INTERNATIONAL JOURNAL OF OPTIMIZATION IN CIVIL ENGINEERING
Int. J. Optim. Civil Eng., 2022; 12(1):91-104

A COUPLED METAHEURISTIC ALGORITHM AND ARTIFICIAL INTELLIGENCE FOR LONG-LEAD STREAM FLOW FORECASTING

S. Anvari[1*†], E. Rashedi[2] and S. Lotfi[3]

[1]Department of Ecology, Institute of Science and High Technology and Environmental Science, Graduate University of Advanced Technology, Kerman, Iran
[2]Department of Electrical and Computer Engineering, Graduate University of Advanced Technology, Kerman, Iran
[3]Bureau of Water and Wastewater Macroplanning, Deputy of Water and Waste Water Affairs, Ministry of Energy, Iran

ABSTRACT

Reliable and accurate streamflow forecasting plays a crucial role in water resources systems (WRS) ecpicially in dams operation and watershed management. However, due to the high uncertainty associated WRS components and nonlinear nature of streamflow generations, the realistic streamflow forecasts is still one of the most challenging issue in WRS. This paper aimed to forecast one-month ahead streamflow of Karun river (Iran) by coupling an artificial neural network (ANN) with an improved binary version of gravitational search algorithm (IBGSA), named ANN- IBGSA. To this end, the best lag number for each predictor at Poleshaloo station was firstly selected by auto-correlation function (ACF). The ANN-IBGSA was used to minimize the sum of RMSE and R^2 and to identify the optimal predictors. Finally, to characterize the hydro-climatic uncertainties associated with the selected predictors, an implicit approach of Monte-Carlo simulation (MCS) was applied. The ACF plots indicated a significant correlation up to a lag of two months for the input predictors. The ANN-IBGSA identified the Tmean (t-1), Q(t-1) and Q(t) as the best predictors. Findings demonstrated that the ANN-IBGSA forecasts were considerably better than those previously carried out by researchers in 2013. The average improvement values were 9.91%, 11.85% and 9.13% for RMSE, R2 and MAE, respectively. The Monte-Carlo simulations demonstrated that all of forecasted values lie within the 95% confidence intervals.

Keywords: streamflow forecast; artificial neural network; uncertainty; gravitational search algorithm; Monte-Carlo simulation, Karun River.

Received: 20 November 2021; Accepted: 20 January 2022

---

[*] Corresponding author: Department of Ecology, Institute of Science and High Technology and Environmental Science, Graduate University of Advanced Technology, Kerman, Iran
[†]E-mail address: s.anvari@kgut.ac.ir (S. Anvari)

1. INTRODUCTION

Prior knowledge of the future streamflow has been an important issue in the management of water resources systems especially in arid and semi-arid regions like Iran. Precise streamflow forecasting is also vital for hydrologists in order to optimize the water resources system, and to mitigate the impact of destructive natural disasters such as floods and droughts. Moreover, various contributors like direct runoff, precipitation and snow mostly influence the streamflow generations. These components and the other hydro-climatic variables of water resource systems (WRS) cause the seasonal and annual variability of streamflow time series. The spatial and temporal variation of these variables, the high uncertainty associated with climate conditions, the complexity of collecting and handling both spatial and non-spatial data make the streamflow forecasting much more challenging. Therefore, hydrologists and water experts from all over the world have developed and adopted several types of data-driven techniques ranging from conventional time series modeling to modern hybrid artificial intelligence (AI) models and soft computing (SC) techniques for future prediction of streamflow (Saghafian et al., 2013; Anvari et al., 2019; Moghaddasi et al., 2022).

Conventional methods (CMs) such as auto regression (AR), AR-moving average (ARMA), AR integrated moving average (ARIMA), have been examined for several case studies and showed the accurate forecast results (Coulibaly et al., 2000; Bazartseren et al., 2003; Kisi, 2005; Aqil et al., 2007). Artificial neural networks (ANNs), adaptive neuro-fuzzy inference system (ANFIS), k-nearest neighbor (K-NN), data mining (DM) techniques, support vector machine (SVM) methods etc. are the most popular techniques in developing streamflow forecasts at different temporal scales around the world (Zealand et al., 1999; Nayak et al., 2004; Kisi, 2006; Kisi, 2009; El-Shafie and Noureldin, 2011; Noori et al. 2011; Kumar et al., 2013; Schnier and Cai, 2014; Yaseen et al., 2015; Cheng et al., 2015; Shiri et al., 2018; Kaveh, 2017 & 2019). Many successful applications of AI and SC techniques have been reported all over the world. For example, Saghafian et al. (2013) employed the ANNs, ANFIS and K-NN to study the effect of spatially distributed climatic data on the monthly flow forecasts. Results demonstrated the distributed precipitation data improved the performance of ANN and ANFIS models. Osman et al. (2016) proposed fast orthogonal search (FOS) model for streamflow forecasting at Aswan High Dam. Results showed outstanding performance of the FOS compared to other AI models. Yang et al. (2017) employed the ANN, random forest (RF), and support vector regression (SVR) to predict one month-ahead reservoir inflows for two headwater reservoirs in USA and China. Results showed all three methods had satisfactory statistics for providing monthly reservoir inflows.

Due to temporal and spatial variations of hydro-climatic factors, the meteorological and hydrological uncertainties arise in water resources systems (WRS). So, incorporating and quantifying such these uncertainties in assessing the performance of forecast modeling approaches is crucial (Bensoussan and Farhi, 2010; Anvari et al., 2017; Anvari et al., 2019). Various approaches exist for the analysis of uncertainties in WRS. Monte Carlo simulation (MCS) (Kuczeraa and Parent 1998; Vrugt et al. 2003; Anvari et al., 2014; Dehghani et al. 2014), generalized likelihood estimation (GLE) (Beven and Binlley 1992), parameter solution (Parasol) (van Griensven and Meixner 2007), and sequential uncertainty fitting (SUFI2) (Abbaspour et al. 2004, 2007) are some methods for incorporating the uncertainty. For example, Paulo and Pereira (2007) employed a Markov chain to understand the stochastic characteristics of the standardized precipitation index (SPI) in Alentejo, southern Portugal. Sonnadara and Jayewardene (2015) used a two-state, first-order Markov chain for describing wet and dry weather patterns based on daily rainfall data in Colombo Sri Lanka. Dehghani et al. (2014) applied the MCS approach to investigate the uncertainty of the Standardized Hydrological Drought Index (SHDI) and monthly streamflow discharge forecasts. Soundharajan et al. (2016) employed the MCS approach to characterize the uncertainties in climate change induced variations in storage requirements of surface water reservoirs. The MSC method provided promising results in these researches.

Review of the literature showed many studies have already been conducted on the context of the streamflow peredictins/forecats especially in arid and semi-arid regions. But, what set this study apart from prior works included (i) to employ an ANN-based optimization model, named ANN-IBGSA, for choosing the best predictors for one-month ahead forecasts of Karun river; (ii) to apply the MSC approach for characterizing the hydro-climatic uncertainties associated with the meteorological and hydrological variables in WRS of Karun river basin, (iii) to generate 100 replicates of the optimal predictors by Thomas–Fiering(TF) method and enter them to ANN models for one month ahead streamflow forecasts (iv) to draw the 95% confidence intervals of one-month ahead streamflow forecasts.

The organization of the paper is as follows: the date, methodology and the formulation of optimization model are described in the next section. Subsequently the results are presented and discussed, followed by a summary and conclusion section

2. DATE AND METHODOLOGY

2.1 Study area and data sets

The great Karun river basin is the largest basin in Iran which is situated in south west of the country and lies between 49° 30' to 52° Eastern longitude and 30° 30' to 32° Northern latitude. This large basin delivers over 20% of the country's surface flows. Karun River is the largest river in Iran which is originated from Zagros mountain ranges and passing through Khuzestan plain and finally reaches to the Persian Gulf. Several cities are situated along Karun River pass and the most important is Ahvaz, the center of Khuzestan province (Afkhami et al, 2007; Saghafian et al., 2013).

Karun River along its meandering path, in north of Gotvand and in 25 Km of north of Shushtar reaches Khuzestan plain. Karun River after joining to Dez River in the site called Bandqyr and through its Continuation path, passed Ahvaz city and passing about 190 km of its course, nearby Bahmanshir divides into two branches and eventually empties into the Persian Gulf. The studied area is a sub-basin of the great Karun basin covering an area of 24202 km^2 at Poleshaloo hydrometric station with an average elevation of 2400 masl (Fig. 1). Precipitation, minimum and average temperature as well as discharge are the data time series used in this paper. All data are in monthly scale and cover a period of 30 water years from 1974–1975 to 2002–2003 water years.

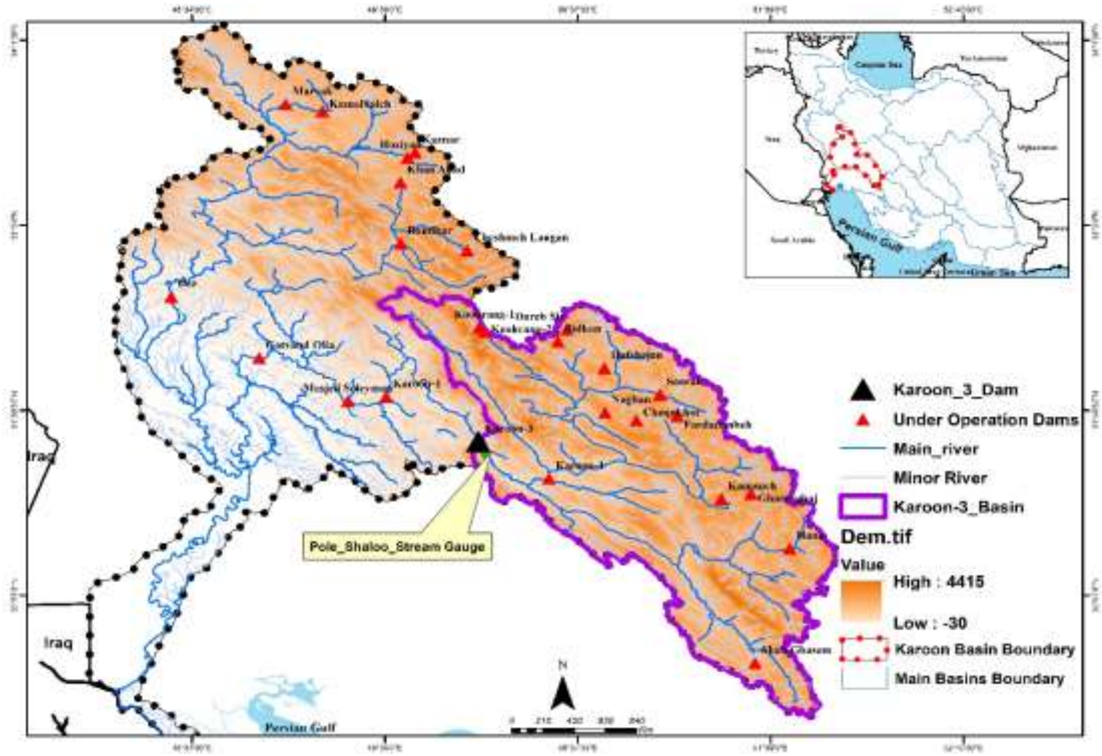


Figure 1. Location of the Great Karun basin and the study sub-basin in Iran

2.2 Artificial neural networks (ANNs)

The artificial intelligence (AI) methods including different kinds of ANN models, such as ANFIS, Radial Basis Function Neural Network (RBFNN), Multi-Layer Perceptron Neural Network (MLPNN) are more popular in the field of streamflow forecasts, reservoir operation planning and scheduling (El-Shafie and Noureldin, 2011; Schnier and Cai, 2014; Yaseen et al., 2015). ANNs are parallel processing systems which can map linear and nonlinear relations between input-output pairs in any phenomenon of interest (ASCE, 2000a,b). The ANNs are made up of a number of interconnected neurons, arranged into three basic layers (input, hidden and output). Developing a multilayer feed forward back-propagation network is a common practice in a range of hydrology and water resources projects (Zealand et al., 1999; ASCE, 2000a; Nayak et al. 2004).

In this paper, the ANNs are three-layer feed-forward networks with sigmoid function and Levenberg–Marquardt (LM) training algorithm. Optimal number of neurons in the hidden layer was determined through trial and error. In addition, to avoid network weight minimization, input and output data were rescaled in [0.1–0.9] range.

2.3 Input variables

Streamflow (Q), precipitation (P), minimum and average temperature (Tmin and Tmean) are the main variables used in this study. The lag number for these variables was determined based on the auto-correlation function (ACF) (Sudheer et al., 2002a; Kisi, 2007; Rezaeianzadeh et al. 2010; Saghafian et al., 2013). So, four primary variables at the present time as well as with two lags, total of 12 variables, were considered as possible predictors. The model output also is one-month ahead streamflow values, labelled as Q(t+1).

2.4 IBGSA based predictor selection for streamflow forecasting using ANN

The procedure for determining main input variables is one of the most important steps in the modelling process. The real and the binary versions of GSA were inspired by the Newtonian laws of gravity (Rashedi et al., 2009; Rashedi et al., 2018). There is an improved version of BGSA (IBGSA) that works well in feature selection problems (Rashedi et al., 2014). In this study, we employed the improved binary version of gravitational search algorithm (IBGSA) in joint with artificial neural networks (ANN) to identify the optimal predictors for streamflow forecasting (Fig. 2). The detail are as follows. To employ IBGSA for predictor selection goals, N objects are considered with the position X_i as:

$$X_i = (x_i^1, ..., x_i^d, ..., x_i^n) \quad , i = 1, 2, ..., \mathrm{N} \tag{1}$$

where x_i^d the binary value of is i^{th} object in the d^{th} dimension and n is the total number of predictors. Every object is a binary random vector that indicates a set of predictors. The corresponding objective function obtained by this set is evaluated and then, the mass of each object is calculated as:

$$M_i(t) = \frac{fo_i(t) - worst(t)}{\sum_{j=1}^{N} (fo_j(t) - worst(t))} \tag{2}$$

where $M_i(t)$ and $fo_i(t)$ represent the mass and the objective function value of the agent i at iteration t, and, $worst(t)$ is the worst objective function in the whole population. Total force, acceleration, and the velocity of the objects are calculated using Eqs. 3-5, accordingly.

$$F_i^d(t) = \sum_{j \in kbest, j \neq i} rand_j^d G(t) \frac{M_j(t) M_i(t)}{R_{ij}(t) + \varepsilon} (x_j^d(t) - x_i^d(t)) \tag{3}$$

$$a_i^d(t) = \frac{F_i^d(t)}{M_i(t)} = \sum_{j \in kbest, j \neq i} rand_j^d G(t) \frac{M_j(t)}{R_{ij}(t) + \varepsilon} (x_j^d(t) - x_i^d(t)) \tag{4}$$

$$v_i^d(t+1) = rand_i^d \times v_i^d(t) + a_i^d(t) \tag{5}$$

where $rand_i$ and $rand_j$ are two uniform random numbers in the interval [0,1], and ε is a small value. $kbest$ is the set of first K agents with the best fitness value. $kbest$ is a function of time, which is initialized as N at the beginning and decreased with time. $R_{ij}(t)$ is the Hamming distance between two objects i and j and it is the number of bit locations in which the two bits are different. The gravitational constant (G) is started from G_0 and reduced by time. The

IBGSA updates the velocity based on the Eq. (5). Then, the position is calculated with a probability according to Eq. (6) and objects move by the rule explained in Eq. (7), where A is a variable parameter. This procedure repeated for T number of iterations and return the best set of predictors that produce the best value of objective function.

$$Tfn(v_i^d(t)) = A + (1-A) \times \left|\tanh(v_i^d(t))\right| \tag{6}$$

$$\begin{aligned} &if \quad rand() < Tf(v_i^d(t+1)) \quad then \\ &\qquad x_i^d(t+1) = complement(x_i^d(t)) \\ &else \quad x_i^d(t+1) = x_i^d(t) \end{aligned} \tag{7}$$

For objective function calculation, the selected predictors by each agents are delivered to the ANN. ANN try to forecast the streamflow using this set of predictors and calculate the RMSE and R^2 values. Objective function is defined using these values. IBGSA try to find the best set of predictors that produce the minimum value for objective function. Fig. 2 illustrates the schematic flowchart of the proposed method. In this method, IBGSA selects the set of predictors that produces the best results in forecasting using ANN.

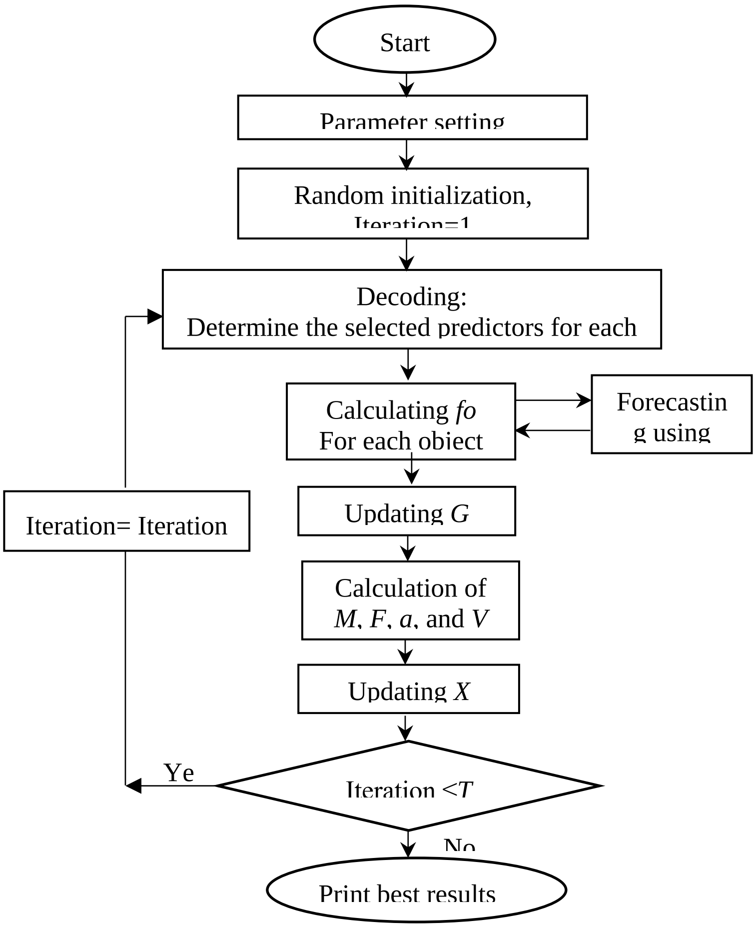


Figure 2. The flowchart of the proposed IBGSA+ANN for Streamflow forecasting

2.5 Stochastic Data Generation and Uncertainty Analysis

To incorporate the meteorological and hydrological uncertainties associated with streamflow forecasts, we employed the MCS to generate several realizations of the best predictors (Adeloye, 2012; Kroese, 2014; Rubinstein & Kroese; 2016). The underlying concept of MCS is based on randomly repeated samplings or synthetically generated sets of an uncertain variable. These random sets are mimicking the statistical distribution of actual data/measurements which are identified by experts and some of the experiences (Talebizadeh et al., 2010; Dehghani et al., 2014). To incorporate the uncertainty associated with the best predictor variables in our case study, the 100 such replicates of these predictors were generated using the Thomas–Fiering (TF) monthly model (1962). The TF method is commonly used and considered as the stochastic approach that is typical for forecasting in hydrology (McMahon and Adeloye, 2005; Cui et al., 2016; Soundharajan et al., 2016). The basis of generating data based on TF is the calculation of the average value, standard deviation, correlation coefficient, regression coefficient, variance coefficient. The common equations of TF Method are:

$$\boldsymbol{x_{i+1}} = \boldsymbol{\bar{x}_{j+1}} + \boldsymbol{b_j(x_i - \bar{x}_j)} + \boldsymbol{t_i S_{j+1}(1 - r_j^2)^{1/2}} \tag{8}$$

where $\boldsymbol{x_{i+1}}$ is discharge on month (i+1); $\boldsymbol{\bar{x}_{j+1}}$ is average of discharge on month (j+1); b_j is regression coefficient for prediction of discharge on month (j + 1) based discharge on month j or regression coefficient between flowrate at month j + 1 with month j; x_i is discharge during the month of synthetic data generation begins; $\bar{x}_j$ is average discharge month j; t_i is the number i of random number in a data series with zero mean and one standard deviation and follows a normal distribution; S_{j+1} is standard discharge deviation for month (j+1); r_j is correlation coefficient between discharge on month j and discharge on month (j+1); j is 1, 2, 3, ..., 12 (January until December) and i is j, 12 month + j, ..., month n + j. Having generated the 100-replicates of the optimal predictors as the training patters, the ANN model was frequently executed. The 95% confidence intervals were finally determined by finding the 2.5th and 97.5th percentiles of the constructed distribution.

3. RESULTS AND DISCUSSION

In this section, an autocorrelation analysis (ACF) of the Q, P, Tmin and Tmean was carried out to discover the most accurate lag numbers for each individual predictor. The ACF plots for the time series of Q, P, Tmin and Tmean showed a significant correlation at the 95% confidence level interval up to two months for these predictors (Table 1).

Table 1. List of potential predictors.

Potential Predictors	Index
Average temperature in month t, t-1 and t-2	Tmean(t),Tmean(t−1),
Minimum temperature in month t, t-1 and t-	Tmin(t), Tmin(t−1), Tmin(t−2)
Precipitation in month t, t-1 and t-2	P(t), P(t−1), P(t−2)
Streamflow in month t, t-1 and t-2	Q(t), Q(t−1), Q(t−2)

Resultantly, four primary variables at the present time with two lags, total of 12 variables (Table 1), were considered as possible predictors or input variables, whereas the inflow values of the subsequent month i.e. Q(t + 1) was the target (dependent) variable for the ANN model.

3.1 Optimal predictor selection using IBGSA

To discover the best set of predictors, that are the input values of ANN, the IBGSA was executed frequently. By defining the proper objective function, IBGSA tries to minimize the sum of RMSE and R^2. To achieve this goal, Eq. 9 is proposed as the IBGSA objective function. In this Eq. RMSE is divided by the maximum value of $RMSEmax$ to normalize RMSE values. Minimizing this function leads to minimizing RMSE and maximizing R^2.

$$f_{obj} = 0.5 \times \frac{RMSE}{RMSEmax} + 0.5 \times \frac{1}{R^2} \tag{9}$$

In the implementation of IBGSA, the total number of iterations (T) is 200, number of objects (N) is 50, number of whole number of predictors (n) is 12 and G0 is 1. IBGSA tries to find the best set of predictors for minimizing the proposed objective function. With respect to this function, a combination of [Tmean(t-1), Q(t-1) and Q(t)] was selected by IBGSA as the optimal predictors leading the most accurate one month ahead forecasts of streamflow.

3.2 ANN forecasts

Having determined the optimal predictors, the ANN model found the relationship between the predictor variables i.e. [Tmean(t-1), Q(t-1) and Q(t)] and the dependent variable, Q(t +1). The three-layer feed-forward networks with sigmoid function and LM training algorithm were also chosen.

The number of neurons in the hidden layer was identified between two and six, by trial and error. Approximately 70 % of the data, (250 monthly values), were used for training the ANN, with 30 % of the data were employed for testing. Fig. 3 illustrates the forecasted and observed streamflow of Karun river that was resulted from the ANN-BGSA model.

The Criteria such as the coefficient of determination (R^2), root mean square error (RMSE), and mean absolute error (MAE) were also used for choosing the best ANN forecast (ASCE, 2000b; Saghafian et al., 2013; Anvari et al., 2014; Dehghani et al., 2014). The R^2 values for observed and forecasted time series of Q(t+1) in both phases of the train and test are equaling 0.81 and 0.82, respectively. The pairs of RMSE and MAE values are (123, 79) and (121, 77) in the train and test phases, respectively. The ANN-BGSA has a better performance in forecasting the high values of seamflow discharges.

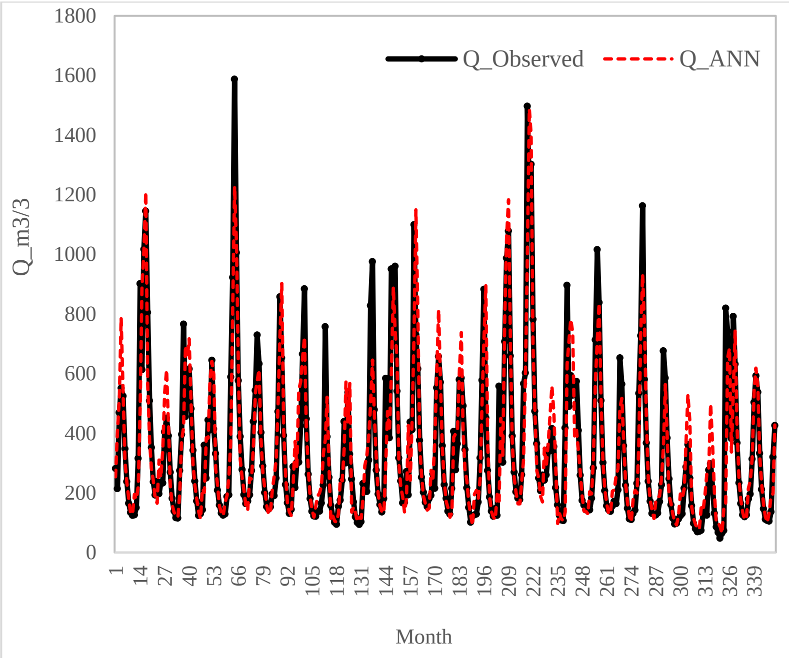


Figure 3. Forecasted and observed streamflow for Karun river using the ANN-BGSA model

To investigate the efficiency of IBGSA optimization algorithm (ANN-IBGSA) in predictor selection procedure and its impact on one-month ahead streamflow forecast, we compared ANN-IBGSA forecasts with those have been carried out by Saghafian et al., 2013. For one-month ahead forecast of Karun river, Saghafian et al. (2013) employed three input selection approaches, coded by NN-1-VARPCA, NN-1-CC and NN-1-TV. As they have mentioned the "NN-1-VarPCA" represents the ANN model for one-month ahead forecast where the main predictors were selected by the principal component analysis (PCA) method. In the NN-1-CC the main predictors were selected by the linear cross-correlation (CC) while in the NN-1-TV, all 12 variables were used. Table 2 summarizes the details about one-month ahead forecasts of Q(t+1) including the models architecture, and evaluation indices of RMSE, R^2, and MAE.

Table 2: Results of ANN models during the test phase based on different input selection scenarios

ANN Input Models	ANN architecture	Test phase		
		RMSE (m^3/s)	R^2	MAE (m^3/s)
NN-1-VARPCA	5-4-1	139.8	0.72	87.13
Degree of improvement (%)		13.43%	-13.89%	11.63%
NN-1-CC	6-3-1	140.04	0.73	88.11
Degree of improvement (%)		13.57%	-12.33%	12.61%
NN-1-TV	12-4-1	124.44	0.75	79.5
Degree of improvement (%)		2.74 %	-9.33%	3.15%
NN- IBGSA	3-3-1	121.03	0.82	77
Average improvement (%)		9.91%	11.85%	9.13%

As shown in above Table, with respect to both ANN architecture and evaluation indices, the NN-IBGSA had superior performance and was known as the selected model. The relative superiority of this model in comparison with the NN-1-VARPCA, NN-1-CC and NN-1-TV, has been also calculated through the degree of improvement (%) index. Table 1 overally indicates that employing the IBGSA model for choosing the optimal input predictors, could improve the performance of the whole models. The average improvement values are 9.91%, 11.85% and 9.13% in RMSE, R2 and MAE, respectively.

Fig. 4 also illustrates the forecasted and observed streamflow obtained from the NN-1-TV model. As shown in this figure, the performance of NN-1-TV model for forecasting high streamflows is weaker than average and low flows. Comparisons between ANN-BGSA and NN-1-TV models in this study proved that ANN-BGSA outperformed the NN-1-TV, especially in forecastin high streamflow values.

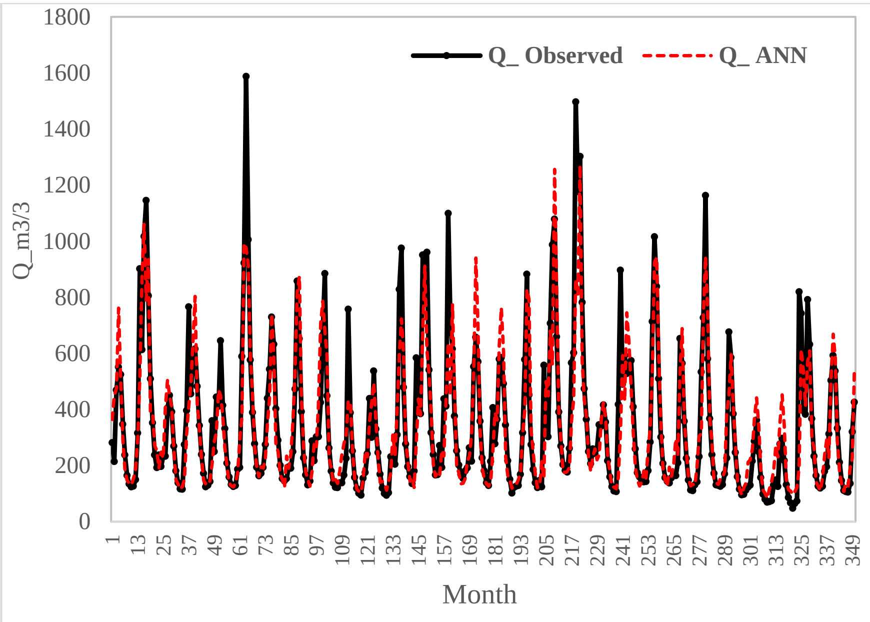
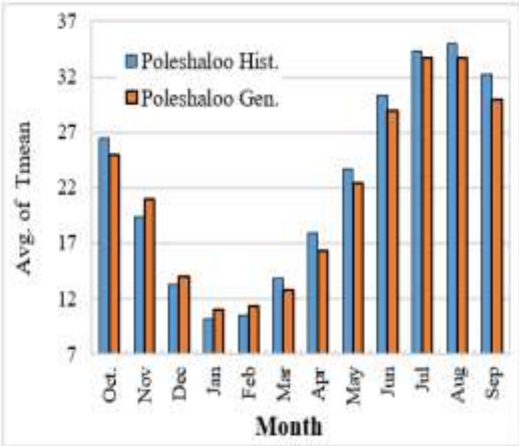


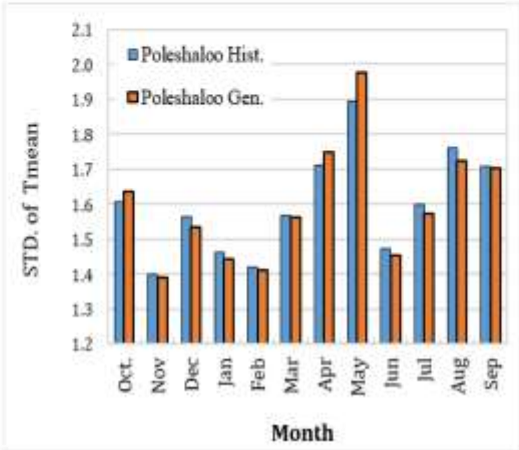
Figure 4. Forecasted and observed streamflow for Karun river using the NN-1-TV model

3.3 Uncertainty analysis using MCS

To generate the 30-year samples of uncertain predictors i.e. Q and Tmean, their historical data were tested to meet the normal statistical distribution requirements and then the 100 different samples of Q and Tmean were generated by TF method. Among all distribution functions, the Normal and Log-normal showed the best fit to the Q and Tmean, respectively.

As seen in Fig. 5, the generated data has similar parameter characteristics as historical data, consisting of average and standard deviation values, so it can be concluded that historical and generated data have close statistical parameters, so the resulting data is considered accurate and can be used for calculation of reliable dependable flow analysis.

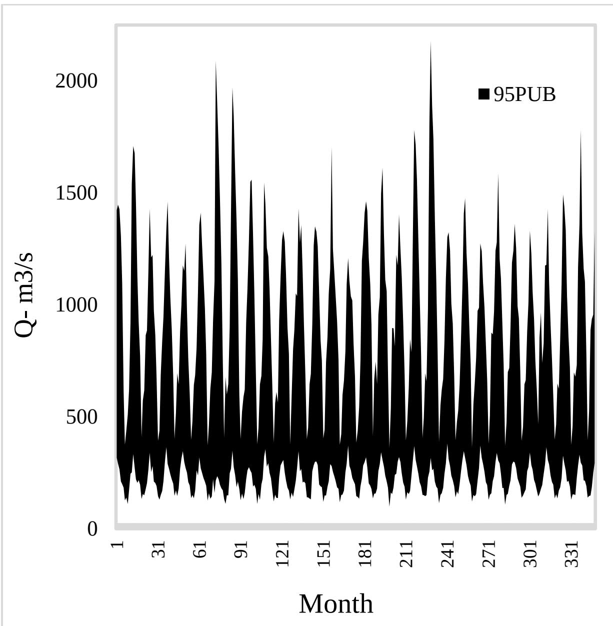


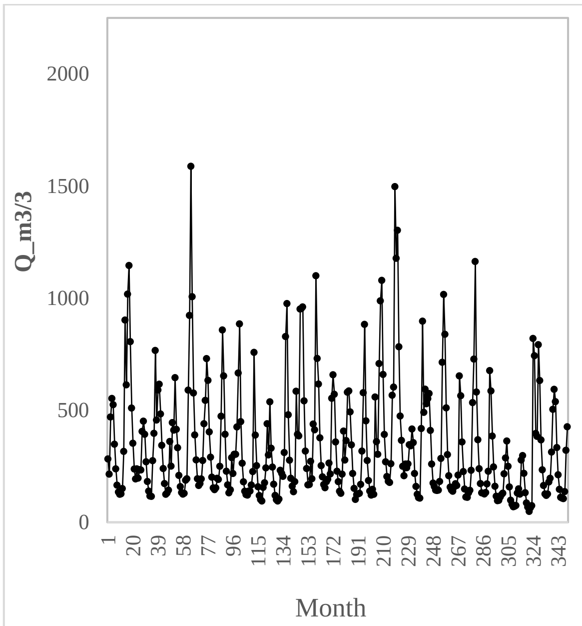


(a) (b)

Figure 5. Comparison between Historical and Generated data of Tmean at Poleshaloo station: (a) Average, (b) Standard Deviation

To develop the 95% prediction uncertainty band (95PUB), the 100 replicates of generated predictors were inputted to ANN and the 2.5 and 97.5 percentile of empirical cumulative distribution of Q(t+1) were subsequently selected as the lower and upper limits of prediction uncertainty band, respectively (Fig. 7.). As illustrated in Fig. 6, the 95% confidence interval of Q(t+1) time series forecasts was determined due to the fact that this confidence interval provides more information than other statistics about the range of uncertainty associated with the forecasts. The wider the interval, the smaller is the accuracy of the forecast and vice versa.





(a) (b)

Figure 6. The 95PPU (a) and observed monthly flow (b) at the Poleshaloo station

4. SUMMARY AND CONCLUSION

Hydrological time-series prediction/forecasting is one of the most important issues in water resource systems (WRS) which makes the water experts able to scientifically manage them. Besides ordinary predictor selection methods, in this study the potential influence of optimization-based approach on the ANN models' performance to forecast one month ahead of Karun was investigated. The ANN was firstly coupled with the IBGSA (ANN- IBGSA) to identify the best predictors for one-month ahead forecasts. In this regard, the best lag number for streamflow, precipitation, minimum and average temperature time series at Poleshaloo station was determined by auto-correlation function (ACF). The ANN-IBGSA was adapted to minimize the sum of RMSE and R^2 and to identify the optimal predictors. Moreover, the MSC approach was used to investigate the meteorological and hydrological uncertainties associated with hydro-climatic inputs of Karun river basin and to draw the 95% confidence intervals of these forecasts.. In this regard, the 100 replicates of the optimal predictors were generated by TF method and the resulted training patterns were inputted to ANN models to forecast the one month ahead streamflow. The findings of this study indicate:

- The ACF plots indicated a significant correlation up to a lag of two months for total predictors.
- The ANN-IBGSA identified the Tmean (t-1), Q(t-1) and Q(t) to be the best predictors for streamflow forecasts.
- The ANN-IBGSA had a better performance in forecasting high values of streamflow. The ANN-IBGSA were also outperformed the models which were previously employed by researchers in our case study. The average improvement values were 9.91%, 11.85% and 9.13% for RMSE, R^2 and MAE, respectively.
- The Monte-Carlo simulations demonstrated that all of forecasted values lie within the 95% confidence intervals.

REFERENCES

1. Afkhami M, Shariat M, Jaafarzadeh N, Ghadiri H, Nabizadeh R. Developing a water quality management model for Karun and Dez Rivers, *J Environment Health Sci Eng* 2007; **4**(2): 99-106.
2. Anvari S, Mousavi SJ, Morid S. Stochastic dynamic programming-based approach for optimal irrigation scheduling under restricted water availability conditions, *Irrig Drain* 2017; **66(4)**: 492-500.
3. Anvari S, Kim JH, Moghaddasi M. The role of meteorological and hydrological uncertainties in the performance of optimal water allocation approaches, *Irrig Drain* 2019; **68(2)**: 342-53.
4. Anvari S, Mousavi SJ, Morid S. Sampling/stochastic dynamic programming for optimal operation of multi-purpose reservoirs using artificial neural network-based ensemble streamflow predictions, *J Hydroinform* 2014; **16(4)**: 907-21.
5. Anvari S, Mousavi SJ, Morid S. Comparison of Dynamic, linear and Nonlinear Programming Approaches in Optimal Operation of Reservoir (Case study: the 1998-2000 Droughts of Zayandeh Rud Agriculthral System), *Iranian Journal of Irrigation & Drainage* 2014; **8(4)**: 713-725.

6. Aqil M, Kita I, Yano A, Nishiyama S. A comparative study of artificial neural networks and neuro-fuzzy in continuous modeling of the daily and hourly behavior of runoff, *J Hydrol* 2007; **337(1-2)**: 22-34.
7. ASCE Task Committee on Application of Artificial Neural Networks in Hydrology. Artificial neural networks in hydrology. I: Preliminary concepts, *J Hydrol Eng* 2000; **5(2):** 115-23.
8. Bazartseren B, Hildebrandt G, Holz KP. Short-term water level prediction using neural networks and neuro-fuzzy approach, *Neurocomput* 2003; **55(3-4)**: 439-50.
9. Bensoussan A, Farhi N. Uncertainties and risks in water resources management. The economics of sustainable development, (Chapter: Uncertainties and risks in water resources management), Publisher: *Econom* 2010: 163-79.
10. Cheng CT, Feng ZK, Niu WJ, Liao SL. Heuristic methods for reservoir monthly inflow forecasting: A case study of Xinfengjiang Reservoir in Pearl River, China, *Water* 2015; **7(8)**: 4477-95.
11. Coulibaly P, Anctil F, Bobée B. Daily reservoir inflow forecasting using artificial neural networks with stopped training approach, *J Hydrol* 2000; **230(3-4)**: 244-57.
12. Cui Q, Wang X, Li C, Cai Y, Liang P. Improved Thomas–Fiering and wavelet neural network models for cumulative errors reduction in reservoir inflow forecast, *J Hydro-Environ Res* 2016; **13**: 134-43.
13. Dehghani M, Saghafian B, Nasiri Saleh F, Farokhnia A, Noori R. Uncertainty analysis of streamflow drought forecast using artificial neural networks and Monte-Carlo simulation, *Int J Climatol* 2014; **34(4):** 1169-80.
14. El-Shafie A, Noureldin A. Generalized versus non-generalized neural network model for multi-lead inflow forecasting at Aswan High Dam, *Hydrol Earth Syst Sci* 2011; **15(3)**: 841-58.
15. Kaveh A. *Applications of Metaheuristic Optimization Algorithms in Civil Engineering*, Springer, 1st edition, Cham, Switzerland, 2017.
16. Kaveh A, Bakhshpoori T. *Metaheuristics: Outlines, MATLAB Codes and Examples*, Springer, 2019.
17. Kişi Ö. Streamflow forecasting using different artificial neural network algorithms, *J Hydrol Eng* 2007; **12(5)**: 532-9.
18. Kişi Ö. Daily river flow forecasting using artificial neural networks and auto-regressive models, *Turkish J Eng Environ Sci* 2005; **29(1)**: 9-20.
19. Kişi Ö. Daily pan evaporation modelling using a neuro-fuzzy computing technique, *J Hydrol* 2006; **329(3-4)**: 636-46.
20. Kişi Ö. Neural networks and wavelet conjunction model for intermittent streamflow forecasting, *J Hydrol Eng* 2009; **14(8)**: 773-82.
21. Kumar ARS, Goyal MK, Ojha CSP, Singh RD, Swamee PK. Application of artificial neural network, fuzzy logic and decision tree algorithms for modelling of streamflow at Kasol in India, *Water Sci Technol* 2013; **68(12)**: 2521-6.
22. Goyal MK, Ojha CS, Singh RD, Swamee PK. Application of artificial neural network, fuzzy logic and decision tree algorithms for modelling of streamflow at Kasol in India, *Water Sci Technol* 2013; **68(12)**: 2521-6.
23. McMahon TA, Adeloye AJ. *Water Resources Yield*, Water Resources Publication; USA, 2005.

24. Moghaddasi, M, Anvari, S. Akhondi, N. A Trade-Off Analysis of Adaptive and Non-Adaptive Future Optimized Rule Curves Based on Simulation Algorithm. *Theor Appl Climatol* 2022. DOI: 10.1007/s00704-022-03930-y.
25. Nayak PC, Sudheer KP, Rangan DM, Ramasastri KS. A neuro-fuzzy computing technique for modeling hydrological time series, *J Hydrol* 2004; **291**: 52–66.
26. Noori R, Karbassi AR, Moghaddamnia A, Han D, Zokaei-Ashtiani MH, Farokhnia A, Gousheh MG. Assessment of input variables determination on the SVM model performance using PCA, Gamma test, and forward selection techniques for monthly stream flow prediction, *J Hydrol* 2011; **401**(3-4): 177-89.
27. Osman A, Allawi MF, Afan HA, Noureldin A, El-shafie A. Acclimatizing fast orthogonal search (FOS) model for river stream-flow forecasting, *HESSD* 2016: 1-28.
28. Rashedi E, Nezamabadi-Pour H. Feature subset selection using improved binary gravitational search algorithm, *J Intell Fuzzy Syst* 2014; **26**(3): 1211-1121.
29. Rashedi E, Nezamabadi-Pour H, Saryazdi S. GSA: a gravitational search algorithm, *Inform Sci* 2009; **179**(13): 2232-48.
30. Rashedi E, Nezamabadi-Pour H, Saryazdi S. BGSA: binary gravitational search algorithm, *Nat Comput* 2010; **9**(3): 727-45.
31. Rashedi E, Rashedi E, Nezamabadi-pour H. A comprehensive survey on gravitational search algorithm, *Swarm Evol Comput* 2018; **41**: 141-58.
32. Rezaeianzadeh MR, Amin S, Khalili D, Singh VP. Daily outflow prediction by multi layer perceptron with logistic sigmoid and tangent sigmoid activation functions, *Water Resour Manag* 2010; **24**(11): 2673-88.
33. Saghafian B, Anvari S, Morid S. Effect of Southern Oscillation Index and spatially distributed climate data on improving the accuracy of Artificial Neural Network, Adaptive Neuro-Fuzzy Inference System and K-Nearest Neighbour streamflow forecasting models, *Expert Syst* 2013; **30**(4): 367-80.
34. Schnier S, Cai X. Prediction of regional streamflow frequency using model tree ensembles, *J Hydrol* 2014; **517**: 298-309.
35. Shiri J. Improving the performance of the mass transfer-based reference evapotranspiration estimation approaches through a coupled wavelet-random forest methodology, *J Hydrol* 2018; **561**: 737-50.
36. Soundharajan BS, Adeloye AJ, Remesan R. Evaluating the variability in surface water reservoir planning characteristics during climate change impacts assessment, *J Hydrol* 2016; **538**: 625-39.
37. Talebizadeh M, Morid S, Ayyoubzadeh SA, Ghasemzadeh M. Uncertainty analysis in sediment load modeling using ANN and SWAT model, *Water Resour Manag* 2010; **24(9)**: 1747-61.
38. Yang T, Asanjan AA, Welles E, Gao X, Sorooshian S, Liu X. Developing reservoir monthly inflow forecasts using artificial intelligence and climate phenomenon information, *Water Resour Res* 2017; **53**(4): 2786-2812.
39. Yaseen ZM, El-Shafie A, Jaafar O, Afan HA, Sayl KN. Artificial intelligence based models for stream-flow forecasting: 2000–2015, *J Hydrol* 2015; **530**: 829-44.
40. Zealand CM, Burn DH, Simonovic SP. Short term streamflow forecasting using artificial neural networks, *J Hydrol* 1999; **214**(1-4): 32-48.