

Long-term Streamflow Forecasting by Adaptive Neuro-Fuzzy Inference System Using K-fold Cross-validation: (Case Study: Taleghan Basin, Iran)

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ABSTRACT

Streamflow forecasting has an important role in water resource management (e.g. flood control, drought management, reservoir design, etc.). In this paper, the application of Adaptive Neuro Fuzzy Inference System (ANFIS) is used for long-term streamflow forecasting (monthly, seasonal) and moreover, cross-validation method (K-fold) is investigated to evaluate test-training data in the model. Then, the results are compared with those of the typical validation method (i.e., using 75% of data for training and the remaining 25% for testing the validity of the trained model). Study area is Taleghan basin located in northwestern Tehran basin, Iran. The data used in this research consists of 19 years of monthly streamflow, precipitation and temperature records. To apply temperature and precipitation data in the model, the whole basin was divided into sub-basins and average values of each parameter for each sub-basin were allocated as model input. Finally, results were compared with those of the ANN model. It was found that the K-fold validation method leads to better performance than the typical method in terms of statistical indices. In addition, the results indicated the superiority of ANFIS model over ANN model in long-term forecasting.

Keywords

Streamflow forecasting, Adaptive Neuro Fuzzy Inference System (ANFIS), K-fold, Sub-basin, Artificial neural network (ANN)

1. Introduction

Streamflow forecasting is an effective and important issue in water resource management (e.g. flood control, drought management, reservoir design, etc.). Streamflow forecasting can be approached in many ways by considering different time steps and methods (conceptual, physical, and black box).

Regression based methods are among the earliest and most widely used procedures in

river flow forecasting. Maidment et al. (1985) used short-term time series for forecasting daily water demands in the United States. Phien et al. (1990) used a regression model for predicting daily streamflow in the Mekong basin with satisfying results. In another study, Dariane et al. (2004) predicted long-term streamflow in Dez River located in southwestern Iran using satellite images along with regression methods. Artificial neural networks have

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succeeded in replacing regression methods in most applications where the relationships among the variables are non-linear and complex. Therefore, in recent decades, artificial neural networks have been successfully used in water resource management. Many of those studies report that the ANNs may offer a promising alternative especially where the relationships among the variables are non-linear and complex (e.g., Minns and Hall, 1996; Sajikumar and Thandaveswara, 1999; Prada and Neira, 2009; Adamowski and Karapataki, 2010).

Kisi (2004) used neural networks and autoregressive methods (AR) for monthly streamflow prediction at Goksudere River in Turkey and concluded that the ANN approach has a better performance than the AR method. Nowadays, neuro-fuzzy system which has advantages of ANN method and fuzzy logic simultaneously has been applied in streamflow forecasting. Nayak et al. (2004) evaluated the potential use of Adaptive Neuro Fuzzy Inference System (ANFIS) in forecasting river flow at Baitarani River, India. They observed that the ANFIS model presented the ability of ANN fully and had good performance in terms of various statistical indices. Other studies show the superiority of ANFIS over ANN in modeling using soft computing methods (e.g., Kurtulus and Razack, 2010; Kisi, 2005; Chang and Chang, 2006).

Beside the above mentioned black box modelling approaches (i.e., regression method, ANN, and ANFIS), a great range of Physical and conceptual methods have been also used in developing river flow forecasting. In general, the results indicate

the superiority of black box methods particularly at peak flows.

Demirel et al. (2009) assessed the results of the ANN and Soil and Water Assessment Tool (SWAT) models in Pracana basin located in Portugal and showed that the ANN model estimates peak flows more accurately than the SWAT model. Also, Talei et al. (2010) in a similar study used neuro-fuzzy and Storm Water Management Model (SWMM) to forecast streamflow in Kranji basin in Singapore. They concluded that ANFIS performs better than SWMM at peak flows.

Also, in recent decades, review of literature indicates that combination of some of these methods have been used to develop river flow forecasting models (Pulido and Portela, 2007; Kuo et al., 2006).

Finding subsets of data which completely cover data trends is necessary in increasing the performance of models that are based on training and test periods (e.g., ANFIS, ANN).

Burman (1989) compared the repeated learning-testing method with K-fold cross-validation and noticed that the combination of K-fold and repeated learning-testing method enhances the accuracy of results. Kohavi (1995) compared different cross-validation methods for accurate parameter estimation and data selection. His results showed that ten-fold cross-validation has the best performance. Bagherinia and Dariane (2010) in investigation and comparison of the regression based runoff forecasting models using satellite data illustrated the application of a jackknife cross-validation method. They indicated that use of this method would result in an

increase in the reliability of the prediction models.

In this study, ANFIS using K-fold cross-validation is applied for long-term streamflow forecasting with monthly and seasonal time steps in Taleghan Basin, northwest of Tehran. In many studies, the in-situ discharge measurement is applied in streamflow forecasting (e.g., Shiri and Kisi, 2010) whereas in this study in order to improve model performance, the other parameters (rainfall and temperature) are utilized as well as discharge parameter in forecasting model. Also, in many studies where the ANNs and other black-box models are used, mainly the point station data (such as rainfall and temperature) have been used as inputs for the model. In this study, it is shown that the use of basin data could enhance the results obtained by the model.

2. Methods

2.1. Artificial Neural Networks (ANNs)

Artificial neural networks (ANNs) are resembled to the biological nervous system. ANNs are composed of processing elements in each layer called neurons which are connected to neurons in the adjacent layer by modifiable weights. A simple ANN could consist of input and output layers with known number of neurons, and one or two hidden layers with variable number of neurons. The model is trained by adjusting the weights in an attempt to minimize the sum of squared errors between the model output and observed data.

The back-propagation algorithm is the main method for training the model. It consists of two steps. In the first step, the

input signal (discharge, rainfall, temperature, etc.) is propagated forward to compute the output (discharge). Then, a backward step is used to adjust the weight vectors between layers with an objective to minimize the network error (Hagan et al., 1996). In this study, a multiple-layer feed-forward neural network that comprises of an input layer, an output layer and one intermediate (hidden) layer is used.

2.2. Adaptive Neuro-Fuzzy Inference System (ANFIS)

Neuro-fuzzy systems are fuzzy systems, which use ANNs to determine their characteristics (fuzzy sets and fuzzy rules) by processing data samples. Neuro-fuzzy systems cover the properties of both ANNs (training data, no prior knowledge) and fuzzy systems (linguistic description, human thinking) in a complementary way to overcome their disadvantages.

Novel architecture of ANFIS first introduced by Jang (1993) and has been used massively in studies because of its good performance in nonlinear relationships.

Generally, the ANFIS model architecture consists of five layers which are illustrated in Fig.1. Selection of the FIS based on specific target system is important.

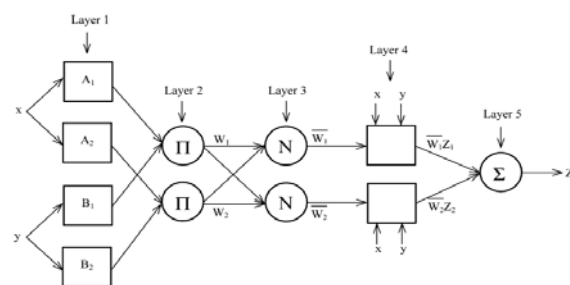


Fig. 1. General architecture of an ANFIS network (Jang, 1993)

Different types of FIS are presented in the studies (Sugeno and Kang, 1988; Mamdani and Assilian, 1975; Tsukamoto, 1979). The current study uses the Sugeno first-order fuzzy model (Sugeno and Kang, 1988) because the consequent part of the FIS model (p_i, q_i, r_i) is a linear equation and the parameters can be calculated by simple Least Square Error (LSE) method.

For instance, consider that the FIS has two inputs (x, y); a common rule set with two fuzzy if-then rules can be expressed as:

Rule 1: if x is A_1 and y is B_1 then

$$z_1 = p_1x + q_1y + r_1 \quad (1)$$

Rule 2: if x is A_2 and y is B_2 then

$$z_2 = p_2x + q_2y + r_2 \quad (2)$$

The output z is the weighted average of the individual rule outputs. Nodes at the same layer have similar functions.

Layer 1: The output of the i th node is defined as O_i^1

$$O_i^1 = \mu_{A_i}(x) \quad \text{for } i = 1, 2 \quad (3)$$

Or

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

Where x (or y) is the input to the i th node and A_i (or B_{i-2}) is the linguistic label associated with this node function. O_i^1 is the membership function of A_i (or B_{i-2}). The membership function for A and B are usually described by bell-shaped with a maximum equal to 1 and minimum equal to 0 such as:

$$\mu_{A_i}(x) = \exp \left\{ - \left(\frac{x - c_i}{a_i} \right)^2 \right\} \quad (5)$$

Where $\{a_i, c_i\}$ is the parameter set. As the values of the parameters change, the bell-shaped functions vary accordingly.

Layer 2: every node in this layer is a fixed node labeled Π and multiplies the incoming signals. Each output node represents the firing strength of a rule. For instance,

$$O_i^2 = \omega_i = \mu_{A_i}(x) \cdot \mu_{B_i}(y), i = 1, 2 \quad (6)$$

Layer 3: each node in this layer is a fixed node and the i th node in this layer calculates the ratio of the i th rule's firing strength to the sum of all rules' firing strength:

$$O_i^3 = \bar{\omega}_i = \frac{\omega_i}{\omega_1 + \omega_2}, i = 1, 2 \quad (7)$$

Layer 4: node i th in this layer is an adaptive node with a node function

$$O_i^4 = \bar{\omega}_i f_i = \bar{\omega}_i (p_i x + q_i y + r_i), i = 1, 2 \quad (8)$$

Where $\bar{\omega}_i$ is the output of layer 3, and $\{p_i, q_i, r_i\}$ is the parameters' set which are referred to as consequent parameters.

Layer 5: the single node in this layer is a fixed node labeled Σ that calculates the final output as the summation of all incoming signals (Jang, 1993).

$$O_i^5 = \sum_{i=1}^2 \bar{\omega}_i f_i = \frac{\omega_1 f_1 + \omega_2 f_2}{\omega_1 + \omega_2} \quad (9)$$

The overall output can be expressed as a linear combination of the consequent parameters:

$$z = \frac{\omega_1}{\omega_1 + \omega_2} f_1 + \frac{\omega_2}{\omega_1 + \omega_2} f_2 = (\bar{\omega}_1 x) p_1 + (\bar{\omega}_1 y) q_1 + (\bar{\omega}_1) r_1 + (\bar{\omega}_2 x) p_2 + (\bar{\omega}_2 y) q_2 + (\bar{\omega}_2) r_2 \quad (10)$$

The learning rule determines how the premise parameters (Layer 1) and consequent parameters (Layer 4) should be updated in order to minimize error which is calculated by the differences between the

network actual output and the desired output. Hybrid learning algorithm, that combines the back propagation gradient descent and least square method, is used as the basic learning rule and searching optimal parameters of the ANFIS.

2.3. K-fold

Where the parameters consist of high ranges, using subsets of data which completely cover data trends is more felt to increase performance of the models. Nowadays, many cross validation methods are utilized in order to overcome this problem, which K-fold cross validation is one of them. Due to dynamic nature of K-fold method, this method is able to cover all data trends in both training and test samples. K-fold is a computer intensive technique, using all available data as training and test samples. It mimics the use of training and test sets by repeating the algorithm K times with a fraction 1/K of training samples left out for testing purposes. Each time, all partitions are used for both training and test samples. Test and training samples are implemented independently (Fig. 2).

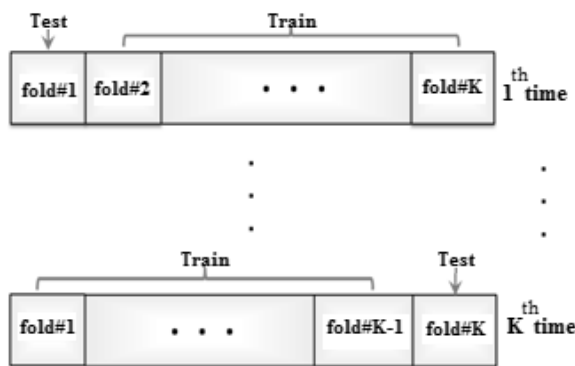


Fig. 2. Schematic view of K-fold cross-validation method

Each model was implemented by K value ranges between 4 and 7 folds (ranges 10-25% sample for each fold). The best K values are identified with the best performance based on statistical evaluation indices.

3. Case study

The Taleghan Basin with a Mediterranean climate is located in northwestern Tehran region (including Taleghan, Karaj, Latiyan, Mamloo, Firouzkooh sub-basins), Iran. Total area of the Taleghan Basin is 960 km². Maximum, average and minimum heights of this basin are located 4337, 2500, and 1675 meters above the sea level, respectively. The basin has a east-west slope and extends from the spatial domain of 36° 05' to 36° 17' N latitude and from 50° 35' to 51° 10' E longitude (Fig. 3). The minimum and maximum temperatures in the basin, according to 50 years records, are -25°C and 35°C, respectively, and the range of average annual precipitation in the Taleghan Basin is 500-600mm (Department of Energy, 2009).

4. Application

4.1. Data

Digital Elevation Model (DEM) operated on Shuttle Radar Topography Mission (SRTM) with spatial resolution of 90 m was used in this study (Fig. 3). In order to extend the number of data, the basin was divided into three sub-basins (which are named A, B and C). River flow at the outlet of the last sub-basin is the inflow to Taleghan reservoir. In addition, in a wide study performed in Tehran region (sub-basins: Taleghan, Karaj, Latiyan, Mamloo and Firouzkooh) the monthly precipitation

(47 stations) and monthly average temperature (13 stations) as shown in Fig. 4 were collected for establishing the regional relations. Moreover, a common period of 19 years starting from 1990-91 through 2007-2008 was used in this study.

4.2. Statistical evaluation

Two statistical evaluation criteria were used to assess the model performance. The first criterion is the Nash-Sutcliffe model efficiency coefficient (E) that has a range from $-\infty$ to 1. It is defined as:

$$E = 1 - \frac{\sum_{t=1}^T (Q_o^t - Q_m^t)^2}{\sum_{t=1}^T (Q_o^t - \bar{Q}_o)^2} \quad (11)$$

Where Q_o is observed discharge and Q_m is modeled discharge. The value of $E=1$ corresponds to a perfect match of modeled output to the observed output. $E=0$ expresses that the modeled outputs are as good as the long-term means in predicting the flow. And $E<0$ indicates inappropriate match of modeled output to the observed output (Nash and Sutcliffe, 1970).

Scatter index (SI) is used as the second criteria and is a dimensionless parameter computed as the ratio of Root Minimum Square Error (RMSE) (Eq. 12) to mean observed streamflow \bar{Q} (Shiri and Kisi, 2010). This parameter can be expressed as Eq. (12):

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n (Q_o - Q_m)^2} \quad (12)$$

5. Results and discussion

5.1. Streamflow forecasting process

Intelligent methods such as ANN and ANFIS require a sufficient amount of

representative data to properly model the system in order to yield an enhanced performance. In this area, the number of observed data is limited. Therefore, to increase the amount of available data the study area was divided into three sub-basins (Fig. 3).

In this model, several input combinations such as monthly streamflow of last three period, which are calculated in the outlet of each sub-basin (m^3/sec), monthly precipitation of previous period (P_{t-1} , in mcm) and average temperature of previous month (T_{t-1} , in $^{\circ}C$) were used to estimate monthly.

streamflows (Q_t in m^3/sec) in each sub-basin outlet (Eq. 14).

$$Q_t = f\left(\sum_{k=1}^3 Q_{t-k}, P_{t-1}, T_{t-1}\right) \quad (14)$$

Data period consists of 19 years (1990-2008) and forecasting is carried out for 6 months starting from April through September in each year.

After extracting regional relations among elevation, temperature, and precipitation records in each station (Whole Tehran Basin, Fig.4), parameter values in each pixel were computed. Finally, the average values of each parameter for each sub-basin were calculated.

To assess model performance in different forecast intervals, study was focused on estimating streamflow in two time steps: monthly and seasonal. In fact, seasonal forecasting is the process of forecasting in next three months. Because intelligent methods (e.g., ANFIS, ANN) are only based on one type of output, therefore compulsively, the average values of three next streamflows were used as the output for seasonal forecasting model.

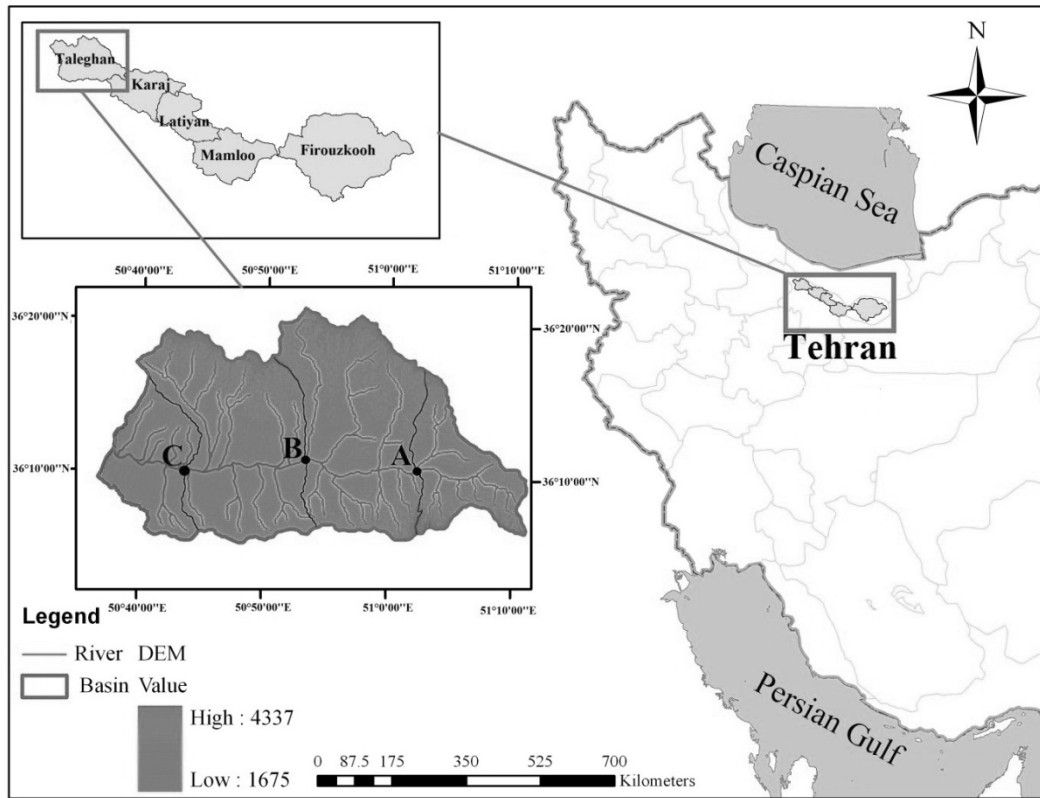


Fig. 3. The study area

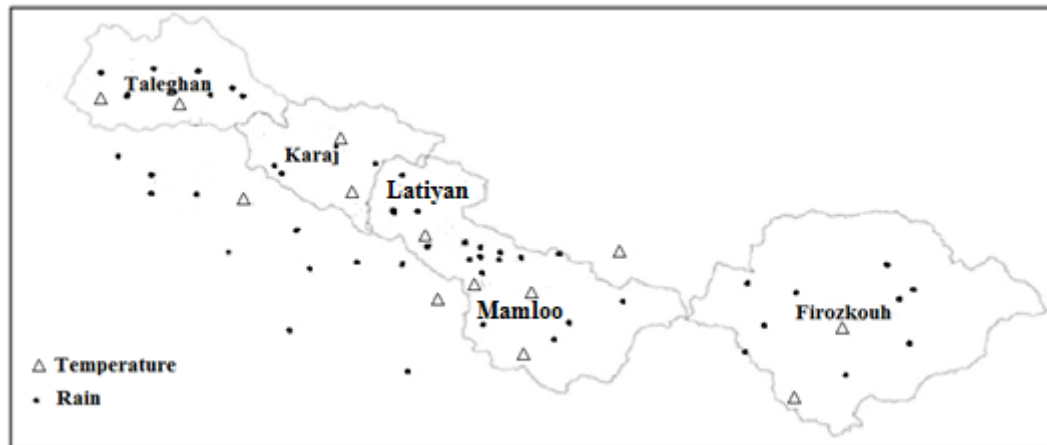


Fig. 4. Location of stations in Tehran region

In this study, the ANFIS model using K-fold Cross-validation method was applied to long-term streamflow forecasting. Also, results were compared with those of the typical method (i.e., using 75% of the whole

data set for training models and the remaining 25% of the whole data set for testing process). In addition, the performance of the ANFIS was compared with the ANN method. Therefore,

streamflow forecasting was performed by two models (ANFIS, ANN) using two cross-validation methods (K-fold, typical) and two forecast intervals (monthly, seasonal).

The model was completed in three gradual steps to assess the effect of each variable on the accuracy of forecasted values. Initially, only last three streamflow data was used (model I), then the monthly precipitation was added (II) and finally the monthly temperature was included in the model (III).

$$Q_t = f \left(\sum_{k=1}^3 Q_{t-k} \right) \tag{I}$$

$$Q_t = f \left(\sum_{k=1}^3 Q_{t-k}, P_{t-1} \right) \tag{II}$$

$$Q_t = f \left(\sum_{k=1}^3 Q_{t-k}, P_{t-1}, T_{t-1} \right) \tag{III}$$

The appropriate values of K were determined by trial and error based on statistical evaluation criteria (E, SI). Table 1 shows the values of K for each model with different forecasting time intervals. For each specific value of K, the model was run K times and the average results of the statistical indices (E, SI) were considered as the model performance. The main point in using k-fold cross-validation method refers to its ability in proper employment of data for training-testing processes which makes the forecasting model more reliable.

Table 1. K-values based on trial and error

Models	K-values	
	Monthly	Seasonal
(I)	6	7
(II)	6	5
(III)	7	7

5.2. ANN model

In this step, the ANN model was used to forecast long-term (monthly, seasonal) streamflows. Table 3 shows the ANN performance model using different cross-validation methods. As it can be seen from Table 3, the model performance in the test period is improved by adding new variables. For instance, The Nash-Sutcliffe model efficiency coefficient, E, in model (II) shows improvements of 0.06 to 0.08 in monthly time steps and 0.09 in seasonal forecasting in both cross-validation methods as compared to model (I). In addition, the results of monthly models are better than those of the seasonal one. For example, the maximum values of E in monthly and seasonal models are 0.83 and 0.74, respectively. Similar trend was observed in the SI index.

Table 3 also demonstrates that in ANN model the application of K-fold method results in better performances than the typical one. The maximum values for the Nash-Sutcliffe coefficient index in monthly models are 0.66 and 0.83 for typical and K-fold methods, respectively. Also, in seasonal models the Nash-Sutcliffe coefficient index has the maximum values of 0.66 and 0.74 for the typical and K-fold methods, respectively. Both results indicate the superiority of the K-fold over typical method in terms of the Nash-Sutcliffe index in the ANN model. However, the main advantage in using k-fold is the proper employment of data for training-testing processes and hence, increasing the reliability of the forecasting model. In doing this, results of k-fold may show inferiority to those of the typical method, but it does not justify the use of typical method since

the evaluation (testing) period is carried out using a very limited period of data as compared to the k-fold where, through iterations, the whole data could be used for the evaluation.

5.3. ANFIS model

The final architecture of the ANFIS models is given in Table 2. It shows the number of membership functions of each input variable. Fuzzy membership functions could have many forms. It depends on the complexity and characteristics of data. Among different types of data, hydrologic and climatologic variables are among those of non-linear ones; therefore membership function with similar characteristics seems to be necessary. Thus, the Gaussian function, in this study, is employed and defined as:

$$f(x, \sigma, c) = e^{-\frac{(x-c)^2}{2\sigma^2}} \quad (15)$$

Where c is center of Gaussian membership function and σ is standard deviation of Gaussian membership function. For instance, the ANFIS model (monthly) for input combination (III) has 3, 3, 3, 3, 3 membership functions for the last three streamflow data (Q_{t-k}), monthly precipitation (P_{t-1}) and monthly temperature (T_{t-1}) inputs, respectively.

Table 2. The number of membership functions

Models	Monthly	Seasonal
(I)	2,2,2	2,2,2
(II)	1,1,1,1	3,3,3,3
(III)	3,3,3,3,3	2,2,2,2,2

Evaluation processes of ANFIS model are identical to those of ANN model. The results of ANFIS model in the test period are demonstrated in Table 3.

It shows that the ANFIS model performance is improved in test period by adding parameters gradually, in both monthly and seasonal forecasts. For instance, the scatter index SI using K-fold cross-validation for monthly and seasonal forecasting has 0.33 and 0.47 improvements in model (III) in comparison with those of model (I). A similar trend is observed in the typical method. Based on results, it can be concluded that the results of monthly ANFIS model are superior to those of the seasonal one. As it was mentioned earlier, similar behavior was also observed in the ANN model. Moreover, results also indicate the superiority of the K-fold over typical method in terms of the Nash-Sutcliffe index in this model as well (again similar to ANN).

Finally, based on both statistical criteria (E, SI), as shown in Table 3, generally the ANFIS model shows a better performance than the ANN one. For instance, in the monthly forecasting model (II) using k-fold cross validation method, the ANN has statistical indices of E=0.67 and SI=0.79, while these values improve to E=0.87 and SI=0.78 for the ANFIS model in the same case. Improvements as high as 0.20 in the Nash-Sutcliffe index can be seen, while there are rare cases where ANN shows slightly better results. Similarly, when the ANFIS model is used, significant improvements is noticed in the SI index in some cases.

Table 3. Statistical measures of ANFIS and ANN models in test period

Forecast intervals		ANN				ANFIS			
		K-fold		Typical		K-fold		Typical	
		E	SI	E	SI	E	SI	E	SI
Monthly	(I)	0.61	0.90	0.54	0.74	0.86	0.90	0.81	0.88
	(II)	0.67	0.79	0.62	0.84	0.87	0.78	0.83	0.77
	(III)	0.83	0.76	0.66	0.83	0.93	0.57	0.87	0.74
Seasonal	(I)	0.56	1.04	0.53	0.91	0.70	1.05	0.60	1.06
	(II)	0.65	0.93	0.62	1.07	0.64	0.81	0.64	0.98
	(III)	0.74	0.91	0.66	1.01	0.85	0.58	0.74	0.61

5.4. Effect of regionalization on model performance

One of the most important issues in hydrologic studies is deficiency and inappropriate distribution of hydro-meteorological stations that deteriorates the model accuracy. On the other hand, in most of the previous studies observed point data of stations have been used instead of areal estimates in the forecasting models (e.g., Shiri and Kisi, 2010). Use of point data may be applicable to small basins but it would introduce errors if the basin is large. The common belief is that in black box methods such as ANN and ANFIS, training process could handle the shortcomings of point data through proper adjustments of parameters and weights. In this paper, we show that although this might be a true assumption to some extent, however, there are at least cases that training process by itself would not be able to justify the use of point station data.

To prove this hypotheses, models are applied using multiple sub-basin and then point data. In the multiple sub-basin data, the average value of each parameter in

whole area (using the regional relations) is specified as the model input. In Taleghan basin, the Glird, Gatedeh and Dizan stations are identified as the precipitation stations, the Zidasht and Jostan stations are specified as the temperature stations and the Taleghan Reservoir inflow is identified as the basin outlet discharge station (Fig. 5), whereas in the multiple sub-basin data, the average value of precipitation and temperature for each sub-basin and the outflow for each sub-basin (A, B and C, which is Taleghan reservoir inflow) which is shown in Fig. 3, are used as the model input. For this purpose, only the typical cross-validation method and monthly forecasts covering 6 months (April- September) are used. Moreover, the results of ANFIS and ANN methods in the models number II and III are evaluated.

Number of input data in ANN and ANFIS models plays a key role in model performance. In this regard, the basin is divided into three sub-basins as shown in Fig. 3. Therefore, the basin is changed to three sub-basins and outflow data for each sub-basin is also used as the response value of the system for given sub-basin areal data

(i.e., precipitation, etc.). Consequently, the number of data for models is tripled through this approach.

The results for the test period as shown in Table 4 indicate that when multiple sub-basin data are used, model performances are substantially improved. For instance, the Nash-Sutcliffe coefficient Index E for ANFIS and ANN methods using point station data in model III are 0.49 and 0.41, whereas these values are respectively improved to 0.87 and 0.66 when multiple sub-basin data and multiple sub-basin method are used.

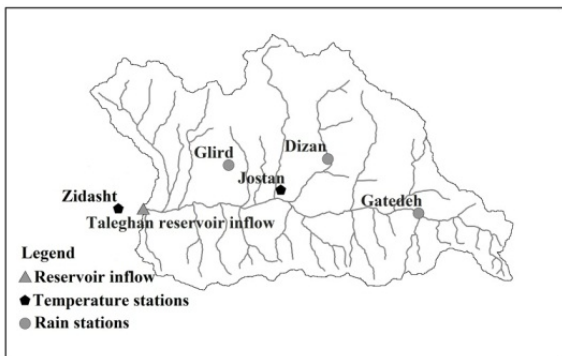


Fig. 5. Location of the data stations

A similar trend is observed in the Scatter Index SI. Therefore, it can be concluded that at least in this case, and possibly in many other cases, the use of multiple sub-basin data could substantially enhance the results of forecasting models including black-box methods. In addition, it is worthwhile to set time and effort necessary for deriving regional relations and computing multiple sub-basin data in the basin.

Table 4. Statistical measures of ANFIS and ANN models in test period

Methods	Model	Station Data		Multiple Sub-Basin Data	
		E	SI	E	SI
ANFIS	(II)	0.43	1.26	0.83	0.77
	(III)	0.49	0.98	0.87	0.74
ANN	(II)	0.36	2.87	0.62	0.84
	(III)	0.41	1.35	0.66	0.83

6. Conclusions

In this study, ANN and ANFIS methods are used for long-term streamflow forecasting in Taleghan Basin. The ANFIS model showed a better performance than the ANN model in predicting the streamflows. It was also shown that using K-fold as the cross-validation method increases model reliability. Moreover, use of multiple sub-basin data could substantially enhance the results of forecasting models including black-box methods (i.e., ANN and ANFIS). In applying the multiple sub-basin data, the number of input data in ANN and ANFIS models could be reduced causing serious problems in proper model training and testing processes. It was shown that dividing the basin into several sub-basins could help in overcoming the problem. Due to problems with ground based stations including; their poor distribution, the absence of in-situ measurements especially in mountainous areas, the use of satellite images can be applied in hydrologic studies, especially streamflow forecasting, for future studies in this field.

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