Artificial Intelligent Models For Flow Prediction: A Case Study On Alara Stream

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Abstract- For designing of water resources structures, information interesting in volume and rate of water is needed. Forecasting of flow in future is important for operating of flood control reservoirs, determining of potential flow in stream, amount of flow in drought periods evaluating of electric generation in a power plant, delivering of domestic and irrigation water, and planning of navigation in streams. A number of methods are used in flow forecasting. Prediction-runoff models or flood routing models are used for short time forecasting whereas water budget models, flood routing models and time series models are used for long time periods. In this study, for flow prediction of Alara Stream in Mediterranean Region artificial intelligent models used in solving of hydrological problems recently are developed as alternative conventional methods. Artificial Neural Networks (ANN) and Adaptive Neural Based Inference Systems (ANFIS) are selected for modeling. Monthly mean flow data from the 9–17 station on the Alara Stream is used for artificial intelligence models. After determining model degree using Markov models, the input layer consisted of previous flows and cos $(2\pi i/12)$, sin $(2\pi i/12)$ (i =1, 2, ..., 12) for the effect of monthly periodicity, and the output layer contained a single flow value for time t for artificial models. When predicting results are compared for two modeling techniques, both low and high flows are better predicted by ANN than ANFIS.

Keywords- Artificial Intelligence Systems, Artificial Neural Networks, Adaptive Neural Based Inference Systems, Markov Models, Flow Predicting.

Akim Tahmini Için Yapay Zeka Modeller:

Alara Çayi Örneği

Özet- Su yapılarının projelendirilmesinde, akım miktarı ile ilgili bilgilere ihtiyaç duyulur. Akım miktarının gelecekte, belli bir tarihte ne olacağının tahmini, taşkın kontrolü amaçlı haznelerin işletilmesinde, akarsudaki su potansiyelinin belirlenmesinde, bir hidroelektrik santral için kurak dönemlerde üretimin nasıl etkileneceğinin bilinmesinde, içme ve sulama suyunun dağıtımında ve akarsulardaki ulaşımın planlanmasında önem taşımaktadır. Akım tahminin de kullanılan metotlar, kısa süreli akım tahmini için, yağış akış modelleri ya da akım öteleme modelleri; uzun süreli akım tahmini için ise indis değişkeni modelleri, su bütçesi modelleri, yağış akış modelleri ve zaman serisi modelleri olarak sayılabilmektedir. Çalışmada Akdeniz Bölgesi içerisinde yer alan, Alara Çayına ait akımların tahmininde mevcut tahmin metotlarına alternatif olarak, son zamanlarda hidrolojik problemlerin çözümünde yaygın kullanıma sahip olan yapay zeka yöntemlerden yapay sinir ağları (YSA) ve adaptif ağ temelli bulanık çıkarım sistemleri (ANFIS) yöntemleri kullanılmıştır. Yapay zeka yöntemlerde kullanılan akım miktarları 9-17 nolu akım gözlem istasyonuna ait aylık ortalama akım değerleridir. Zaman serileri akım tahmini çalışması sonucunda Markov modelleri ile mertebesi belirlenen Alara Çayı için, yapay zeka yöntemlerle akım tahmin yaklaşımında girdi değişkenleri olarak önceki yılların akım değerleri ve periyodiklik için de cos$(2\pi i/12)$, sin$(2\pi i/12)$ değerleri seçilmişlerdir. Karşılaştırma sonucunda, YSA ile elde edilen tahminlerin geçmiş akım verileri ile daha uyumlu sonuçlar verdiği görülmüştür.

Anahtar Kelimeler- Yapay Zeka Sistemler, Yapay Sinir Ağları, Adaptif Ağ Temelli Bulanık Çıkarım Sistemleri, Markov Modelleri, Akım Tahmini.

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1. INTRODUCTION

The identification of suitable generation models for future streamflows is an important precondition for successful planning and management of water resources.
More recently, artificial intelligence systems have gained attention. In the artificial intelligence models the overall error is not considered globally as in the stochastic methods but propagated to each variable in different proportions depending on the significance of the hydrological factor in the prediction process. The comparison is based on the prediction graphs and the root mean square errors. On the other hand, artificial intelligence models have also been used by many researchers in hydrology [1, 2, 3, 4, 5, 6, 7]. Artificial neural networks (ANN) reconstruct links between input–output pairs for the system being modeled. The ANN has to be trained in order to generate the desired output. Artificial neural networks have been shown to give useful results in many fields of hydrology and water resources research [8, 9]. [10] used neural networks for time series prediction and they investigate impact of using heuristics. [11], suggested data transformation for improving peak flow estimates. [12], demonstrated that developed two step ahead neural network has efficient ability to learn and has comparable accuracy for time series prediction as the refitted ARMAX model. [13], presented an approach for modeling daily flows during flood events using artificial neural network. They suggested that the approach adopted for modeling produced reasonably satisfactory results for data of catchments from different geographical locations. [14], applied two lumped conceptual hydrological models namely, tank and NAM and a neural network model to flood forecasting in two river basins in Thailand, the Wichianburi on the Pasak River and Tha Wang Pha on the Nan River. They found that neural network model give good forecasts based on available rainfall, evaporation and runoff data. The Adaptive Neural based Fuzzy Inference System (ANFIS) model and its principles proposed by Jang (1992) [15] have been applied to study many problems. The model identifies a set of parameters through a hybrid learning rule combining the back-propagation gradient descent and a least squares method. It can be used as a basis for constructing a set of fuzzy IF–THEN rules with appropriate membership functions in order to generate the preliminary stipulated input–output pairs. Some researchers have applied ANFIS in hydrological modeling. [16] studied the intelligent control of a real-time reservoir operation model and found that, given sufficient information to construct the fuzzy rules, the ANFIS helps to ensure more efficient reservoir operation than the classical models based on rule curve. The first purpose of this paper is to develop artificial intelligence models, for flow prediction of Alara Stream in Mediterranean Region as alternative conventional methods. Artificial Neural Networks (ANN) and Adaptive Neural Based Inference Systems (ANFIS) are selected for modeling. Monthly mean flow data from the 9–17 station on the Alara Stream is used for artificial intelligence models. Then, evaluations of models performances are made.

2. MATERIALS AND METHODS

The ANN and ANFIS methodologies were applied to river flow predicting in Alara Stream in the southern part of Turkey. Monthly mean flow data from the 9–17 station on the Alara Stream and study region map were taken from General Directorate of Electrical Power Resources Survey and Development Administration in Turkey. Record period was consisting of monthly mean flows between 1969-2003 years. The mean flow of Alara stream was 31.1 m^3/sn. The map given in Figure 1 shows the Alara stream chatment including the stream stations.

3. ARTIFICIAL NEURAL NETWORK (ANN)

Neural Networks are promising new generation of information processing systems that demonstrate the ability to learn, recall, and generalize from training patterns or data. Artificial neural networks (ANNs) are systems that are deliberately constructed to make use of some organizational principles resembling those of the human brain. ANNs are inspired by modelling networks of real (biological) neurons in the brain. Hence, the processing elements in ANNs are also called artificial neurons, or simply neurons. Fig.2 shows a simple mathematical model of biological neuron proposed by McCulloch and Pitts (1943) [17], usually called an M-P neuron. In this model, the *i*th processing element computes a weighted sum of its inputs and outputs y_i=1 (firing) or 0 (not firing) according to whether this weighted input some is above or below a certain threshold θ_i:

$$y_i(t+1) = a\left(\sum_{j=1}^{m} w_{ij} x_j(t) - \theta_i\right) \tag{1}$$

$$a(f) = \begin{Bmatrix} 1 & if\ f \geq 0 \\ 0 & otherwise \end{Bmatrix} \tag{2}$$

where the activation function a(*f*) is a unit step function. The weight w_{ij} represents the strength of the synapse (called the connection or link) connecting neuron j (source) to neuron i (destination).

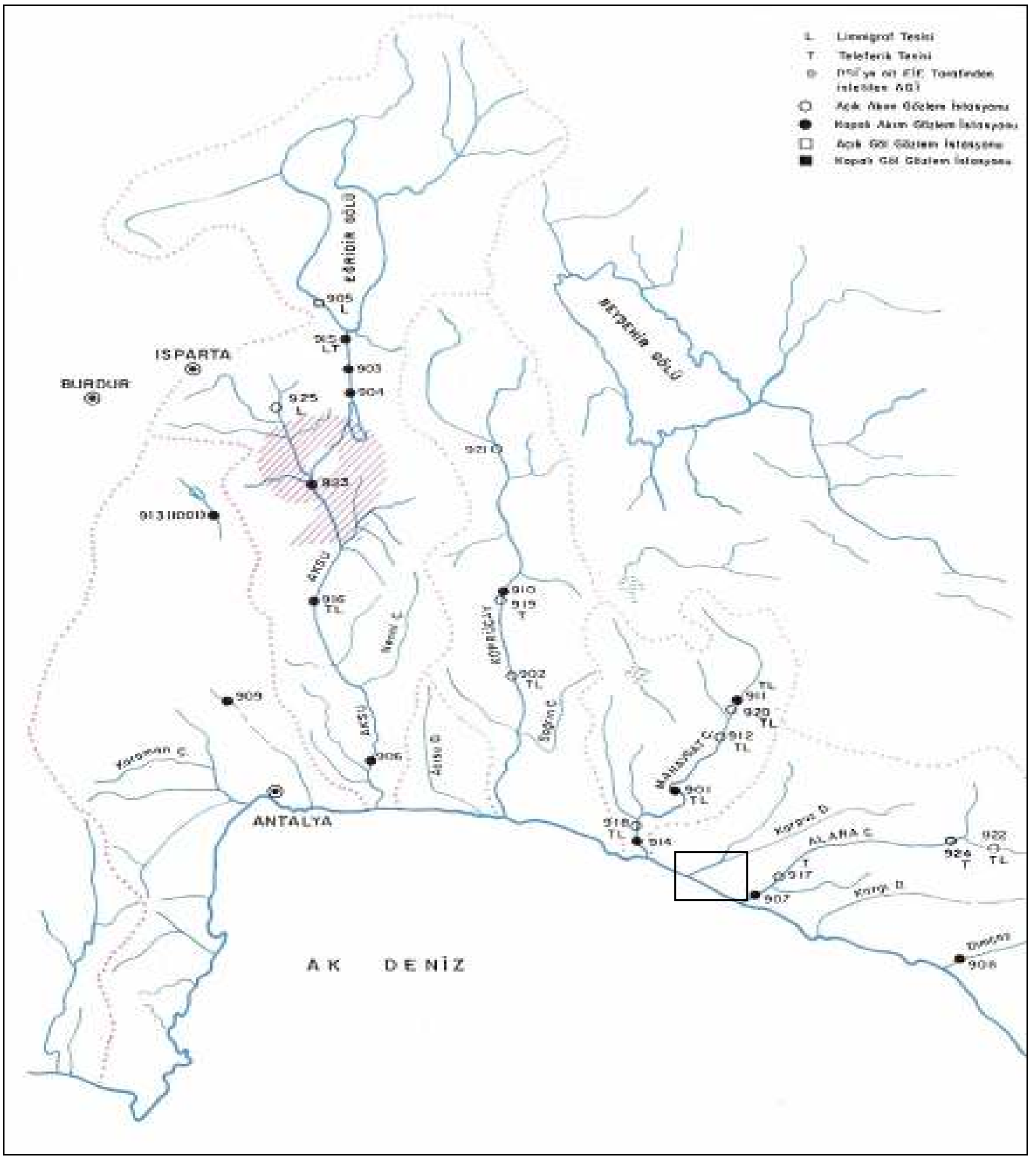

Figure 1. The Alara stream chatment is located including the stream stations[18]

A positive weight corresponds to an excitatory synapse, and a negative weight corresponds to an inhibitory synapse. If $w_{ij}=0$, then there is no connection between the two neurons. In Eq.(1), it is assumed that a unit relay elapses between the time instants t and (t+1). This assumption will also be used in our further discussion of this subject. Although simplicity models a biological neuron as a binary threshold unit, a McCulloch-Pitts neuron has substantial computing potential. It can perform the basic logic operations NOT, OR, and AND when weights and thresholds are selected accordingly. Since any multivariable combinational function can be implemented by these basic logic operations, a synchronous assembly of such neurons is capable of performing universal computations, much like an ordinary digital computer [19].

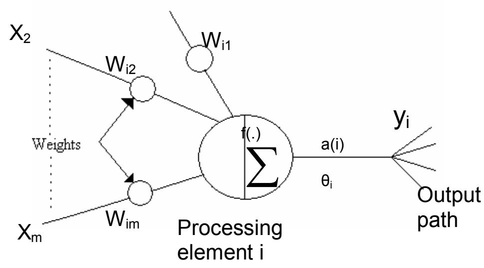

Figure 2.Schematic diagram of a McCulloch and Pitts neuron.

4. THE ADAPTIVE NEURAL BASED FUZZY INFERENCE SYSTEM MODEL(ANFIS)

The ANFIS model, based on a fusion of ideas from fuzzy control and neural networks, possesses the advantages of both neural networks and fuzzy control systems. In this way one can bring the low-level learning and computational power of neural networks to fuzzy control systems and also provide the high-level, IF–THEN rule reasoning of fuzzy control systems to neural networks. In brief, neural networks can improve their transparency, being closer to fuzzy control systems, while fuzzy control systems can self-adapt, being closer to neural networks. There is a number of methods proposed for partitioning the input space and for addressing the structure identification problem. Fundamentally, ANFIS is a graphical network representation of a Sugeno-type fuzzy system, endowed by neural learning capabilities. The network is comprised of nodes with specific functions, or duties, collected in layers with specific functions [20].

In order to illustrate representational strength of ANFIS, the neural fuzzy control system considered here is based on Tagaki-Sugeno-Kang (TSK) fuzzy rules whose consequent parts are linear combinations of their preconditions. The TSK fuzzy rules are in the following forms:

$$\begin{aligned}&R^j: \textbf{IF } x_1 \textbf{ is } A_1^j \textbf{ AND } x_2 \textit{ is } A_2^j \textbf{ AND...AND } x_n \textbf{ is } A_n^j \\ &\textbf{THEN } y = f_j = a_0^j + a_1^j x_1 + a_2^j x_2 + \ldots + a_n^j x_n\end{aligned} \quad (3)$$

where x_i (i = 1, 2, …, n) are input variables (flow effecting factors), y is the output variable (monthly flow measurements), A_i^j are linguistic terms of the precondition part with membership functions $\mu_{A_i^j(Xi)}$, a_1^j ЄR are coefficients of linear equations f_i (x_1, x_2, …, x_n) (j = 1, 2, ..., m, i= 1, 2, …, n). To simplify the discussion it is necessary to focus on a specific neuro-fuzzy controller (NFC) referred to as an adaptive neural-based fuzzy inference system (ANFIS). Assume that the fuzzy control system under consideration has two inputs x_1 and x_2 and one output y and that the rule base contains two TSK fuzzy rules as follows:

$$R^1: \textbf{IF } x_1 \textbf{ is } A_1^1 \textbf{ AND } x_2 \textit{ is } A_2^1, \textbf{ THEN } y = f_1 = a_0^1 + a_1^1 x_1 + a_2^1 x_2 \quad (4)$$

$$R^2: \textbf{IF } x_1 \textbf{ is } A_1^2 \textbf{ AND } x_2 \textbf{ is } A_2^2, \textbf{ THEN } y = f_2 = a_0^2 + a_1^2 x_1 + a_2^2 x_2 \quad (5)$$

In fuzzy logic approaches, for given input values x_1 and x_2, the inferred output y^* is calculated by:

$$y^* = (\mu_1 f_1 + \mu_2 f)_2 / (\mu_1 + \mu_2) \quad (6)$$

where μ_j are firing strengths of R^j (j = 1, 2), and are given by [19]:

$$\mu_j = \mu_{A_1^j}(x_1) x \mu_{A_2^j}(x_2), \quad j = 1, 2 \quad (7)$$

A stochastic model is set up and AR (3) model is selected for data from the 9–17 station on the Alara Stream in the Middle Mediterranean part of Turkey. Hence, flow inputs in models F_{t-3}, $F_{t-2,}$ F_{t-1} are given. Monthly flow data were used, covering the time span of 35 years (420 months), i. e. the observation period between 1969 and 2003.

5. RESULTS AND DISCUSSION

The data belonging to the period between 1969 and 1996 are used to develop the training part of the ANN and ANFIS model. The remaining years of data (1996 – 2003) are used to test the ANN and ANFIS model.

The adequacy of the flow models are evaluated by estimating the coefficients of determination (R^2) and mean square error (MSE) defined based on the flow prediction errors as,

$$R^2 = \frac{F_o - F}{F_o} \quad (8)$$

$$F_o = \frac{1}{n}\sum_{i=1}^{n}\left(F_i - F_{(predicted)}\right)^2 \quad (9)$$

$$F = \frac{1}{n}\sum_{i=1}^{n}\left(F_i - F_{i(predicted)}\right)^2 \quad (10)$$

Where F_i and $F_{i(predicted)}$ are historical monthly flow and models flow estimation values, respectively. The the mean square error (MSE) is defined as

$$MSE = \frac{1}{n}\sum_{i=1}^{n}\left(E_i - E_{i(predicted)}\right)^2 \quad (11)$$

where n is the number of observed data. In models, the input layer consisted of previous three flows (F_{t-3}, $F_{t-2,}$ F_{t-1}) and cos(2π*i*/12), sin(2π*i*/12) (*i* =1, 2, ..., 12) for the effect of monthly periodicity, and the output layer contained a single flow value (F_t) for time *t* for artificial models. In this study, ANN(i,j,k) indicates a network architecture with i, j and k neurons in input, hidden and output layers, respectively. Herein, i is 5; j assumes different neuron values for one hidden layer whereas k = 1 is adopted in order to decide about the best ANN model alternative. Prior to execution of the model, standardization of the data, X_i, (i = 1, 2, …,n) is done according to the following expression such that all data values fall between 0 and 1.

$$x_i = (X_i - X_{\min})/(X_{\max} - X_{\min}) \qquad (12)$$

where x_i is the standardized value but $X_{\max}$ and $X_{\min}$ are the maximum and minimum measurement values. Such standardization procedure renders the data also into dimensionless form. For ANN models the learning rate and momentum parameters affect the speed of the convergence of the back-propagation algorithm. A learning rate of 0.001 and momentum 0.1 are fixed for selected network after training and model selection is completed. The number of membership functions for flow inputs and output of ANFIS are set to three while number of membership functions for periodicity inputs are set to five. Membership function types for inputs and output are selected as Gaussian (or bell-shaped), and linear, respectively. Predicted flows are compared with the observed values in Fig.3 for two modelling techniques. Both low and high flows are better predicted by ANN than ANFIS. For flow prediction by ANN using observed data, R^2 and *MSE* values are found to be 0.95 and 22 in the training stage, and 0.91 and 20 in the testing stage, respectively while for flow prediction by ANFIS using observed data, R^2 and *MSE* values are found to be 0.69 and 160 in the training stage, and 0.66 and 148 in the testing stage, respectively.

6. CONCLUSION

Monthly streamflow estimation is vital in hydrological practices. There are plenty of methods used to predict streamflows. In this study, adaptive neural-based fuzzy inference system (ANFIS) and Artificial Neural Network (ANN) are applied to estimate streamflows. The comparisons of historical and predicted streamflow values showed that there are sufficient agreements between the results of ANN model and historical flow values. Existing streamflow methods need more parameters than ANN models. Hence, less data yields reliable streamflow estimations by the ANN approach. ANN method can be used to better predict and manage the water resources in the region than ANFIS model although the ANFIS method possesses additional advantages of both ANN and fuzzy control systems as model inputs are consisting of same variables as flow records in different times. If different input variables were used, ANFIS model predicts would be better than ANN. But we have not data of different variables for study region. Hence ANFIS model performance was not be tested for different input variables. The ANN approach can be regarded as a promising tool in hydrological studies with flow predicting being one of potential fields of applicability. With the help of flow prediction model, it is possible to estimate missing or unmeasured data.

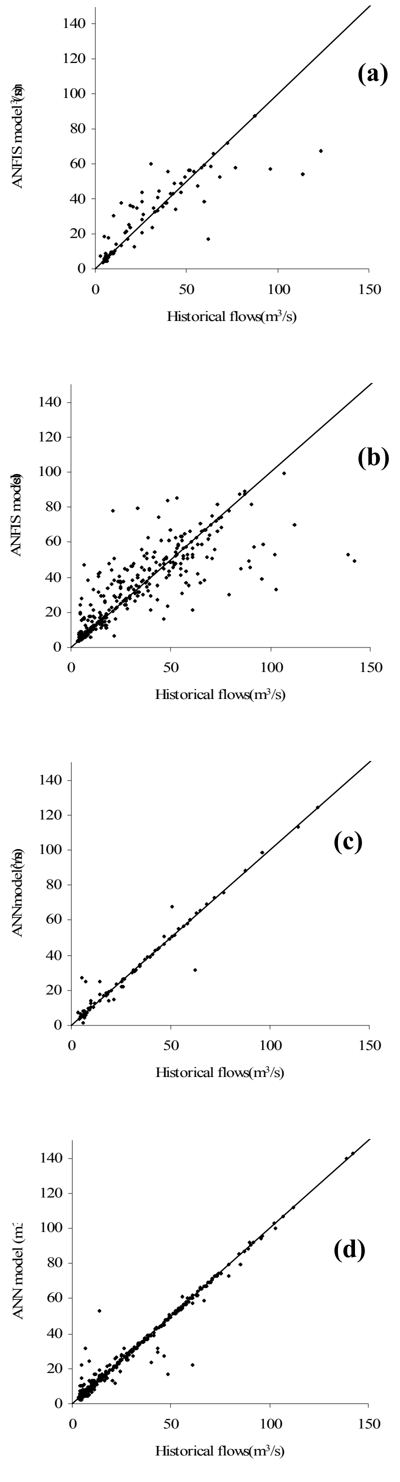

Figure 3. Scatter diagrams
(a) Testing stage for ANFIS, (b) Training stage for ANFIS,
(c) Testing stage for ANN, (d) Training stage for ANN

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