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Abstract

The development of the stage-discharge relationship is a fundamental issue in hydrological modeling. Due to the complexity of the stage-discharge relationship, discharge prediction plays an essential role in planning and water resource management. The present study was conducted for modeling of discharge at the Gaula barrage site in Uttarakhand state of India. The study evaluated, Adaptive Neuro-Fuzzy Inference System (ANFIS), Artificial Neural Network (ANN) and Wavelet-Based Artificial Neural System (WANN) based models to estimate the discharge. The daily data of 12 years (2007-2018) were used to train and test the models. The Gamma test was used to identify the best model for discharge prediction. The input data having a stage with one-day lag and discharge with one and two-days lag and current-day discharge as output was used for discharge modeling. In the case of ANN models, the back-propagation algorithm and hyperbolic tangent sigmoid activation function was used. WANN used Haar, a trous based wavelet function. In ANFIS models, triangular, psig, generalized bell, and Gaussian membership functions were used to train and test the models. The models were evaluated qualitatively and quantitatively using correlation coefficient, root means square error, Willmott index, and coefficient of efficiency. It was found that ANFIS model performed better than ANN and WANN-based models for discharge prediction at the Gaula barrage.

Keywords: Artificial neural network, Stage-discharge relationship, forecasting hydrological-modeling, neural network, Gaula barrage.

1. Introduction

Modeling stage-discharge correlation is critical and among the most severe challenges in hydrology, planning and management of water resources. As a result, accurate rainfall and runoff modeling are essential for increasing the storage capacity of reservoirs, flood mitigation and protection, supply of water, hydroelectric project design, and water resource management in an area with high topography variability (Davies and Hall, 1992). It can mitigate the environmental effects of climatic occurrences and improve the efficiency of the outputs. During floods measurement of direct discharge is expensive, time-consuming and perhaps impossible due to the complexity of the hydrological system. Mostly discharge records are obtained by converting recorded water levels to discharges using an expressed functional connection in a rating curve. A calibrated stage-discharge rating is a simple, inexpensive, and rapid method of estimating discharge (Kennedy, 1984; Herschy, 1999). The following power curve is commonly used to represent the stage-discharge rating (Herschy 1999):

$$Q = m(n + H)^{\alpha} \quad (1)$$

Where Q = discharge (L^3T^{-1}), H = stage (L), α is an index exponent, depending on the topic of study, while m and n are constants.

The functional relation between discharge and stage is complex and time-varying process and cannot be handled by a simple rating curve (Bhattacharya and Solomatine 2000). Apart from this, data-based models establish input-output relationships without considering the physical rules and can be calibrated using a relatively small data set. In recent years artificial neural networks (ANNs), statistical models, wavelets and neuro-fuzzy coupled with WANN and multi-layer perceptron neural network (MLPNN) (Rath et al. 2013; Sehgal et al. 2014b; Akrami et al. 2014; Saha et al. 2015; Atiaa 2015; Al-Abadi 2016; Malik et al. 2017, 2018; Singh et al. 2018; Sanikhani et al. 2019; Khan et al. 2020; Dalkiliç and Hashimi 2020; Rehamnia et al. 2021). ANN is the most commonly used machine learning technique and is widely used in different areas of

water-related research, including rainfall-runoff modeling(Akrami et al. 2014; Adnan et al. 2021a; Annayat et al. 2021), discharge prediction, and water quality prediction(Tayfur and Singh 2011; Li and Cheng 2014; Taormina and Chau 2015), estimation of parameters in groundwater (Karahan and Ayvaz 2008; Sadeghi-Tabas et al. 2016; Eryigit 2021), water retention curve (Bayat et al. 2013; D’Emilio et al. 2018; Amanabadi et al. 2019), soil temperature at different soil depth (Wu et al. 2013).

In several hydrological process for wavelet-based hybrid models have been effectively used in water resources studies with excellent results (Sahay and Srivastava 2014; Sehgal et al. 2014a). In the last decade, wavelet-based hybrid model for a vast number of research areas, namely daily river discharge and streamflow(Güneş et al. 2021; Kambalimath S and Deka 2021; Saraiva et al. 2021; Wang et al. 2021), rainfall and runoff (Alizadeh et al. 2017; Vahid et al. 2019; Adnan et al. 2021b) forecasting of the hydrological event (Liu et al. 2011; Nourani and Andalib 2015; Al-Abadi 2016; Shoaib et al. 2016), annual precipitation trends (Partal and Küçük, 2006) flood forecasting (Adamowski, 2008), soil temperature at different soil depth (Hariharan et al. 2009; Araghi et al. 2017). Many researchers have found that the WNN model, which is constructed by combining wavelet analysis with ANN usage, can make accurate predictions. Coulibaly and Burn (2004) and Özgür (2009) used it to predict the river discharge of the Aegean River and create a WNN model, the streamflow values from the previous days were used as an input parameter in the WNN model.

Jang introduced the concept of ANFIS in 1993 (Jang 1993). A versatile hydrologic modeling technique can predict rainfall-runoff forecasting and flood risk management. In ANFIS, IF-THEN rules are paired with membership functions that can output inputs and produce outputs. The group of researchers that modeled the flow of the Baitarani River in India modeled the flow with ANFIS using the hydrological time series (Nayak et al. 2004); a successful estimation emerged using ANFIS that the original flow series' statistical properties were preserved. Dastorani et al. (2010) suggested a hybrid adaptive neuro-fuzzy inference system (ANFIS) and

wavelet can be used to predict the missing data of streamflow (gauging stations) using data from nearby places, and Ozger (2010) addressed a wavelet-neuro fuzzy model for significant wave height modeling. Shiri and Kisi (2010) suggested utilizing a wavelet and neuro-fuzzy conjunction model for short-term and long-term streamflow forecasting. The adaptive neuro-fuzzy inference system (ANFIS) was created to represent the fundamentally unpredictable nature of hydrologic systems(Abebe et al. 2000; Vafakhah and Kahneh (2016).

Now a day's machine learning has been used to simulate non-linear hydrologic systems. Particularly, ANNs (Bayat et al. 2013;Taormina and Chau 2015; Alizadeh et al. 2017; D'Emilio et al. 2018; Sihag et al. 2019a; Karimi et al. 2020; Dalkiliç and Hashimi 2020; Annayat et al. 2021; Bajirao et al. 2021), adaptive neuro-fuzzy inference system ANFIS(Nayak et al. 2004; Dastorani et al. 2010; Sehgal et al. 2014a; Vafakhah and Kahneh 2016; Amanabadi et al. 2019; Sihag et al. 2019b; Sanikhani et al. 2019; Sihag et al. 2019a; Dalkiliç and Hashimi 2020) WANN (Nourani and Andalib 2015; Alizadeh et al. 2017; Araghi et al. 2017; Bajirao et al. 2021)and support vector machine (SVM) (Jain 2012; Li and Cheng 2014; Sudheer et al. 2014; Kalteh 2015; Nourani and Andalib 2015; Sihag et al. 2017; Saraiva et al. 2021) have been recognized as effective tools for modeling complex hydrologic systems.

This paper aims to study ANNs, ANFIS, WANN models for stage-discharge forecasting evaluated the model's performance with actual field data. Actual input factor and actual length of training data are specific objectives of this study. Two different multi-artificial intelligence models for hydrological modeling were used in this work. In additional model assessment indices were used to provide a better understanding of the estimated data using models. The study results evaluated for future research of hydrological processes using different indexes (Pearson correlation coefficient (PCC), root mean squared error (RMSE), Nash-Sutcliffe efficiency (CE), and Willmott Index (WI) and coefficient of determination (R^2)). This study aimed to determine the stage-discharge values of the Gaula barrage is located at Kathgodam near Haldwani (Nainital) Uttarakhand with objectives of gamma test using, ANN, ANFIS, and WANN approaches .

2 Study area, climatic & Soil characteristics, and Data Acquisition

A barrage across the Gaula river known as Gaula barrage is located at Kathgodam near Haldwani (Nainital). The Barrage is a landmark for the local residents and provides irrigation water for the Bhabhar area. The Gaula river originates in the lower Himalayas from a place called Sattal lake and flows south past Kathgo dam, Haldwani, Kiccha, finally joining the Ramganga river about 15 km north-west of Bareilly in Uttar Pradesh. It is a 578 km long river. It is mainly a spring-fed river and is a source of water for Haldwani and Kathgodam. The area lies in sub-tropical to sub-humid climates and located at 29.27° N and 79.53° E Latitude and Longitude, respectively. The average elevation of the area is 554 m from the sea surface. The location of the Gaula river basin area is depicting in Fig. 1. There are four seasons viz. the cold season (November to February), the hot season (March to May) and southwest monsoon season occurs (Mid-June to September) following the post-monsoon season (October to November). The annual average rainfall in the area is 2095 mm and the maximum annual precipitation received from June to October. The highest average monthly maximum temperature of 35.5° C is recorded in June. In contrast, the lowest of 8.3° C is recorded in December.

Fig. 1 Location map of Gaula barrage is located at Kathgodam near Haldwani (Nainital)
Uttarakhand.

Owing to countless weathering resulting in folding, faulting, and thrusting, the upper level of the Gaula region is composed of slates, quartzites, and graphite. The upper reach of the Gaula region is separated from the Ramgarh region, which comprises slates, phyllites, quartzites, and marble integrally associated with granite and quartz. The Ramgarh region is separated from the Jaunsar region, which consists of basalticrocks intimately associated with quartzite and slates. The valley slopes of the Gaula region are dominantly deep, well-drained, fine-loamy soils having moderately acidic characteristics and having low water capacity soils. The everyday meteorological information of 12 years (2007-2018) was gathered from the Office of Irrigation Division, Kathgodam (Nainital), Uttarakhand.

3 Methodology

In this study ANN, ANFIS and WANN models for estimation of stage-discharge relationship were developed. These different models used for anticipating every day stage-discharge relationship. The flowchart of the proposed methodology for Stage-Discharge estimation at the Gaula Barrage is illustrated Fig.2.

Fig. 2 Flowchart of Stage-Discharge relationship methodology of the study.

3.1 ANN

A neural network is a type of artificial intelligence that replicates a human brain activity. In machine learning, categorization, speech, vision, and control systems, neural networks are main computing tools for solution of complex non-linear problems. The network consists of many simple processing devices connected by weighted connections following a predetermined architecture. A neuron is made up of multiple inputs and a single output. The number of input and

output neurons in the input and output layers is determined by the problem being simulated. The number of input variables equaling the number of input neurons and the number of output variables equaling output neurons. The ideal number (hidden layers) and hidden neurons are frequently challenging to determine because there is no standard way for doing so. By altering the connection weights, these networks learn from the training data. Artificial neural network designs are built and deployed in a variety of hydrology and hydraulics domains.

Most research using neural networks to solve water resource challenges has used backward propagation and radial basis function types (Govindaraju and Rao 2013). There are different types of ANNs used based on structures. The Multilayer Perceptron (MLP) network was used in several ANN paradigms (Lippmann 1987; Hornik et al. 1989). Layers of parallel processing nodes make up the MLP network.

Forward feed neural network arranged in layers to neurons and one or more hidden layers exist between input and output layer. Each layer's units are connected to the subsequent layer's units via a connection weight w that is modified during training. A data pattern is consisting of the values x_i in the input layer i is carried forward to the first hidden layer j . Each remote unit is fed the weighted outputs $w_{ji}x_i$ from the previous layer's units. These are added together to give a net value, translated via an activation function into an output value. The components of an ANN design and its processing unit are depicted in Fig.3 (a) and (b).

In Fig. 3 (a), five-layer feed-forward ANN consisting of three layers: input, hidden, and output. $x_1, x_2, x_3, x_4..x_d$ are the input layer neurons; $k_1, k_2, k_3, k_4..k_d$ are the hidden layer neurons; and $y_1, y_2, y_3, y_4..y_d$ are the output layer neurons. Multiple inputs and a single output make up a neuron. A summation function is obtained by adding the inputs and their weights. An activation function, which might be a step, sigmoid, threshold, linear, and so on, determines a neuron's output.

Fig.3. (a) Artificial neural network architecture with a single hidden layer; (b) A processing node with widely used non functions

The five-layer neural network depicted in Fig. 3(a-b) is composed of layers i , j , and k with inter-connection weights w_{ij} and w_{jk} between the layers of neurons. Each neuron in a layer receives and analyses weighted input from the preceding layer and then transmits its output via links to nodes in the subsequent layer. The weight coefficient w_{ij} is used to describe the link between the i^{th} and j^{th} neurons, while the threshold coefficient b is used to describe the i^{th} neuron. The weight

201 coefficient indicates the significance of a particular connection in the network. The i^{th} neuron's
 202 output value is calculated as follows(Haykin and Lippmann 1994; Haykin 2010):

$$x_i = f(\epsilon_i) \quad (2)$$

$$\epsilon_i = b_i + \sum_{j \in \Gamma_i^{-1}} w_{ij} x_j \quad (3)$$

203 Where, $f(\epsilon_i)$ = activation function. With formally added neuron j , where $x_j = 1$, Sigmoid shape
 204 activation functions are typically defined as:

$$f(\epsilon_i) = \frac{1}{1 + e^{-\epsilon}} \quad (4)$$

205 The weight updates are calculated using the following formula

$$\Delta w_{ij}(t) = -\eta \frac{\partial E}{\partial w_{ij}} + \mu \Delta w_{ij}(t-1) \quad (5)$$

206 Where

207 η = learning rates and μ = momentum rates, E = error or objective function, and $\Delta w_{ij}(t)$ = weight
 208 increments between nodes i and j for iterations t and $\Delta w_{ij}(t-1)$ are the weight increments
 209 between nodes i and j for iterations $t-1$. The algorithm can be found in Fausett (2006), Haykin
 210 (2010), and (Haykin and Lippmann 1994).

211 3.2 ANFIS

212 Jang (1993) was the first to introduce ANFIS, which uses a neural network learning method. The
 213 development of ANFIS, introduced by Jang, combines ANN learning and fuzzy logic to produce
 214 good learning in quantity and modeling (1993). In terms of peak flow forecast accuracy and
 215 computational error, ANFIS outperforms the ANN model (Nourani and Komasi 2013). ANFIS
 216 uses linguistic knowledge from fuzzy logic and ANN learning capabilities for automated fuzzy.
 217 The ANFIS model with fuzzy inputs and neural network can solve complex problems..Fuzzy
 218 inference systems are also helpful because they merge the informative essence of membership

functions with the strength of neural networks. Using fuzzy rules as a pre-processor to a neural network helps one integrate human intelligence to draw inferences and make decisions. The ANFIS model uses back-propagation to optimize the member function parameters (fuzzy rules). The neural network's duty is made more accessible by fuzzification, which characterizes inputs that aren't distinct, resulting in a more robust overall model.

ANFIS govern different set rules which can have the potential to learning non-linear equations. The directional links are connected through nodes. Each node has a specific function and consists of fixed parameters (Genç et al. 2014). Takagi-Sugeno type fuzzy system is an essential fuzzy system and stores IF-THEN rules (Ebtehaj and Bonakdari 2014). Takagi-Sugeno is the most accurate and frequently used in fuzzy modeling (Jang 1993). Sugeno model (First order), with two fuzzy is as follows;

$$\text{Rule 1: if } x \text{ is } A_1 \text{ and } y \text{ is } B_1, \text{ then } f_1 = p_1x_1 + q_1y + r_1 \quad (6)$$

$$\text{Rule 1: if } x \text{ is } A_2 \text{ and } y \text{ is } B_2, \text{ then } f_2 = p_2x_2 + q_2y + r_2 \quad (7)$$

A_i and B_i are the fuzzy sets for input x and y , respectively, and p_i , q_i , and r_i are the consequent/output function (f). These design parameters are estimated during the training process. Weights w_1 and w_2 are assigned to rules 1 and 2, respectively (Eq. 6-7). The weighted average is calculated as:

$$f = \frac{w_1f_1 + w_2f_2}{w_1 + w_2} \quad (8)$$

In a range of domains, including groundwater investigations, such as estimating hydraulic parameters, ANFIS can produce better results with fewer constraints than ANN and FIS models. There are five layers in the ANFIS structure. In the first layer, input nodes: Using the membership function, each node in this layer generates membership values dependent on each appropriate fuzzy set.

239 Layer 1 Each input are fuzzified for each node output in this layer. This fuzzy set's membership
 240 functions can be a triangular, trapezoidal, generalized bell, or Gaussian. In this layer, every node
 241 function of every node i has a membership function that determines every node i ($Q_{I,i}$).

$$O_{1,i} = \mu_{A_i}(x) \text{ for } i = 1, 2 \quad (9)$$

$$O_{1,i} = \mu_{B_{i-2}}(y) \text{ for } i = 3, 4 \quad (10)$$

242 where, x and y are the input to the node i ($i = 1, 2$ for x and $i = 3, 4$ for y) and A_i (or B_{i-2}) is the
 243 fuzzy set associated with this node, and MFs characterize it μ_{A_i} and $\mu_{B_{i-2}}$, respectively. A and B
 244 can be any membership functions. For the Generalized bell function, the output of the first layer
 245 (i^{th} node) is determined as:

$$O_{1,i} = \mu_{A_i}(x) = \frac{1}{1 + \left(\frac{(x - c_i)}{a_i}\right)^{2b_i}} \quad (11)$$

246 **Layer 2:** The AND/OR operator is used in this layer to generate a single output that indicates the
 247 firing strength of a rule that conducts the fuzzy operation. Each node in this layer is classified as a
 248 stable node that multiplies incoming signals before sending them to the next layer.

$$O_{2,i} = w_i = \mu_{A_i}(x)\mu_{B_i}(y) \text{ for } i = 1, 2 \quad (12)$$

249 **Layer 3:** In the third layer, medium node to determine the ratio of each ignition factor i to the
 250 sum of all ignition laws. Each node in this layer is a fixed node labeled N. The i^{th} node calculates
 251 the ratio of the i^{th} rule strength to the sum of all rule's strength.

$$O_{3,i} = \overline{w}_i = \frac{w_i}{w_1 + w_2} \text{ for } i = 1, 2 \quad (13)$$

252 **Layer 4:** This layer is called as de-fuzzification layer, in which every node is adaptive
 253 (adjustable) and marked by a square. The output of this layer (i^{th} node) is obtained from the
 254 product of the normalized firing strength ($\overline{w}_i$, the output of layer 3) and the consequent function
 255 (f), which is expressed as:

$$O_{4,i} = \overline{w}_i f_i = \overline{w}_i (p_i x + q_i y + r_i) \text{ for } i = 1, 2 \quad (14)$$

256 The $\overline{w}_i$ is the output of the antecedent layer, and r_i , p_i , and q_i are consequent parameters of i^{th}
 257 node.

258 **Layer 5:** The fifth layer, also called output node, the single node in this layer is the system's
 259 overall output, which is the summation of all coming signals. Therefore, each fuzzy rule are
 260 transformed into non-fuzzy output.

$$O_{4,i} = \sum_i \overline{w}_i f_i = \frac{\sum_i w_i f_i}{\sum_i w_i} \text{ for } i = 1, 2 \quad (15)$$

261 Thus, the input vector fed layer by layer through the network layer. The two key steps for
 262 applying ANFIS to applications are the identification process of the structure and the
 263 identification step of the parameters. The identification phase of the parameters involves the
 264 adjustment of the premise and consequence parameters.

265 ANFIS is a TSK fuzzy inference system utilized with the hybrid learning algorithm to model
 266 stage-discharge relationships. A fuzzy system is a method of integration where the final fuzzy
 267 system is optimized via ANN training. It maps input through the membership function and its
 268 associated parameters. Neural network training algorithms fit different parameters. Initial fuzzy
 269 rules and fuzzy structure provide some information for generating the FIS. ANFIS used a hybrid
 270 algorithm for training which is a combination of least square and gradient descent methods. In
 271 this study, the Sugeno type of FIS with a hybrid learning optimization method was used to
 272 develop stage-discharge models in MATLAB software.

273 **3.3 Wavelet neural networks (WNNs)**

274 It is seen that Fourier analysis has some severe drawbacks; while transforming data to the
 275 frequency domain, all the time information is lost. In other words, it becomes impossible to
 276 predict when a particular event occurs. Wavelet analysis is helpful to capture low-frequency

information having long time intervals and high-frequency information having short time intervals as per need (Rajaei et al. 2009).

Dennis Gabor (1947) analyzed a small section of signal using windowing technique of Short Time Fourier Transform (STFT), which maps a signal into the 2-D function of time and frequency (Gabor 1946). STFT represents both time and frequency of the signal. The window size can vary according to signal length to determine the time and frequency more accurately. Two types of Wavelet transform, such as Continuous Wavelet Transformations (CWT) and Discrete Wavelet Transformations (DWT), are used. DWT is more accurate than CWT because the transformation made by DWT does not show extra noise, which is not necessary for model evaluation. Based on Fourier analysis during signal processing of DWT, approximate coefficient produced by low pass filter and complex coefficient produced by high pass filter (Akrami et al. 2014). CWT forms an infinite number of wavelets, making it difficult to find desired results from transformed data. Using DWT, such difficulty does not occur because it calculates wavelet coefficients on discrete dyadic scales with time. Hence, DWT analysis is mainly preferred for forecasting problems of water resource systems because it needs short computational time. In DWT, the original signal is passed via low pass and high pass filters, followed by down-sampling using both filters after passing through the low pass and high pass filters. As a function of decomposition, the high pass filter followed by down-sampling information.

The low pass filter coupled with the scaling function which produces the information. Once the necessary level of breakdown has been reached, the decomposition procedure is repeated. The length of the data determines the maximum number of levels. Until the approximation coefficient is split into a large number of smaller components, the process is repeated several times. In a time-series signal, an approximate coefficient describes the general trend of the signal. In contrast, a detail coefficient represents the high-frequency components of the original time series signal (Seo et al. 2015).

302 A wavelet is a small wave of limited duration with zero average value. The wavelet family
 303 starts with orthogonal functions, namely scaling function $\phi(t)$ and wavelet functions $\psi(t)$.
 304 Wavelet function must have finite energy. The real-time data can be analyzed either by
 305 movement of Wavelet along the time axis at a different location called translation or by stretching
 306 and squeezing the Wavelet known as scale or dilation for data transformation.

307 Suppose you use the Down sampling with both filters' method. In that case, your signal
 308 $x(n)$ travels through a low pass filter and a high pass filter before being downsampled using the
 309 low pass filter. High pass filter followed by downsampling created detail information $cD(n)$. In
 310 contrast, low pass filters associated with scaling functions produced approximation information
 311 cA at the decomposition level (n) . Once the necessary level of breakdown has been reached, the
 312 decomposition procedure is repeated. The length of the transmission determines the maximum
 313 number of levels. The process of iterating until the approximation coefficient is decomposed into
 314 several lower resolution components. At this point, the procedure is completed. The following
 315 criterion is satisfied by the decomposition of signal $x(n)$ by DWT:

$$x(n) = cD_1 + cA_1 = cD_1 + cD_2 + cA_2 = cD_1 + cD_2 + cD_3 + cA_3 \text{ and so on...} \quad (16)$$

316 Standard wavelets used for wavelet analysis. The most significant advantage of employing
 317 wavelets is that they are spatially localized. These algorithms used for data compression, data
 318 processing, and the solution of differential equations. WNN models are constructed using the
 319 Haar wavelet in this study since it is the most straightforward, easily imagined, and historically
 320 earliest wavelet family. As an illustration, the following is the wavelet function of the Haar
 321 wavelet:

$$\psi(x) = \begin{cases} 1, & 0 \leq x < \frac{1}{2} \\ -1, & \frac{1}{2} \leq x < 1 \\ 0, & \text{otherwise} \end{cases} \quad (17)$$

322 The scaling function of the Haar wavelet is:

$$\psi(x) = \begin{cases} 1, & 0 \leq x < 1 \\ 0, & \text{otherwise} \end{cases} \quad (18)$$

3.4 Gamma Test

The gamma test can be used to make decisions about selecting input data or inputs that affect the result of developed models. The gamma test, in general, is a multi-objective and unbiased technique for determining the substantial effect of each input variable. The gamma test was first introduced by Stefánsson et al., (1997), and it was later utilized by other researchers (Remesan et al. 2009; Kakaei Lafdani et al. 2013; Malik et al. 2017). The gamma test is used to determine whether continuous non-linear models have the minimum standard error for each set of input-output data. The number of inputs was chosen depending on the gamma (Γ) and V-ratio of the system. Using continuous non-linear models, the gamma test can estimate the minimum standard error for each pair of input-output data sets. Consider the following representation of a data sample:

$$\{x_i(i), \dots, x_m(i), y_i\} = \{x_i, y_i\} [1 \leq i \leq M] \quad (19)$$

The input variables $x_i, \dots, x_m$ are referred to as the inputs vector; the number of input variables is m ; the number of related outputs is y_i , and M is the number of patterns. To compute the gamma coefficient (Γ), a linear regression line between the input (X) and the output (Y) is constructed as follows:

$$y = f(X_i, \dots, X_m) + \Gamma \quad (20)$$

Here f = smooth function, and Γ = random variable denoting noise. The result Y from Eq. 19 gives helpful information regarding how the model's complexity has been increased or decreased. If the value is near zero, we have input parameters that are more appropriate for the situation. Increasing the gradient implies that we have a more intricate model; conversely, decreasing the gradient shows that we have a simpler model. In general, a smaller standard error (SE) of a gamma value indicates a more dependable gamma result. The predictability of variable (target) is shown by the V-ratio calculated by Eq. 21.

$$V_{\text{ratio}} = \frac{\Gamma}{\sigma^2(y)} \quad (21)$$

Where $\sigma^2(y)$ = output variance of y , gamma (Γ)= the gamma function. It is represent higher degree of predictability if If V-ratio is close to 0. In situations where the V-ratio is near zero, we have a better degree of predictability. Suppose the values of gamma, gradient, SE, and V-ratio are smaller. In that case, we will be able to create a high-quality mathematical model. As part of this study, the most influential input combinations (variables) were selected based on their lowest value of Γ , SE, and V-ratios(J. et al. 2009; Malik et al. 2017) to evaluate their influence on the stage-discharge modeling, from which meaningful combinations are derived. The gamma test was carried out in this study with the help of the winGamma software.

3.5 Model performance evaluation indices

The Pearson correlation coefficient (PCC), Nash-Sutcliffe efficiency (CE), root mean squared error (RMSE), Willmott Index (WI), and coefficient of determination (R^2) were used to evaluate the effectiveness of the designed models.

$$PCC = \left(\frac{\sum_{i=1}^N (O_i - \bar{O})(P_i - \bar{P})}{\left(\sqrt{\sum_{i=1}^N (O_i - \bar{O})^2} \sqrt{\sum_{i=1}^N (P_i - \bar{P})^2} \right)} \right)^2 \quad (-1 < PCC < 1) \quad (22)$$

$$RMSE = \left(\frac{1}{n} \sum_{i=1}^N (O_i - P_i)^2 \right)^{0.5} \quad (0 < RMSE < \infty) \quad (23)$$

$$WI = 1 - \frac{\sum_{i=1}^N (O_i - P_i)^2}{\sum_{i=1}^N (|P_i - \bar{O}| + |O_i - \bar{O}|)^2} \quad (0 < WI \leq 1) \quad (24)$$

$$COE = 1 - \left(\frac{\sum_{i=1}^N (O_i - P_i)^2}{\sum_{i=1}^N (O_i - \bar{P})^2} \right) \quad (-\infty < COE < 1) \quad (25)$$

3.6 Training and Testing of Different Stage-Discharge Models

ANN, ANFIS, and WANN have been executed in the present investigation to anticipate the daily discharge from the Gaula barrage site situated at Kathgodam near Haldwani (Nainital) Uttarakhand, India. The outcomes demonstrated that the wavelet-based model could foresee high and low peak discharges, utilizing multi-scale time arrangements. In this manner, in the current study, the daily wise data of stage and discharge during the years were considered to advance models. Table 1 shows the year-by-year statistics for stage and discharges with a time lag and lag between stages.

Table1. Pairs in training and testing for stage-discharge models (Input-output)

Year (i)	Days (j)	Input for j th day					Output
		X ₁	X ₂	X ₃	X ₄	X ₅	Y
		H _{i,j-2}	H _{i,j-1}	H _{i,j}	Q _{i,j-2}	Q _{i,j-1}	Q _{i,j}
1	3	H _{1,1}	H _{1,2}	H _{1,3}	Q _{1,1}	Q _{1,2}	Q _{1,3}
	4	H _{1,2}	H _{1,3}	H _{1,4}	Q _{1,2}	Q _{1,3}	Q _{1,4}
	5	H _{1,3}	H _{1,4}	H _{1,5}	Q _{1,3}	Q _{1,4}	Q _{1,5}
		...	...	...	...	...	...
	122	H _{1,120}	H _{1,121}	H _{1,122}	Q _{1,120}	Q _{1,121}	Q _{1,122}
2	3	H _{2,1}	H _{2,2}	H _{2,3}	Q _{2,1}	Q _{2,2}	Q _{2,3}
	4	H _{2,2}	H _{2,3}	H _{2,4}	Q _{2,2}	Q _{2,3}	Q _{2,4}
	5	H _{2,3}	H _{2,4}	H _{2,5}	Q _{2,3}	Q _{2,4}	Q _{2,5}
	...	...	...	...	...	...	...
	122	H _{2,120}	H _{2,121}	H _{2,122}	Q _{2,120}	Q _{2,121}	Q _{2,122}
...	...	...	...	...	...	...	...
12	3	H _{12,1}	H _{12,2}	H _{12,3}	Q _{12,1}	Q _{12,2}	Q _{12,3}
	4	H _{12,2}	H _{12,3}	H _{12,4}	Q _{12,2}	Q _{12,3}	Q _{12,4}
	5	H _{12,3}	H _{12,4}	H _{12,5}	Q _{12,3}	Q _{12,4}	Q _{12,5}

...	...	...	...	...	...	...
122	$H_{12,120}$	$H_{12,121}$	$H_{12,122}$	$Q_{12,120}$	$Q_{12,121}$	$Q_{12,122}$

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This work used MATLAB software to train and test feed-forward MLP based ANN and WANN models, which were then used to analyze the results. Table 2 lists the various training variables and the values assigned to them used for the development of ANN and WANN models during stage-discharge modelling in MATLAB and the values assigned to them.

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Table 2. ANN and WANN models training variables and their assigned values

Training variables	Assigned values
Neural network type	Feed forward Multilayer perceptron
Number of inputs	3
Number of outputs	1
Number of hidden layers	1
Number of processing element/neurons in hidden layer	1 to 2_{n+1}
Training function/Learning rule	Levenberg-Marquardt (LM)
Activation function in hidden layer	Hyperbolic tangent sigmoid
Maximum epoch	1000

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With the help of a hybrid learning method and the TSK (fuzzy inference) system, several ANFIS models were created in MATLAB software. MATLAB software is used to train ANFIS models for stage-discharge modeling. Table 3 lists the various training variables and the values assigned to them throughout the training process. It is primarily through grid partition and subtractive clustering that the FIS structure is produced. Jang (1993) proposed the use of grid partitioning for the solution of problems with fewer than six input variables in order to save time. To construct the ANFIS structure in this work, the grid partition method of FIS generation was employed.

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Table 3 ANFIS models (training variables and their assigned values)

Training variables	Assigned value
FIS generation method	Grid partition
FIS Type	TSK
Number of membership function per input	2, 3
Types of input MFs	Gaussmf, Trimf, Gbellmf, Psigmf
Types of output MFs	Linear
Epoch	100
Error tolerance	0.001
Learning algorithm	Hybrid

3.7 Development of Models stage-discharge modeling

Different ANN models were developed for hydrological modeling using daily (stage) and discharge data during monsoon season to predict daily discharge in the Gaula river basin. The observed time series of current-day and preceding days lag were taken as input variables and recent day discharge as the output variable, taking into account the monsoon season starting from 1st June to 30th September only. In this case, $N = 122$ days (1st June to 30th September) in a year and $M = 12$ years (2007-2018). Let the observed values of stage and discharge be represented as $H_{i,j}$ and $Q_{i,j}$ respectively for the j^{th} day of the i^{th} year ($i = 1, 2, 3, \dots, M$ and $j = 1, 2, 3, \dots, N$) and standards for time lag which are taken as two in the present study. The functional form of the ANN model can be represented by Eq. 25.

$$Q_t = f(H_t, Q_{t-1}, Q_{t-2}) \quad (26)$$

The daily hydrological data was used for stage-discharge prediction and development of ANFIS models. As the estimation of regular discharge is a complex and dynamic process, it requires a suitable time lag for its simulation. Therefore, various combinations of stage and discharge (i.e.,

stage of the current day, the preceding day, preceding two days and discharge of preceding day, preceding two days) as input and discharge of current day as output was used in discharge estimation and can be functionally expressed as Eq. (26).

$$Q_{i,j} = f(H_{i,j}, H_{i,j-1}, H_{i,j-2}, \dots, H_{i,j-m}, Q_{i,j-1}, Q_{i,j-2}, \dots, Q_{i,j-m}) \quad (27)$$

In Wavelet-based ANN models for stage-discharge modeling, the observed time series of stage and discharge data is resolved at three-level using Haar algorithm, and the transformed time series of stage and discharge is used as input variables instead of original time series; however, all other resolved parameters were taken in their original form. The decomposed components of time series by DWT like $H_{Di}(t), \dots, H_{Di}(t-n), H_{Ai}(t), \dots, H_{Ai}(t-n)$ and $Q_{Di}(t-1), \dots, Q_{Di}(t-n), Q_{Ai}(t-1), \dots, Q_{Ai}(t-n)$ were used for stage-discharge modelling. Where $H_{Di}(t), \dots, H_{Di}(t-n)$, and $H_{Ai}(t), \dots, H_{Ai}(t-n)$ is the detailed and approximated sub-signals of stage time series, respectively. Here, D_i represents detail sub-signal decomposed at the i^{th} level. A_i represents approximated sub-signal decomposed at the i^{th} level. Then, the decomposed stage (H) and discharge (Q) sub-time series at approximate levels (i) were fed as input to the ANN model to predict daily discharge. The functional form of the model is expressed by Eq. 27.

$$Q_t = f(H_{D1}(t), \dots, H_{Di}(t), H_{Ai}(t-n), \dots, H_{Di}(t-n), H_{Ai}(t-n), Q_{D1}(t-n), \dots, Q_{Di}(t-n), Q_{Ai}(t-n)) \quad (28)$$

4 Results and Discussions

Stage-discharge modeling for Gaula barrage site located in Gaula river, twelve years daily data of stage (H) and discharge (Q) of monsoon season from June to September were used for analysis. The data was divided into two parts: training data for calibration of the models and testing data to validate the models. Training data was used to calibrate the models, and testing data was used to validate the models. The models' performance was evaluated qualitatively through visual observation and quantitatively through the use of different statistical and hydrological criteria, including RMSE, R^2 , WI and CE.

4.3 Statistical Analysis

The statistical parameters such as mean, median (minimum and maximum value), standard deviation (Std. Dev), skewness for the stage (H), coefficient of variation (CV) and discharge (Q) datasets for training, testing, and the entire period, is summarized Table 4. These statistical parameters represent the variability of data across time. In order to have the same statistical population in training and testing subsets and required cross-validate the data. The high skewness coefficient has had a significant detrimental impact on the model's performance, as has been demonstrated. This station's calibrated and validated skewness coefficients are low, as shown by the low skewness coefficients for both the calibration and validation coefficients for the stated station.

4.1 Model input variable selection using gamma test

When dealing with non-linear models, the selection of model inputs is a critical and challenging topic. In the current study, different input combinations (Table 5) were created and studied to assess how they influenced the stage (H) - discharge (Q) at the Gaula barrage site. In Table 5, H_{t-1} , H_{t-2} , Q_{t-1} , and Q_{t-2} are the stage and discharge values of previous one ($t-1$) and two ($t-2$) days. The gamma test method was conducted to test which input variables were most efficient for the ANN, ANFIS, and WANN models. Table 5 contains the results of the tests. Table 5 Clearly, models 24 with mask 11,001 provide the smallest values for many parameters such as gradient gamma value (Γ), standard error (SE), and V-ratio. The mask specifies the number of active input variables that are being used at any given moment; for example, mask 11,001 indicates that a total of eleven input variables are being used at the same time to produce an output, i.e., discharge. Model numbers 24 and 12 were chosen for further investigation out of 31 possible combinations.

Table 4. Statistics of discharge, stage and variables during during study Station.

Statistical Parameter	Training		Testing		Entire	
	<i>H</i>	<i>Q</i>	<i>H</i>	<i>Q</i>	<i>H</i>	<i>Q</i>
	(m)	(ft ³ /sec)	(m)	(ft ³ /sec)	(m)	(ft ³ /sec)
Mean	24.022	40.510	18.540	37.665	22.296	39.824
Median	80.000	135.000	85.000	147.000	85.000	135.000
Minimum	0.000	0.000	0.000	0.000	0.000	0.000
Maximum	885.000	184.000	100.000	184.000	885.000	184.000
Standard deviation	44.922	48.925	25.004	47.844	39.851	48.958
Coefficient of variance	56.153	36.241	127.023`	134.868	178.736	122.935
Skewness	7.361	-1.144	-1.733	-1.245	7.181	-1.151

Table 5. Selection of the best input combination for stage-discharge modelling using Gamma test.

Model No.	Model Input Combination	Mask	Gamma value	V-ratio	Standard Error
M1	$H_{(t)}$	00001	-0.0035505	-0.0042018	0.0488806
M2	$Q_{(t-1)}$	01000	0.2172343	0.8689372	0.1207246
M3	$H_{(t-1)}$	00010	0.0996951	0.3987803	0.1371814
M4	$H_{(t-2)}$	00100	0.2223312	0.8893246	0.1230553
M5	$Q_{(t-2)}$	10000	0.1990454	0.7961815	0.1364132
M6	$H_{(t)}, Q_{(t-1)}$	10010	-0.0061830	-0.0247321	0.0096368
M7	$H_{(t)}, Q_{(t-2)}$	10001	-0.0083674	-0.0334697	0.0082618
M8	$H_{(t)}, H_{(t-1)}$	00011	-0.0037797	-0.0151188	0.0062380
M9	$H_{(t)}, H_{(t-2)}$	00101	-0.0068699	-0.0274797	0.0066910
M10	$Q_{(t-1)}, H_{(t-2)}$	01100	0.1444147	0.5776588	0.0159508
M11	$Q_{(t-1)}, H_{(t-1)}$	01010	0.1432440	0.5729759	0.1291274
M12	$Q_{(t-2)}, H_{(t-1)}$	10010	0.1125862	0.4503450	0.0255596
M13	$Q_{(t-2)}, H_{(t-2)}$	10100	0.1850115	0.7400460	0.1142124
M14	$H_{(t-1)}, H_{(t-2)}$	00110	0.1491141	0.5964564	0.0277311

M15	$\mathbf{H_{(t-2)},Q_{(t-2)},H_{(t-1)}}$	10110	0.0978218	0.3912870	0.0259878
M16	$\mathbf{H_{(t-2)},Q_{(t-2)},Q_{(t-1)}}$	11100	0.1062280	0.4249120	0.0252639
M17	$\mathbf{H_{(t-1)},H_{(t-2)},Q_{(t-1)}}$	01110	0.1473661	0.5894643	0.0139836
M18	$\mathbf{Q_{(t-1)},Q_{(t-2)},H_{(t-1)}}$	11010	0.1171521	0.4686083	0.0230245
M19	$\mathbf{H_{(t)},Q_{(t-2)},H_{(t-2)}}$	10101	-0.0102464	-0.0409856	0.0114874
M20	$\mathbf{H_{(t)},H_{(t-1)},H_{(t-2)}}$	00111	-0.0059118	-0.0236473	0.0075705
M21	$\mathbf{H_{(t)},H_{(t-1)},Q_{(t-2)}}$	10011	-0.0068414	-0.0273657	0.0075121
M22	$\mathbf{H_{(t)},H_{(t-1)},Q_{(t-1)}}$	01011	-0.0087202	-0.0348808	0.0092684
M23	$\mathbf{H_{(t)},H_{(t-2)},Q_{(t-1)}}$	01101	-0.0031104	-0.0124416	0.0043302
M24	$\mathbf{H_{(t)},Q_{(t-2)},Q_{(t-1)}}$	11001	-0.0114180	-0.0456721	0.0089775
M25	$\mathbf{Q_{(t-1)},Q_{(t-2)}}$	11000	0.1188092	0.4752367	0.0235302
M26	$\mathbf{H_{(t)},H_{(t-2)},H_{(t-1)},Q_{(t-1)}}$	01111	-0.0027419	-0.0109675	0.0058150
M27	$\mathbf{H_{(t)},H_{(t-2)},H_{(t-1)},Q_{(t-2)}}$	10111	-0.0052684	-0.0210738	0.0074483
M28	$\mathbf{H_{(t)},Q_{(t-1)},Q_{(t-2)},H_{(t-1)}}$	11011	-0.0087173	-0.0348692	0.0078268
M29	$\mathbf{H_{(t)},Q_{(t-1)},Q_{(t-2)},H_{(t-2)}}$	11101	-0.0040099	-0.0160394	0.0064002
M30	$\mathbf{H_{(t-1)},H_{(t-2)},Q_{(t-2)},Q_{(t-1)}}$	11110	0.1036413	0.4145651	0.0255454
M31	$\mathbf{H_{(t)},H_{(t-1)},H_{(t-2)},Q_{(t-2)},Q_{(t-1)}}$	11111	-0.0039276	-0.0157103	0.0062793

H : stage at present time (day)

$H_{(t-1)}$: stage at previous day

$H_{(t-2)}$: stage at previous two days

Q : discharge at present time (ft^3/s)

$Q_{(t-1)}$: discharge at previous day (ft^3/s)

$Q_{(t-2)}$: discharge at precious two days (ft^3/s)

4.2 Artificial neural networks (ANN) models for discharge prediction

Qualitative performance was evaluated (graphically) by visual observation of time series and scatter plot of predicted discharge versus observed discharge. For the best-selected ANN-6 model, the observed and predicted discharge values were observed to be in close agreement with low and medium discharge values, as shown in Figs. 4-5. The R^2 value of the selected model was observed to be 0.9690 and 0.9878 during training and testing, respectively. Using Tansig function in the hidden layer, pure line activation function in the output layer, and Levenberg-Marquardt learning algorithm, the single hidden layer networks having higher values of Pearson correlation coefficient (PCC), Willmott index (WI), coefficient of efficiency (COE) and lower value of root mean square error (RMSE) have been selected, as shown in Table 6. For training, the values of RMSE, PCC, WI, and COE range from 17.0685 to 4.57 ft³/sec, 0.93 to 0.98, 0.92 to 0.98, and 0.87 to 0.96, respectively. For testing, the value of RMSE, PCC, WI and COE ranges from 17.65 ft³/s to 4.25 ft³/s, 0.95 to 0.99, 0.79 to 0.96 and 0.86 to 0.99. ANN-6 model with architecture (3-6-1) was observed to be the best model compared to others based on quantitative criteria of performance evaluation. RMSE, PCC, WI, and COE values of the selected ANN-6 model were observed to be 4.57 ft³/sec, 0.98, 0.98, and 0.96, respectively, during training 4.25 ft³/sec, 0.99, 0.96, and 0.99, respectively during testing.

Table 6. Comparison of various ANN models to select the best model during training and testing periods.

Model	Architecture	Training				Testing			
		RMSE(ft ³ /sec)	PCC	WI	COE	RMSE(ft ³ /sec)	PCC	WI	COE
ANN-1	3-1-1	17.06	0.93	0.92	0.87	17.65	0.95	0.79	0.86
ANN-2	3-2-1	4.76	0.99	0.97	0.99	7.84	0.98	0.93	0.97
ANN-3	3-3-1	9.32	0.98	0.97	0.96	5.98	0.99	0.95	0.98
ANN-4	3-4-1	9.59	0.98	0.96	0.96	8.91	0.98	0.92	0.96
ANN-5	3-5-1	4.79	0.99	0.98	0.99	7.32	0.98	0.95	0.97
ANN-6	3-6-1	4.57	0.98	0.98	0.96	4.25	0.99	0.96	0.99
ANN-7	3-7-1	6.23	0.99	0.97	0.98	9.06	0.98	0.93	0.96

Fig. 4 Predicted and observed discharge and their corresponding scatter plot for ANN (3-6-1) model during training period (01/06/2007 to 18/07/2015)

Fig. 5 Predicted and observed discharge and their corresponding scatter plot for ANN (3-6-1) model during testing period (19/07/2015 to 30/09/2018)

4.3 ANFIS models for discharge prediction

Different ANFIS models for discharge prediction were developed using the ANFIS editor in MATLAB software with a hybrid learning algorithm. The grid partition method was used to build the ANFIS structure. Input membership functions like Triangular, p-sigmoidal, generalized bell, Gaussian, and output MF such as linear were used, varying the MF per input from 2 to 3. Rule base was prepared with OR logical operation by a varying number of rules from 2 to 3. ANFIS models were formulated by keeping the error tolerance of 0.001 and epochs of 100. Qualitatively, the observed and predicted discharge values of the selected ANFIS-08 model were found to be in close agreement with each other having an R^2 value of 0.99 during training and 0.99 during testing, as shown in Figs. 6-7.

Fig. 6 Predicted and observed discharge and scatter plot for ANFIS-08 model during training period (01/06/2007 to 18/07/2015).

Fig.7 Predicted and observed discharge and their corresponding scatter plot for ANFIS-08 model during testing period (19/07/2015 to 30/09/2018)

The results of different statistical and hydrological performance indicators of developed ANFIS models are presented in Table 7. It was revealed that RMSE, PCC, WI and COE values ranged from 2.38 to 7.16 ft³/sec, 0.98 to 0.99, 0.97 to 0.99 and 0.97 to 0.99 and 2.22 to 8.20 ft³/sec, 0.98 to 0.99, 0.92 to 0.98 and 0.97 to 0.99 during training and testing, respectively. It can be seen from Table 7 that all ANFIS models performed well during training. However, the ANFIS-08 model with Gaussian input MF, linear output MF, and 3 MFs per input performed well during training and testing based on quantitative performance evaluation criteria. RMSE, PCC, WI, and COE values of the selected ANFIS-08 model were observed to be 2.38 ft³/sec, 0.99, 0.99, and 0.99 2.22 ft³/sec, 0.99, 0.98 and 0.99 during training and testing, respectively.

Table 7 Comparison of various ANFIS models to select the best model during training and testing periods.

MODEL	Input MF	MFs/Input	Training				Testing			
			RMSE(ft ³ /sec)	r	WI	CE	RMSE(ft ³ /sec)	r	WI	CE
ANFIS-01	Traingular	2	6.2896	0.9916	0.9848	0.9833	3.6021	0.9973	0.9721	0.9944
ANFIS-02	pSig	2	7.1633	0.9891	0.9749	0.9783	8.2042	0.9863	0.9275	0.9712
ANFIS-03	Generalised bell	2	6.4251	0.9912	0.9801	0.9826	5.1714	0.9946	0.9562	0.9885
ANFIS-04	Gaussian	2	6.1298	0.9920	0.9827	0.9841	5.1627	0.9947	0.9583	0.9886
ANFIS-05	Traingular	3	5.7742	0.9929	0.9851	0.9859	4.9826	0.9948	0.9643	0.9894
ANFIS-06	pSig	3	2.4528	0.9987	0.9950	0.9975	2.3820	0.9985	0.9821	0.9950
ANFIS-07	Generalised bell	3	2.5447	0.9986	0.9953	0.9973	2.4920	0.9987	0.9891	0.9973
ANFIS-08	Gaussian	3	2.3823	0.9988	0.9949	0.9976	2.2230	0.9990	0.9897	0.9979

4.4 WANN model for daily discharge prediction

Based on visual observations, the predicted and observed discharge values were in close agreement with each other during training and testing periods having R^2 values of 0.9910 and 0.9880, as shown in Fig.8-9.

Fig. 8 Predicted and observed discharge and their corresponding scatter plot for WANN (12-25-1) model during training period (01/06/2007 to 18/07/2015).

Fig. 9 Predicted and observed discharge and their corresponding scatter plot for WANN (12-25-1) model during testing period (19/07/2015 to 30/09/2018).

The Wavelet-based artificial neural network (WANN) models for daily discharge prediction were developed using the best input combinations considering lags of stage and discharge given by the Gamma test. In this Wavelet coupled ANN model, the first actual data of stage and discharge got

transformed with three decomposition levels, reconstruction, and then put into developing the models. The network with a single hidden layer having higher values of PCC, WI, and COE and lower value lower values of RMSE was selected as the best model. The quantitative performance of different WANN models was assessed through different statistical and hydrological performance indicators, as presented in Table 8. It is revealed that RMSE, PCC, WI, and COE varied from 11.85 to 4.65 ft³/sec, 0.87 to 0.99, 0.91 to 0.98, and 0.72 to 0.99 during training and testing, respectively. RMSE, PCC, WI, and COE values of the selected WANN-25 model were found to be 4.65 ft³/sec, 0.99, 0.98, and 0.99, respectively during training and 5.51 ft³/sec, 0.99, 0.96 and 0.99, respectively during testing.

Table 8 Comparison of various WANN models to select the best model during training and testing periods.

Model	Architecture	Training				Testing			
		RMSE(ft ³ /sec)	PCC	WI	COE	RMSE(ft ³ /sec)	PCC	WI	COE
WANN-1	12-1-1	11.8560	0.9699	0.9649	0.9406	9.1805	0.9850	0.9170	0.9639
WANN-2	12-2-1	9.0007	0.9828	0.9702	0.9658	8.5688	0.9856	0.9258	0.9685
WANN-3	12-3-1	9.9451	0.9792	0.9653	0.9582	7.5953	0.9882	0.9370	0.9753
WANN-4	12-4-1	6.3685	0.9914	0.9825	0.9829	6.8362	0.9920	0.9463	0.9800
WANN-5	12-5-1	5.5280	0.9937	0.9787	0.9871	10.9847	0.9805	0.9837	0.9861
WANN-6	12-6-1	5.7982	0.9929	0.9847	0.9858	10.9033	0.9744	0.9459	0.9491
WANN-7	12-7-1	5.7100	0.9933	0.9794	0.9862	7.2179	0.9916	0.9383	0.9777
WANN-8	12-8-1	6.5118	0.9912	0.9805	0.9821	6.4168	0.9924	0.9445	0.9824
WANN-9	12-9-1	5.3610	0.9941	0.9826	0.9879	6.5155	0.9928	0.9453	0.9818
WANN-10	12-10-1	5.3590	0.9939	0.9837	0.9879	7.0365	0.9898	0.9480	0.9788
WANN-11	12-11-1	4.8389	0.9951	0.9859	0.9901	5.7197	0.9937	0.9537	0.9860
WANN-12	12-12-1	8.1627	0.9859	0.9759	0.9718	7.8843	0.9875	0.9325	0.9734
WANN-13	12-13-1	6.0035	0.9924	0.9861	0.9848	6.5410	0.9910	0.9533	0.9817

WANN-14	12-14-1	5.8640	0.9931	0.9819	0.9855	6.2329	0.9925	0.9457	0.9834
WANN-15	12-15-1	5.4803	0.9937	0.9837	0.9873	5.9711	0.9936	0.9503	0.9847
WANN-16	12-16-1	8.0212	0.9871	0.9723	0.9728	7.2843	0.9918	0.9296	0.9773
WANN-17	12-17-1	6.5554	0.9919	0.9763	0.9818	6.7425	0.9920	0.9365	0.9805
WANN-18	12-18-1	5.0396	0.9947	0.9878	0.9893	5.4004	0.9935	0.9563	0.9875
WANN-19	12-19-1	5.6334	0.9933	0.9834	0.9866	6.1212	0.9927	0.9486	0.9839
WANN-20	12-20-1	4.9586	0.9949	0.9824	0.9896	6.0462	0.9929	0.9503	0.9843
WANN-21	12-21-1	4.7566	0.9955	0.9786	0.9904	6.9186	0.9902	0.9363	0.9795
WANN-22	12-22-1	7.6611	0.9876	0.9787	0.9752	6.7957	0.9924	0.9440	0.9802
WANN-23	12-23-1	5.9175	0.9927	0.9841	0.9852	5.7255	0.9938	0.9522	0.9860
WANN-24	12-24-1	5.5238	0.8786	0.9430	0.7247	5.4145	0.9939	0.9595	0.9874
WANN-25	12-25-1	4.6522	0.9955	0.9882	0.9909	5.5121	0.9940	0.9684	0.9970

4.5 Comparison among ANN, ANFIS, and WANN models for discharge prediction

The finest selected models were evaluated and compared with one another to determine the most precise estimation with the highest prediction performance when assessing the prediction accuracy for discharge prediction at the Gaula barrage location. A further round of comparisons was conducted between the best models identified from each approach, this time based on qualitative and quantitative performance evaluation criteria. Different performance measures, such as the Pearson correlation coefficient (PCC), root mean squared error (RMSE), the Nash-Sutcliffe efficiency (CE), and Willmott Index (WI) and coefficient of determination (R^2), were utilized to determine the best accurate single model for daily discharge forecast at the Gaula barrage location. During testing periods, the performance of the best models picked from each technique is demonstrated using various performance indicators, as indicated in Table 9. It is evident from Table 9 that during testing, different indicators showed significant differences among different models. During testing RMSE, PCC, WI and COE varied from 2.20 to 5.51 ft³/sec, 0.99 to 0.99, 0.96 to 0.98 and 0.99 to 0.99, respectively.

As presented in Table 9, the ANFIS model outperformed the simple ANN model and WANN models. Among ANFIS models, Gaussian based ANFIS model with input MF-3 performed better. The best model should be selected by considering its performance during the testing period. As evident from Table 9, the ANFIS model performed better than all other models during testing periods. RMSE, PCC, WI, and COE values of the best selected ANFIS model were observed to be 2.2230, 0.9990 and 0.9897, and 0.9979 during testing, respectively. The order of superiority for discharge prediction was observed as ANFIS, WANN, and ANN. After considering all models of different techniques, it was observed that the performance of Gaussian-3 based ANFIS significantly achieves superior to all other models and could be applied for daily discharge prediction of Gaula barrage site.

Table 9 Performance evaluation of best-chosen models during testing period using ANN, ANFIS and WANN approaches.

Performance indicators	ANN network	ANFIS network	WANN network
	3-6-1	Gaussian-3	12-25-1
	Testing period	Testing period	Testing period
RMSE (ft³/sec)	4.25	2.22	5.51
r	0.99	0.99	0.99
WI	0.96	0.98	0.96
CE	0.99	0.99	0.99

5 Conclusion

Discharge prediction is critically essential for water resource planning and management. The transformation of stage into discharge must be calculated through various non-linear equations. The present study was conducted to create and assess ANN, ANFIS, and WANN models for daily monsoon discharge forecasting at the Gaula site in the Indian state of Uttarakhand. The non-linear correlations between input and output data sets can be identified using an ANN, a flexible, convenient, and simple mathematical framework. ANN is distributed, adaptive, and non-linear learning machine that is built from many neurons followed the training algorithm's instructions; each of these neurons gets links from other neurons or from itself. The artificial neural network (ANN) has a constructive approach that can analyze the complex non-linear relationship between dependent and independent data. The ANFIS model has become a trendy research tool due to its ability to exploit understanding of fuzzy logic while also leveraging the learning capabilities of an ANN at the same time, which is a rare combination. The ANFIS models were trained for discharge prediction using a hybrid learning method explicitly developed for this purpose. The appropriate learning parameter for the Gaula river location was achieved by trial and error using a

Gaussian membership function and a TSK fuzzy rule, respectively. Based on the performance indices, among artificial neural network models, the ANN-6 model (3-6-1) outperformed other ANN models in daily discharge prediction. Wavelet coupled artificial neural network WANN-25 model outperformed other WANN models in daily discharge prediction for the study area. Adaptive neuro-fuzzy inference system ANFIS-08 (Gaussian) model outperformed other ANFIS models in daily discharge prediction for the study area. The ANFIS models performed better than ANN and WANN models in discharge prediction for the study area based on the overall performance.

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