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RESEARCH PAPER

Streamflow Prediction Based on Artificial Intelligence Techniques

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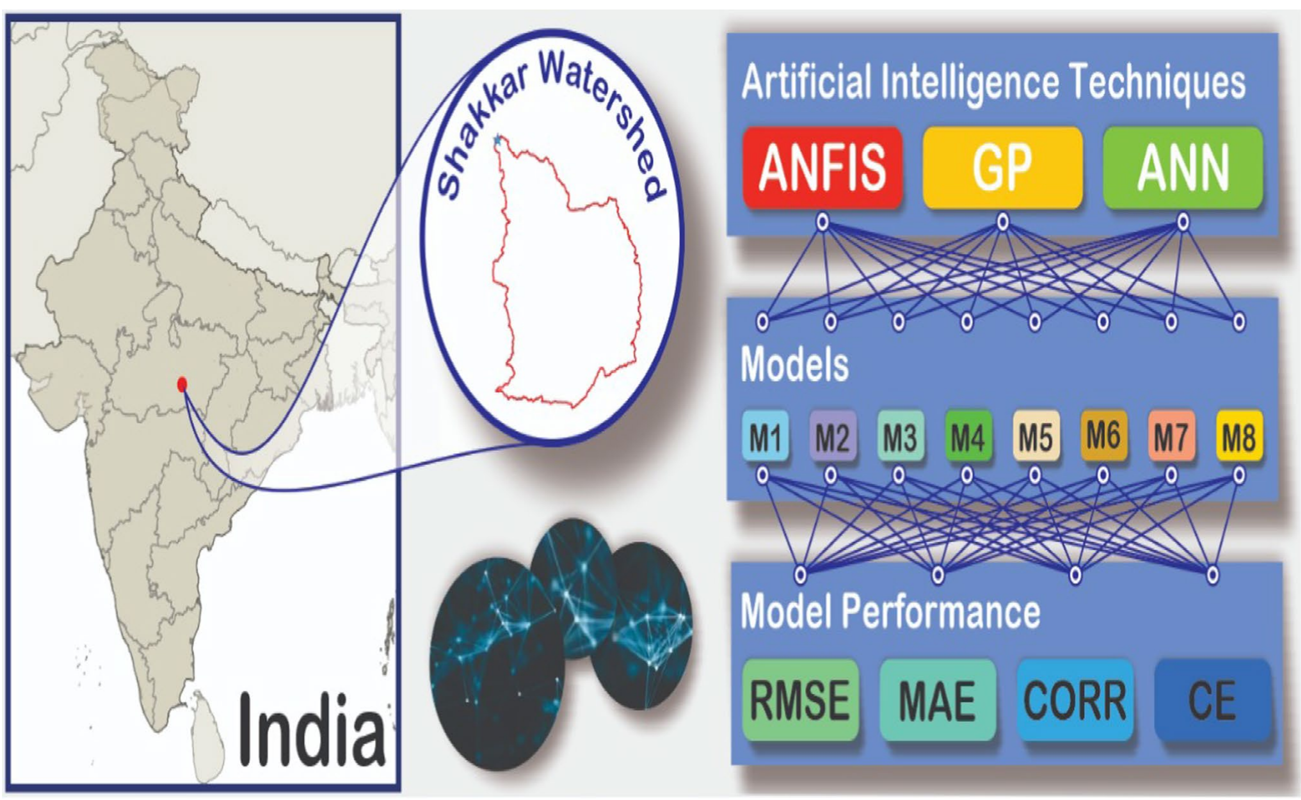
Abstract

The application of Artificial Intelligence (AI) techniques has become popular in science and engineering applications since the middle of the twentieth century. In this present study, three AI techniques (ANFIS, GP and ANN) have been used for forecasting streamflow into Shakkar watershed (Narmada Basin), India. The models have been used considering previous streamflow and cyclic terms in the input vector to provide a suitable time series model for streamflow forecasting. To evaluate the model performance, RMSE, MAE, CORR and CE were employed. Results showed that the ANFIS has the best performance in forecasting streamflow time series for Shakkar watershed. The GP and ANN are in the 2nd and 3rd ranks, respectively. According to the results, in all the AI methods (ANFIS, GP and ANN), the model with cyclic terms had better performance compared to those models not considering periodic nature and being applied by only considering the previous streamflow.

Graphical Abstract



Keywords Artificial Intelligence models · Cyclic Term · Streamflow · Forecasting · Artificial Neural Network

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1 Introduction

Forecasting of river flow and reservoir inflow plays a fundamental part in water resources management as one of the most challenging tasks in the area of hydrology. Forecasting is useful for a better management in reservoir operation, water optimization and allocation, hydropower generation, supplying water to industry, agriculture or municipality, and drought management, and is a necessary tool for an accurate and reliable streamflow forecasting (Meshram et al. 2019a, b). Reliable forecasting of streamflow at different time scale can considerably enhance the ability to predict the availability of water in the future. Recently, many researchers have paid much attention to hydrologic time series forecasting. Consequently, during the last decade, various models have been proposed in order to predict hydrologic time series. According to Wang et al. (2009), these models could be represented by three groups as follows: time series models, regression-based methods, and AI based models. The autoregressive moving-average models (ARMA) (Box and Jenkins 1970) have been extensively applied to model hydrological time series in the last few decades. ARIMA is another popular model, which has also been widely used by researchers (e.g., Salas 1993; Toth et al. 2000; Srikanthan and McMahon 2001); Artificial intelligence (AI) models such as fuzzy inference systems (FIS), support vector machine (SVM), artificial neural networks (ANN), genetic programming (GP) and wavelet-artificial neural network (WANN) have recently attracted the attention of research for forecasting the hydrological variables. ANNs have been assessed successfully in different fields of hydrologic modeling, especially streamflow prediction (Nourani et al. 2012; Abrahart et al. 2012; Mugumo 2012; Valipour et al. 2013; Santos and Silva 2013; Farias et al. 2013; Santos et al. 2019; Freire et al. 2019; Honorato et al. 2019; Ghorbani et al. 2020; Khatibi et al. 2020; Meshram et al. 2021a, b; Saraiva et al. 2021). Moreover, fuzzy logic and fuzzy set theory-based approaches proposed by Zadeh (1965) has been widely applied in hydrological modeling (Shiri and Kisi 2010; Lohani et al. 2006, 2012; Goyal et al. 2013). Genetic programming have been also used during recent years in a variety of hydrological applications for predicting and simulating the hydrological processes and water resources management (Dorado et al. 2003; Alavi et al. 2008). Wang et al. (2009) used ANN, neural-based fuzzy inference system (ANFIS), genetic programing (GP) and support vector machine (SVM) using long-term observations in China for monthly inflow forecasting. The results showed that ANFIS, GP and SVM presented the best performances according to different criteria for evaluation. Londhe and Charhate (2010) applied GP, ANN and model trees (MT) for streamflow forecasting one-day ahead for two stations in Narmada River basin, in India. Their obtained results suggested that the MT and ANNs techniques presented almost the same performance; however, the GP showed better performance. On the other hand, Nayak et al. (2004) assessed the neuro-fuzzy approach to predict streamflow time series, and Rasouli et al. (2012) applied SVM for daily streamflow forecasting using various meteorological variables and large-scale climate indices in British Columbia, Canada, and found out that the SVM model provides good performance criteria for modeling daily streamflow. Guven (2009) used linear genetic programming (LGP), which is a type of the GP, and two ANN to predict daily streamflow in Schuylkill River, located in the USA, and concluded that the LGP satisfactorily performed better than ANN methods. AR, ANN and ANFIS models were applied by Lohani et al. (2012) to forecast reservoir inflow. They included cyclic terms in the ANN and ANFIS for considering the effect of monthly periodicity on the flow data. The results revealed that the ANFIS provides more accurate forecasting than the AR and ANN models. Moreover, Danandeh Mehr et al. (2013), using linear genetic programming (LGP) and a neuro-wavelet technique for streamflow forecasting, also found that LGP performed better than WANN among the analyzed models.

The river streamflow has undergone changed due to the climate change phenomenon, which has also caused recent droughts and diminished water resources. Therefore modeling the streamflow is vital to developing successful water resources policies and management. In this study, ANFIS, ANN and GP models are applied to forecast monthly streamflow in the Shakkar watershed (Narmada Basin), India. In addition, cyclic terms are often considered in AI models (e.g., ANFIS, ANN and GP) used to assess the impact of monthly periodicity on streamflow data.

2 Description of Selected AI Models

2.1 Adaptive Neural-based Fuzzy Inference System

Zadeh (1965) first published the fuzzy logic and fuzzy set theory, when presented a fuzzy set as a class of objects based on a continuum of grades of membership. The fuzzy-rule based modeling is a scheme based on a qualitative modeling and the system is represented as a natural language. It is worth noting that the Fuzzy Inference System (FIS) can be expressed as the key unit of a fuzzy logic system to model imprecise or even linguistic information. FIS is also called fuzzy rule-based system, which is being applied to a large variety of situations concerning uncertainty and vagueness (Zimmermann 1996). In general, fuzzy inference system consists by the following functional components: (i) the rule base, which contains the fuzzy IF–THEN rules; (ii) the database, which is formed by the membership functions of the fuzzy sets applied in the fuzzy rules; (iii) the decision-making unit, which operates the rules; (iv) the fuzzification interface unit, which transforms the crisp quantities into fuzzy quantities; and (v) the defuzzification interface unit, which is intend to transform the fuzzy quantities into crisp quantities.

According to Jang (1993) and Reddy (2006) the ANFIS architecture basically is formed by five layers, which are composed by nodes, i.e., input nodes, rule nodes, average nodes, consequent nodes, and output nodes. These layers are designed as premise part, implication, normalization, consequent part, and output, whose functionalities are briefly described as follows:

Layer 1 computes the membership grades. Each node i in this layer generates a membership grade for which are belong to appropriate fuzzy sets using membership functions.

$$Q_i^1 = \mu_{A_i}(x) \text{ for } i = 1,\ 2 \tag{1}$$

$$Q_i^1 = \mu_{B_{i-2}}(y) \text{ for } i = 3,\ 4 \tag{2}$$

where Q_i^1 is the membership function of fuzzy sets A_i and B_i; x, y are the crisp inputs to node i; and A_i and B_i are the linguistic labels (short, long etc.) which are respectively characterized by suitable membership functions, μ_{Ai} and μ_{Bi}. Any continuous and piecewise differential functions such as triangular or trapezoidal membership functions could be used. In water resources fields, these are the most used membership functions. However, due to the smoothness and concise notation, the bell shaped and Gaussian membership functions are popular for specifying fuzzy sets. In the present study, the bell shaped membership function is used, which is given as:

$$\mu_{A_i} = \frac{1}{1 + \left|\frac{x-c_i}{a_i}\right|^{2b_i}} \tag{3}$$

$$\mu_{B_i} = \frac{1}{1 + \left|\frac{y-c_i}{a_i}\right|^{2b_i}}$$

in which a_i, b_i, and c_i are the parameters set of the membership functions in the premise part of fuzzy if–then rules that changes the shapes of the membership function. As the first layer belongs to premise part, parameters in this layer are pointed as premise parameters.

Layer 2 combines the membership grades of layer 1 to form the firing strengths. The T-norm operator is adopted for implication of the rules. Such an operator multiplies the incoming signals and produces one single output, which represents the firing strength (antecedent part) for that rule.

$$Q_k^2 = w_k = \mu_{A_i}(x) * \mu_{B_j}(y) \text{ for } k = 1, 2, 3, 4;\ i = 1, 2;\ j = 1, 2 \tag{5}$$

Firing strength gives the degree to which the antecedent part of a fuzzy rule is satisfied, and it shapes the output function for the rule.

Layer 3 normalizes the firing strengths. In this layer, the ith node calculates the ratio of the ith rule's firing strength to the sum of firing strengths of all rules. The normalized firing strength is given as:

$$Q_i^3 = \overline{w_i} = \frac{w_i}{\sum_{k=1}^{4} w_k} \text{ for } i = 1,\ \ldots,\ 4 \tag{6}$$

Layer 4, based on the node function, computes the contribution of the ith rule towards the total output, expressed as:

$$Q_i^4 = \overline{w}_i(p_i x + q_i y + r_i) \text{ for } i = 1,\ \ldots,\ 4 \tag{7}$$

in which w_i is the ith node output from the previous layer; $\{p_i, q_i, r_i\}$ are the coefficients of the consequent part and are also known as the consequent parameters.

Layer 5, according to the single node, computes the overall output by summing up all the incoming signals.

$$Q_i^5 = \overline{w}_i f_i = \frac{\sum_{i=1}^{4} w_i f_i}{\sum_{i=1}^{4} w_i} \tag{8}$$

In this method, the modifiable parameters in layer 1 determine the shapes and positions of membership functions, and those in layer 4 specify the output linear equation of each rule. In layer 1, all the parameters have nonlinear behavior, so it requires a nonlinear optimization technique, and in layer 4, all the parameters are linear in nature, and any traditional or advance optimization technique can be used (Reddy 2006).

2.2 Artificial Neural Networks (ANN)

Artificial neural networks (ANN) have been developed as generalizations of biological nervous systems for mathematical models (Haykin 1999). Usually, an ANN is based on three layers, in which the input layer the data are introduced to the network, then there is one or more hidden layers, in which the data are processed to finally proceed to the output layer, when the final results are obtained (Freire et al. 2019). Formally, the neurons within the layers are connected either as feedforward or recurrent networks. In feedforward networks, neurons are arranged in many layers, and the information flows only in one direction. The flow direction is from the input layer to output layer. The neurons are arranged in one or more layers and feedback is implemented either internally in the neurons to other neurons within the same layer or to neurons in the preceding layers (Hsu et al. 1995; Honorato et al. 2019). Usually the neural networks are represented as a three layered feed-forward network because they can be easily applied to several types of problems (Lohani et al. 2012).

2.3 Genetic Programing

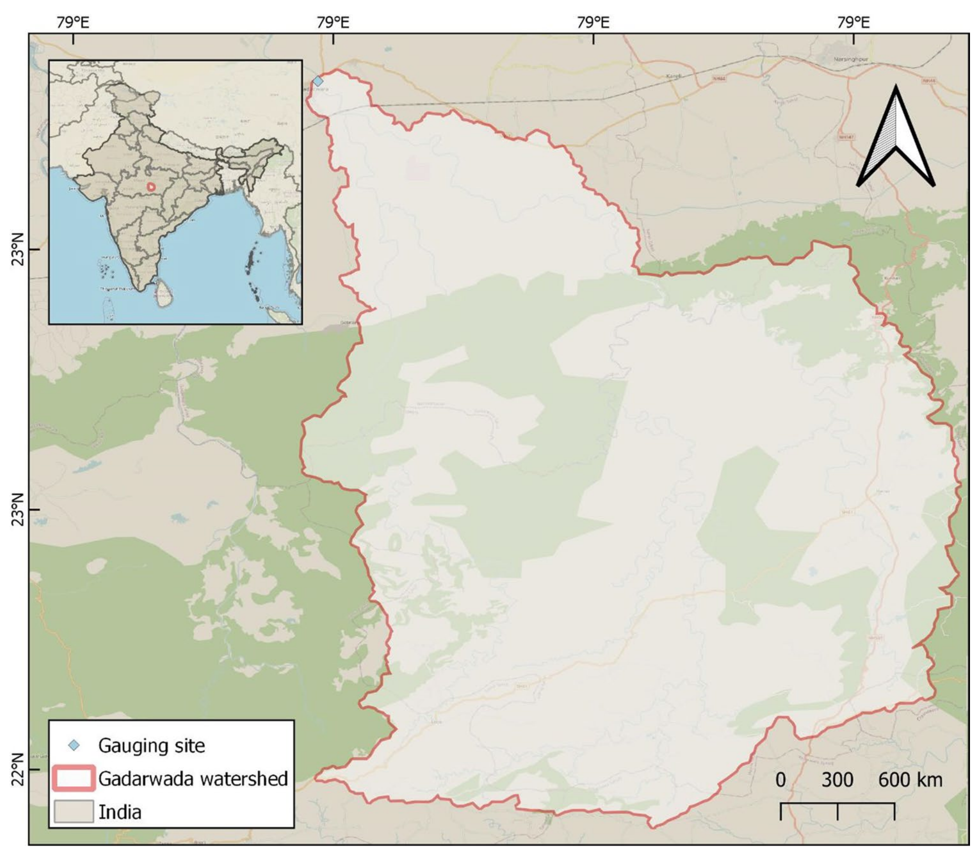
Genetic programing is a technique of evolving programs, starting from a population of unfit random programs, fit for a specific task. Genetic programing applies operations similar to natural genetic processes to the population of programs, and automatically solves problems with no need to specify the structure of the solution in prior (Danandeh Mehr 2013). Differently from statistical techniques such as decision trees, ANN and others, genetic programing is an automatic parameterizing which, with no need of user tuning, builds models. The main inputs for the genetic programing model are (i) patterns for learning, (ii) fitness function, (iii) functional and terminal set, and (iv) parameters for the genetic operators, e.g., crossover and mutation probabilities (Sreekanth and Datta 2011). Usually, genetic programing solves any problem based on the following stages: (i) generation of an initial population (computer programs) randomly by the functions and terminals of the problem; (ii) execution of each program with certain fitness value; (iii) creation of a new population of computer programs based on reproduction, mutation and crossover operators; (iv) comparison of new fitness values, and (v) selection of the best computer program (Danandeh Mehr 2013).

3 Materials and Methods

3.1 Study Area and Data Description

The present study was conducted in Gadarwada gauging station, one of the gauged watershed of the Shakkar watershed (Fig. 1). The Shakkar River is a major stream of Narmada River. Shakkar watershed lies between 22°23′ N latitude and 78°52′ E longitude. The total catchment area of this watershed is 2220 km^2. The topography of the watershed is undulating. The climate of the Shakkar watershed is dry, except in the monsoon season. Rainfall occurs mainly during June to October, due to the southwest monsoon. The soil in the watershed can be classified into clay to loamy texture. The collection of the hydrological data at the Gadarwada station was started in 1990 by the Central Water Commission (CWC) Bhopal. The monthly streamflow data (Q) (m^3/s) from 1990 to 2015 were collected for the study. Streamflow

Fig. 1 Location of the study area



is mainly confined to the monsoon period (June-October), then the models were tested for the monsoon period only. The statistical parameters of streamflow are shown in Table 1.

The data in multi-layer networks are divided into 60, 20 and 20%, for calibration, verification and validation, respectively. Then, the training dataset was divided again into two datasets, i.e., one for verification and another for validation. It is worth noting that this procedure is important to avoid system over-fitting during the training process (Jang et al. 2002). The training dataset is intended to compute the gradient and update the network weights and biases, whereas the validation dataset is intended to quantify the general model performance (Lohani et al. 2012). The statistics criteria and box plot of the two datasets (calibration and validation) are given in Fig. 2 and Table 1.

3.2 Data Processing

Normalization is an essential stage before using the ANN-based models. Such normalization is intended to make the data dimensionless and to confine the data within a desired range. There are two main reasons to proceed a pre-processing procedure. This pre-processing procedure has been reported by Dawson and Wilby (2001) as important process, because it ensures that the variables may receive equal attention during the training and it makes the training algorithm more efficient. There are many equations developed and used by researchers for normalizing data. The following equation was used for normalizing the streamflow data (Huang et al. 2014):

$$x_i = \frac{x_i - x_{\min}}{x_{\max} - x_{\min}} \tag{9}$$

3.3 Development of AI Models

Usually, in hydrological forecasting models, researchers are interested in predicting output from inputs based on past time and there are no fixed rules. The objective on predicting streamflow using antecedent values is to generalize a relationship of the following form (Wang et al. 2009):

Table 1 Summary statistics of the calibration and validation datasets (1990–2015)

Month	Calibration period					Validation period				
	Mean (m^3/s)	SD (m^3/s)	CV	Skewness	Kurtosis	Mean (m^3/s)	SD (m^3/s)	CV	Skewness	Kurtosis
Jun	15.04	46.59	3.10	7.00	59.38	19.16	51.11	2.67	4.72	27.31
July	113.28	264.44	2.33	5.11	32.73	142.35	274.97	1.93	7.68	77.54
Aug	169.72	257.26	1.52	4.79	31.22	261.54	459.31	1.76	6.69	53.57
Sep	168.56	429.97	2.55	8.17	84.32	168.20	249.86	1.49	8.17	88.43
Oct	29.44	43.58	1.48	5.48	41.76	30.96	29.95	0.97	1.57	2.09

SD Standard deviation, *CV* Coefficient of variation

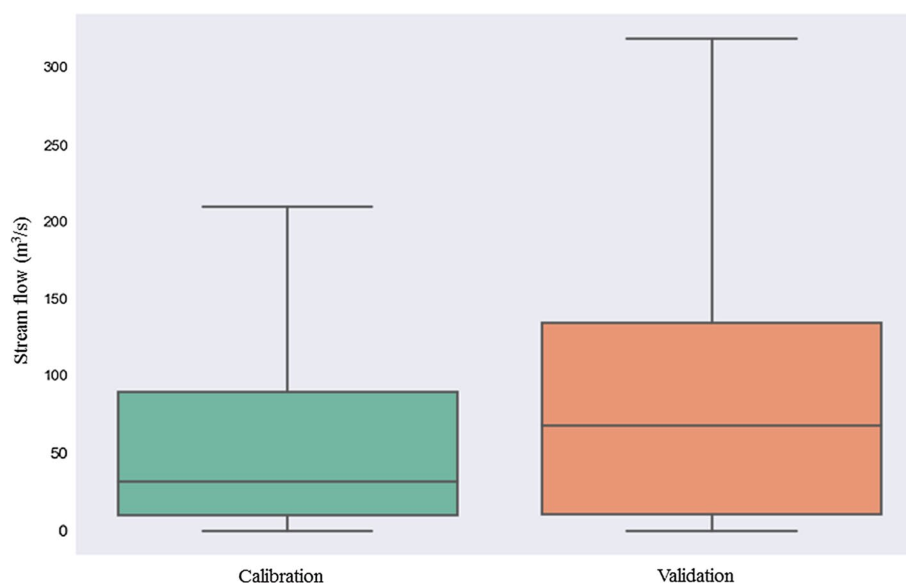


Fig. 2 Box plot of the validation and calibration datasets

$$Y = f(X^m) \tag{10}$$

in which X^m is a m-dimensional input vector composed by variables $x_1, \dots x_i, \dots, x_m$, whereas Y is the output variable. In streamflow modeling, the x_i values may have different time lags and the Y value is usually the streamflow for the next step. Usually, the number of the previous values within the vector X^m is not known a prior. In streamflow forecasting by an AI model, the selection of appropriate model input is important to obtain a good result.

Furthermore, in the present study, to consider monthly periodicity, cyclic terms (cos2π.*i*/12) and (sin2π.*i*/12), (i = 1, 2… 12) were considered also in the input vector. Then, the performance of the considered AI models was evaluated by some evaluation criteria based on Lohani et al. (2012). To develop an adequate time series model for streamflow forecasting, eight combinations of input vectors were considered as follows. At the first stage, M_1 to M_4 models considered only previous streamflow in the input vector, and at the second stage, M_5 to M_8 models considered previous streamflow and cyclic term in the input vector:

M_1: $Q(t) = f(Q[t-1])$.

M_2: $Q(t) = f(Q[t-1],\ Q[t-2])$.

M_3: $Q(t) = f(Q[t-1],\ Q[t-2],\ Q[t-3])$.

M_4: $Q(t) = f(Q[t-1],\ Q[t-2],\ Q[t-3],\ Q[t-4])$.

M_5: $Q(t) = f(Q[t-1],\ \cos\left[2\pi.i/12\right],\ \sin\left[2\pi.i/12\right])$.

M_6:$Q(t) = f\left(Q[t-1],\ Q[t-2],\ \cos\left[2\pi.i/12\right],\ \sin\left[2\pi.i/12\right]\right)$.

M_7:$Q(t) = f\left(Q[t-1],\ Q[t-2],\ Q[t-3],\ \cos\left[2\pi.i/12\right],\ \sin\left[2\pi.i/12\right]\right)$.

M_8: $Q(t) = f(Q[t-1],\ Q[t-2],\ Q[t-3],\ Q[t-4],\ \cos\left[2\pi.i/12\right],\ \sin\left[2\pi.i/12\right])$.

3.4 Application of the Models

In this study, the network (grid) partitioning technique was used with ANFIS for modeling. There are two training algorithms, i.e., back-propagation and hybrid learning algorithms, which were used in this study for optimizing the parameters of the membership function. As for constructing the initial fuzzy model in the network partitioning technique, eight membership functions, which are supported by ANFIS, were used for fuzzification of input variables. In summary, at first, the initial structure of ANFIS model was constructed by using network (grid) partitioning technique and then it was trained with both of back-propagation and hybrid learning algorithms.

In genetic programing process, the selection of different initial random populations (called the training dataset in the genetic programming process), which are effective in the process for training the mechanism of governing process, will increase the complexity of the pattern, will use more memory, and will decrease model accuracy. Therefore, in architecting the streamflow, different patterns should be tested to choose the most effective set of observations as the training dataset. Another important point in GP modeling is selection of the model functions (operators) for calculation processes. In this study, the combination operator was used for forecasting monthly streamflow. Different input patterns were considered for GP modeling , which were divided in two main classes, including periodic and non-periodic. In addition, in the present study, as for the application of ANN, the tangent–sigmoid transfer function was used in the hidden layer, the linear transfer function was chosen for the output layer, and the Levenberg–Marquardt algorithm was selected for the training. For every input pattern, different network architectures were constructed and trained by changing the number of hidden layer and number of neurons. Then, the pattern with the lowest error was selected for further analysis. For evaluating of GP and ANN model in forecasting the monthly streamflow, the used architectures of input variables were similar to those used for ANFIS model, i.e., four non-periodic models and four periodic models.

4 Model Performance Evaluation

The model performance was evaluated according to the following indices: root mean square error (RMSE), mean absolute error (MAE), correlation coefficient (r) and Nash–Sutcliffe coefficient of efficiency (CE).

4.1 Root Mean Square Error (RMSE)

This performance criterion determines the accuracy of the model in a quantitative sense. RMSE is defined as:

$$\mathrm{RMSE} = \sqrt{\frac{1}{T}\sum_{t=1}^{T}(Q_o^t - Q_m^t)^2} \tag{11}$$

4.2 Mean Absolute Error (MAE)

This performance criterion is a simple weighted average of the absolute errors and is defined as:

$$\mathrm{MAE} = \frac{1}{T}\sum_{t=1}^{T}\left|Q_o^t - Q_m^t\right| \tag{12}$$

4.3 Correlation Coefficient (r)

The correlation coefficient gives the strength of the relationship between observed and modeled values as follows:

$$r = \frac{\sum_{t=1}^{T} (Q_o^t - \overline{Q_o})(Q_m^t - \overline{Q_m})}{\sqrt{\sum_{t=1}^{T} (Q_o^t - \overline{Q_o})^2 \sum_{t=1}^{T} (Q_m^t - \overline{Q_m})^2}} \tag{13}$$

4.4 Nash–Sutcliffe Coefficient of Efficiency (CE)

This performance criterion measures the goodness-of-fit of the model with respect to the observed values (Nash and Sutcliffe 1970) and is useful to assess the predictive characteristic of hydrologic models.

$$\mathrm{CE} = 1 - \frac{\sum_{t=1}^{T} (Q_o^t - Q_m^t)^2}{\sum_{t=1}^{T} (Q_o^t - \overline{Q_o})^2} \tag{14}$$

where in all of the above equations, the subscript 'o' denotes to observed data and the subscript 'm' denotes to model predicted values. T is total number of data points, Q_o is observed discharge, Q_m is modeled discharge, Q_t is discharge at time t and $\overline{Q_o}$, $\overline{Q_m}$ are the mean values of observed and modeled discharges, respectively.

5 Results and Discussion

The effectiveness of the models was examined by comparing the forecasted and observed streamflow values at the study location. The performance of the models in prediction of streamflow was estimated using a set of statistical metrics (RMSE, MAE and R) and visual inspection of data through line plots and box plots. The obtained results are as follows:

Table 2 shows the values of performance criterion of the AI models for the calibration and validation. According to the results, the ANFIS models without considering the periodicity of flows (i.e., M1 to M4 models) have lower accuracy than the other models that considered the periodicity. Based on the results, the M1 and M3 models had the best value of evaluation criteria among non-periodic models, and among the models which considered periodicity (M5 to M8 models), M5 and M7 models had the highest accuracy in forecasting monthly streamflow. Generally, the M7 model showed the best accuracy among all eight considered models. Figure 3 shows the scatter plot of the observed and modeled monthly streamflow using the M7 model.

Furthermore, the performances during the training and validation periods of all GP models developed are given in Table 2. The results suggest that the periodic models (M5 to M8 Models) outperform the non-periodic models (M1 to M4

Table 2 Performance criterion of the AI models during calibration and validation periods

			M1	M2	M3	M4	M5	M6	M7	M8
ANFIS	Calibration	RMSE	96.10	95.23	97.72	89.09	96.22	97.18	98.39	80.89
		MAE	68.01	68.03	68.10	78.17	68.01	68.09	58.14	58.27
		R	0.83	0.83	0.81	0.89	0.83	0.81	0.80	0.87
	Validation	RMSE	108.61	90.70	98.77	100.95	98.78	89.83	97.50	85.57
		MAE	88.53	74.66	68.59	86.70	68.54	58.62	58.49	58.93
		R	0.75	0.84	0.81	0.78	0.85	0.83	0.98	0.84
GP	Calibration	RMSE	49.69	41.24	47.04	51.67	59.44	40.68	56.10	51.85
		MAE	28.02	24.10	28.18	29.69	35.90	29.60	33.95	30.69
		R	0.997	0.997	0.998	0.996	0.98	0.95	0.98	0.997
	Validation	RMSE	89.18	95.33	80.29	87.00	83.21	51.91	72.17	87.24
		MAE	58.03	62.26	57.54	56.28	46.58	32.63	46.49	57.98
		R	0.80	0.78	0.84	0.82	0.84	0.88	0.86	0.83
ANN	Calibration	RMSE	220.99	207.26	193.91	189.47	219.29	206.53	192.71	190.07
		MAE	58.69	56.25	60.19	56.88	57.40	57.38	60.98	57.71
		R	0.79	0.74	0.87	0.89	0.80	0.84	0.88	0.89
	Validation	RMSE	269.67	256.00	256.91	252.53	265.87	255.34	257.36	252.01
		MAE	67.96	55.68	69.02	61.40	65.49	56.16	70.61	62.08
		R	0.77	0.76	0.74	0.76	0.74	0.75	0.74	0.80

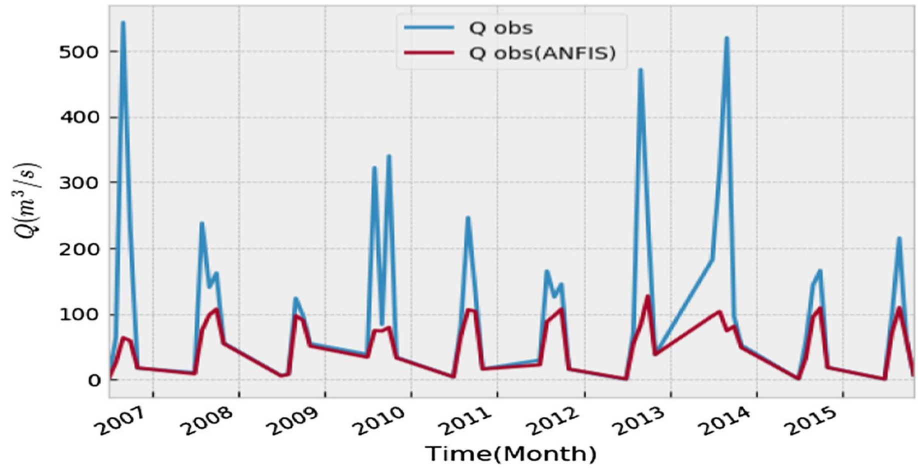


Fig. 3 Time series of monthly mean streamflow of the ANFIS (validation results)

models). The input pattern with 3 months lag time had the best performance among the non-periodic models, and among periodic models, M6 model, considering the seasonality effect and 2 months lag time, showed the highest accuracy during the validation period and was selected as the best pattern for constructing GP. Figure 4 presents the comparison between measured and forecasted monthly streamflow using the best pattern of GP and M6 model, during validation period.

Table 2 shows that the input pattern including streamflow with 2 months lag time had the best performance among the non-periodic models with ANN, but considering the periodicity in input patterns resulted in an improvement in the accuracy of the models, and thus M8 model was selected as the best architecture based on the MAE and RMSE values. According to the results, the values of MAE and RMSE for non-periodic models are greater than the values for periodic models. This result was observed in all considered methods. Figure 5 presents the comparison between observed and forecasted streamflow time series by using the selected ANN (M7 model).

The time series of monthly mean streamflow forecasted and comparison between observed and forecasted values of all considered AI methods are presented in Fig. 6. According to the results (Table 3), it can be observed that all considered AI methods had almost the same performance in forecasting the streamflow, but the ANFIS had better performance than two other methods. It should be mentioned again that the performance of the AI methods were compared for the best input pattern, i.e., for the ANFIS and ANN, the results of M7 model, and for the GP, the results of M6 model were compared to identify the suitable method for forecasting the streamflow time series.

According to the literature review, AI techniques are superior to conventional methods in predicting streamflow (Asati and Rathore 2012). Some exemples are as follows. It was observed that streamflow prediction by ANN_Conjugate gradient and ANN_Cascade correlation was superior compared to that using ANN_Back propagation and ANN_Levenberg–Marquardt (Kisi 2007). Al-Aboodi et al. (2017) compared the data-driven modeling techniques for predicting river flow in an arid region. It was observed that ANFIS model was better than ARIMA model, and slightly better than ANN model. The ANFIS model produced a

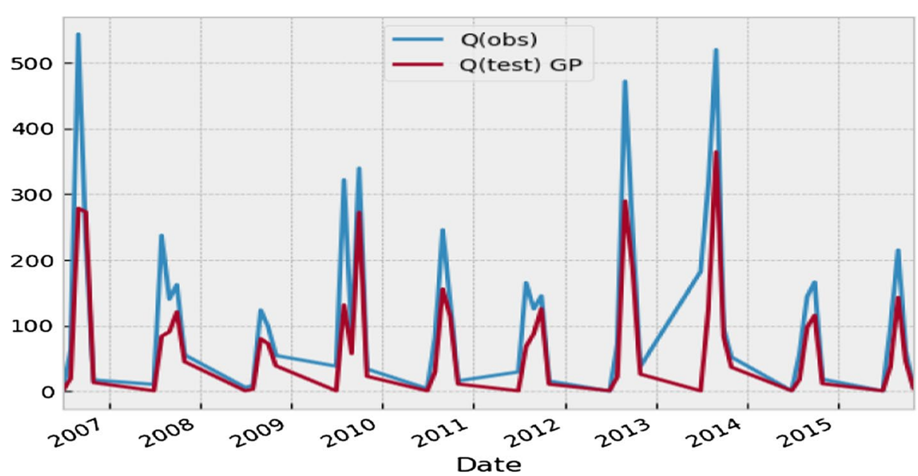


Fig. 4 Time series of monthly mean streamflow of the GP (validation results)

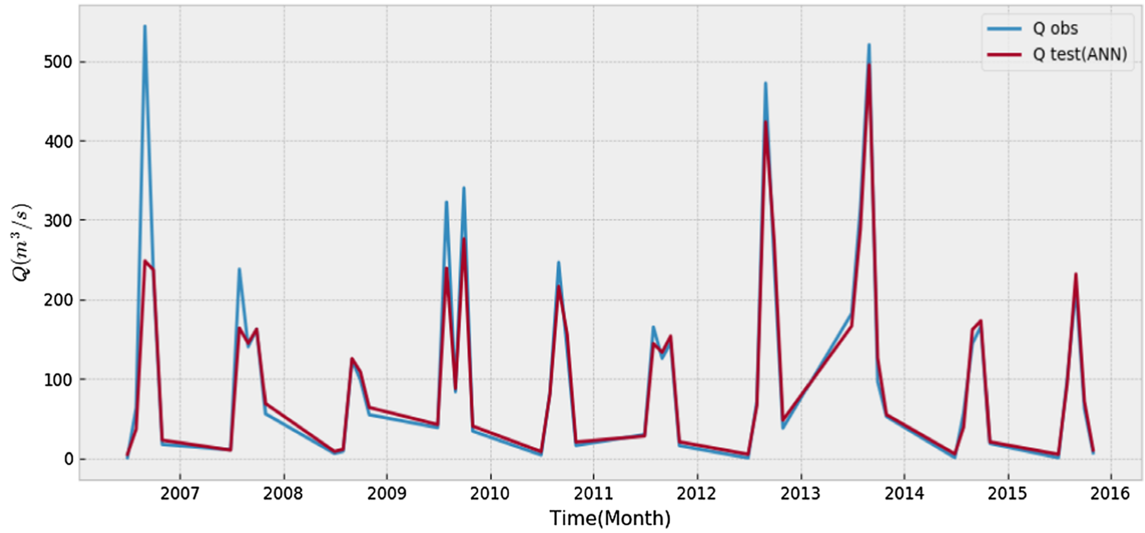


Fig. 5 Time series of monthly mean streamflow estimated by the ANN (validation results)

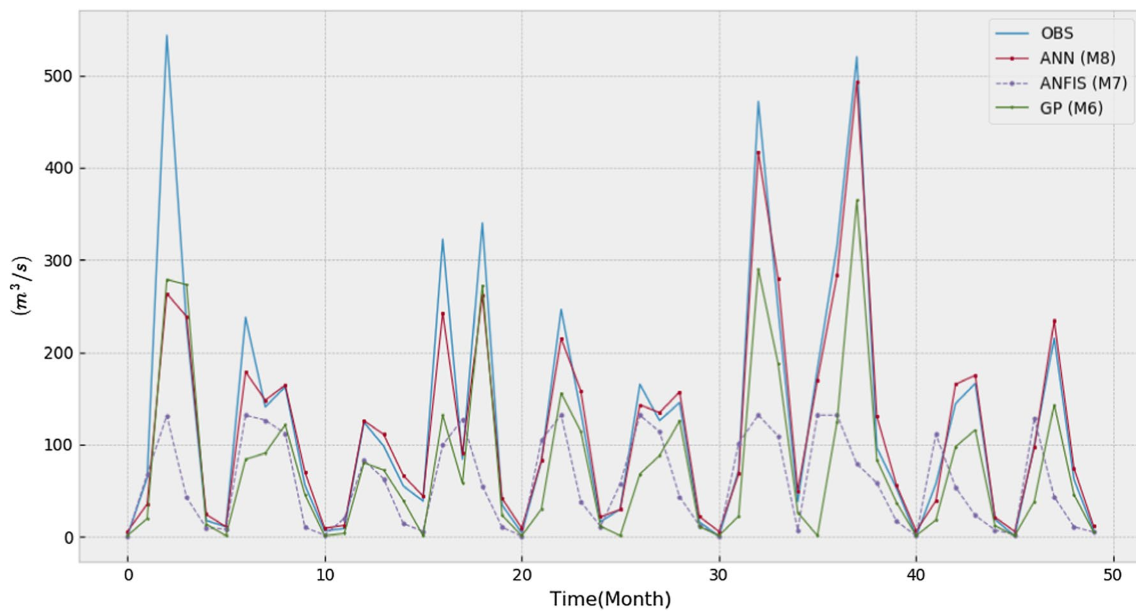


Fig. 6 Time series of monthly mean streamflow forecasted by the different AI methods (validation results)

slightly better result than multi-layer perceptron neural network (MLP-NN) model with lower RMSE and MAPE values (Adli Zakaria et al. 2021).

6 Conclusion

The present work aimed to identify the most suitable models for forecasting monthly streamflow, considering three AI methods, including ANFIS, ANN and GP. The same basis of comparison, calibration and validation datasets were applied for all the aforementioned models, and four performance statistical indices (MAE, RMSE, r and CE) were applied to evaluate the performance of the various developed AI models. Then, according to the results, ANFIS has the best performance in forecasting streamflow time series, and the GP and ANN are the next best, respectively. It should be mentioned that the results presented in Table 3 were calculated for the best pattern all every AI methods, which were selected based on the results in Table 2. Moreover, it was observed that in all considered AI methods, the models with periodic input architecture

Table 3 Performance criteria of the AI models

Models	Criteria performance	Value
ANFIS (M7)	RMSE	97.50
	MAE	58.49
	r	0.98
	CE	0.89
GP (M6)	RMSE	51.91
	MAE	32.63
	r	0.88
	CE	0.76
ANN (M8)	RMSE	252.01
	MAE	62.08
	r	0.80
	CE	0.69

had better performance compared to those models without considering the periodic nature of the underlying process under consideration. The outcomes of ANFIS model could be useful for hydrologists and environmentalists to construct truthful smart decision-support system for precise prediction of streamflow in Shakkar River. In future, other AI models can be employed to evaluate their performance in forecasting streamflow in Shakkar River. Besides, different optimization methods can be used for the optimization of AI model parameters to improve their prediction capability.

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Declarations

Conflict of interest All Authors declares that they have no conflict of interest.

Ethical Approval This article does not contain any studies with human participants or animals performed by any of the authors.

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