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Monthly River Flow Prediction using Adaptive Neuro-Fuzzy Inference System (A Case Study: Gharasu Watershed, Ardabil Province-Iran)

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ABSTRACT There is different methods for simulating river flow. Some of thesemethods such as the process based hydrological models need multiple input data and high expertise about the hydrologic process. But some of the methods such as the regression based and artificial inteligens modelsare applicable even in data scarce conditions. This capability can improve efficiency of the hydrologic modeling in ungauged watersheds in developing countries. This study attempted to investigate the capability of the Adaptive Neuro-Fuzzy Inference System (ANFIS) for simulating the monthly river flow in three hydrometric stations of Pole-Almas, Nir, and Lai; which have different rate of river flow. The simulations are conducted using three input data including the precipitation, temperature, and the average monthly hydrograph (AMH). The study area islocated in the Gharasu Watershed, Ardabil Province, Iran. For this aim, six groupsof input data (M_1, M_2, … M_6) were defined based on different combinations of the above-mentioned input data. Theconducted simulations in Pole-Almas and Nir stations have presented an acceptable results; but in Lai station it was very poor. This different behavoirs was referred to the lower volume of flow and consequently irregularity and variability of flow in Lai station, which cause the decrease of accuracy in the simulation. The AMH parameter had an important role in increasing the accuracy of the simulations in Pole-Almas and Nir stations. The findings of this study showed that ANFIS is an efficient tool for river flow simulation; but in application of ANFIS, the selection and utilization of relevant and efficient input data will have a determinativerole in achieving to a successful modeling.

Key words: *Artificial neural network, Average monthly hydrograph, Fuzzy logic, Rainfall-runoff modeling*

1 INTRODUCTION

Accurate prediction of river flow is necessary for many purposes such as appropriate management of drought, reservoir operation, environmental protection, and water supply operation. There are a large number of mathematical hydrologic models that are developed to be used for river flow simulation. These models can be classified as either physically based or system theoretic models (Mutlu *et al.*, 2008). Physically based models involve a detailed description of various

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physical processes that control the hydrologic behavior of a system. Physically based models such as, Areal Nonpoint Source Watershed Environment Response Simulation (ANSWERS) (Bouraoui *et al.,*1996), Agricultural Non-Point Source Pollution Model (AnnAGNPS) (Bosch *et al.,* 1998) and Soil and Water Assessment Tool (SWAT) (Arnold *et al.,* 1998), often need a large number of input parameters that are not easily available in all regions. System theoretic models as an alternate method for runoffestimation are particularly useful in areas such as the Gharasu Watershed, where there is a lack of environmental data. The Adaptive Neuro-fuzzy Inference System (ANFIS), is a type of artificial intelligence models that is classified as a system theoretic model, and is capable for creating an acceptable simulation of complex and non-linear processes even in data scarce conditions (Kadhim, 2011). These models don't consider the physical characteristics of the parameters and they map the data from input to output using transfer functions (Mutlu *et al.*, 2008). Development, calibration, and application of the process based hydrological models for a river flow simulation has always been atedious and time consuming work for the experts (Akbari *et al.,* 2013). Construction of a artificial intelligence based rainfall-runoff model that uses just three easily available input data (precipitation, temperature, and the average monthly hydrograph (AMH)) is valuable in the field of hydrologic modeling. The AMH of a river provide information on the long term river regime, influenced by watershed characteristics such as topography and climate watersheds. ANFIS has been gained considerable popularity in various fields of hydrologic modeling in recent years.

A review of the application of ANFIS in hydrologic studies is represented in Chang *et al.* (2001), Chen *et al.* (2006), Aqil *et al.* (2007), Firat (2007), Elabdand Schlenkhoff (2009), Jothiprakash and Garg (2009), Wang *et al.* (2009), Talei *et al.* (2013), He *et al.* (2014), Vafakhah *et al.* (2014) and Hsu *et al.* (2015). Most of these studies used the one step-ahead and/or multi steps-ahead methods for river flow simulation. But there is some researches in which attempted to use environmental independent data as input parameters for river flow simulation. Kumar *et al.* (2005) have used the precipitation data in real time and previous days for modeling the daily river flow in two Indian RiverBasins, and they obtained the accuracy of simulation by coefficient of determination (R^2) of 0.86. Nayak *et al.* (2004) used different combinations of the precipitation data in four previous days (t_{n-1}, t_{n-2}, t_{n-3} and t_{n-4})for daily river flow simulation in Pennsylvania– USA, and obtained the accuracy of simulations, R^2=0.3, 0.25, 0.34, and 0.27different groups of the input variables. Hosseini and Mahjouri (2016) in application of artificial intelligence models for rainfall-runoff modeling in Qomrud Watershed, have used different combinations of rainfall and river flow data as inputs, in the way of some steps ahead method.Their results showed that use of precipitation data as an input parameter couldn't increase the accuracy of the simulation.

A literature review revealed that there is no history of use the AMH parameter as an input parameter for river flow simulation, whereas it is expected that this parameter can considerably improve the accuracy of the simulation.

Assessment of the ANFIS models capability for a rainfall-runoff simulation is the main objective of this study, and the second objective is to investigate the effect of the AMH as an input data in improving the accuracy of river flow simulation.

In order to simulate a long term river flow using rainfall-runoff modeling, it is needed to define a systematic relationship between input weather data and the output river flow, using a suitable and efficient interface. The learning and simulation capabilities of the ANFIS can provide this system. This study has attempted to employ the ANFIS for simulation of monthly flow in three hydrometric stations in Gharasu

Watershed, Iran, using six different groups of input data, including M_1 (P_t, T_t), M_2 (P_t , T_t , AMH), M_3 (P_t , P_{t-1} , AMH, T_t , T_{t-1}), M_4 (P_t , P_{t-1} , P_{t-2} , AMH, T_t , T_{t-1} , T_{t-2}), M_5 (P_t , P_{t-1} , P_{t-2}, T_t , T_{t-1} , T_{t-2}) and M_6 (P_t , P_{t-1}, P_{t-2} , AMH), where P, T and AMH refer to precipitation, temperature and the average monthly hydrograph, respectively. Three parameters of the monthly precipitation, monthly temperature, and average monthly hydrograph (AMH), are used as inputs of the ANFIS models.

2 MATERIAL AND METHODS

This study is carried out to simulate monthly discharge of Pole-Almas, Nir, and Lai stations on the Gharasu Watershed, Ardabil Province, Iran (Figure 1). The study area with an annual average precipitation and temperature of 361 mm and 8.4 ºC respectively, and generally crop land cover, is located in the hillside of the Sabalan Mountains in Ardabil Province, Iran. Drainage area and average outflow of the Pole-Almas, Nir, and Lai stations are 112.669, 27.236 and 5.395 ha and 3.7, 1.3 and 0.12 m^3s^{-1}, respectively. In Pole-Almas and Nir, 17 years data series of monthly data have been used for the period of training. The data used for training in Lai was a 15 years data series. Lack of sufficient recorded data in Lai stationcaused this inequality. The length of the used data series for the testing period in all the three stations were 6 years.

The ANFIS as a combination of the Artificial Neural Network (ANN) and the fuzzy logic, is a powerful tool for modeling the hydrologic process (Firat, 2007; Wang *et al.*, 2009). A comprehensive presentation of ANFIS for hydrological simulation can be found in the literature (Nayak *et al.*, 2004; Keskin *et al.*, 2006; Shu and Ouarda, 2008; Vafakhah, 2012). The learning ability of the ANN for defining the input-output relationship, and reasoning capability of the fuzzy logic for obtaining the system results are combined in ANFIS to construct a powerful intelligent system.

The ANN has the ability to learn from examples, recognize a pattern in the data, adapt solutions over time, and process information rapidly (Kisi, 2003). The artificial neurons in the ANN run in parallel. This function causes that the information rapidlyprocess in ANN. Outlining of a relationship between input and output data, requires to find the right weights in the neurons structure.

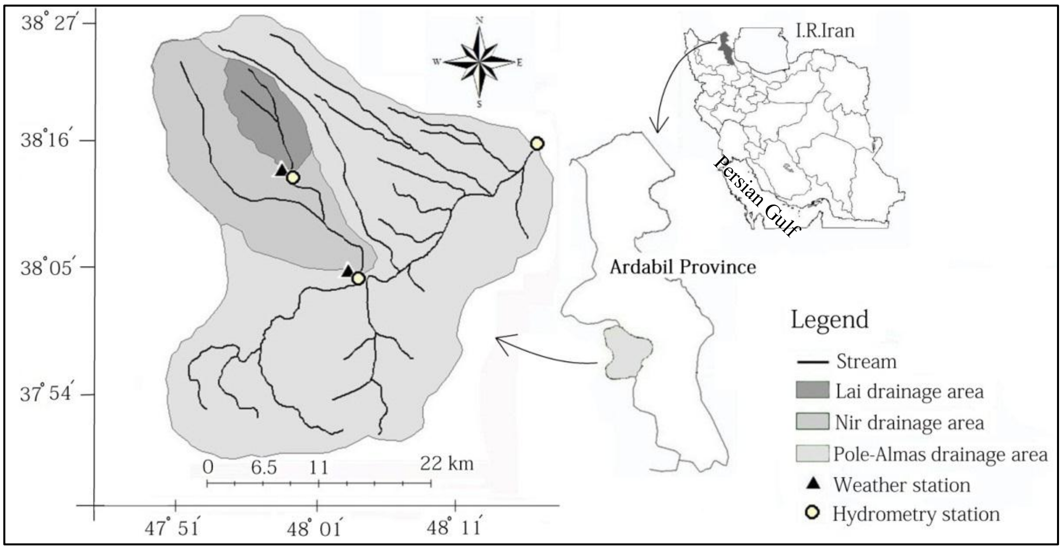

Figure 1 A general view and location of the Gharasu Watershed in Ardabil Province, Iran

Data processing in ANNis done by minimizing the mean square error of the difference between observed data and simulated results of ANN. The feed-forward back propagation algorithm (FFBP) with a Levenberg-Marquardt learning method was used to train the network configuration (Wang *et al.,* 2009). This algorithm involves a phase of feed-forward in which each neuron in a layer receives the weighted inputs from a previous layer and after a summation function (Eq.1) transmits its output to neurons in the next layer; and a phase of back propagation in which modification to the connection strengths are made based on the differences between the computed and observed information signals at the output units (Firat, 2007; Vafakhah, 2012).

$$Y_{net} = \sum_{i=1}^{N} (Y_i.w_i + w_0) \qquad (1)$$

where, Y_{net} is the summation of weighted inputs, Y_i is the neuron input, w_i is weight coefficient of each neuron input, w_0 is bias.

Fuzzy inference system consists of three components. A rule-base, containing fuzzy if-then rules, a data-base, defining the membership function, and an inference system, combining the fuzzy rules and producing the system results (Firat, 2007).

In application of ANFIS for hydrologic modeling, the ANFIS is based on the first-order Sugeno fuzzy model and its neural network is used in a multiple layer feed-forward back-propagation network. An ANFIS architecture based on a first-order Sugeno model, with two fuzzy if–then rules areshown as (Eqs. 2 and 3):

Rule 1: If x is A_1 and y is B_1; then $f_1=p_1.x+q_1y.r_1$ (2)

Rule 2: If x is A_2 and y is B_2; then $f_2=p_2.x+q_2y.r_2$ (3)

where,x and y are the inputs, A_i and B_i are the membership functions for inputs, p_i, q_i and r_i are the parameters of the output function which are determined during the training process.

Generally, the ANFIS structure is composed of five layers (Figure 2). The first layer, consistinginput nodes generates the membership grades based on the appropriate fuzzy set they belong to using membership functions. The second layer, consisting rule nodes, generates the firing strengths by multiplying the incoming signals and outputs operator results. The third layer, consisting average nodes computes the normalized firing strengths. The fourth layer, consisting consequent nodes calculates the first-order Takagi-Sugeno rules for each fuzzy rule based on the model output. Takagi-Sugenorulesis a systematic approach to generating fuzzy rules from a given input-output dataset. The fifth layer, includingsingle output node, calculates the overall output of the ANFIS as the summation of incoming signals (Jang, 1993).

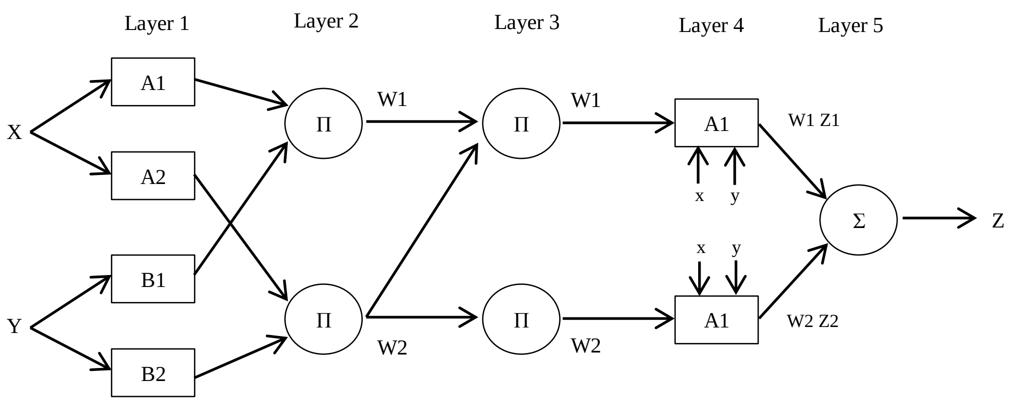

Figure 2 A typical ANFIS architecture used in this study (Takagi and Sugeno, 1985)

This rainfall-runoff modeling in study was performed based on six different groups of input parameters which were consisted of monthly precipitation (P), monthly temperature (T) and the average monthly hydrograph (AMH) (Table 1). The precipitation and temperature of one and two previous months are defined and participated in the modeling as the parameters of P_{t-1}, P_{t-2}, T_{t-1} and T_{t-2}.

In order to calculate and prepare the AMH parameter, at the first step, the average river flow for each month was calculated based on the recorded data for each of the three stations,separately. The consequence of these processeswas a set of 12 values data that is considered as a one year hydrograph by monthly time step. Then, this 12 values dataset repeated and extended continuously to result a time series that is named AMH.The calculation processes of the AMH parameter is represented schematically in the Figure 3.

Table 1 Six ANFIS models with the corresponding input parameters

Model	Input parameters
M_1	P_t , T_t
M_2	P_t , T_t , AMH
M_3	P_t , P_{t-1} , AMH, T_t , T_{t-1}
M_4	P_t , P_{t-1} , P_{t-2} , AMH, T_t , T_{t-1} , T_{t-2}
M_5	P_t , P_{t-1} , P_{t-2}, T_t , T_{t-1} , T_{t-2}
M_6	P_t , P_{t-1}, P_{t-2} , AMH

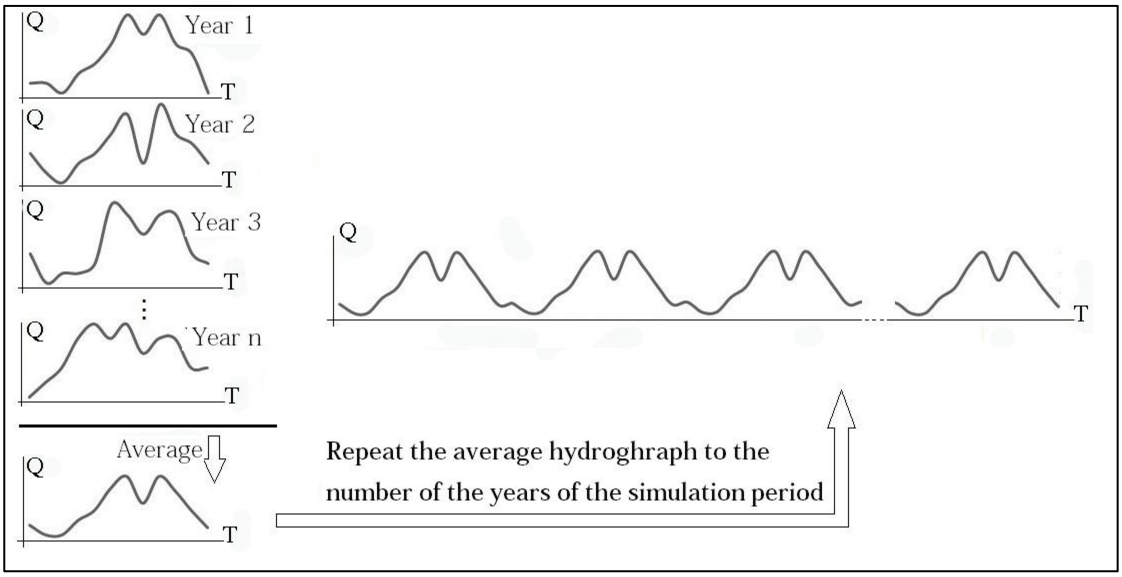

Figure 3 Calculation processes of the AMH parameter

Data normalization, is a frequently used preprocess in application of ANFIS models (Kisi, 2003). There are two main advantages in normalizing the data before applying ANFIS to streamflow simulation. One advantage is to avoid attributes in greater numeric ranges dominating those in smaller numeric ranges, and the other advantage is to avoid numerical difficulties during the calculation (Vafakhah, 2012). In this study, the input and target data were normalized into 0 to1, using (Eq.4):

$$N_i = \frac{X_i - X_{min}}{X_{max} - X_{min}} \qquad (4)$$

where N_i is the normalized data, X_i is the original data, X_{min} is the minimum and X_{max} is the maximum of the data series.

For cunstructing the ANFIS model, during a trial and error process and continuous change on the type of themembership functions and the number of membership functions, two generalized bell-shaped membership functions were used for input variables.It is notable that gbellmf is one of the most commonly used membership functions in the field of river flow simulation (Vafakhah, 2012). The grid partitioning method was used for generation of fuzzy inference system (FIS).This partitioning strategy works well when only few number of inputs are involved, and so it requires only a small number of membership function for each input.The Sugeno fuzzy model was used as theFIS, since the consequent part of this FIS is a linear equation and the parameters can be estimated by a simple least squares error method (Nayak *et al.,* 2004). The ANFIS is trained using the back propagation algorithm to determine the parameters defining the shape of the generalized bell-shaped membership function and least-squares estimation technique to estimate the parameters in the output function.The complementary informations about the conducted ANFIS modelsare presented in Table 2.

Table 2 Some informaion about the conducted ANFIS models structure for the study stations

Characteristic	Pole-Almas	Nir	Lai
Number of nodes	34	92	21
Number of linear parameters	8	32	4
Number of nonlinear parameters	18	30	12
Number of training data pairs	202 (75%)	202 (75%)	178 (72%)
Number of testing data pairs	70 (25%)	70 (25%)	70 (28%)
Number of fuzzy rules	8	32	4

Results of the ANFIS models were compared with the observed data and were evaluated using four statistic measures including R^2, Nash-Sutcliffe (NS), root mean square error (RMSE) and percent error in mean (PEM) (Eqs. 5 to 8)(Green and Stephenson, 1986).

$$R^2 = (\frac{\sum_{i=1}^{n}(O_i-\bar{O})(P_i-\bar{P})}{\sqrt{\sum_{i=1}^{n}(O_i-\bar{O})^2}\sqrt{\sum_{i=1}^{n}(P_i-\bar{P})^2}} \quad (5)$$

$$NS = 1 - \frac{\sum_{i=1}^{n}(O_i-P_i)^2}{\sum_{i=1}^{n}(O_i-\bar{O})^2} \quad (6)$$

$$RMSE = \sqrt{\frac{1}{n}\sum(O_i - P_i)^2} \quad (7)$$

$$PEM = \frac{\bar{P}-\bar{O}}{\bar{O}} \quad (8)$$

where, O_i is the observed data, P_i is the simulated data, $\bar{O}$ is the average of the observed data and $\bar{P}$ is the average of the simulated data.

3 RESULTS AND DISCUSSION

In this study, the results of the conducted simulations in the Pole-Almas and Nir stations wasrelatively acceptable and in some cases has been obtained good (Table 3 and Figure 4). But the results of the Lai station are quite distinct from them, and are very poor. The value of the efficiency indices used for evaluating the ANFIS models results in the training periods ispresented in Table3.

The simulated hydrographs in the training period along with the observed data are shown in Fiqure 4. These hydrographs are related to the models that had the best results in the testing period.

Table 3 Accuracy of ANFIS models results in training period

Station	Indices	M 1	M 2	M 3	M 4	M 5	M 6
Pole-Almas	R^2	0.57	0.78	0.85	0.81	0.72	0.82
	NS	0.57	0.78	0.84	0.80	0.68	0.81
	PEM	-0.02	-0.04	0.00	-0.01	-0.03	-0.05
	RMSE	2.14	1.53	1.30	1.44	1.85	1.44
Nir	R^2	0.42	0.50	0.56	0.53	0.46	0.52
	NS	0.41	0.49	0.55	0.52	0.44	0.51
	PEM	0.04	-0.04	-0.01	0.00	-0.05	0.00
	RMSE	0.65	0.61	0.57	0.59	0.64	0.59
Lai	R^2	0.21	0.36	0.36	0.37	0.36	0.33
	NS	0.20	0.36	0.35	0.37	0.35	0.32
	PEM	0.03	0.01	0.03	0.00	0.00	-0.01
	RMSE	0.06	0.05	0.06	0.05	0.06	0.06

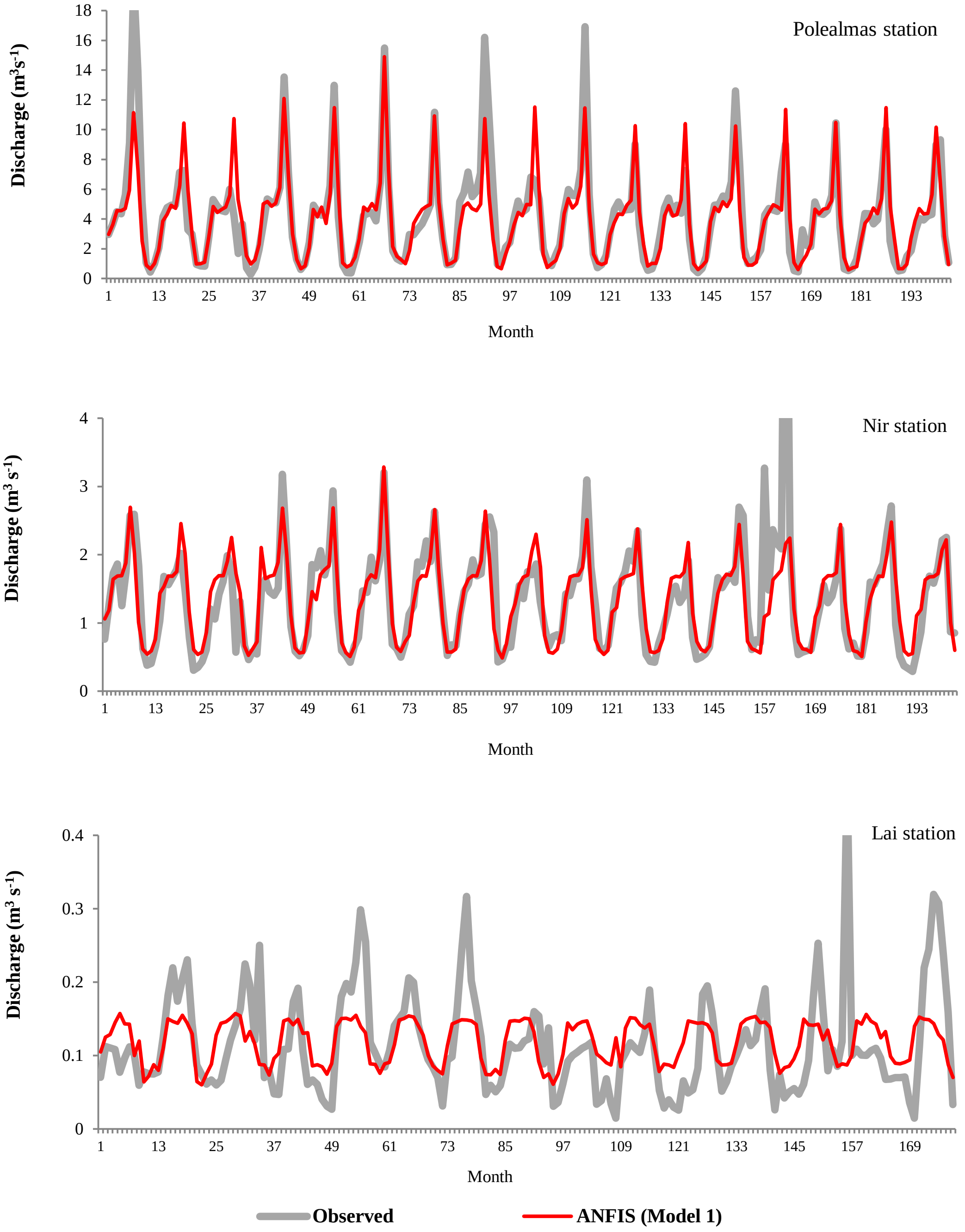

Figure 4 The simulated hydrographs of the ANFIS models in the training period in comparison with the observed data

The simulated hydrographs of the best resulted ANFIS models in the testing period in comparison with the observed data in all three stations are shown in Figure 5.

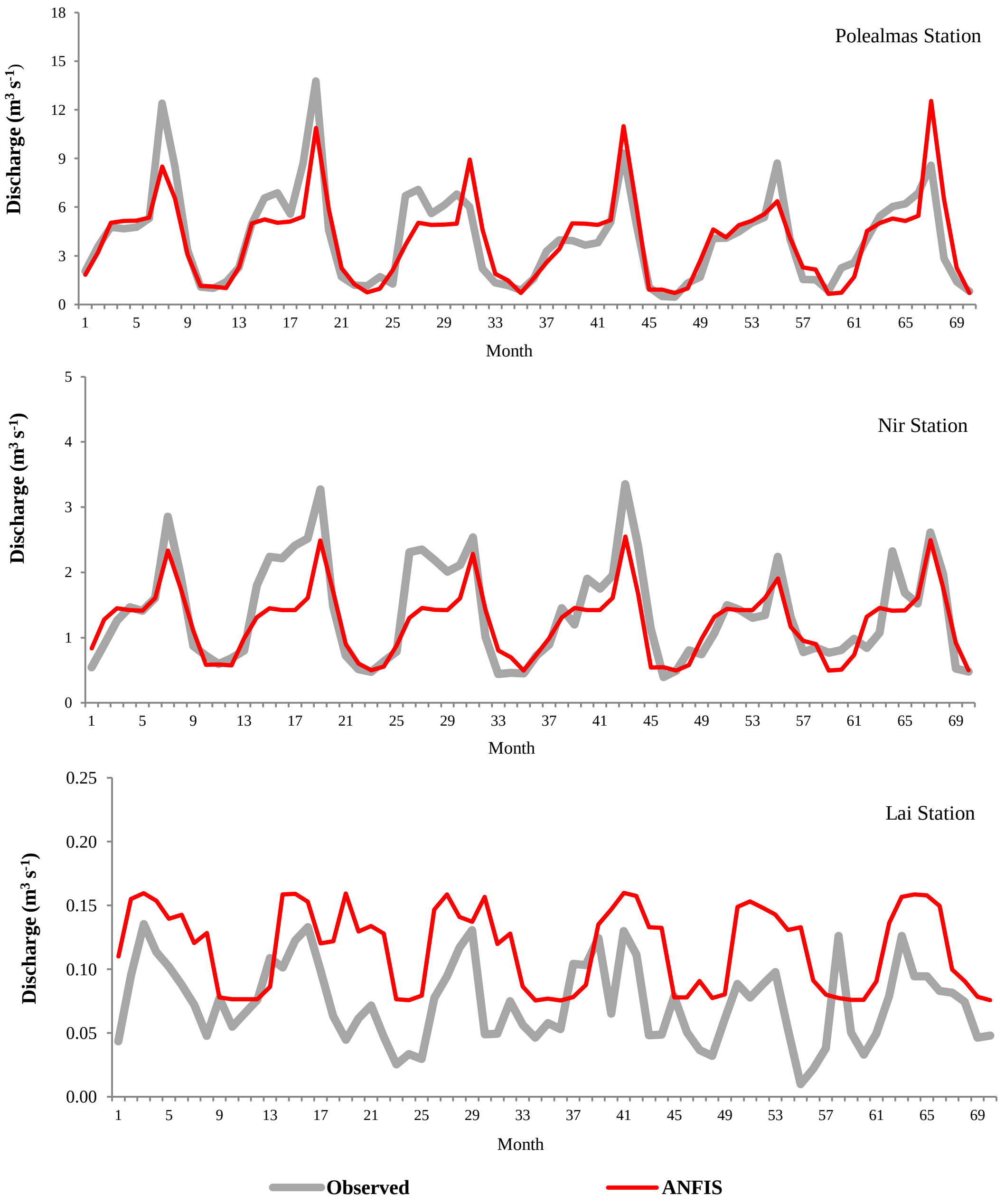

Figure 5 The simulated hydrographs of the ANFIS models in the testing period in comparison with the observed data

Table 4 Accuracy of the ANFIS models results in the testing period

Station	Index	M 1	M 2	M 3	M 4	M 5	M 6
Pole-Almas	R^2	0.52	**0.77**	0.73	0.75	0.67	0.75
	NS	0.50	**0.76**	0.72	0.74	0.65	0.75
	PEM	-0.08	**-0.04**	0.01	0.01	-0.04	-0.02
	RMSE	1.98	**1.39**	1.49	1.43	1.66	1.41
Nir	R^2	0.51	0.75	**0.77**	0.74	0.60	0.71
	NS	0.51	0.66	**0.74**	0.69	0.57	0.65
	PEM	-0.01	-0.11	**-0.08**	-0.08	-0.07	-0.11
	RMSE	0.53	0.44	**0.39**	0.42	0.49	0.44
Lai	R^2	**0.22**	0.06	0.05	0.02	0.09	0.09
	NS	**-1.86**	-2.73	-3.51	-3.24	-1.77	-2.71
	PEM	**0.56**	0.56	0.64	0.58	0.52	0.60
	RMSE	**0.05**	0.06	0.07	0.06	0.05	0.06

The results of the simulations in the Pole-Almas and Nir stations were acceptable, but the simulation in the Lai station, wasaccompanied by a large error. Considering the fact thatapplication of different number of input parameters and different number of fuzzy rules in ANFIS model couldn't increase the accuracy of the simulation in Lai, it can be resulted that the river flow in this station is inherently prone to a weak simulation, due to its low flow and highly variable condition (Poof and Ward, 1989). In other words, it can be said that there is some other environmental variablessuch as snow melt process and agricultural water use, needed to be used as an input parameter in this modeling to achieve a more accurate result. In this station the mean of the flow is 0.12 m^3s^{-1}, and as it is evident in the Figure 4, the river flow is quite irregular and variable. So, in this situation a high accuracy of prediction is somewhat out of the reach. Accordingly, it can be deduced that, what ever the rate of a river flow is higher, its simulation can be more accurate.

Because of that the partitioning of the data for training and testing periods were coducted arbitrarily in two continuous time series instead of the randomly partitioning method, the river flow regime in these two parts is possible not to be the same. It is notable this partitioning is directed because of that the simulation of a continuous time series of river flowis more useful in water resource management and hydrologic studies.

It is clear that, participation rate of the snowmelt runoff, groundwater and/or other hydrologic components in outflow can be variant in some years. In this condition, the accuracy of the results in a river flow simulation by a specific input parameters may be variant in different time series in a specific hydrometric station data.Accordingly, it can be

deduced that, what ever the rate of a river flow is higher, its simulation can be more accurate.
A survey in the input parameters of the investigated ANFIS models and their efficiency values show that the AMH parameter was quite effective as a sensitive parameter for river flow simulation. This parameter representing the average of the monthly flow, is more efficient for the data series that have low rate of variation in different years.

The results showed that the efficiency ranking of the investigated models are as the orders of "M2, M6, M4, M3, M5, M1" in the Pole-Almas station, and "M3, M4, M2, M6, M5, M1" in the Nir station, and "M1, M5, M6, M2, M3, M4" in the Lai station. In the Pole-Almas and Nir stations, the ANFIS models without the input parameter of the AMH (M1 and M5) had the weakest results. When the AMH parameter was added as an input to the M1 and created M2, the accuracy of the prediction improved considerably (Table 3). This result proves that the AMH parameter can be a helpful and effective parameter in river flow simulation. Of course, it should be noted that, this parameter can not be helpful in the low flow and highly variable rivers. This point is evident in the results of the Lai stations, where the ANFIS models without the input parameter of AMH (M1 and M5) had the best results, and addition of this parameter to the inputs have caused a reduction in the accuracy of the results. To verify this, the results of the M1 and M2were compared.

The results presented that the parameters of P_{t-1}, P_{t-2}, T_{t-1}, T_{t-2} hadn't important effect on the accuracy of the predictions. This can be understood by a comparison between the results of the M2 (P_t , AMH, T_t), M3 (P_t, P_{t-1}, AMH, T_t, T_{t-1}), and M4 (P_t, P_{t-1}, P_{t-2}, AMH, T_t, T_{t-1}, T_{t-2}) which are quite similar. The insensitivity of this parameters may be related to the small drainage area of the catchments, in where the lag time of the underground flow is less than a month.

The results of this study in Pole-Almas and Nir stations were acceptable. This result is similar to the results of Kumar *et al.* (2005). But it wasn't satisfactory in Lai station. This result is similar to the results of Nayak *et al.* (2004) and Hosseini and Mahjouri (2016). The difference of behavior in the mentioned sitescan be a proof for the fact that the complexity of the hydrological process in different sites isn't similar, and it cann't be expected to have a successful prediction of river flow based on just a few number of environmental factors.

4 CONCLUSIONS

This study was an attempt to a rainfall-runoff modeling using ANFIS models with the input parameters of the precipitation, temperature, and the average monthly hydrograph. The results of the study confirmed the validity of this method.

A comparison between the results of the conducted simulations in the Pole-Almas, Nir, and Lai stations confirmed that rivers with low flow are unlikely to be simulated in a high precision. Because that the presence of irregularities and variabilities in their flow prevents from achieving a precise prediction.

The AMH parameter was introduced in this study, and its effect on the accuracy of the river flow prediction was investigated. The results showed that this parameter can cause an undeniable role in improving the accuracy of the prediction. In general, it can be said that in application of ANFIS for river flow modeling, selection and utilization of relevant and efficient input parameters have a decisive role in achieving to a successful results.

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پیش‌بینی جریان ماهانه رودخانه با استفاده از سیستم استنتاج عصبی-فازی تطبیقی (مطالعه موردی: حوزه آبخیز قره‌سو استان اردبیل)

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چکیده روش‌های مختلفی برای شبیه‌سازی جریان رودخانه وجود دارد. برخی از این روش‌ها مانند استفاده از مدل‌های هیدرولوژیکی فرآیند محور نیازمند به داده‌های ورودی متعدد و داشتن تخصص کافی در مورد فرآیندهای هیدرولوژیکی هستند. ولی، برخی از روش‌ها مانند مدل‌های رگرسیونی و هوش مصنوعی حتی در شرایط کمبود داده نیز قابلیت استفاده دارند. این قابلیت می‌تواند کارایی مدل‌سازی‌های هیدرولوژیکی در آبخیزهای بدون ایستگاه اندازه‌گیری در کشورهای در حال توسعه را افزایش دهد. در پژوهش حاضر سعی شده است قابلیت سامانه استنتاج عصبی فازی تطبیقی (ANFIS) برای شبیه‌سازی جریان ماهانه رودخانه در سه ایستگاه هیدرومتری دارای میانگین دبی متفاوت شامل پل الماس، نیر و لای، ارزیابی شود. در این شبیه‌سازی‌ها از سه داده بارش، دما و میانگین دبی ماهانه (AMH) به‌عنوان ورودی مدل‌ها استفاده شده است. منطقه مورد مطالعه، حوزه آبخیز قره‌سو در استان اردبیل می‌باشد. در این تحقیق، شش ترکیب مختلف (M_1، M_2، ... M_6) از داده‌های ورودی اشاره شده، تعریف و به‌عنوان ورودی در مدل‌ها استفاده شده است. شبیه‌سازی‌های انجام شده در ایستگاه‌های پل الماس و نیر نتایج قابل قبولی داشتند، ولی در ایستگاه لای نتایج ضعیف بود. این رفتار متفاوت را می‌توان به پایین بودن دبی جریان در ایستگاه لای و در نتیجه، نامنظم و متغیر بودن جریان ارتباط داد که باعث می‌شود این نوع جریان‌ها به راحتی قابل پیش‌بینی نباشند. پارامتر AMH نقش مهمی در افزایش دقت شبیه‌سازی در ایستگاه‌های پل الماس و نیر داشت. یافته‌های این تحقیق بیان می‌کند که ANFIS یک ابزار کارآمد و سریع برای شبیه‌سازی بارش-رواناب است، ولی در استفاده از ANFIS انتخاب و استفاده از پارامترهای ورودی کارآمد نقش تعیین‌کننده‌ای در دست‌یابی به یک شبیه‌سازی موفق است.

کلمات کلیدی: شبکه عصبی مصنوعی، مدل‌سازی بارش-رواناب، منطق فازی، هیدروگراف میانگین ماهانه