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ABSTRACT There is different methods for simulating river flow. Some of these methods 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 models are 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 is located in the Gharasu Watershed, Ardabil Province, Iran. For this aim, six groups of input data (M₁, M₂, … M₆) were defined based on different combinations of the above-mentioned input data. The conducted simulations in Pole-Almas and Nir stations have presented an acceptable results; but in Lai station it was very poor. This different behaviors 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 determinative role 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...
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.


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_{n1}, t_{n2}, t_{n3} and t_{n4}) for daily river flow simulation in Pennsylvania– USA, and obtained the accuracy of simulations, R^2=0.3, 0.25, 0.34, and 0.27 different 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 \( M_1(P_t, T_t, \text{AMH}) \), \( M_2(P_t, P_{t-1}, \text{AMH}, T_t, T_{t-1}) \), \( M_3(P_t, P_{t-1}, \text{AMH}, T_t, T_{t-1}, T_{t-2}) \), \( M_4(P_t, P_{t-1}, P_{t-2}, T_t, T_{t-1}, T_{t-2}) \), and \( M_5(P_t, P_{t-1}, P_{t-2}, T_t, T_{t-1}, T_{t-2}) \). Here, \( P, T \) and \( \text{AMH} \) 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 °C 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 m³ s⁻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 station caused 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 rapidly process 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](image-url)
Data processing in ANNs is 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).

\[ \text{\textbf{\textit{Y}}}_{\text{net}} = \sum_{i=1}^{N} (Y_i.w_i+w_0) \]  

where, \( \text{\textbf{\textit{Y}}}_{\text{net}} \) 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 are shown as (Eqs. 2 and 3):

Rule 1: If \( x \) is \( A_1 \) and \( y \) is \( B_1 \); then \( f_1 = p_1.x+q_1.y.r_1 \)  

Rule 2: If \( x \) is \( A_2 \) and \( y \) is \( B_2 \); then \( f_2 = p_2.x+q_2.y.r_2 \)  

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, consisting input 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-Sugeno rules is a systematic approach to generating fuzzy rules from a given input-output dataset. The fifth layer, including single 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 processes was 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>
<thead>
<tr>
<th>Model</th>
<th>Input parameters</th>
</tr>
</thead>
<tbody>
<tr>
<td>$M_1$</td>
<td>$P_t$, $T_t$</td>
</tr>
<tr>
<td>$M_2$</td>
<td>$P_t$, $T_t$, AMH</td>
</tr>
<tr>
<td>$M_3$</td>
<td>$P_t$, $P_{t-1}$, AMH, $T_t$, $T_{t-1}$</td>
</tr>
<tr>
<td>$M_4$</td>
<td>$P_t$, $P_{t-1}$, $P_{t-2}$, AMH, $T_t$, $T_{t-1}$, $T_{t-2}$</td>
</tr>
<tr>
<td>$M_5$</td>
<td>$P_t$, $P_{t-1}$, $P_{t-2}$, $T_t$, $T_{t-1}$, $T_{t-2}$</td>
</tr>
<tr>
<td>$M_6$</td>
<td>$P_t$, $P_{t-1}$, $P_{t-2}$, AMH</td>
</tr>
</tbody>
</table>

**Table 1** Six ANFIS models with the corresponding input parameters

![Figure 3 Calculation processes of the AMH parameter](image-url)
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 to 1, using (Eq.4):

$$N_i = \frac{X_i - X_{\min}}{X_{\max} - X_{\min}}$$

(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 constructing the ANFIS model, during a trial and error process and continuous change on the type of the membership 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 the FIS, 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 models are presented in Table 2.

<table>
<thead>
<tr>
<th>Characteristic</th>
<th>Pole-Almas</th>
<th>Nir</th>
<th>Lai</th>
</tr>
</thead>
<tbody>
<tr>
<td>Number of nodes</td>
<td>34</td>
<td>92</td>
<td>21</td>
</tr>
<tr>
<td>Number of linear parameters</td>
<td>8</td>
<td>32</td>
<td>4</td>
</tr>
<tr>
<td>Number of nonlinear parameters</td>
<td>18</td>
<td>30</td>
<td>12</td>
</tr>
<tr>
<td>Number of training data pairs</td>
<td>202 (75%)</td>
<td>202 (75%)</td>
<td>178 (72%)</td>
</tr>
<tr>
<td>Number of testing data pairs</td>
<td>70 (25%)</td>
<td>70 (25%)</td>
<td>70 (28%)</td>
</tr>
<tr>
<td>Number of fuzzy rules</td>
<td>8</td>
<td>32</td>
<td>4</td>
</tr>
</tbody>
</table>
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).

\[
R^2 = \left( \frac{\sum_{i=1}^{n}(O_i - \bar{O})(P_i - \bar{P})}{\sqrt{\sum_{i=1}^{n}(O_i - \bar{O})^2 \sum_{i=1}^{n}(P_i - \bar{P})^2}} \right)
\]

(5)

\[
NS = 1 - \frac{\sum_{i=1}^{n}(O_i - P_i)^2}{\sum_{i=1}^{n}(O_i - \bar{O})^2}
\]

(6)

\[
RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^{n}(O_i - P_i)^2}
\]

(7)

\[
PEM = \frac{\bar{P} - \bar{O}}{\bar{O}}
\]

(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 were relatively 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 is presented in Table 3.

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

<table>
<thead>
<tr>
<th>Station</th>
<th>Indices</th>
<th>M 1</th>
<th>M 2</th>
<th>M 3</th>
<th>M 4</th>
<th>M 5</th>
<th>M 6</th>
</tr>
</thead>
<tbody>
<tr>
<td>Pole-Almas</td>
<td>$R^2$</td>
<td>0.57</td>
<td>0.78</td>
<td>0.85</td>
<td>0.81</td>
<td>0.72</td>
<td>0.82</td>
</tr>
<tr>
<td></td>
<td>NS</td>
<td>0.57</td>
<td>0.78</td>
<td>0.84</td>
<td>0.80</td>
<td>0.68</td>
<td>0.81</td>
</tr>
<tr>
<td></td>
<td>PEM</td>
<td>-0.02</td>
<td>-0.04</td>
<td>0.00</td>
<td>-0.01</td>
<td>-0.03</td>
<td>-0.05</td>
</tr>
<tr>
<td></td>
<td>RMSE</td>
<td>2.14</td>
<td>1.53</td>
<td>1.30</td>
<td>1.44</td>
<td>1.85</td>
<td>1.44</td>
</tr>
<tr>
<td>Nir</td>
<td>$R^2$</td>
<td>0.42</td>
<td>0.50</td>
<td>0.56</td>
<td>0.53</td>
<td>0.46</td>
<td>0.52</td>
</tr>
<tr>
<td></td>
<td>NS</td>
<td>0.41</td>
<td>0.49</td>
<td>0.55</td>
<td>0.52</td>
<td>0.44</td>
<td>0.51</td>
</tr>
<tr>
<td></td>
<td>PEM</td>
<td>0.04</td>
<td>-0.04</td>
<td>-0.01</td>
<td>0.00</td>
<td>-0.05</td>
<td>0.00</td>
</tr>
<tr>
<td></td>
<td>RMSE</td>
<td>0.65</td>
<td>0.61</td>
<td>0.57</td>
<td>0.59</td>
<td>0.64</td>
<td>0.59</td>
</tr>
<tr>
<td>Lai</td>
<td>$R^2$</td>
<td>0.21</td>
<td>0.36</td>
<td>0.36</td>
<td>0.37</td>
<td>0.36</td>
<td>0.33</td>
</tr>
<tr>
<td></td>
<td>NS</td>
<td>0.20</td>
<td>0.36</td>
<td>0.35</td>
<td>0.37</td>
<td>0.35</td>
<td>0.32</td>
</tr>
<tr>
<td></td>
<td>PEM</td>
<td>0.03</td>
<td>0.01</td>
<td>0.03</td>
<td>0.00</td>
<td>0.00</td>
<td>-0.01</td>
</tr>
<tr>
<td></td>
<td>RMSE</td>
<td>0.06</td>
<td>0.05</td>
<td>0.06</td>
<td>0.05</td>
<td>0.06</td>
<td>0.06</td>
</tr>
</tbody>
</table>
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
The results of the simulations in the Pole-Almas and Nir stations were acceptable, but the simulation in the Lai station, was accompanied by a large error. Considering the fact that application 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 variables such 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$^3$s$^{-1}$, 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 conducted 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 flow is 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 M2 were compared.

The results presented that the parameters of $P_{1:1}$, $P_{1:2}$, $T_{1:1}$, $T_{1:2}$ hadn’t important effect on the accuracy of the predictions. This can be understood by a comparison between the results of the M2 ($P_1$, AMH, $T_1$), M3 ($P_1$, $P_{1:1}$, AMH, $T_1$, $T_{1:1}$), and M4 ($P_1$, $P_{1:1}$, $P_{1:2}$, AMH, $T_1$, $T_{1:1}$, $T_{1:2}$) 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 sites can be a proof for the fact that the complexity of the hydrological process in different sites isn’t similar, and it can’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.

5 REFERENCE

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پیش بینی جریان ماهانه رودخانه با استفاده از سیستم استنتاج عصبی-فازی تطبیقی

(مطالعه موردی: بحوزه آبخیز قره سو استان اردبیل)

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چکیده
روش‌های مختلفی برای شبیه‌سازی جریان رودخانه وجود دارد. برخی از این روش‌ها مانند استفاده از مدل‌های هیدرولوژیکی، قراین محور نیازمند به داده‌های ورودی متعدد و داشتن تحقیق کافی در مورد فرایند هیدرولوژیکی هستند. ولی برخی از روش‌ها مانند مدل‌های رگرسیونی و هوش مصنوعی حتماً در شرایط کمبود داده نیز قابلیت استفاده دارند. این قابلیت در ایستگاه مدل‌های هیدرولوژیکی ایزی‌تر از استفاده از مدل‌های کمپیوتری در حال توسعه را افزایش می‌دهد. در یک روش از دستیابی به پردازش حساسیت سنجش است قابلیت سامانه استنتاج عصبی فازی تطبیقی (ANFIS) برای شبیه‌سازی جریان ماهانه رودخانه در سه استگاه هیدرومتری دارای میانگین دیسیمپتیمی طولی بالا، نیز و لایه ارژی‌گذار، در این شبیه‌سازی مدل‌های سطحی ایستگاه ایستگاه‌های پل الواط، داده‌های ورودی مدل‌ها استفاده شده است. منطقه مورد مطالعه، بحوزه آبخیز قره‌سوم استان اردبیل می‌باشد. این تحقیق شش ترکیب مختلف (M1، M2، ..، M6) از نتایج Sال رودی لر، است. برای تعیین ۶ عناصر ورودی در این استفاده شده است. شبیه‌سازی‌های انجام شده از نتایج کاهشی و نتایجی در سطح وارداتی در این است. برای شبیه‌سازی مدل‌های ANFIS یک اشاره کارآهذ، سازگاری شبیه‌سازی در استان اردبیل می‌باشد. در این تحقیق برای شبیه‌سازی مدل‌های ANFIS و برای شبیه‌سازی برای شبیه‌سازی و انتخاب است. ANFIS یکی از بانک‌هایی است که انتخاب و استفاده از بازارهای ورودی کارآمد نشان می‌دهد. کلمات کلیدی: شبکه عصبی مصنوعی، مدل‌های سازی، پارامتر، استخراج، هیدرولوژی، شبیه‌سازی، ماهانه

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