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# Simulation of rainfall-runoff process using geomorphology-based adaptive neuro-fuzzy inference system (ANFIS)

**Shabanali Gholami[1], Mehdi Vafakhah[2*], Kamal Ghaderi[1], Mohammad Reza Javadi[1]**

*1. Department of Natural Resources, Noor Branch, Islamic Azad University, Noor, Iran*
*2. Department of Watershed Management Engineering, Faculty of Natural Resources, Tarbiat Modares University, Noor, Iran*

** Corresponding author's E-mail: vafakhah@modares.ac.ir*

## ABSTRACT

This research was conducted to present an integrated rainfall-runoff model based on the physical characteristics of the watershed, and to predict discharge not only in the outlet, but also at any desired point within the basin. To achieve this goal, a matrix of hydro-climatic variables (i.e. daily rainfall and daily discharge) and geomorphologic characteristics such as upstream drainage area (A), mean slope of watershed (S) and curve number (CN) was designed and simulated using artificial intelligence techniques. Integrated Geomorphology-based Artificial Neural Network (IGANN) model with Root Mean Squared Error (RMSE) of 0.02786 $m^3 s^{-1}$ and Nash-Sutcliffe Efficiency (NSE) of 0.9403 and Integrated Geomorphology-based Adaptive Neuro-Fuzzy Inference System (IGANFIS) model with RMSE of 0.02795 $m^3$ $s^{-1}$ and NSE of 0.94467 were able to predict the discharge values of all hydrometric stations of the Chalus River watershed with a very low error and high accuracy. The results of cross validation stage confirmed the efficiency of models. Hydro-climatic variables and geomorphologic parameters selected in the study were: discharge of one day ago, discharge of two days ago, rainfall of current day and rainfall of one day ago and S, CN and A, respectively. In addition, the IGANN model shows superiority compared with the IGANFIS model.

**Key words:** Physical characteristics of watershed, Rainfall-runoff modeling, Black box modeling, Artificial intelligence, Geomorphologic unit hydrograph.

## INTRODUCTION

Accurate prediction of hydrological phenomena such as rainfall- runoff process can provide effective information for urban planning and water resources management, which plays an important role in reducing flood and drought impacts on the water resources systems. Understanding the Rainfall- Runoff (RR) model of a catchment is one of the most complicated of hydrologic activities because it involves temporal and spatial variations. It is very difficult to determine uncertainty for all of the physical parameters of watersheds. It is not surprising that black box models can convert input to output data and have more accurate results than physical models. The artificial intelligence (AI) methods are black box modeling tools that have recently been applied in several sectors including RR modeling (Nayak *et al.* 2007; Nourani *et al.* 2011; Talei & Chua 2012; Nourani & Komasi 2013). The success of artificial neural network (ANN) in any hydrological modeling process depends on the quantity and quality of data used to train model. The model used to simulate the rainfall-runoff process is usually uncertainties. For example, the average amount of rainfall was measured by point rainfall stations in whole of watershed, that it has been usually attributed to the entire basin. Using such a method for calculating rainfall in the watershed as an input layer of ANN can be a source of uncertainty. In such a situation, fuzzy theory is used to solve the uncertainties involved in real-world issues (Nash & Sutcliffe 1970; Nourani & Komasi 2013). From this point of view, the ANN compound and the fuzzy system are the focal points of the research focus. The Adaptive Neuro-Fuzzy

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Inference (ANFIS) uses the advantages of both ANN and fuzzy systems. A review article on the application of a comparative neuro-fuzzy inference system in river flow prediction by Jacquin and Shamseldin (2009) has/ been published. In this paper, the comparative Neuro-Fuzzy Inference System is introduced as an effective tool for predicting flow and its application is relatively limited in comparing with the Artificial Neural Network models. Several studies have been conducted on the use of ANFIS in rainfall-runoff modeling (Wang *et al.* 2009; Kurtulus & Razack 2010; Talei *et al*. 2010; Vafakhah 2012; Lohani *et al*. 2012; Asadi *et al.* 2013; Ghose *et al.* 2013; Kisi *et al*. 2013; Jayawardena *et al.* 2014). Nourani & Komasi (2013) applied Integrated Geomorphology-based ANFIS (IGANFIS) model in multi-station modeling of rainfall-runoff process. They approved usage of IGANFIS model. Accordingly, the purposed model by Nourani & Komasi (2013) was applied in this study. They used rainfall and discharge variables and geomorphologic characteristics such as upstream drainage area (A), mean slope of watershed (S) and Curve Number (CN) as inputs in an integrated matrix of available stations within the basin. The distinction between the current research and the above research is used the Subtractive Clustering instead of Fuzzy C-means (FCM) Clustering. The Chalus catchment is included wide part of south of Noushahr and Chalus cities in north of Iran. In the past years, these areas have been affected by devastating and destructive floods (floods in 1994 & 2003 years).

**The study area characteristics**

The Chalus River basin with longitude 51˚ 00' to 51˚ 35' East and Latitude 36˚ 08' to 36˚ 43' North is located on the northern slopes of central Alborz and in the south of the Chalus city, draining to the Caspian Sea after cross short distances from the Khazari plain (Fig. 1). The Chalus River basin is limited from west to the Sardabrood basin and from east to the Korcorsar basin and from south to the Karaj basin and north to the Caspian Sea (Moghimi *et al.* 2009). The maximum and minimum heights of studied area are 4260 and 158 m above sea level, respectively. It is a mountainous region and extremely steep and also has a general northern direction. In terms of climate, it has different climates. According to Emberger's climatic classification, the most dominant climate conditions are recognized in most of regions semi-humid cold to cold and in some places are semi-arid cold. The average annual rainfall and average discharge is 836 mm 8.13 $m^3 s^{-1}$ and it has an average fresh water annually 44.38 MCM, some amount of that consume for agricultural (rice fields), and the remainder deployed to the Caspian Sea (Eshagh Teimori *et al.* 2012).

**METHODOLOGY**

Daily discharge data from seven hydrometric stations and daily rainfall data from three weather stations within the watershed were collected in Iran Water Resources Management Company (IWRM). Location of these stations is shown in Fig.1. Table 1 illustrates characteristics of weather stations within the watershed.

**Table 1.** Characteristics of weather stations within the watershed.

| Station no. | Name | Station type | Organization | Lat. (m) | Long. (m) | Elevation (m a.s.l.) |
|---|---|---|---|---|---|---|
| 1 | Pol-e-Zoghal | Evaporator | Ministry of Energy (Iran) | 529649 | 4040537 | 360 |
| 2 | Vaspol | Raingauge | Ministry of Energy (Iran) | 520647 | 4018419 | 1000 |
| 3 | Siah Bisheh | Synoptic | Iran Meteorological Organization | 526952 | 4011719 | 1855 |

The data during 2002-2003 to 2006-2007 (1 Nov. 2002 to 31 Sept. 2007) were selected for modeling due to the construction of the Siyah Bisheh Dam in 2012 and its effect on discharge data recorded by hydrometric stations and, the availability land use map in 2006. Daily rainfall data from Pol-e-Zoghal, Vaspol and Siah Bisheh stations were used for Pol-e-Zoghal and Doab catchments, Abshar and Vaspol catchments and Harijan, Valiabad and Polemergan catchments, respectively. Table 2 presents characteristics of hydrometric stations within the watershed. The slope map of Chalus watershed was derived from digital elevation model with 1:25000 scale by ArcGIS9.3 software. Maps of land use and hydrologic soil groups with 1:50,000 scale were collected from Sari Natural Resources and Watershed Management Administration, Iran and then Curve Number (CN) of the sub-basins was prepared by combining land use and soil hydrologic groups layers through Soil Conservation Service (SCS) method. To determine appropriate input variables (rainfall and discharge) to the IGANFIS models, the autocorrelation, partial autocorrelation and cross correlation between rainfall and discharge were used (Vafakhah 2012). Fig. 2 illustrates IGANFIS modeling flowchart. In Fig. 2, numbers of 1 to 6 displays Pol-e-Zoghal, Doab, Abshar, Valiabad, Harijan and Pol-e-Mergen sub-basins, respectively and V symbol exhibits Vaspol sub-basin. I, Q, A, S and CN respectively are rainfall, discharge, area, slope and curve number.

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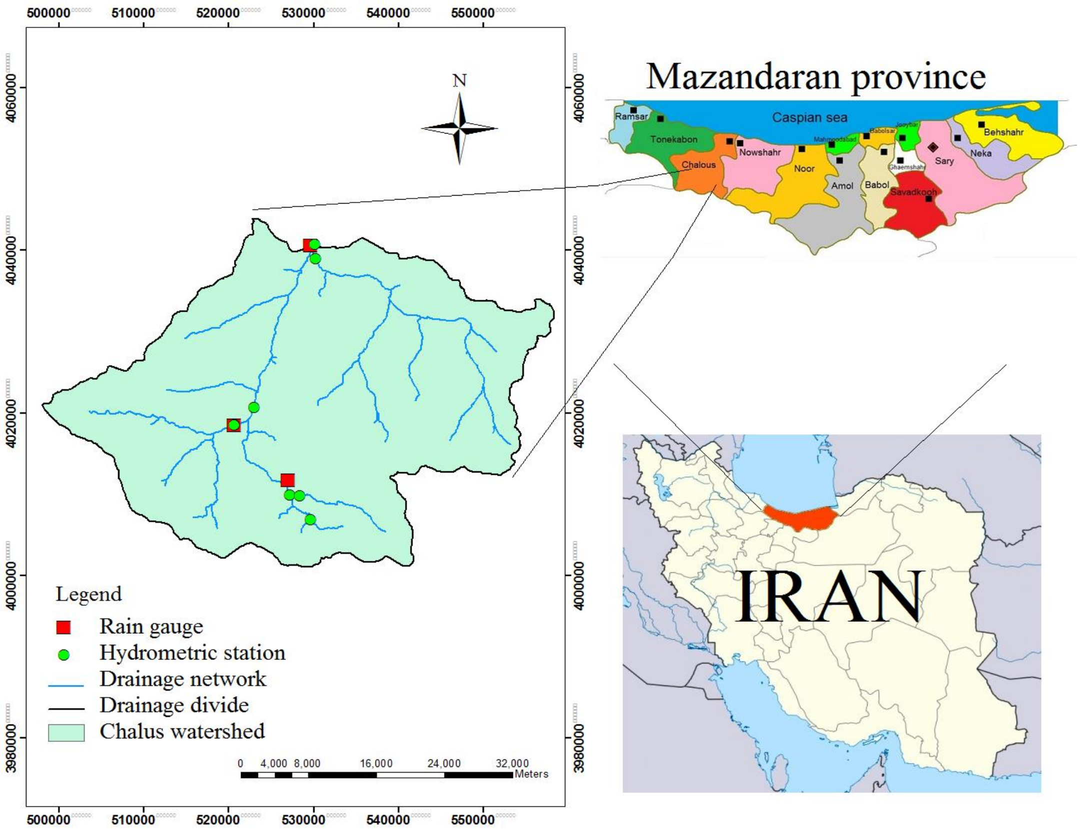


**Fig.1.** Location Chalus Watershed in Mazandaran, Iran.

**Table 2.** Characteristics of hydrometric stations within the watershed.

| Station no. | Name | River | Lat. (m) | Long. (m) | Elevation m a.s.l. |
|---|---|---|---|---|---|
| 1 | Pol-e-Zoghal | Chalus | 530171 | 4040631 | 351 |
| 2 | Abshar | Chalus | 522961 | 4020643 | 823 |
| 3 | Vaspol | Anguran | 520672 | 4018449 | 963 |
| 4 | Pol-e-Mergan | Zangule | 529664 | 4006798 | 2170 |
| 5 | Harijan | Harijan | 528356 | 4009782 | 1814 |
| 6 | Valiabad | Chalus | 527208 | 4009871 | 1749 |
| 7 | Doab | Hanisk | 530202 | 4038875 | 390 |

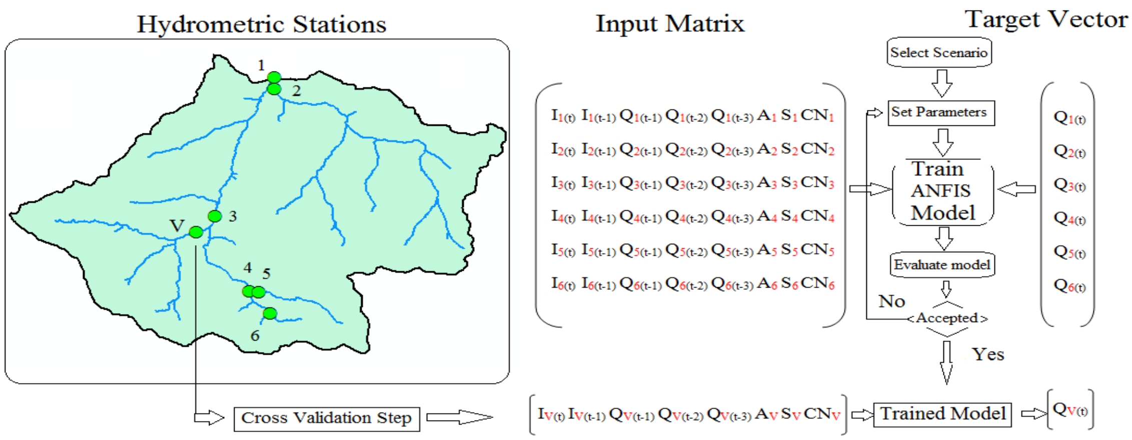


**Fig. 2.** IGANFIS Modeling Flowchart.

## Data normalization

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Data normalization, as one of the data processes in the development of IGANFIS models data is performed due to problems caused by large amounts of descriptive. It recommended each amounts placed as a linear scale range (1.0, 9.0), (+1, -1) or (0, 1). In the modeling process, all data of rainfall and discharge are normalized between 0.1 and 0.9 according to equation 1:

$$N_i = 0.8 \times \left(\frac{X_i - X_{min}}{X_{max} - X_{min}}\right) + 0.1 \quad \textbf{(1)}$$

where, $N_i$ is the normalized amount, $X_i$ is original data and $X_{min}$ and $X_{max}$ are the minimum and maximum of rainfall and discharge, respectively (Rashidi *et al*. 2016).

As input variables of geomorphology have different units, they were also normalized as ($\frac{A_i}{A_T}$, $\frac{S_i}{\bar{S}}$ and $\frac{CN_i}{\overline{CN}}$), where $A_i$ and $A_T$ are area of each sub-basin and Chalus Watershed, $S_i$ and $\bar{S}$ are average slope of each sub-basin and Chalus watershed and $CN_i$ and $\overline{CN}$ are curve number each sub-basin and Chalus Watershed, respectively.

**Compiling the ANFIS model**

For run of ANFIS was used ANFIS code through MATLAB software. Inputs were divided into three categories: training (60%), testing (20%) and validation (20%). For compiling ANFIS, a fuzzy inference model in Sugeno type with grid partitioning and subtractive clustering methods were used (Jang 1993). Type of membership functions (triangular, trapezoidal, generalized bell-shaped, Gaussian, Gaussian type II, Π-shaped and circular) was then designated (Jacquin & Shamseldin 2006). Type of output membership function was selected linear. In the optimization procedure, it used a hybrid learning rule combining the back propagation gradient descent and a least-squares method. Optimal error was considered zero. Then the model was trained with these characteristics (Aalami & Hosseinzadeh 2010). ANFIS training parameters used in the study are presented in Table 3.

**Table 3.** Learning parameters in ANFIS model.

| Type | Sugeno |
|---|---|
| AND method | Product |
| OR method | Probabilistic |
| Implication method | Product |
| Aggregation method | Sum |
| Deffuzzification method | Weighted Average |

**First scenario of IGANFIS**

In the first scenario, discharge as an input of model was not considered, for checking in the absence of the pervious discharge as an input, therefore rainfall, A, S and CN were used as inputs to predict current day discharge according to equation 2:

$$Q_i(t) = f\left(I_i(t), I_i(t-1), \frac{A_i}{A_T}, \frac{S_i}{\bar{S}}, \frac{CN_i}{\overline{CN}}\right) \quad \textbf{(2)}$$

where i shows number of the sub-basin and $I_i(t)$, $I_i(t-1)$ and $Q_i(t)$, are subsequently pervious and current day rainfall and current day discharge as output of the model. $A_i$ and $A_T$ are area of each sub-basin and Chalus Watershed, $S_i$ and $\bar{S}$ are average slope of each sub-basin and Chalus watershed, while $CN_i$ and $\overline{CN}$ are curve numbers of each sub-basin and Chalus watershed, respectively.

**Second scenario of IGANFIS**

In the second scenario, one day ago discharge was applied in the model as an input to select the best ANFIS model.

$$Q_i(t) = f\left(I_i(t), I_i(t-1), Q_i(t-1), Q_i(t-2), Q_i(t-3), \frac{A_i}{A_T}, \frac{S_i}{\bar{S}}, \frac{CN_i}{\overline{CN}}\right) \quad \textbf{(3)}$$

**Cross validation**

Capability of IGANFIS model was measured for spatiotemporal RR modeling process through the cross validation method for a station. To achieve this goal, Since Vaspol station is close to Abshar station. Vaspol station was not used in training model, but in the playoff validation process, Vaspol station statistics was modeled into the matrix

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instead of the Abshar station. Recreation and interaction of data stations, which through the training phase of model is learned, the model helps to predict for cross validation (Vaspol station).

**Criteria efficiency**

To evaluate the efficiency of different models and components used in this study, the following performance criteria were used.

Root Mean Squared Error (RMSE) values vary from zero (for perfectly accurate predictions) to high positive values (when the difference between observed and computed values is greater).

$$\mathrm{RMSE} = \sqrt{\frac{\sum_{i=1}^{N}(Q_{\mathrm{obs}_i} - Q_{\mathrm{com}_i})^2}{N}} \qquad \textbf{(4)}$$

The higher the Nash-Sutcliff Efficiency (NSE) (at most 1), the model is more efficient (Nash & Sutcliffe 1970).

$$NSE = 1 - \frac{\sum_{i=1}^{N}(Q_{obs_i} - Q_{com_i})^2}{\sum_{i=1}^{N}(Q_{obs_i} - \bar{Q}_{com_i})^2} \qquad \textbf{(5)}$$

Pearson’s correlation coefficient (R) is one of the important coefficients to determine the correlation between two variables and varies between -1 and +1.

$$R = \sqrt{\frac{\sum_{i=1}^{N}\left[\left(Q_{obs_i} - \bar{Q}_{obs}\right)\left(Q_{com_i} - \bar{Q}_{com}\right)\right]^2}{\sum_{i=1}^{N}\left(Q_{obs_i} - \bar{Q}_{obs}\right)^2 \left(\sum_{i=1}^{N} Q_{com_i} - \bar{Q}_{com}\right)^2}} \qquad \textbf{(6)}$$

The relative error of peak discharge (REp) shows the near-peak computed and observed values. Due to the importance of peak values in a hydrological process, this performance criterion was also used to fully evaluate the model's performance (Green & Stephenson 1986).

$$\mathrm{RE_P}(\%) = \frac{1}{M}\sum_{j=1}^{M} \frac{\left|QP_{\mathrm{obs_j}} - QP_{\mathrm{com_j}}\right|}{QP_{\mathrm{obs_j}}} \qquad \textbf{(7)}$$

where $N$, number of observations**,** $Q_{obs_i}$, observed discharge, $Q_{com_i}$, computed discharge, $\bar{Q}_{obs}$, mean of the observed discharge, $\bar{Q}_{com}$, the mean of computed discharges, M, number of peak values, $QP_{\mathrm{obs_j}}$, the observed peak discharge value, $QP_{\mathrm{com_j}}$, the computed peak discharge.

## RESULTS

Descriptive statistics characteristics of variables such as rainfall, temperature and discharge are presented in Table 4. To determine the number of the lag times, autocorrelation, partial autocorrelation and cross correlation between rainfall and discharge for 10 lag times were calculated for all meteorological and hydrometric stations, and the results are presented in Tables 5 - 7.

As shown in Table 5, autocorrelation coefficients and partial autocorrelation coefficients of rainfall in the first lag time for all three meteorological stations were significant at 5% confidence level.

The results of the cross correlation between rainfall and discharge (Table 7) for five out of seven stations (except for Pol-e-Zoghal and Doab) were significant. Consequently, rainfall was selected with one day ago, as an input the model.

Discharge autocorrelation coefficients calculated for 10 lag times for each seven hydrometric stations were significant at 95% confidence level, but since in the 4$^{th}$ lag time, the auto correlation coefficient was only significant for one station (Abshar station).

Consequently, discharge was selected with three days ago as inputs of the model. The cross correlation between rainfall and discharge was also significant, from first up to third lag times at least four stations.

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**Table 4.** Descriptive statistics characteristics of data used in the study.

| Station | Step | Mean | Minimum | Maximum | Standard deviation | Skewness |
|---|---|---|---|---|---|---|
| Pol-e-Zoghal | Training | 17.326 | 4.6 | 79.2 | 11.504 | 1.358 |
| Doab | Discharge | 3.344 | 1.28 | 18.2 | 1.437 | 2.445 |
| Abshar | ($m^3 s^{-1}$) | 12.504 | 2.93 | 60 | 9.377 | 1.245 |
| Valiabad | | 4.207 | 0.118 | 29.2 | 4.551 | 1.832 |
| Harijan | | 1.551 | 0.033 | 11/9 | 1.691 | 1.948 |
| Polemergan | | 1.972 | 0.294 | 11.3 | 1.975 | 1.401 |
| Vaspol | | 8.042 | 1.99 | 40.5 | 6.124 | 1.391 |
| Pol-e-Zoghal | Training Rainfall | 0.967 | 0 | 40 | 3.438 | 6.027 |
| Siah Bisheh | (mm) | 1.595 | 0 | 40 | 4.315 | 4.315 |
| Vaspol | | 1.538 | 0 | 95 | 5.205 | 8.114 |
| Pol-e-Zoghal | Training | 15.055 | -1 | 29.5 | 7.16 | -0.167 |
| Siah Bisheh | Temperature (℃) | 10.299 | -8.9 | 27 | 7.748 | -0.298 |
| Pol-e-Zoghal | Testing | 12.154 | 4.39 | 41.5 | 7.216 | 1.296 |
| Doab | Discharge | 2.332 | 1.32 | 3.46 | 0.549 | 0.293 |
| Abshar | ($m^3 s^{-1}$) | 10.217 | 4.32 | 31.5 | 6.640 | 1.446 |
| Valiabad | | 2.911 | 0.303 | 15.3 | 3.307 | 1.664 |
| Harijan | | 1.366 | 0.161 | 8.88 | 1.777 | 2.049 |
| Polemergan | | 1.386 | 0.269 | 5.91 | 1.596 | 1.650 |
| Vaspol | | 5.405 | 2.53 | 17.9 | 2.780 | 1.571 |
| Pol-e-Zoghal | Testing Rainfall | 0.568 | 0 | 14 | 1.867 | 4.791 |
| Siah Bisheh | (mm) | 1.446 | 0 | 30 | 4.101 | 4.029 |
| Vaspol | | 1.036 | 0 | 50 | 3.789 | 7.696 |
| Pol-e-Zoghal | Validation | 16.607 | 5.17 | 91 | 16.267 | 2.015 |
| Doab | Discharge | 3.231 | 1.51 | 10.2 | 1.478 | 1.925 |
| Abshar | ($m^3 s^{-1}$) | 12.381 | 4.54 | 45.9 | 9.583 | 1.447 |
| Valiabad | | 3.332 | 0.979 | 21.1 | 3.268 | 2.816 |
| Harijan | | 1.841 | 0.248 | 16 | 2.578 | 2.555 |
| Polemergan | | 1.596 | 0.368 | 7 | 1.587 | 1.515 |
| Vaspol | | 7.392 | 2.75 | 27 | 5.217 | 1.336 |
| Pol-e-Zoghal | Validation | 1.026 | 0 | 36 | 2.990 | 5.965 |
| Siah Bisheh | Rainfall | 1.908 | 0 | 37 | 4.524 | 3.925 |
| Vaspol | (mm) | 1.345 | 0 | 20 | 3.303 | 3.037 |

**Table 5.** Autocorrelation and partial autocorrelation coefficients of the daily rainfall from lag-1 (r1) to lag-10 (r10).

| Station | Autocorrelation coefficients | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | r1 | r2 | r3 | r4 | r5 | r6 | r7 | r8 | r9 | r10 |
| Pol-e-Zoghal | 0.107 | -0.02 | -0.017 | 0.038 | 0.022 | -0.025 | 0.008 | 0.023 | 0.031 | 0.004 |
| Vaspol | 0.205 | 0.197 | 0.127 | 0.061 | 0.033 | 0 | 0.007 | 0.014 | 0.004 | 0.003 |
| Siah Bisheh | 0.286 | 0.039 | 0.039 | 0.039 | 0.071 | 0.021 | 0.028 | -0.005 | 0.024 | 0.005 |
| **Station** | **Partial autocorrelation coefficients** | | | | | | | | | |
| | **r1** | **r2** | **r3** | **r4** | **r5** | **r6** | **r7** | **r8** | **r9** | **r10** |
| Pol-e-Zoghal | 0.107 | - 0.032 | - 0.11 | 0.041 | 0.012 | -0.027 | 0 | 0.022 | 0.024 | 0 |
| Vaspol | 0.205 | 0.162 | 0.064 | - 0.002 | - 0.009 | - 0.032 | 0.003 | 0.016 | 0.001 | - 0.002 |
| Siah Bisheh | 0.286 | - 0.047 | 0.045 | 0.019 | 0.06 | - 0.019 | 0.031 | -0.028 | 0.034 | - 0.02 |

* Values that are significant at a confidence level of 95% are highlighted.

## Selection of different input combinations

Based on the results of autocorrelation and partial autocorrelation coefficients, and cross correlation between

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rainfall and discharge, eight various combinations of rainfall and discharge were selected as inputs of the initial RR model for ANFIS model (Table 8).

**Table 6.** Autocorrelation and partial autocorrelation coefficients of the daily discharge from lag-1 (r1) to lag-10 (r10).

| **Station** | **Autocorrelation coefficients** | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | **r1** | **r2** | **r3** | **r4** | **r5** | **r6** | **r7** | **r8** | **r9** | **r10** |
| Pol-e-Zoghal | 0.968 | 0.932 | 0.905 | 0.88 | 0.858 | 0.841 | 0.826 | 0.815 | 0.807 | 0.802 |
| **Station** | **Partial autocorrelation coefficients** | | | | | | | | | |
| | **r1** | **r2** | **r3** | **r4** | **r5** | **r6** | **r7** | **r8** | **r9** | **r10** |
| Pol-e-Zoghal | 0.968 | - 0.076 | 0.143 | - 0.032 | 0.079 | 0.05 | 0.046 | 0.075 | 0.038 | 0.078 |

* Values that are significant at a confidence level of 95% are highlighted.

**Table 7.** Cross correlation coefficients of the rainfall and discharge from lag-0 (r0) to lag-10 (r10).

| **Station** | **Cross correlation between rainfall and discharge** | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | **r0** | **r1** | **r2** | **r3** | **r4** | **r5** | **r6** | **r7** | **r8** | **r9** | **r10** |
| Pol-e-Zoghal | 0.07 | 0.032 | 0.008 | 0.008 | 0.006 | 0.009 | 0.007 | 0.012 | 0.011 | 0.009 | 0.02 |
| Doab | 0.057 | 0.04 | 0.018 | 0.008 | 0.01 | 0 | 0.008 | 0.014 | 0.011 | 0.006 | 0.002 |
| Abshar | 0.109 | 0.087 | 0.069 | 0.06 | 0.051 | 0.045 | 0.05 | 0.061 | 0.059 | 0.068 | 0.069 |
| Valiabad | 0.189 | 0.173 | 0.145 | .111 | 0.096 | 0.091 | 0.096 | 0.104 | 0.099 | 0.093 | 0.093 |
| Harijan | 0.143 | 0.142 | 0.116 | 0.094 | 0.08 | 0.089 | 0.087 | 0.083 | 0.085 | 0.081 | 0.088 |
| Polemergan | 0.123 | 0.137 | 0.132 | 0.12 | 0.113 | 0.104 | 0.105 | 0.116 | 0.115 | 0.11 | 0.109 |
| Vaspol | 0.085 | 0.063 | 0.044 | 0.031 | 0.023 | 0.018 | 0.03 | 0.041 | 0.039 | 0.041 | 0.06 |

**Table 8.** Different combinations of rainfall and discharge for initial modeling of ANFIS

| **No.** | **Combination** | |
|---|---|---|
| 1 | $R_t$ | rainfall of current day |
| 2 | $R_tQ_{t-1}$ | rainfall of current day, discharge of one day ago |
| 3 | $R_tQ_{t-1}Q_{t-2}$ | rainfall of current day, discharge of one day ago, discharge of two days ago |
| 4 | $R_tQ_{t-1}Q_{t-2}Q_{t-3}$ | rainfall of current day, discharge of one day ago, discharge of two days ago, discharge of three days ago |
| 5 | $R_tR_{t-1}$ | rainfall of current day, rainfall of one day ago |
| 6 | $R_tR_{t-1}Q_{t-1}$ | rainfall of current day, rainfall of one day ago, discharge of one day ago |
| 7 | $R_tR_{t-1}Q_{t-1}Q_{t-2}$ | rainfall of current day, rainfall of one day ago, discharge of one day ago, discharge of two days ago |
| 8 | $R_tR_{t-1}Q_{t-1}Q_{t-2}Q_{t-3}$ | rainfall of current day, rainfall of one day ago, discharge of one day ago, discharge of two days ago, discharge of three days ago |

## RR model results of ANFIS

Eight different combinations were implemented with eight fuzzy sets and two membership functions. The best result is shown in Table 9. According to the results of the validation stage, the composition ($R_t$, $R_{t-1}$, $Q_{t-1}$ i.e. current day rainfall, one day ago rainfall, one day ago discharge) were selected with the lowest RMSE (0.029693) and the highest Nash-Sutcliff coefficient (0.94658) as the best combination of ANFIS. In the combinations considered only rainfall is as inputs of the model, the $R_t$, $R_{t-1}$ model had a better performance than $R_t$.

## IGANFIS results

At first scenario, discharge was not applied as the input of the model and three geomorphologic parameters including A, S and CN along with the best combination of ANFIS model i.e. $R_t$, $R_{t-1}$ was performed (Table 10). According to the results of validation stage, it was observed that, S and A have been able to reduce the amount of error combination of $R_t$, $R_{t-1}$ (0.117525) and combination of $R_t$, $R_{t-1}$, S has been performed with the best result (0.116538). In the second scenario, discharge was also applied as the input of the model and three geomorphologic parameters including A, S and CN along with the best combination of ANFIS model i.e. $R_t$, $R_{t-1}$, $Q_{t-1}$ was performed (Table 11). According to the results of validation stage, It was observed that, only S has been able to reduce the amount of combination error of $R_t$, $R_{t-1}$, $Q_{t-1}$ (0.0796) and combination of $R_t$, $R_{t-1}$, S has been performed with the best result (0.03795). The slope combination (S) with other inputs has not helped to increase the performance of the model. The results of second scenario of the IGANFIS model were implemented with subtractive clustering method in the various combinations of three geomorphologic parameters with $R_t$, $R_{t-1}$, $Q_{t-1}$ combination using generalized bell-shaped membership function that are presented in Table 12. As can be observed, all compounds except combinations of ($R_t$, $R_{t-1}$, $Q_{t-1}$, S) had better results than their corresponding

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combinations in the subtractive clustering, but none of them could have reduced the best ANFIS combination error namely $R_t$, $R_{t-1}$, $Q_{t-1}$ combination. Due to the above results, the IGANFIS model with grid partitioning method and generalized bell-shaped membership function and $R_t$, $R_{t-1}$, $Q_{t-1}$, S combination was selected as the best model. Fig. 3 illustrates the comparison of computed and observed data of the IGANFIS model in five years from six stations.

**Table 9.** RMSE and NSE of the ANFIS models.

| No. | Combination | Membership Function | Criteria | Training | Testing | Validation |
|---|---|---|---|---|---|---|
| 1 | $R_t$ | Pimf | RMSE | 0.113 | 0.0931 | 0.1183 |
| | | | NSE | 0.0124 | -0.1650 | 0.0088 |
| 2 | $R_tQ_{t-1}$ | gbellmf | RMSE | 0.0291 | 0.0139 | 0.0281 |
| | | | NSE | 0.9349 | 0.9740 | 0.9439 |
| 3 | $R_tQ_{t-1}Q_{t-2}$ | Trimf | RMSE | 0.0282 | 0.0141 | 0.0293 |
| | | | NSE | 0.9389 | 0.9732 | 0.9389 |
| 4 | $R_tQ_{t-1}Q_{t-2}Q_{t-3}$ | trapmf | RMSE | 0.0267 | 0.0142 | 0.0325 |
| | | | NSE | 0.9453 | 0.9726 | 0.9250 |
| 5 | $R_tR_{t-1}$ | gaussmf | RMSE | 0.1129 | 0.0932 | 0.1175 |
| | | | NSE | 0.0251 | -0.1670 | 0.0224 |
| 6 | $R_tR_{t-1}Q_{t-1}$ | gbellmf | RMSE | 0.0282 | 0.0141 | 0.0279 |
| | | | NSE | 0.9389 | 0.9729 | 0.9446 |
| 7 | $R_tR_{t-1}Q_{t-1}Q_{t-2}$ | gbellmf | RMSE | 0.0226 | 0.0146 | 0.0295 |
| | | | NSE | 0.9459 | 0.9711 | 0.9380 |
| 8 | $R_tR_{t-1}Q_{t-1}Q_{t-2}Q_{t-3}$ | Pimf | RMSE | 0.0260 | 0.146 | 0.0371 |
| | | | NSE | 0.9482 | 0.9712 | 0.9024 |

*Since all data are normalized, the RMSE has no dimension.

**Table 10.** RMSE of the IGANFIS models with grid partitioning method in the first scenario.

| No | combination | training | testing | validation |
|---|---|---|---|---|
| 1 | $R_tR_{t-1}$A | 0.1119 | 0.0932 | 0.1167 |
| 2 | $R_tR_{t-1}$S | 0.1119 | 0.0926 | 0.1165 |
| 3 | $R_tR_{t-1}$CN | 0.1114 | 0.0927 | 0.1175 |
| 4 | $R_tR_{t-1}$CNS | 0.1094 | 0.0946 | 0.1168 |
| 5 | $R_tR_{t-1}$AS | 0.1105 | 0.0962 | 0.1178 |
| 6 | $R_tR_{t-1}$ACN | 0.1094 | 0.0951 | 0.1168 |
| 7 | $R_tR_{t-1}$ASCN | 0.1087 | 0.1153 | 0.1172 |

*Since all data are normalized, the RMSE has no dimension.

**Table 11.** RMSE and NSE of the IGANFIS models with grid partitioning method in the second scenario.

| No. | Combination | Criteria | Training | Testing | Validation |
|---|---|---|---|---|---|
| 1 | $R_tR_{t-1}Q_{t-1}$A | RMSE | 0.0266 | 0.0148 | 0.0320 |
| | | NSE | 0.9459 | 0.9702 | 0.9350 |
| 2 | $R_tR_{t-1}Q_{t-1}$S | RMSE | 0.0273 | 0.0146 | 0.0279 |
| | | NSE | 0.9427 | 0.9710 | 0.9446 |
| 3 | $R_tR_{t-1}Q_{t-1}$CN | RMSE | 0.0268 | 0.0159 | 0.0296 |
| | | NSE | 0.9451 | 0.9658 | 0.9377 |
| 4 | $R_tR_{t-1}Q_{t-1}$CNS | RMSE | 0.0255 | 0.0167 | 0.0315 |
| | | NSE | 0.9498 | 0.9620 | 0.9296 |
| 5 | $R_tR_{t-1}Q_{t-1}$AS | RMSE | 0.0257 | 0.0187 | 0.0322 |
| | | NSE | 0.9490 | 0.9527 | 0.9262 |
| 6 | $R_tR_{t-1}Q_{t-1}$ACN | RMSE | 0.0252 | 0.174 | 0.0335 |
| | | NSE | 0.9514 | 0.9589 | 0.9204 |
| 7 | $R_tR_{t-1}Q_{t-1}$ASCN | RMSE | 0.0241 | 0.0280 | 0.0341 |
| | | NSE | 0.9554 | 0.8940 | 0.9176 |

*Since all data are normalized, the RMSE has no dimension.

From 6576 days of training, every 1096 days are related to one station (respectively, Pol-e-Zoghal, Dawab, Abshar, Validabad, Harjian, Pol-e-Morgen), and from 2190 days of test (from 6576 to 8766) and validation (from 8766 up to 10956), each 365 days are related to base station in order to list each one, respectively. Fig. 4 exhibits

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the comparison of computed and observed data of the IGANFIS model in the last year (validation period) for the six stations separately.

**Table 12.** RMSE and NSE of the IGANFIS models with subtractive clustering method in the second scenario.

| No | Combination | Criteria | Training | Testing | Validation |
|---|---|---|---|---|---|
| 1 | $R_tR_{t-1}Q_{t-1}A$ | RMSE | 0.0298 | 0.0141 | 0.0285 |
| | | NSE | 0.9322 | 0.9732 | 0.9421 |
| 2 | $R_tR_{t-1}Q_{t-1}S$ | RMSE | 0.0291 | 0.0138 | 0.0283 |
| | | NSE | 0.9350 | 0.9743 | 0.9429 |
| 3 | $R_tR_{t-1}Q_{t-1}CN$ | RMSE | 0.0297 | 0.0146 | 0.0284 |
| | | NSE | 0.9321 | 0.9712 | 0.9428 |
| 4 | $R_tR_{t-1}Q_{t-1}CNS$ | RMSE | 0.0298 | 0.0143 | 0.0284 |
| | | NSE | 0.9318 | 0.9722 | 0.9425 |
| 5 | $R_tR_{t-1}Q_{t-1}AS$ | RMSE | 0.0293 | 0.0139 | 0.0284 |
| | | NSE | 0.9338 | 0.9738 | 0.9428 |
| 6 | $R_tR_{t-1}Q_{t-1}ACN$ | RMSE | 0.0295 | 0.0138 | 0.0285 |
| | | NSE | 0.9332 | 0.9743 | 0.9422 |
| 7 | $R_tR_{t-1}Q_{t-1}ASCN$ | RMSE | 0.0292 | 0.0138 | 0.0284 |

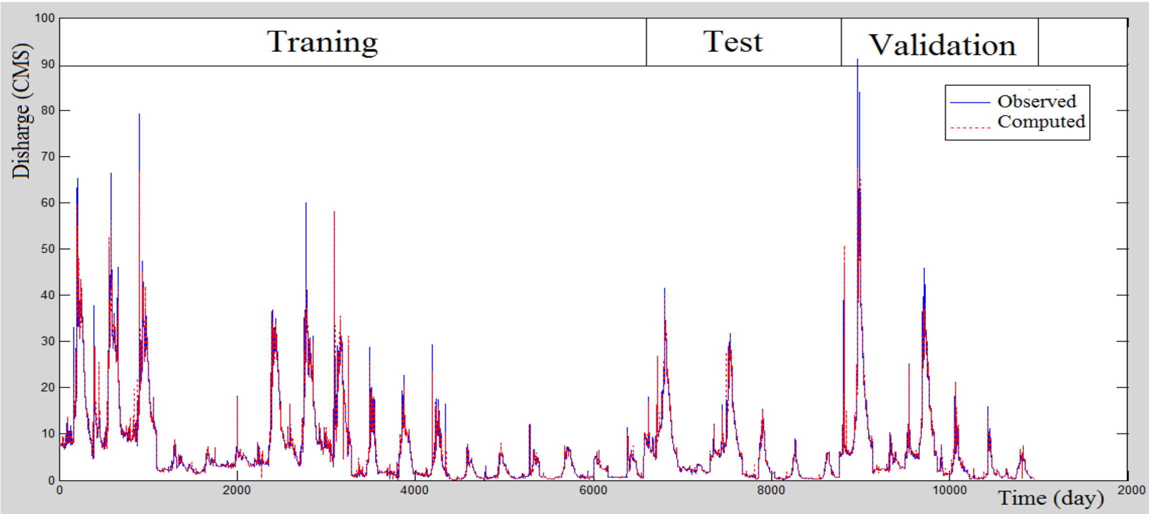


**Fig. 3.** Comparison of computed and observed of the IGANFIS model in five years for six stations.

**Cross Validation of IGANFIS model**

At this stage, in order to check validity of the model at each station that did not have data in the training of model (Vaspol), this was done as follows: instead of data of Abshar station, which is the adjacent to Vaspol station, data of the current day and one day ago rainfall and one day ago discharge of Vaspol station were entered into the input matrix of the model and again the IGANFIS model was executed by combining the $R_t$, $R_{t-1}$, $Q_{t-1}$, S and the subtractive clustering. Results are displayed in Table 14. RMSE of the whole model was obtained at validation stage (0.0291) and RMSE of Vaspol station (0.0346). Coefficient of performance (0.98941) and correlation coefficient (0.9496) for Vaspol station indicate high accuracy of the model in cross validation stage.

Fig. 5 exhibits the comparison of computed and observed data of IGANFIS model in the last year (validation period) as well as separately for the Vaspol station.

**Table 13.** Cross validation results of the best combination IGANFIS model ($R_tR_{t-1}Q_{t-1}S$)

| Combination | Criteria | Training | Testing | Validation |
|---|---|---|---|---|
| All stations | RMSE | 0.0268 | 0.0139 | 0.0291 |
| | RMSE | 0.0271 | 0.0146 | 0.0346 |
| Vaspol | NSE | 0.9544 | 0.9358 | 0.8491 |
| | R | 0.977 | 0.9676 | 0.9469 |

The best results of the models are given in Table 14. As shown in Table 14, IGANFIS has been able to increase performance of ANFIS. Finally, the IGANFIS with grid partitioning method was selected as the best model.

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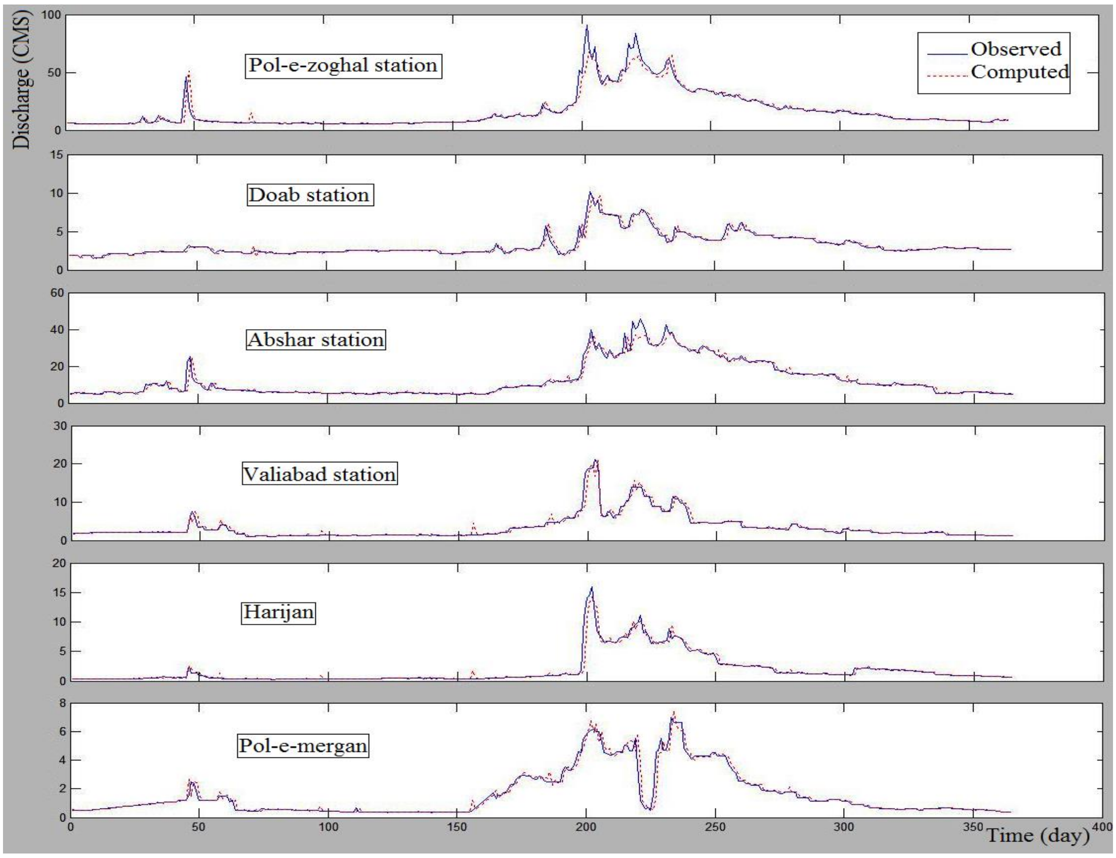


**Fig. 4.** Comparison of computed and observed of the last year (validation period) of the IGANFIS model.

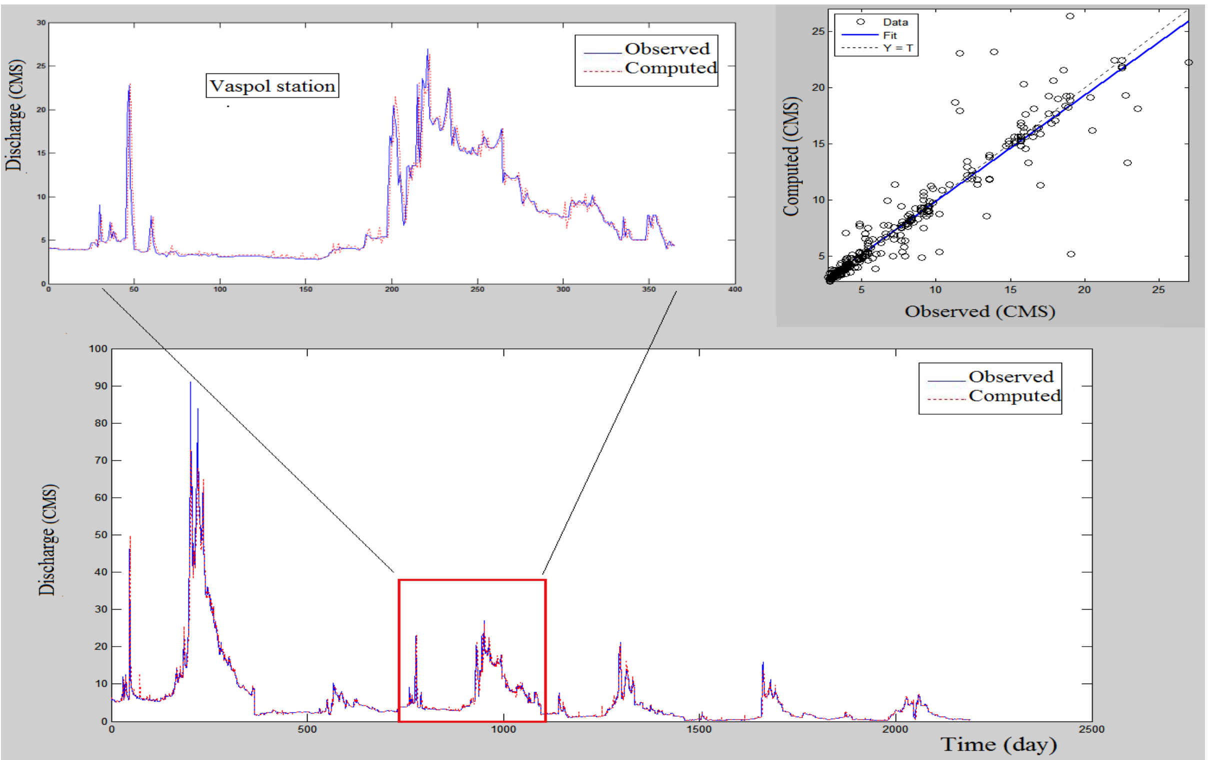


**Fig. 5.** Comparison of computed and observed discharge data of the last year (validation period) of the IGANFIS model during the omit validation stage in the whole station and Vaspol station.

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**Table 14.** Final comparison of models using RMSE and NSE.

| No | Combination | Criteria | Training | Testing | Validation |
|---|---|---|---|---|---|
| 1 | ANFIS | RMSE | 0.0282 | 0.0141 | 0.02796 |
| | | NSE | 0.9389 | 0.9729 | 0.94465 |
| 2 | IGANFIS with grid partitioning method | RMSE | 0.0273 | 0.146 | 0.02795 |
| | | NSE | 0.9427 | 0.9710 | 0.94467 |
| 3 | IGANFIS with subtractive clustering method | RMSE | 0.0291 | 0.0138 | 0.0283 |
| | | NSE | 0.9350 | 0.9743 | 0.9429 |

Since all data are normalized, the RMSE has no dimension.

Amount of peak discharge error have been obtained based on five peak discharge in the fifth year (validation period, Table 15). All models were underestimated. However, the ANFIS model exhibited a better estimation of the peak discharge than the others.

**Table 15.** Comparing the maximum values of forecasted peak discharge.

| No. | Model | Relative error % |
|---|---|---|
| 1 | ANFIS | 19.16 |
| 2 | IGANFIS with grid partitioning method | 20.26 |
| 3 | IGANFIS with subtractive clustering method | 23.43 |

## DISCUSSION

### RR modeling using ANFIS

It can be concluded that the ANFIS model with RMSE (0.0279) and NSE (0.9466) with low error and high accuracy can predict the RR process (Table 9). It is confirmed by the results of Nayak *et al.* (2004), Firat & Güngör (2007) and Nourani & Kalantari (2010). In 3 out of 8 combinations used in the ANFIS models (Table 9) and also in the best ANFIS composition, the generalized bell-shaped membership function was the best fuzzier.

In combinations which only rainfall is considered as the input of the model, in ANFIS models, the combination ($R_t$, $R_{t-1}$) has a better performance than $R_t$ combination, which indicates the effect of rainfall in the one day ago on increasing saturation, reducing soil permeability and increasing runoff. However, in the combinations which rainfall and discharge of previous days were considered, the best rainfall and discharge combinations were $R_t$, $R_{t-1}$, $Q_{t-1}$ and $R_t$, $R_{t-1}$, $Q_{t-1}$, $Q_{t-2}$ respectively.

### RR modeling using IGANFIS model

Modeling in this method was carried out with two different scenarios. At the first scenario, rainfall was only considered as input, and in the second one, in addition to rainfall, discharge were also considered as an input. Furthermore, we examined in the first scenario, different geomorphologic combinations with the best rainfall composition ($R_tR_{t-1}$) and in the second one with the best combination of rainfall and runoff ($R_tR_{t-1}Q_{t-1}$). The results of the first scenario exhibit that $R_tR_{t-1}S$ has been able to reduce the error of the ANFIS model with the combination ($R_tR_{t-1}$) (RMSE = 0.116538). This result reveals that the slope is a determinant factor in outflow runoff, consistent with results of Nourani & Komasi (2013). The area and CN were not affected. The reason why the slope combination with other factors did not exhibit better results may be due to weak nature of ANFIS in estimating models with inputs greater than number 4 (Dastorani *et al.* 2012).The results of second scenario (Table 11) also indicate that the geomorphology model ($R_t$, $R_{t-1}$, $Q_{t-1}$, S) has been able to reduce the error of the ANFIS model with the combination ($R_t$, $R_{t-1}$, $Q_{t-1}$). In this case, slope as the determining factor in output runoff, is in accordance with the first scenario of the present study, as well as with the results of Nourani & Komasi (2013).

Clearly, the model has been able to predict the output of all stations with high precision. This model is based on geomorphology in cross validation stage that can predict discharge of Vaspoul station in the current day which it was not involved initial training (Table 13) with high accuracy and these results also in line with results of Nourani & Komasi (2013).

### IGANFIS with subtractive clustering method

To investigate the effect of data clustering on modeling, IGANFIS with subtractive clustering method was implemented. According to the results (Table 12), the data cluster segregation has been clearly able to increase the efficiency of 6 out of 7 combinations, due to the efficiency of ANFIS with the large inputs and complexity of

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the structure. The clustering decreases the complexity of the structure of the model by decreasing the number of rules

**Integrated modeling of RR**

Typical rainfall-runoff models, such as ANN and ANFIS ones which is used in various papers, generally consider a single hydrometric station in the watershed output as a model output, but in the models used in this study, an integrated matrix was used to include total existing stations in the basin to model the rainfall-runoff process of Chalus River basin. Given the fact that they have been trained by the data of six hydrometric stations (instead of an outlet station), they are very promising and highly accurate, and the results of the cross validation stage can be pointed out as the witness that the Vaspol station has no role in the initial training of the model, but by placing the station in the input matrix.

## CONCLUSIONS

The purpose of this study was to predict runoff, not only at the basin outlet but also at any desired point within the catchment area. In order to achieve this goal, a matrix of hydro-climatic variables (rainfall and discharge) and physical properties (area, slop and CN) of the catchment area were created and highly desirable results with high accuracy by ANFIS model. So that the geomorphologic-adaptive fuzzy inference system (IGANFIS) with RMSE value equal to 0.02795 and the amount of NSE coefficient equal to 0.94467, as well as the models exhibited the predicted discharge value in the outlet of all Chalus basin stations with very low error and high precision. The results of cross validation phase at the Vaspol Station also verified this issue. The effective hydro-climatic factors were respectively selected discharge at the outlet of basin (the current and one-day ago rainfalls, the one, two and three days ago discharges) as well as the effective geomorphologic factors (average slope, curve number and upstream basin area) respectively. Meanwhile, the results of IGANFIS exhibited superior to the ANFIS model. Support Vector Machine (SVM) may also be used for modeling RR and their accuracies may be compared with each other.

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## REFERENCES

Aalami, MT, Hosseinzadeh, H 2010, Modeling rainfall – runoff process in Lighvan Chai basin using conditional threshold temperature neuron. *Water and Soil Science*, 20: 97-110.

Asadi, S, Shahrabi, J, Abbaszadeh, P Tabanmehr, S 2013, A new hybrid artificial neural networks for rainfall–runoff process modeling. *Neurocomputing*, 121: 470-480.

Dastorani, MT, Sharifi Darani, H, Ali, T, Moghadam Nia, A 2012, Evaluation of the application of artificial neural networks and adaptive neuro-fuzzy inference systems for rainfall-runoff modelling in Zayandeh_rood Dam Basin. *Iranian Journal of Water and Wastewater*, 22: 114-125.

Eshagh Teimori, MA, Habibnejad, M, Kaviyan, A, Shahedi, K 2012, Estimation of rainfall-runoff process in basin with low data using wms model (Case study: Chalus Watershed). *Irannian Journal of Irrigation & Water Engineering*, 3:12-25.

Firat, M, Güngör, M 2007, River flow estimation using adaptive neuro fuzzy inference system. *Mathematics and Computers in Simulation*, 75: 87-96.

Ghose, D, Panda, S, Swain, P 2013, Prediction and optimization of runoff via ANFIS and GA. *Alexandria Engineering Journal*, 52: 209-220.

Green, I, Stephenson, D 1986, Criteria for comparison of single event models. *Hydrological Sciences Journal*, 31: 395-411.

Jacquin, AP, Shamseldin, AY 2006, Development of rainfall–runoff models using Takagi–Sugeno fuzzy inference systems. *Journal of Hydrology*, 329: 154-173.

Jacquin, AP, Shamseldin, AY 2009, Review of the application of fuzzy inference systems in river flow forecasting. *Journal of Hydroinformatics*, 11: 202-210.



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Article type: Research

Jang, J-S 1993, ANFIS: adaptive-network-based fuzzy inference system, IEEE transactions on systems. *Man, and Cybernetics*, 23: 665-685.

Jayawardena, A, Perera, E, Zhu, B, Amarasekara, J, Vereivalu, V 2014, A comparative study of fuzzy logic systems approach for river discharge prediction. *Journal of Hydrology,* 514: 85-101.

Kisi, O, Shiri, J, Tombul, M 2013, Modeling rainfall-runoff process using soft computing techniques. *Computers & Geosciences*, 51: 108-117.

Kurtulus, B, Razack, M 2010, Modeling daily discharge responses of a large karstic aquifer using soft computing methods: Artificial neural network and neuro-fuzzy. *Journal of Hydrology,* 381: 101-111.

Lohani, A, Kumar, R, Singh, R 2012, Hydrological time series modeling: A comparison between adaptive neuro-fuzzy, neural network and autoregressive techniques. *Journal of Hydrology*, 442: 23-35.

Moghimi, A, Mousavi Harami, R, Motamed, A, Ahmadi, H 2009, Investigating the effect of morphometric variables of watershed on maximum flood discharge in the Chalous river basin using statistical methods and mathematical models. *Journal of Land and Resources*, Islamic Azad University, Lahijan Branch, 2: 65-80.

Nash, JE, Sutcliffe, JV 1970, River flow forecasting through conceptual models part I—A discussion of principles. *Journal of Hydrology*, 10: 282-290.

Nayak, P, Sudheer, K, Jain, S 2007, Rainfall-runoff modeling through hybrid intelligent system. *Water Resources Research*, 43, W07415, doi:10.1029/2006WR004930.

Nayak, PC, Sudheer, K, Rangan, D, Ramasastri, K 2004, A neuro-fuzzy computing technique for modeling hydrological time series. *Journal of Hydrology,* 291: 52-66.

Nourani, V, Kalantari, O 2010, Integrated artificial neural network for spatiotemporal modeling of rainfall–runoff–sediment processes. *Environmental Engineering Science*, 27: 411-422.

Nourani, V, Kisi, Ö, Komasi, M 2011, Two hybrid artificial intelligence approaches for modeling rainfall–runoff process. *Journal of Hydrology*, 402: 41-59.

Nourani, V, Komasi, M 2013, A geomorphology-based ANFIS model for multi-station modeling of rainfall–runoff process. *Journal of Hydrology*, 490: 41-55.

Rashidi, S, Vafakhah, M, Lafdani, EK, Javadi, MR 2016, Evaluating the support vector machine for suspended sediment load forecasting based on gamma test. *Arabian Journal of Geosciences*, 9: 583.

Talei, A, Chua, LH 2012, Influence of lag time on event-based rainfall–runoff modeling using the data driven approach. *Journal of Hydrology*, 438: 223-233.

Talei, A, Chua, LHC, Wong, TS 2010, Evaluation of rainfall and discharge inputs used by Adaptive Network-based Fuzzy Inference Systems (ANFIS) in rainfall–runoff modeling. *Journal of Hydrology*, 391: 248-262.

Vafakhah, M 2012, Application of artificial neural networks and adaptive neuro-fuzzy inference system models to short-term streamflow forecasting. *Canadian Journal of Civil Engineering*, 39: 402-414.

Wang, W-C, Chau, K-W, Cheng, C-T, Qiu, L 2009, A comparison of performance of several artificial intelligence methods for forecasting monthly discharge time series. *Journal of Hydrology*, 374: 294-306.

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# شبیه‌سازی فرآیند بارش-رواناب با استفاده از روش استنتاج عصبی-فازی تطبیقی مبتنی بر ژئومورفولوژی در حوزه آبخیز چالوس

شعبانعلی غلامی[۱]، مهدی وفاخواه[۲*]، کمال قادری[۱]، محمدرضا جوادی[۱]

۱-گروه منابع طبیعی، دانشگاه آزاد اسلامی واحد نور، نور، ایران

۲-گروه مهندسی آبخیزداری، دانشکده منابع طبیعی دانشگاه تربیت مدرس، نور، ایران

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## چکیده

پیش‌بینی دقیق دبی رودخانه یکی از ضروریات مدیریت منابع آب حوزه آبخیز برای برنامه‌ریزی و کنترل اثرات سیل و خشکسالی به حساب می‌آید. در این راستا مدل‌سازی فرآیند بارش رواناب به منظور درک بهتر آن و پیش بینی دقیق‌تر دبی در کانون توجه قرار گرفته است. این تحقیق به منظور ارائه یک مدل بارش رواناب یکپارچه که مبتنی بر خصوصیات فیزیکی حوزه آبخیز باشد، انجام شده است. هدف از این تحقیق این بود که پیش بینی رواناب نه فقط در خروجی حوضه، بلکه در هر نقطه دلخواه در داخل حوضه قابل انجام باشد. برای وصول به این هدف، ماتریسی از پارامترهای هیدروکلیماتیک (بارش روزانه و دبی روزانه) و خصوصیات ژئومورفولوژیک (مساحت، شیب و CN) طراحی شد و با استفاده از روش‌های هوش مصنوعی اجرا شد. مدل شبکه عصبی مصنوعی یکپارچه مبتنی بر ژئومورفولوژی (IGANN) با مقدار RMSE برابر ۰/۰۲۷۸۶ و ضریب کارایی برابر ۰/۹۴۵۰۳ و سیستم استنتاج عصبی فازی تطبیقی یکپارچه مبتنی بر ژئومورفولوژی (IGANFIS) با مقدار RMSE برابر ۰/۰۲۷۹۵ و ضریب کارایی برابر ۰/۹۴۴۶۷ توانستند با خطای بسیار کم و دقت بسیار بالا، دبی خروجی همه ایستگاه های هیدرومتری حوزه آبخیز چالوس را پیش‌بینی کنند. نتایج مرحله اعتبارسنجی حذفی در ایستگاه واسپول نیز این مسئله را تایید کرد. عوامل هیدروکلیماتیک موثر در خروجی دبی به ترتیب (دبی روز قبل، دبی دو روز قبل، بارش روز جاری و بارش روز قبل) و عوامل ژئومورفولوژیک موثر به ترتیب (شیب متوسط، شماره منحنی و مساحت حوضه بالادست) انتخاب شد. در ضمن نتایج مدل IGANN نسبت به IGANFIS برتری نشان داد.

*مؤلف مسئول

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