Monthly Flow Estimation in Akarçay Basin Using Artificial Neural Network

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Abstract

Six approaches for modeling monthly flows of an Akarçay basin in Turkey using Artificial Neural Network (ANN) were presented. The monthly stream flows was modeled by multi-layer perceptron type of ANN. The six approaches contain three input values as calendar month order, former year's monthly observations and the standardized value the observations, and theirs two different usage in the network. The results were tested using the mean absolute error, traditional determination coefficient and Nash-Sutcliffe efficiency. The study demonstrates that the approach which uses the months order as input data produces reasonably satisfactory results for data of the basin. It is seen that the ANNs can be assumed as successful modeling techniques of complex and nonlinear systems. Internal structures of ANN have not been comprehended clearly but high success on the research is sound as good proof to use in monthly stream flow estimation.

Key Words: Artificial Neural Network, Monthly stream flow, Modeling, Akarcay

Akarça Havzasında Yapay Sinir Ağları ile Aylık Akım Tahmini

Özet

Türkiye Akarçay havzası aylık akım gözlemleri altı yaklaşım kullanılarak Yapay Sinir Ağları (YSA) ile modellenmiştir. Modellemede aylık akımlar çok katmanlı algılayıcı YSA kullanılmıştır. Altı yaklaşım, ayın takvim sıra sayısı, önceki yılın gözlemleri ve bu gözlemlerin standardize değerleri şeklinde üç girdi değeri ile bunların iki farklı şekilde ağa tanıtılmasından oluşmuştur. Sonuçlar ortalama mutlak hata, determinasyon katsayısı ve Nash-Sutcliffe yeterlilik ölçütü ile sınandı. Araştırma soncu, ay sıra sayısının girdi olarak kullanıldığı YSA modellerinin iyi sonuç verdiğini göstermiştir. Karmaşık ve doğrusal olmayan sistemlerde YSA'nın başarılı modelleme yaptığı kabul edilebilir. YSA'nın içyapısı açıkça anlaşılamamış olmakla beraber başarılı sonuçlar aylık akım tahmini için kullanılabileceğini göstermektedir.

Anahtar Kelimeler: Yapay Sinir Ağları, Aylık akım, Modelleme, Akarçay

1. Introduction

The efficient usage of water resources requires planning, design, operation and management studies. One of the most important variables in these studies is flow estimation in river for location (Srinivasulu and Jain, 2006). Estimation of flow data is very complex, highly nonlinear, and exhibits both temporal and spatial variability due to a lot of effects such as topographic, geologic and geographic etc. properties and precipitation. Therefore, researchers use deterministic approaches, which use physical properties of the basin, or probabilistic approaches, which use statistical properties of the observations, in the modeling studies. In the deterministic approaches, unit hydrograph and empiric models, and in the probabilistic approaches, regression models are mostly used. However, these simpler models normally fail to represent the non-linear dynamics, which are inherent in the process of stream flows (Rajurkara et al., 2003; Srinivasulu and Jain, 2006; McCuen, 1989).

Artificial neural networks (ANNs) mimics the behavior of the central nervous system with the hope that the biologically inspired computing capabilities of the ANN will allow the cognitive and sensory tasks to be performed more easily and more satisfactorily than with conventional rule-based computing. Neurocomputing is much less restrictive than the conventional computing because it is not constrained by any assumptions. In addition to learning, the complexity of size and connections that provide the important and indispensable structural aspects also need to be better and more fully understood (Bose and Liang, 1996).

The adoption of the ANN technique for stream flow modeling has added a new dimension to the modeling approach and it has been applied in recent years as a successful tool to solve various problems concerned with hydrology and water resources engineering (Rajurkara et al., 2003). Recently, Cigizoglu (2003) were aimed to explore the applicability of ANNs to estimate, forecast and extrapolate of daily river flows. In the study, a multi-layer perceptron NN model and conventional statistical and stochastic models were compared. The performance analyses of the methods showed that ANN was more efficient than the conventional models (Cigizoglu, 2003). Kumar et al. (2004) forecasted monthly river flow using feed forward NN and recurrent NN. The recurrent neural network provides the number of persistence component (memory) in the hydrological time series. The memory was provided by the state of the network in previous time step. They stated that the recurrent NN performed better than the feed forward NN (Kumar et al. (2004). Cigizoglu (2005) forecasted monthly mean flow using generalized regression NN which does not require an iterative training procedure as required in the back propagation method. The method approximated any arbitrary function between input and output vectors, drawing the function estimate directly from the training data. The study stated that the generalized regression NN to be superior to the conventional feed forward back propagation, regression and ARIMA methods. However, the method overestimates some of the low flows and feed forward back propagation approach has shorter training time (Cigizoglu, 2005). Hu et al. used a modified NN to improve river flow prediction. In the method, different forms of NNs were applied to several watersheds to test the performance in daily rainfall-runoff modeling. They stated that the prediction accuracies of the ANN based techniques are highly dependent on many issues associated with network structure identification and the network parameter optimization, and also, merging prior hydrological knowledge with the NN learning algorithm is highly recommended (Hu et al. (2005)). Chibanga et al. modeled and forecasted the hydrological time series using ANNs. In the study, derived flow series for ungauged parts of the basin and time series of historic flow were used. The ANN results were compared and were found better goodness of fit statistics than those of their ARMAX counterparts (Chibanga et al. (2003)). Sudheer et al. were improved peak flow estimates using raw and transformed data in ANN river flow models. The transformation performed in three steps as Log-transformation, Standardization and Wilson-Hilferty transformation. They stated that the proposed methodology lead to better estimates of the peak flows, however, further empirical studies may be required to reinforce the conclusion (Sudheer et al. (2003).

In addition to these researches presented above, Dibike and Solomatine, Rajurkara et al., Baratti et al., Riad et al., Wang et al., Lallahem and Mania, Srinivasulu and Jain, modeled a rainfall runoff process using various and modified ANNs. All these researcher indicate that the, ANNs can be used successfully in many practical engineering applications where the main aim would be to make accurate hydrologic predictions, in cases where a physically-based description of the rainfall-runoff process is not possible (Dibike and Solomatine (2001); Rajurkara, et al., (2003); Baratti et al. (2003); Riad et al. (2004); Wang et al. (2005); Lallahem and Mania (2003); Srinivasulu and Jain, (2006)).

The aim of the present study is to model the monthly stream flows gauged from 9 monitoring stations of the Akarcay basin located in semiarid climate in Turkey using a multi-layer perceptron type of ANN methodology. First of all, the effects of the ANN configurations on the results were investigated using various alternatives, and then, the best combination of the parameter values were determined and used in model studies. In the modeling studies, three data types and two input-output types were used and the results were compared. The first two of the data types used different input but same expected (output) data. The third model used transformed data as input and expected data. One of the input-output types used one input-output, and the other used 12 inputs-outputs. The last 12 observations in various numbers did not add to training stages of the models and used to compare with the model estimations. A code in Visual Basic compiler was written for the network calculations and the SPSS software was used to calculate the descriptive statistic and model performance.

2. Artificial Neural Networks

A neural network, broadly classified as recurrent or nonrecurrent, consists of numerous processing elements that are variously called neurons, units, cells, or nodes (Bose and Liang, 1996). Each neuron in a layer is connected to other neurons in different layers by means of interlayer connections. Each interlayer connection associated with weight that represents information being used by the net to solve a problem. The network usually has two or more layers of processing units where each processing unit in each layer is connected to all processing units in the adjacent layers (Fig. 1) (Bose and Liang, 1996; Srinivasulu and Jain, 2006).

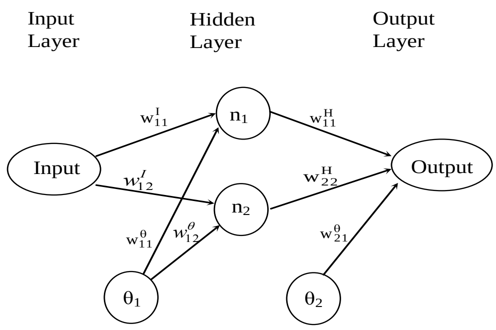

Figure 1. A neural networks structure including one input, one hidden layer having two neurons and one output, (n_i is the i^{th} neuron, w is the weight, Θ_i is the i^{th} threshold).

In general, network architecture consists of an input layer, various hidden layers and one output layer. The entire layer comprises various neurons. ANN algorithms usually contain three steps:

1. The neurons in the input layer are summed with various weight coefficients named linkage weights such as

$$g(x) = \sum_{j=1}^{N} w_{ij} x_j - \theta_i \qquad (1)$$

where, g(x) is the summing function, N is the input number, w_{ij} is the linkage weight from the i^{th} neuron to the j^{th} neuron, x_j is the input value, θ_i is the threshold of the i^{th} neuron. In the hidden layer, x_j values are in the transfer function results of the summing function values of the former layer.

2. Transfer function values of the summed values are calculated as

$$y_i = \Psi(g(x)) \qquad (2)$$

where, y_i is the i^{th} output value, $\Psi(g(x))$ is the transfer function. Different types of transfer functions are available but the sigmoid function is used generally. Sigmoid function is described by

$$\Psi(g(x)) = \frac{1}{1+\exp(-g(x))} \qquad (3)$$

3. The expected value and transfer function results are compared and the differences are considered as error (TE).

$$\mathrm{TE} = \frac{1}{N}\sum_{i=1}^{N}(y_i - o_i)^2 \qquad (4)$$

where, N is the output number, y_i is the i^{th} output, o_i is the expected value of the i^{th} neuron of the output layer. Considering the error, the linkage weights are corrected using the delta rules:

$$\Delta w_{ij}(n) = \alpha.\delta_j(n).y_i(n) + \beta.\Delta w_{ij}(n-1) \qquad (5)$$

where, $\Delta w_{ij}(n)$ is the correction of the linkage weight (w_{ij}) between the i^{th} neuron of the former layer and j^{th} neuron of the next layer at the n^{th} iteration, α is the learning rate, $\delta_j(n)$ is the local change (error gradient), $y_i(n)$ is the input for neuron j, β is the momentum rate between 0 and 1. The momentum rate is used to prevent the local solution. If the neuron j is output neuron, then, the error (local change) is calculated with the expected output value. If the neuron j is in the hidden layer, then, the local change is calculated from the derivate of the local change function and weighted sum of the neuron changes of the next layers. The calculation repeated until the accepted error rate is obtained (Efe and Kaynak, 2000; Bose and Liang, 1996.).

3. Case Study

3.1. The Study Area and Data

Akarçay basin is a closed, graben type clayey basin with 7337 km^2 total drainage area. It has a 160 km length and 70 km with approximately (Fig. 2). The most important stream of the basin is Akarcay (Tezcan, 1999). The climate of the area is a hot and arid summer and a cold and rainy winter. In the basin, all rain types occur (HRR, 1998). State Hydraulic Works observations of the Akarcay flows started in 1960 at one station and then continued in 9 stations with various periods (SIHM, 2003).

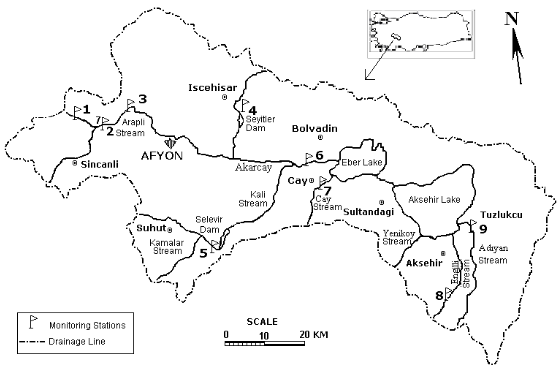

Figure 2. Stream flow monitoring stations of Akarcay.

3.2. Development of the ANN model

Stream flow estimation model involves six steps as: a) Selection of the data set, b) Determination of the layer and neuron numbers, c) Scaling the data between 0 and 1,

d) Training the ANN model, e) Testing of the model, f) Performance tests of the model.

a) Three different data sets and two different input-output types for NN, therefore 6 different models (A1, B1, C1, A12, B12 and C12), were used. In the first data set (A) the calendar order of the month were used as input variables (1, 2, …, 12). The second set (B) used the observed monthly data of the former year as input variables. The last set (C) used normalized and standardized flow observations instead of the raw data used in the second set. One of the two data inputs types used one input and one output (A1, B1, C1) (Fig.1), the others used 12 inputs and 12 outputs (A12, B12 and C12) due to months number in a year is 12 (Fig 3.). In the normalization procedure of the C type data, the Box-Cox transformation was used in which;

$$y_i = \begin{cases} \dfrac{x_i^{\lambda} - 1}{\lambda} & \text{for } \lambda \neq 0 \\ \log(x_i) & \lambda = 0 \end{cases} \qquad (6)$$

where y_i is the transformed data; x_i is the original data, and λ is a parameter value such that y_i have zero skewness. λ may be estimated by trial and error such that the coefficient of skewness of the transformed data (y_i) is zero (McMahon and Mein, 1986). The standardization can be performed as

$$z_i = \frac{y_i - \mu}{\sigma} \qquad (7)$$

where, z_i is the standardized values, μ is the mean and σ is the standard deviation of the y_i.

Because of the containing negative values of the standardize data, the absolute of the smallest value of the standardized data added to make all of the data positive. All of the data except the last 12 of them were used in the training stage. All the linkage weights are determined as:

$$w_{ij} = \frac{i + j}{n_i + n_j} \qquad (8)$$

where w_{ij} is the linkage weights between the i^{th} and j^{th} neurons of the previous and following layers, respectively; and n_i and n_j are the total neuron numbers of the two layers.

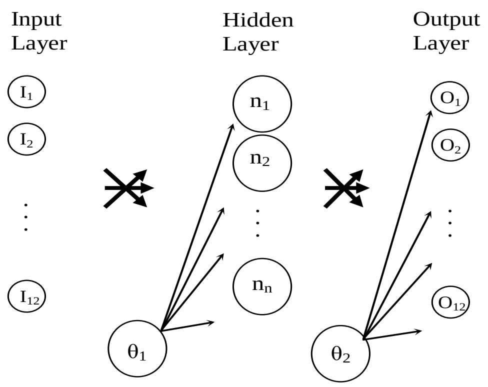

Figure 3. Neural networks structure including twelve inputs (I), one hidden layer and twelve outputs (O), (n_i is the i^{th} neuron, Θ_i is the i^{th} threshold).

b) Learning rate, momentum rate was used as 0.3 and 0.7 respectively. The effect of the layer and neuron numbers were investigated by changing the layer numbers from 3 to 10 and neuron numbers from 1 to 12. Only the training error in tolerance limits is not enough for successful model. Therefore, training and test errors were evaluated together to get consistent results. The layer and neuron numbers giving the smallest absolute differences of unit errors (ADUE) were selected. ADUE can be calculated as:

$$ADUE = \left| \frac{TTrainingE}{NTD} - \frac{TTestingE}{NTD} \right| \qquad (8)$$

where, TTraining E: Total of training errors, TTesting E: Total of testing errors, NTD: Number of total data.

c) The A and B data sets were scaled between 0 and 1 dividing to the biggest value of its appertained series. The C data were scaled between 0 and 1 using the equation (9):

$$x' = \frac{x + |x_{min}|}{x_{max} + |x_{min}|} \qquad (9)$$

where x' is the scaled value between 0 and 1, x is the standardize value, $|x_{min}|$ is the absolute of the minimum and x_{max} is the maximum value of the data.

d) The iteration number to the training was 10000.

e) The models estimated the last 12 months,

f) The mean of the absolute errors (differences) (MAE) and square of Pearson correlation coefficients (determination coefficient, R^2) of observed flow (O) with estimated flows were calculated. Pearson correlation coefficient is commonly used statistics to see the linear relationship between the variables. But, if there are tendency to extreme values in the model, the correlation coefficient may not be a successful indicator on the relationships. And also, this correlation coefficient is valid on some assumptions of the data such as normal distribution (Srinivasulu and Jain, 2006). Therefore, Nash-Sutcliffe efficiency (E) was also calculated to observe the model performance. Nash-Sutcliffe efficiency can be calculated as:

$$E = 1 - \frac{\sum_{i=1}^{N}(E_i - O_i)^2}{\sum_{i=1}^{N}(O_i - \overline{O})^2} \qquad (10)$$

where, N is the number of the test data and $\overline{O}$ is the mean of the observed flow. The E value near 1.0 indicates good model performance (Hu et al, 2005; Srinivasulu and Jain, 2006).

3.3. Results

The descriptive statistics of the observations used in the test study were presented in Table 1. ADUE variations with network layer and neuron numbers were explored using the α=0.3 and β=0.7 values with iteration 1000. The best layer numbers were found for the models A1, B1, C1, A12, B12 and C12 as 4, 4, 3, 3, 5, and 7, respectively. And the best neuron numbers were found as 9, 5, 2, 11, 3 and 3. Mean ADUE values of the model estimations are: 1.6E-5 for A1, 1.1E-4 for B1, 9.4E-4 for C1, 1.3E-3 for A12, 1.6E-3 for B12 and 2.6E-2 for C12 models.

Table 1.Descriptive statistics of the observations.

SN	TN	Mean	Min	Max	σ	Cv	Cs	k
1	396	3.50	0.00	11.10	3.67	1.05	0.88	-0.48
2	228	5.22	0.01	23.20	6.04	1.16	1.38	1.92
3	312	7.42	0.08	31.60	9.99	1.35	1.40	0.60
4	339	0.86	0.00	4.60	1.31	1.52	1.77	2.17
5	372	4.46	0.00	16.80	5.80	1.30	1.21	-0.10
6	384	13.92	0.00	69.17	21.25	1.53	1.67	1.46
7	132	2.15	0.36	6.85	1.61	0.75	1.92	3.77
8	369	1.44	0.01	8.01	2.07	1.44	2.08	4.10
9	444	3.58	0.00	12.00	4.24	1.18	1.05	-0.36
Mean	**331**	**3.31**	**0.25**	**11.05**	**3.51**	**1.05**	**1.19**	**0.75**

SN: Station no; TN: Total data numbers; Min: Minimum; Max: Maximum; σ: Standart Deviation; Cv: Variation coefficient; Cs:Skewness; k: Kurtosis.

In the C1 and C12 models, standardized data were used and inverse transformation was applied to the results to obtain actual flow estimations. The model estimations were presented in Fig.3-9. The mean of the absolute errors (MAE), the determination coefficients (R^2) and Nash-Sutcliffe efficiencies (E) of the models were presented in Tables 2-4. In the

Tables, the underlines show the best of the total result and asterisks show the best of the same type input-outputs.

4. Discussions

6 models were used in the calculations. Descriptive statistics of the observed values (O) explain that all the data have skewed distribution (Table 1). The standard deviations of the O vary between the 1.31-21.25 (Table 1). Considering the mean values of the performance criteria; A1 for MAE and R^2, and B12 for the E sound good results. Considering the data input-output types separately; for single input-output: A1 for MAE and R^2; C1 for E; for twelve inputs-outputs: A12 for MAE and R^2; B12 for E are successful models. Considering the purposed results of the criteria for the stations MAE and R^2 suggest A1 and A12, but E suggests C1 and C12 mostly. In other words, MAE and R^2 criteria explain the success of the model which uses calendar months order numbers, E criteria explains the success of the model which uses standardize data. That mean, in general, the MAE and R^2 criteria gave the confirmed results. These results may be concluded from the figures of observations and estimated flows (Figures 4-12):

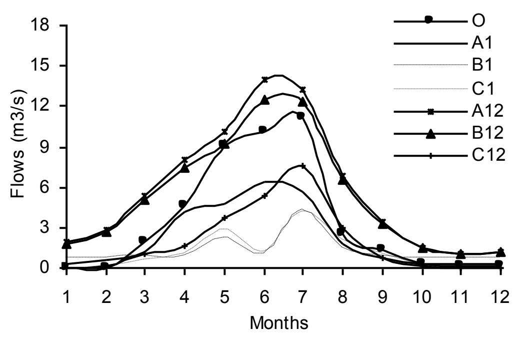

Figure 4. Observations and model estimations in station 1.

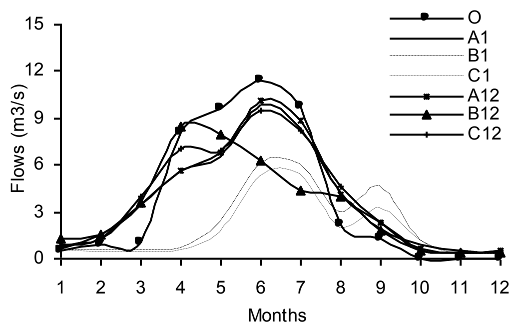

Figure 5. Observations and model estimations in station 2.

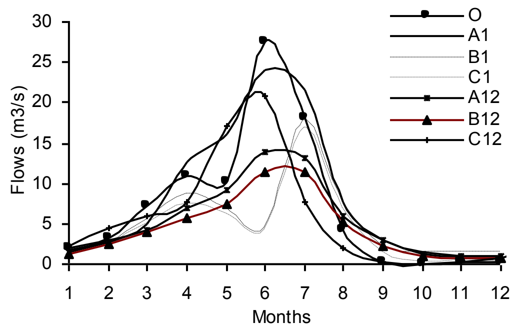

Figure 6. Observations and model estimations in station 3.

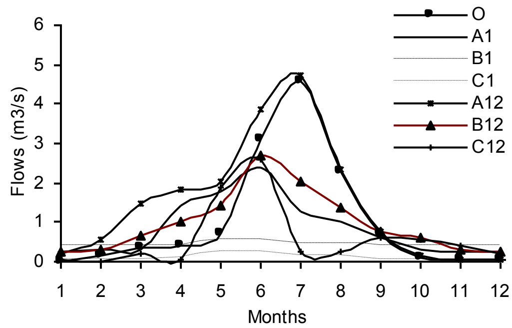

Figure 7. Observations and model estimations in station 4.

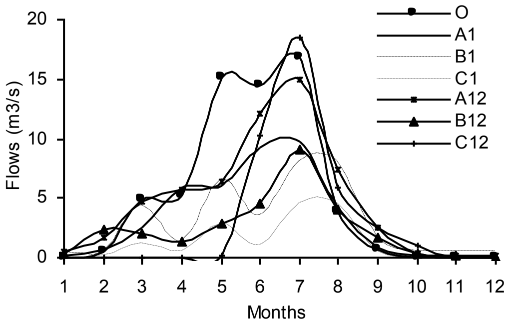

Figure 8. Observations and model estimations in station 5.

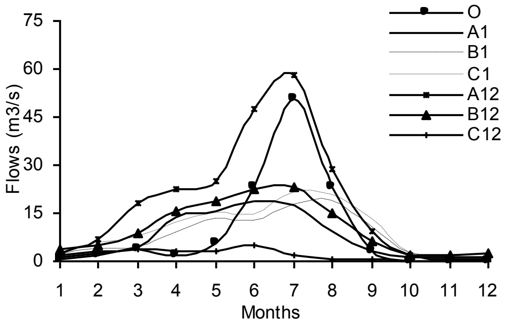

Figure 9. Observations and model estimations in station 6.

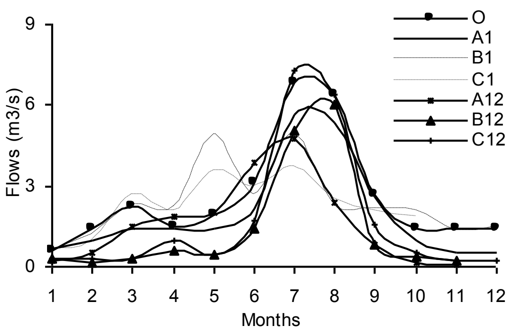

Figure 10. Observations and model estimations in station 7.

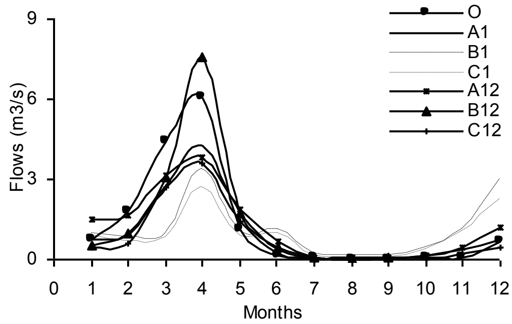

Figure 11. Observations and model estimations in station 8.

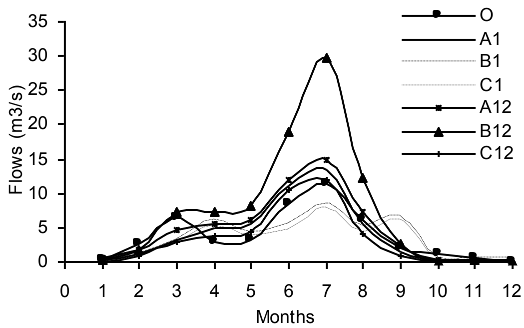

Figure 12. Observations and model estimations in station 9.

For the stations 1, 4 and 8 the B12 model,
for the station 2 and the A1 and A12 models,
for the stations 3 and 7 the A1 model,
for the station 5 the A12 model,
for the station 6 the C12 for low level flow and the A12 for high level,
for the station 9 the C12 are preferable than the other models.

In general, MAE and R^2 proposed the A1 and A12 models; E proposed the C1 and C12 models. In 4 stations MAE and R^2, in 1 station E result is appropriate with the graphical representation. In 4 stations none of the performance criteria are consistent with the graphical representation (Table 2-4, Fig.8). Icaga stated that the stations 4, 5, 6, and 9 have autoregressive models at the first degree (AR(1)) (Icaga, 2001). The selected ANN models are not identical with the AR models, therefore, the ANN results (Table 2-4) do not probably affected from the autocorrelations. Calendar month order is more successful than the models which uses standardize values. This result is surprisingly contrary to the advice of the Hu et al. (2005) and Sudheer et al (2003)'s studies. In the station 6 which has a big range of the observed data, determination coefficient of the models which uses one input-output are less than 0.5. For this station, only the A12 has high determination coefficient. Nevertheless, it is difficult to say that this model, which has the highest determination coefficient, represents the observations with great success (Table 2- 4, Fig.9).

Table 2. Mean absolute errors (MAE) of the models.

Station	A1	B1	C1	A12	B12	C12
1	<u>1.42</u>*	2.00	2.26	2.35*	1.94	3.05
2	1.35*	2.59	2.58	<u>1.26</u>*	1.66	1.94
3	<u>2.28</u>*	3.33	3.30	2.83	3.36	2.74*
4	0.60*	0.64	0.82	0.76	<u>0.46</u>*	0.69
5	2.12*	3.28	3.96	<u>1.78</u>*	4.41	4.16
6	<u>6.71</u>*	7.74	7.52	8.93	6.94*	8.14
7	0.62*	0.70	0.74	0.71	<u>0.57</u>*	0.77
8	0.47*	1.05	1.00	0.56	<u>0.45</u>*	0.54
9	<u>1.37</u>*	1.83	1.93	1.54*	4.04	1.28
Mean	1.88	2.57	2.68	2.30	2.65	2.59

The superiority of the A1 and A12 then the others may be from the variability of the data. Input variability may be caused by many things. It is understandable from the minimum values usually equal to zero as in the Table 1 that the main source of the river is precipitation because of the high clay density. Therefore, in the modeling studies, the other hydrological and meteorological factors like the precipitation, evaporation, temperature etc. should be considered so that the estimation success (correlation coefficient) of which average value is 93% may reach more satisfactorily results.

Table 3. Determination coefficients (R^2) of the models.

Station	A1	B1	C1	A12	B12	C12
1	<u>0.95</u>*	0.73	0.59	0.94*	0.93	0.38
2	0.91*	0.41	0.48	<u>0.92</u>*	0.75	0.60
3	<u>0.91</u>*	0.33	0.37	0.90*	0.89	0.82
4	<u>0.84</u>*	0.58	0.54	0.62	<u>0.84</u>*	0.72
5	<u>0.88</u>*	0.54	0.37	0.81*	0.12	0.30
6	0.47	0.40	0.48*	<u>0.81</u>*	0.57	0.06
7	<u>0.97</u>*	0.33	0.38	0.60	0.95*	0.53
8	0.94*	0.36	0.39	0.90	0.90	<u>0.95</u>*
9	0.86*	0.55	0.55	0.90	<u>0.91</u>*	0.86
Mean	**<u>0.86</u>**	**0.47**	**0.46**	**0.82**	**0.76**	**0.58**

Table 4. Nash-Sutcliffe efficiencies (E) of the models.

Station	A1	B1	C1	A12	B12	C12
1	0.32	0.39	0.56*	0.41	0.30	1.35*
2	0.14	0.74	0.81*	0.13	0.31	0.55*
3	0.12	0.72	0.73*	0.31	0.45*	0.28
4	0.36	0.60	1.06*	0.55	0.19	0.63*
5	0.35	0.64	1.10*	0.22	1.02*	1.23
6	0.61	0.70*	0.54	0.67	0.49	1.23*
7	0.15	0.70	0.74*	0.71	0.57	0.77*
8	0.18	0.65	0.69*	0.20	0.12	0.25*
9	0.26	0.46	0.50*	0.34*	3.88	0.22
Mean	**0.28**	**0.62**	**0.75**	**0.39**	**0.81**	**0.72**

5. Conclusions

Six approaches for modeling monthly flows using Artificial Neural Network (ANN) was presented. Alternative solutions were performed to determine layer number and neuron number for network configuration. The results show that the approach which uses the calendar month order as input is more successful then the those using the former year's monthly observations. The smallest performance of the first approaches is 90% as Pearson correlation coefficient. This superiority of the first model may be caused from variability of the former year's observations. For this reason, calendar month order is more suitable in the estimation studies by NN.

Successful modeling of flow estimation in a basin having innumerable factors on the flow regime is suitable using the NN as a numerical modeling of the basin. According to the results, the parameters values used in the network configuration vary with the data properties. In spite of this variability of the parameters, the NN is a useful and powerful tool to handle complex problems like the model of monthly flow in semiarid region in which the flows are very irregular. However, the performance criteria (MAE, R^2 and E) which are used in literature mostly are not perfect performance indicators, therefore, these criteria and graphical representations should be considered together.

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