incorporated multiple hydrometeorological variables, including precipitation, temperature, and land-use data, to enhance predictive capabilities. The research found that ANN models, when combined with data assimilation techniques, significantly improved forecast accuracy. The study's results emphasized the importance of hybrid approaches, integrating AI with traditional hydrological models for robust watershed management solutions. **Jain and Srinivasulu (2004):** Jain and Srinivasulu conducted a comparative analysis of ANN and physical-based hydrological models for runoff estimation. Their research indicated that ANN models performed exceptionally well in data-driven scenarios, where empirical relationships were difficult to establish. Despite concerns over interpretability, the study demonstrated that ANN models could serve as complementary tools alongside traditional models, improving forecasting accuracy in complex hydrological systems. Their findings reinforced the role of ANN in real-time hydrological applications. The literature review on incorporation of Artificial neural network and Multi linear regression as well as some data-driven techniques in Hydrology specially in hydrological modelling. References found, were authors shown their interest for using both artificial neural network and Multi Linear Regression particularly in runoff modelling. Two data-driven modelling techniques ANN and MLR are used in the present work to predict runoff one day ahead using previous years' data of precipitation and runoff.

B. Scope of the Study

The present work explains soft computing techniques of Artificial Neural Network (ANN) and regression analysis of Multi Linear Regression (MLR) are used to forecast runoff at 3 locations in Amba river basin and their results are compared. ANN is a relatively new soft computing technique particularly in modelling runoff. ANN is a non-linear model, combination of input and desired output variables in Hydrology. The second technique used is Multi Linear Regression, which is based on multiple linear equations. It is an automatic programming technique for evolving computer programs to solve, or approximately solve, problems.

C. Study Area

In the present study runoff-runoff model and rainfall- runoff model to forecast runoff one day ahead were developed at three rain gauge stations namely, Tuksai, Pali and Salinde in Amba river basin. The river Amba rises in the Sahyadri ranges at an altitude of 822 meters at 3.20kms south of village Khandala at Rajmachi in Borghat of Tal. Maval Dist. Pune. Then travelling by 78.17kms and flowing towards west. This river meets Dharmatar Creek near village Dherand of Tal. Alibag Dist. Raigad at 0.00 meters level and then merges in Arbian Sea. The Amba River flows through the minute area of Dist. Pune and major part of District Raigad in the state of Maharashtra.

Table 1 Location and catchment area of Amba river

LOCATION	LATTITUDE		LONGITUDE		CATCHMENT AREA
	From	To	From	To	
Amba River	18.45° N	18.85° N	73.21° E	72.92° E	1175.48 sq.km. (As per Hydrology Map) 929.75 sq.km. (As per Geographical Map)

Table 2 Topographical description of Amba basin

DIRECTIONS	SUB-BASIN
North	Patalganga Sub-basin.
East	Sahydri Mountains, Bhima Sub-basin.
West	Arbian sea.
South	Sub-basin Kundalika.

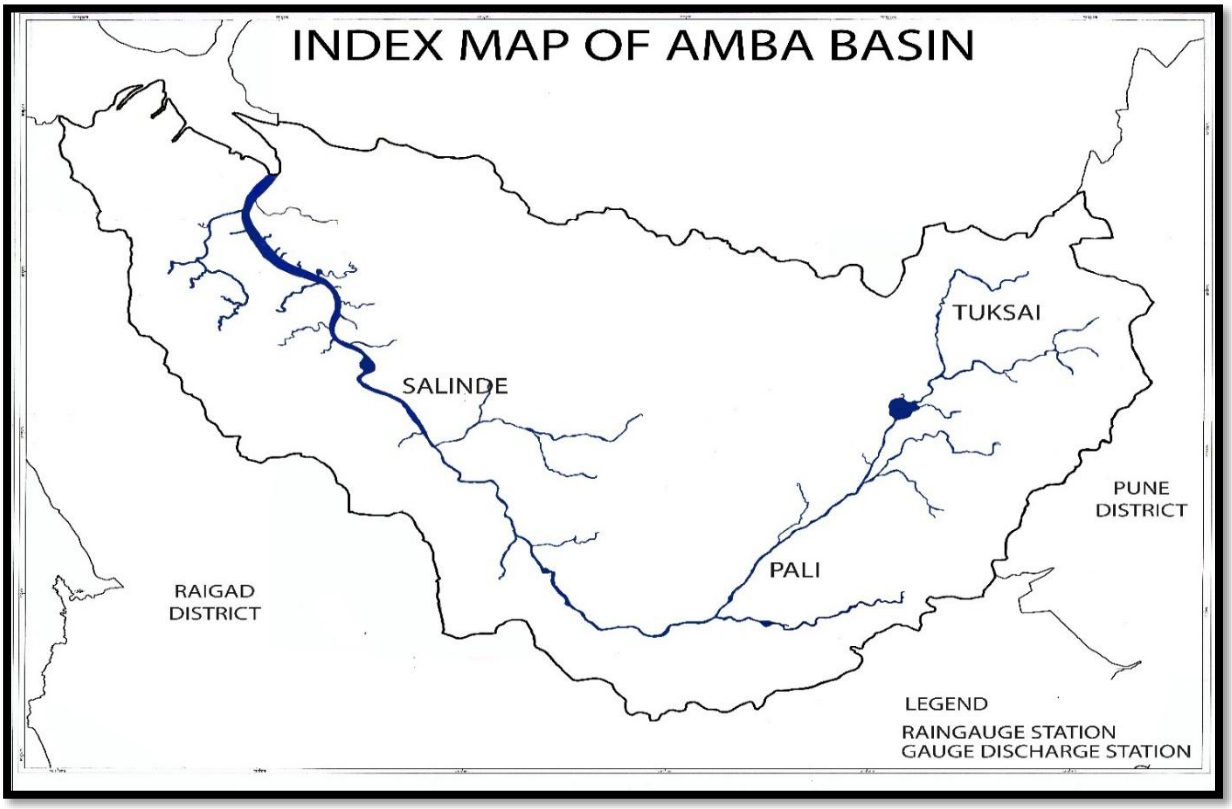


Fig. 1. Index map of Amba basin

Table 3 Locations of Rain gauge and Gauge discharge stations in Amba river basin

S.R. NO	LOCATION	LATITUDE	LONGITUDE	TYPE
1	Tuksai	18°42'44.82"N	73°18'16.28"E	GD,ARG
2	Pali	18°32'13.76"N	73°13'20.55"E	GD,ARG
3	Salinde	18°38'50.70"N	73°05'05.01"E	GD

Collection of data: All the data was collected from the Hydrology Project, Water Resource Department, Government of Maharashtra (Surface water) are presented in Table 4.

Table 4 Data availability on river gauge station

SR. No.	Station Name	Dist.	Tal.	River	Tributary	Data available	Training data points	Testing data points	Validating data points
1	Tuksai	Raigad	Khalapur	Amba	Amba	1991-2004	304	65	65
2	Pali	Raigad	Sudhagad	Amba	Amba	1980-2010	673	144	144

3	Salinde	Raigad	Pen	Amba	Nigadi	1994-2010	369	79	79

III. OBJECTIVES AND METHODOLOGY

A. Objectives

The main objective of the present study is to develop models for prediction of runoff one day ahead using Artificial Neural Network and Multi Linear Regression methods by using rainfall, runoff data. The specific objectives of the present study are:

1. To develop a model for forecasting one day ahead runoff at Ajara Ramtirth station and Kadal station located at Hiranyakeshi rivulets, which is the sub basin of Krishna River using the technique of artificial neural network (ANN) model and multi linear regression (MLR) model
2. To analyse performance of artificial neural network model and multi linear regression model on basis of statistical measures.
3. To suggest best technique among artificial neural network (ANN) model and multi linear regression (MLR) model for forecasting one day ahead runoff.

B. RESEARCH METHODOLOGY

The research work includes the development of Artificial Neural Network (ANN) and Multi-Linear Regression (MLR) models for forecasting one-day-ahead runoff. The steps involved are:

1. Data Collection: Rainfall, runoff, and evaporation data were collected for various stations.
2. Data Transformation: Logarithmic transformation was applied to normalize data distribution.
3. Model Design:

- Input variables: Precipitation, evapotranspiration, and runoff (daily values).
- ANN architecture: Multi-layer perceptron with single hidden layer.
- Training algorithm: Feed-forward back-propagation.

4. Model Training and Testing: ANN and MLR models were trained and tested using historical data.

- Performance Evaluation: The models were estimated on basis of:

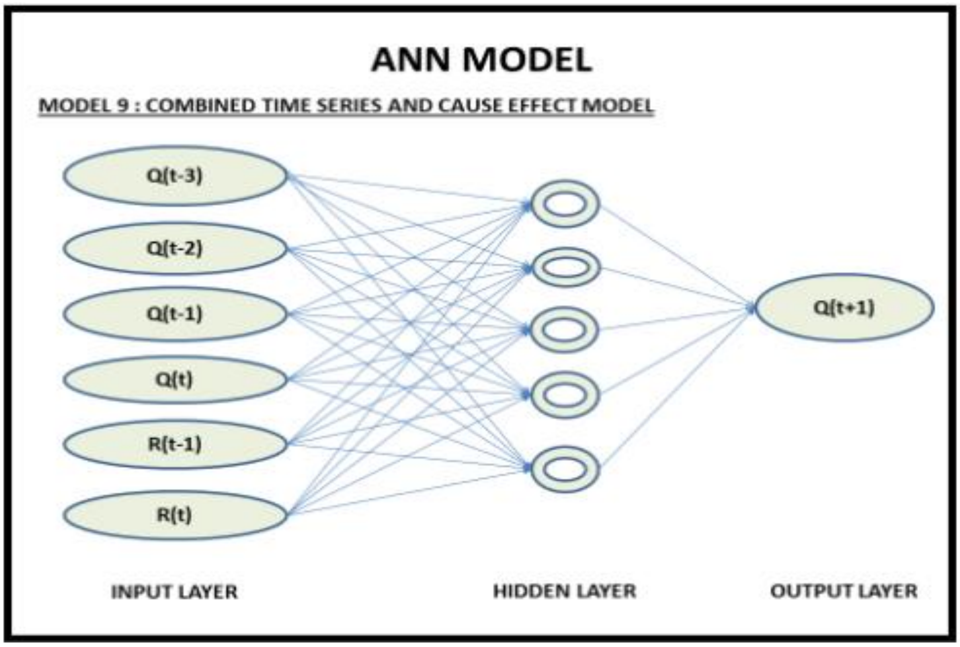
Correlation coefficient (R)
Mean Square Error (MSE)
Root Mean Square Error (RMSE)
Hydrographs
Scatter plots

In the present paper hydrological models were developed to forecast runoff one-day advance rainfall excess at rain gauge stations, Tuksai, Pali and Salinde in Amba river in Taluka Maval district Pune.

IV. MODELLING

Model Formulation Using ANN

The modelling technique approach used in the present study is based on artificial neural network method in modelling of hydrologic input-output relationship. MATLAB can be incorporated effectively to enhance understanding and enabling the researcher actively to put theory into practice. This software is known are friendly user and flexible with high capability for analysis and design the hydrologic processes. Results of this study will permit the identification of the best models for the rainfall-runoff modelling.
The data used for model was divided as 70% data was taken for first phase i.e. training the model, 15% data was taken for second phase i.e. testing the model and remaining data for third phase i.e. validation purpose of model. The developed models were evaluated for their accuracy by employing statistical measures. In addition to that model forecasting was compared by the hydrographs and scatter plots. ANNs have the ability of performing with a good amount of observation from the patterns on which they are trained. Several methods do exists to train a network. One of the most successful and extensively used training algorithm is multi-layered perceptron (MLP). Simplified model of an artificial neural netrwork can be seen in Flow Structure.



Typical structure of ANN model

V. RESULTS AND ANALYSIS

Model Performance:

ANN consistently produced higher correlation coefficients (R) and lower error values (MSE, RMSE) than MLR.

Table 5 R, MSE, RMSE for the best model developed by ANN

SR. NO.	MODEL NAME	CORRELATION COEFFICIENT R	MEAN SQUARE ERROR MSE	ROOT MEAN SQUARE ERROR RMSE
1	TkJune4	0.9414	0.0063	0.0794
2	TkJuly4	0.9333	0.0066	0.0760
3	TkAug7	0.9329	0.0055	0.0742
4	TkSep5	0.9342	0.0040	0.0638
5	TkOct4	0.9085	0.0033	0.0448
6	PJune9	0.9190	0.0019	0.1362
7	PJuly9	0.9322	0.0095	0.0977
8	PAug4	0.9156	0.0076	0.0875
9	PSep9	0.9224	0.0054	0.0734
10	POct9	0.9552	0.0053	0.0732
11	SdJune3	0.9015	0.0064	0.0802
12	SdJuly3	0.9373	0.0076	0.0875
13	SdAug3	0.9028	0.0097	0.0987
14	SdSep3	0.9035	0.0084	0.0918
15	SdOct3	0.9340	0.0025	0.0509

Table 6 Multi Linear Regression equation obtained from all the best selected models of ANN.

SR.NO.	MODEL NAME	MULTI LINEAR REGRESSION EQUATIONS
1	TkJune4	Y = 0.058 + 0.006*Qt-1 + 0.8419*Qt - 0.0136*Rt
2	TkJuly4	Y = 0.04734 – 0.1385*Qt-1 + 0.7862*Qt + 0.1893* Rt
3	TkAug7	Y = 0.054 + 0.002*Qt-2 – 0.045*Qt-1 + 0.689*Qt – 0.02*Rt-1 + 0.207*Rt
4	TkSep5	Y = 0.0437 – 0.05318*Qt-1 + 0.8621*Qt – 0.00842*Rt-1 + 0.04074*Rt

5	TkOct4	Y = 0.0504 + 0.167*Qt-2 + 0.5471* Qt-1 + 0.067*Rt
6	PJune9	Y = 0.0469 + 0.084*Qt-3 + 0.014*Qt-2 + 0.0574*Qt-1 + 0.730*Qt + 0.05347*Rt-1 – 0.19*Rt
7	PJuly9	Y = 0.0999 – 0.0384*Qt-3 + 0.0514*Qt-2 – 0.004*Qt-1 + 0.760*Qt – 0.09547*Rt-1 + 0.24*Rt
8	PAug4	Y = 0.1754 – 0.062*Qt-1 + 0.747*Qt + 0.1795*Rt
9	PSep9	Y = 0.100 + 0.0048*Qt-3 + 0.056*Qt-2 – 0.07*Qt-1 + 0.82*Qt – 0.04*Rt-1 + 0.078*Rt
10	POct9	Y = 0.0416 – 0.0123*Qt-3 + 0.015*Qt-2 – 0.0713*Qt-1 + 0.9415*Qt -0.0283* Rt-1 + 0.07468*Rt
11	SdJune3	Y = 0.1234 + 0.02*Qt-3 + 0.088*Qt-2 – 0.150*Qt-1 + 0.72*Qt
12	SdJuly3	Y = 0.09918 – 0.022*Qt-3 + 0.01413*Qt-2 – 0.09391*Qt-1 + 0.9454*Qt
13	SdAug3	Y = 0.0088265 – 0.04851*Qt-3 + 0.120216*Qt-2 – 0.19389*Qt-1 + 0.9815*Qt
14	SdSep3	Y = 0.092 – 0.08475*Qt-3 + 0.0899*Qt-2 – 0.055*Qt-1 + 0.8518*Qt
15	SdOct3	Y = 0.0367 + 0.0450*Qt-3 – 0.000644*Qt-2 – 0.09*Qt-1 + 0.9288*Qt

After selecting best performing model, that model was compared for two techniques ANN and MLR that comparison was done on basis of R, MSE, RMSE as well as hydrographs and scatter plotted in Fig 2 and Fig 3

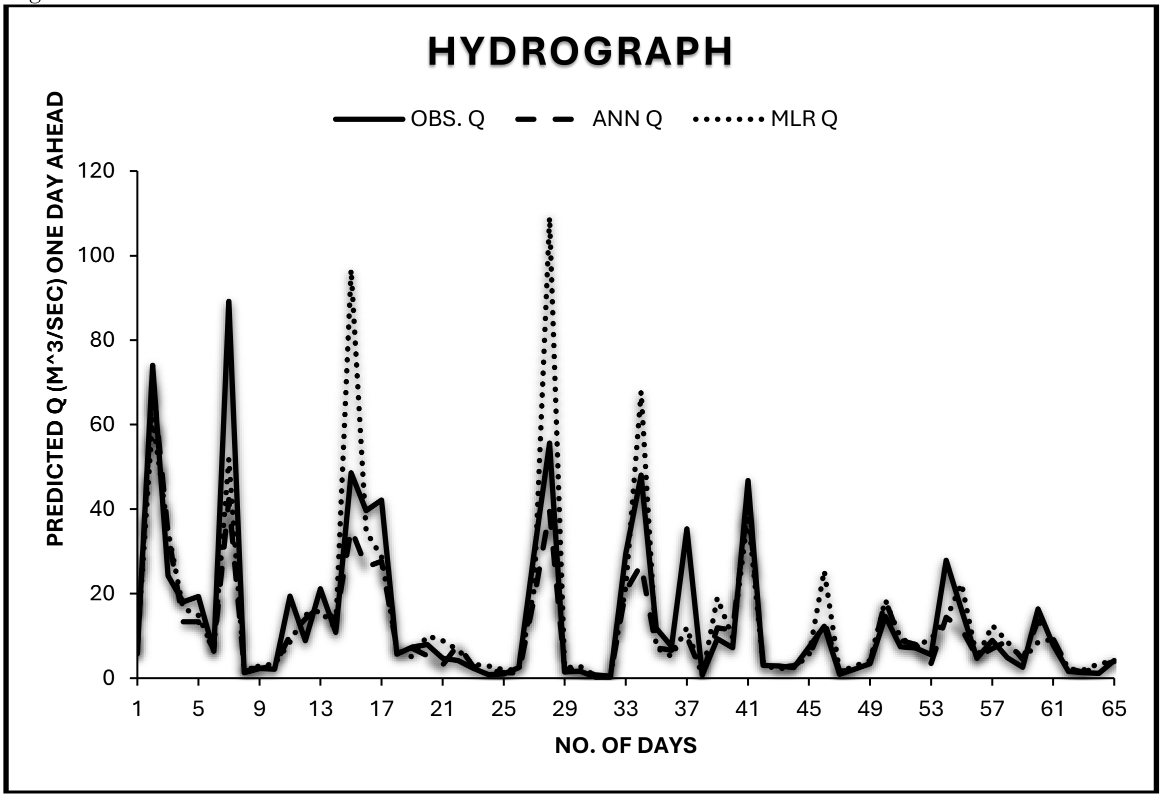


Fig. 2. Hydrograph for TkJuly4 Model to compare ANN and MLR

Table 7 Performance Criteria (STATION – TUKSAI, MONTH – JULY)

Model Name	R		MSE		RMSE	
	ANN	MLR	ANN	MLR	ANN	MLR
TkJuly4	0.9333	0.9227	0.0058	0.0071	0.0760	0.0839

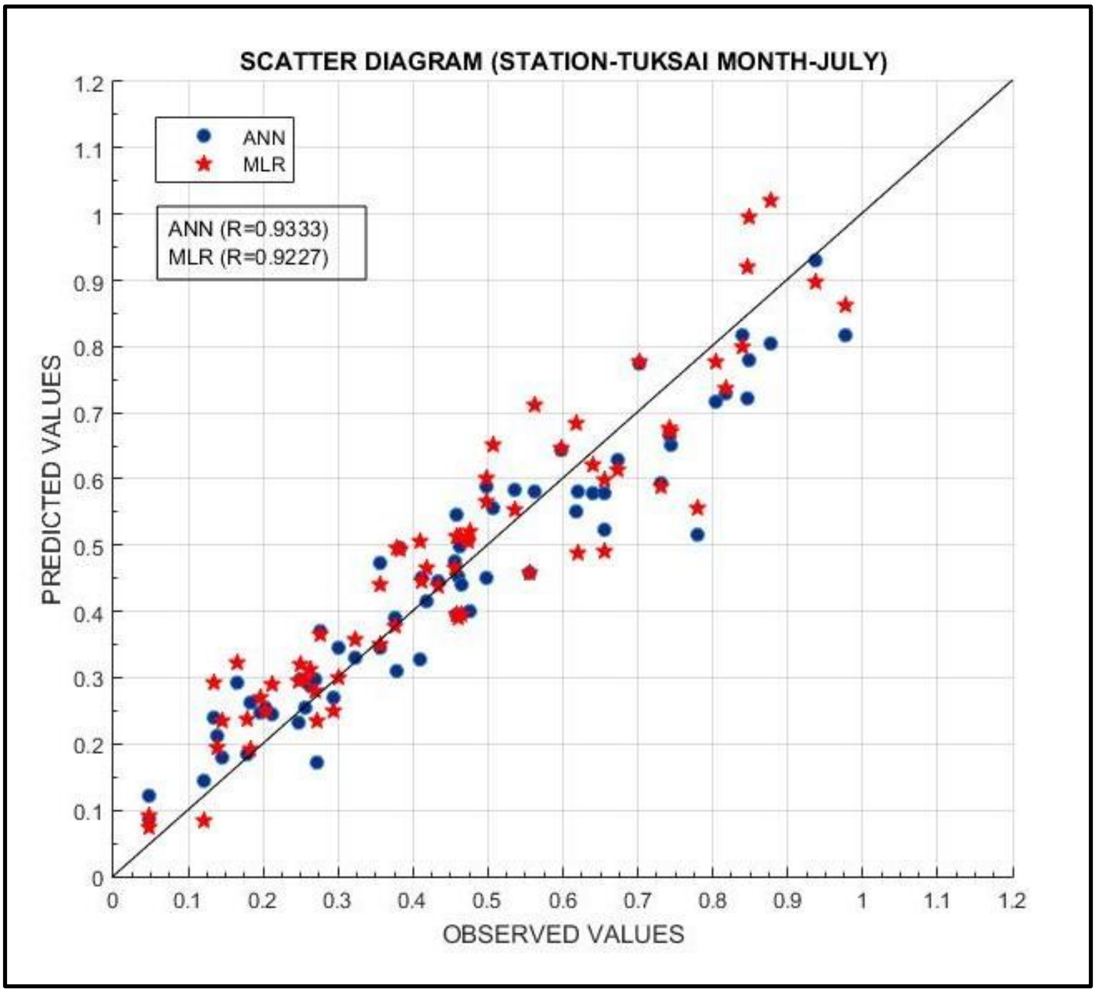


Fig. 3. Scatter Plot for TkJuly4 Model to compare ANN and MLR

The best performing model for month of June for Tuksai station for three attributes Qt-1, Qt, Rt and 1 output parameter as one day ahead discharge (Qt+1). Hydrograph explains ANN under predicts peak and low discharge very well as compared to MLR prediction. In MLR, hydrograph over predicts observed values (55.61 m^3/sec) on 28 day (109.10 m^3/sec). In scatter diagram shows the +Ve correlation as group is rising from left to right. The data points, circular and of blue colours are very close to 45 degrees line which concludes that ANN have significant value compared to MLR.

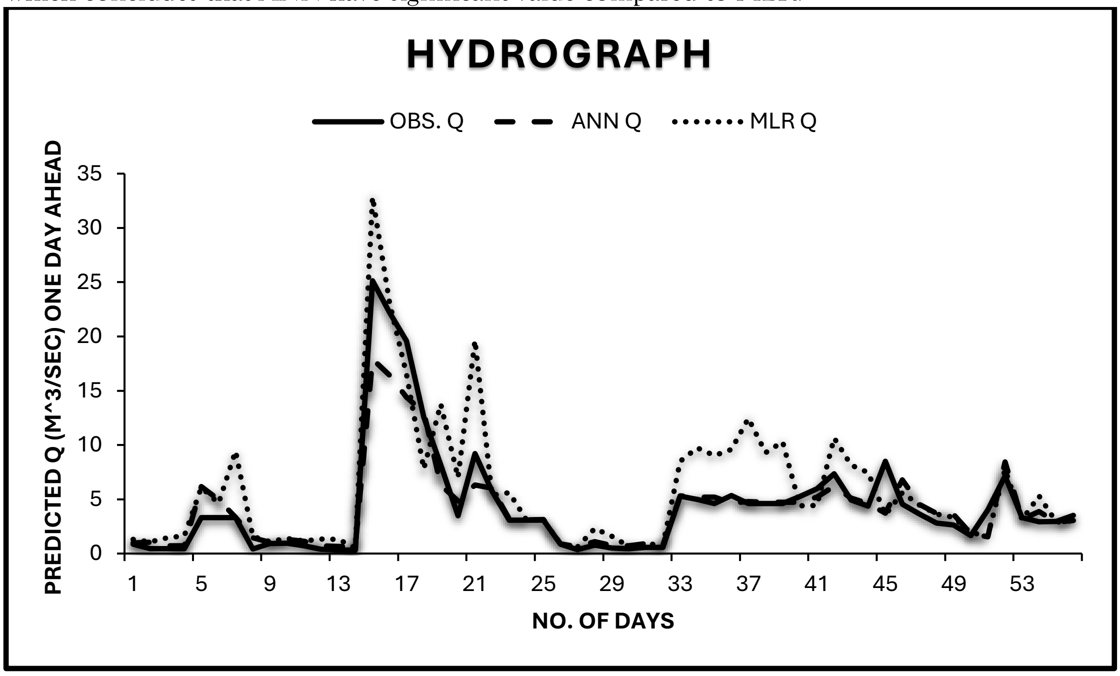


Fig. 4. Hydrograph for SdOct3 Model to compare ANN and MLR

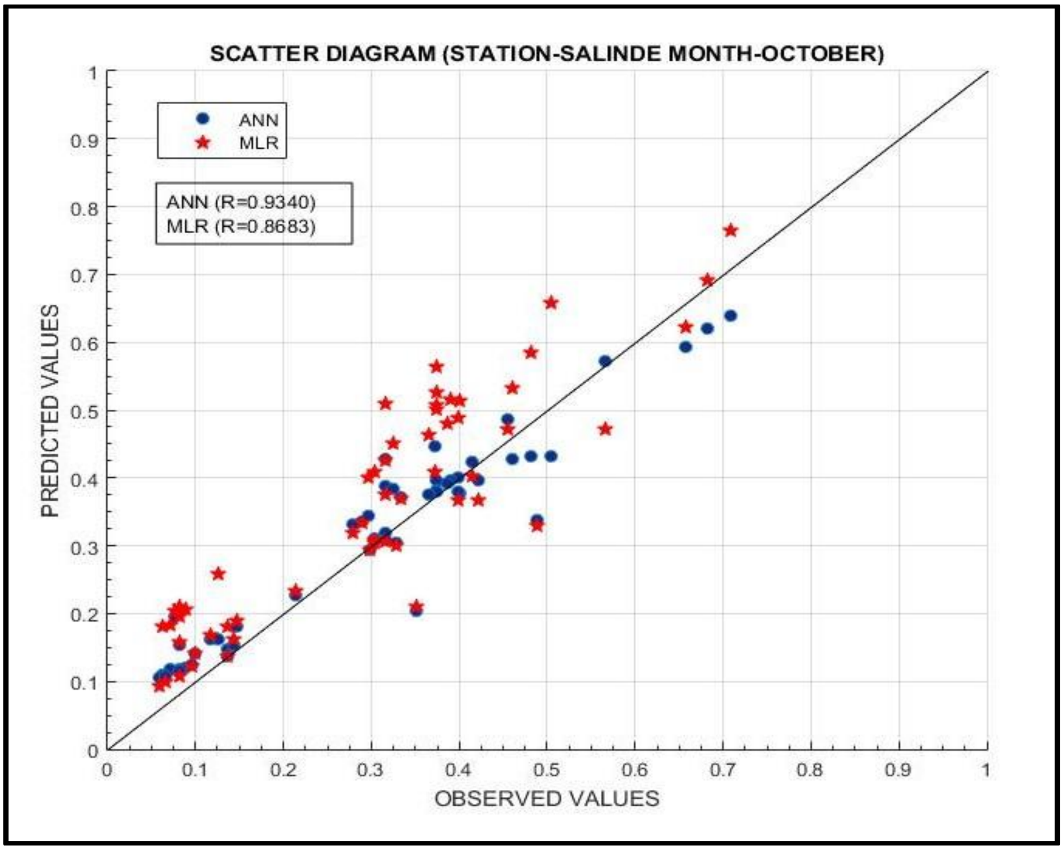


Fig. 5 Scatter Plot for SdOct3 Model to compare ANN and MLR

The best performing model for month of October at Salinde station shows with four attributes Qt-3, Qt-2, Qt-1, Qt and 1 output as one day ahead runoff (Qt+1). Hydrograph explains that only ANN under predicts peak and low discharges very well. In MLR analysis, they over predicts discharges (32.85 m^3/sec) over observed values (25.13 m^3/sec) on 15 day. In scatter diagram, the blue and red groups designates that influence of correlation analysis. The more gathering of blue points as compared to red one indicates that ANN have more impact on MLR analysis

VI. CONCLUSION

ANN models provided superior performance over MLR models for predicting one-day-ahead runoff.

The inclusion of rainfall data improved model accuracy, while adding evaporation data did not significantly enhance predictions.

The use of large datasets (18-20 years) improved ANN model reliability.

ANN models are beneficial for flood-prone regions due to quick and accurate runoff predictions.

Future studies should explore additional basin characteristics like slope, geology, and meteorological factors to enhance predictive accuracy.

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