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Araştırma Makalesi Research Article

MONTHLY STREAM FLOWS ESTIMATION IN THE KARASU RIVER OF EUPHRATES BASIN WITH ARTIFICIAL NEURAL NETWORKS APPROACH

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Keywords

Artificial Neural Network, Rainfall-Runoff Relationship, Air Temperature, Potential Evapotranspiration, Karasu Aşağıkağdariç.

Abstract

This study aims to estimate streamflow values with artificial neural networks (ANN) using various meteorological parameters. In developing the ANN model, various combinations of precipitation, air temperatures, and potential evapotranspiration values were used as inputs, and streamflow values were obtained. Meteorological data is divided into 70% train, 15% test, and 15% validation. In the model's design, various training algorithms, network architecture, input combinations, and the number of iterations were tried, and the most suitable model was tested. Correlation coefficient (R), coefficient of determination (R^2), absolute error (AE), and absolute relative error (ARE) coefficients were compared, and the most suitable model was selected. According to the analysis results, the optimal model was obtained using 2000 iterations, the architecture of the 4-4-1 model, and the Quasi-Newton algorithm. It was determined that the ANNs successfully modeled the rainfall-runoff relationship and produced reliable estimates. In addition, it was revealed that the inclusion of potential evapotranspiration values obtained by the Thornthwaite method into the model increases the model's success.

FIRAT HAVZASI KARASU NEHRİNDEKİ AYLIK AKIMLARIN YAPAY SİNİR AĞLARI YAKLAŞIMINI İLE TAHMİNİ

Anahtar Kelimeler

Yapay Sinir Ağı, Yağış-Akış İlişkisi, Hava sıcaklığı, Potansiyel Evapotranspirasyon, Karasu Aşağıkağdariç.

Öz

Bu çalışma çeşitli meteorolojik parametreler kullanarak yapay sinir ağları (ANN) ile akım değerlerinin tahmin edilmesini amaçlanmaktadır. ANN modelinin geliştirilmesinde yağış, hava sıcaklıkları ve potansiyel evapotranspirasyon değerlerinin çeşitli kombinasyonları girdi olarak kullanılmış ve akım değerleri elde edilmiştir. Modelin tasarlanmasında çeşitli eğitim algoritmaları, ağ mimarisi, girdi kombinasyonları ve isterasyon sayıları denenerek en uygun model sınanmıştır. Korelasyon katsayısı (R), belirlilik katsayısı (R^2), mutlak hata (AE) ve göreceli mutlak hata (ARE) katsayıları karşılaştırılarak en uygun model seçilmiştir. Analiz sonuçlarına göre 2000 iterasyon, 4-4-1 modelinin mimarisi ve Quasi-Newton algoritması kullanılarak optimal model elde edilmiştir. ANN modellerinin yağış-akış ilişkisini modellemede ve güvenilir tahminler üretmede başarılı olduğu tespit edilmiştir. Ayrıca Thornthwaite yöntemi ile elde edilen potansiyel evapotranspirasyon değerlerinin modele dâhil edilmesinin modelin başarısını arttırdığı ortaya konmuştur.

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1. Introduction

It is very significant to identify the rainfall-runoff (R-R) relationship in the development and planning of water resources. Several mathematical models have been developed from the existing meteorological measurements to predict future flow values. Determination of future flow values is crucial for the operation of reservoirs for flood control, preparation for arid periods, provision of hydropower production, and planning of river access (Ahmad and Simonovic, 2005; Tombul and Oğul, 2006; Sert et al., 2007).

The fundamental parameter that creates the flow, which is one of the essential components of the hydrological cycle, is the amount of precipitation falling on the ground. When the parts such as evaporation, transpiration, and infiltration are removed in the falling rainfall, the remaining part forms the surface flow. Parametric and black box (such as artificial neural networks (ANN)) models can be employed to model the transformation of precipitation into runoff. Since parametric models are challenging to implement, artificial intelligence models are widely used to establish precipitation flow models today (Bayazıt, 1998). The ANN concept has emerged with the idea that the working principles of the brain are imitated numerically on computers. The first studies are based on mathematical and statistical modeling of biological nerve cells, that is, neurons that make up the brain. ANN systems can perform operations such as learning, associating, classifying, generalizing, predicting, characterizing, and optimizing. These capabilities make ANN systems attractive for solving physical problems in complex and dynamic properties such as flow systems. Besides, the advantages of ANN systems, such as linearity, parallelism, and thus speed, ease of analysis, and design, provide a great advantage in creating a flow control strategy, especially for real-time systems (Agatonovic-Kustrin, and Beresford 2000; Yilmaz et al 2001). ANNs are composed of simple nerve cells that operate in parallel. These elements are inspired by biological nerve cells. Similar in nature, communication between the components is provided by a network (Krse and van der Smagt 1996; Elshorbagy et al. 2010).

In this study, ANN, a black-box model, has been applied because of its success in modeling nonlinear system behavior., various combinations of precipitation (P), temperature (T), and the difference between precipitation and potential evapotranspiration (P-PET) values are used as input, and stream flows are obtained as output to determine the rainfall-runoff relationship. The various numbers of neurons and iterations were tried, and six different training algorithms were used to choose the optimal model. Statistical parameters such as correlation coefficient (R), determination coefficient (R^2) absolute error, and (AE) absolute relative error (ARE) are used to test the performance of the models. The optimum model with the smallest error rates and highest R^2 values emerged when P, T, and P-PET values were used.

2. Literature Survey

ANNs have recently been used extensively in hydrological models. Modeling of the R-R relationship in a basin, calculating the suspension item, flood forecasting in rivers, dam reservoir operation studies, calculation of a water level change in a lake, etc. are examples of work done in such areas. ANN is used to model the R-R relationship (Young and Liu, 2015; Vyas et al. 2016; Kumar et al. 2016; Dounia et al., 2016; Asadi et al. 2019), to predict rainfall (Lee et al., 1998; Mirabbasi et al. 2019), to predict river flow (Guimaraes Santos and Silva, 2014; Shi et al., 2016; Zemzami and Benaabidate, 2016; Wagena et al. 2020; Adnan et al. 2021), to predict reference evapotranspiration (Aytek, 2008; Qasem et al. 2019; Tikhamarine et al. 2019; Elbeltagi et al. 2022), to predict discharge and water-level (Khan et al., 2016; Nacar et al. 2018; Anilan et al. 2020; Damla et al. 2020; Temiz et al. 2021), to predict snowmelt–runoff (Yilmaz, 2011), ANNs have also been regarded as a powerful tool for use in a variety of underground water problems (Malik et al. 2021; Wunsch et al. 2021). ANNs can be used for other purposes is unit hydrograph derivation (Lange, 1998), flood frequency analysis (Campolo, 2003; Dawson, et al., 2006; Samantaray et al. 2021), drought analysis (Shin and Salas, 2000; Ochoa-Rivera, 2008; Banadkooki et al. 2021; Ozan Evkaya and Sevinç Kurnaz, 2021), suspended sediment data estimation (Jimeno-Sáez, 2018; Khan et al. 2019; Meshram et al. 2020), Modelling the infiltration process (Samantaray and Sahoo et al. 2021; Sihag et al. 2021; Singh et al. 2021), estimation of hydroelectric generation (Uzlu et al., 2014; Niu et al., 2019; Ozigis et al. 2021).

3. Material and Method

3.1. Study Area and Data

In this study, monthly average flow data of the Karasu Aşağıkağdariç stream gauging station between the years 1970-2009, measured by the General Directorate of Electrical Power Resources Survey and Development Administration (EİE) in the Euphrates Basin, and monthly total precipitations data of 17096 Erzurum Airport stations measured by General Directorate of Meteorology between 1970-2015 are used. In Figure 1, the location map of the Euphrates basin and the distribution of some stations are shown.

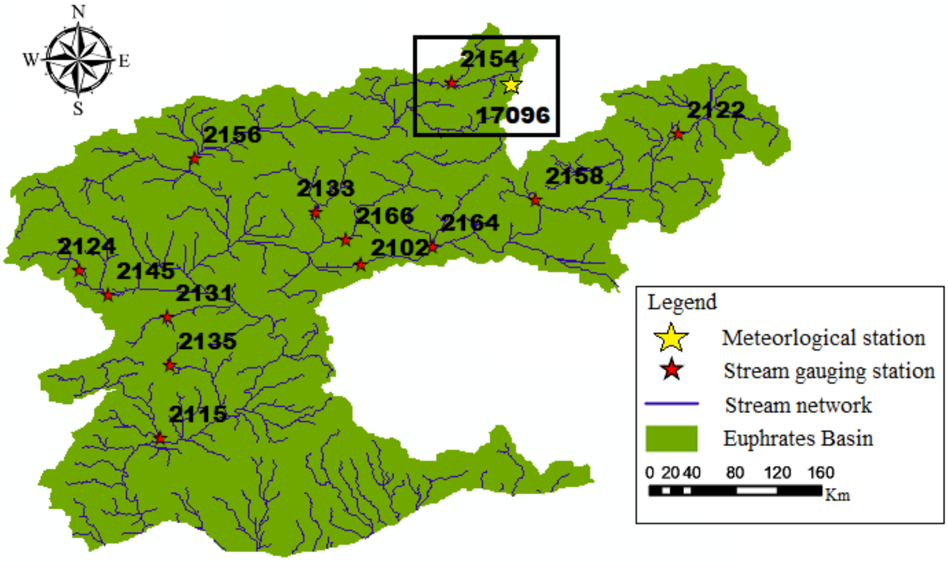

Figure 1. Rainfall and streamflow gauging station in the Euphrates Basin (Katipoğlu, 2020)

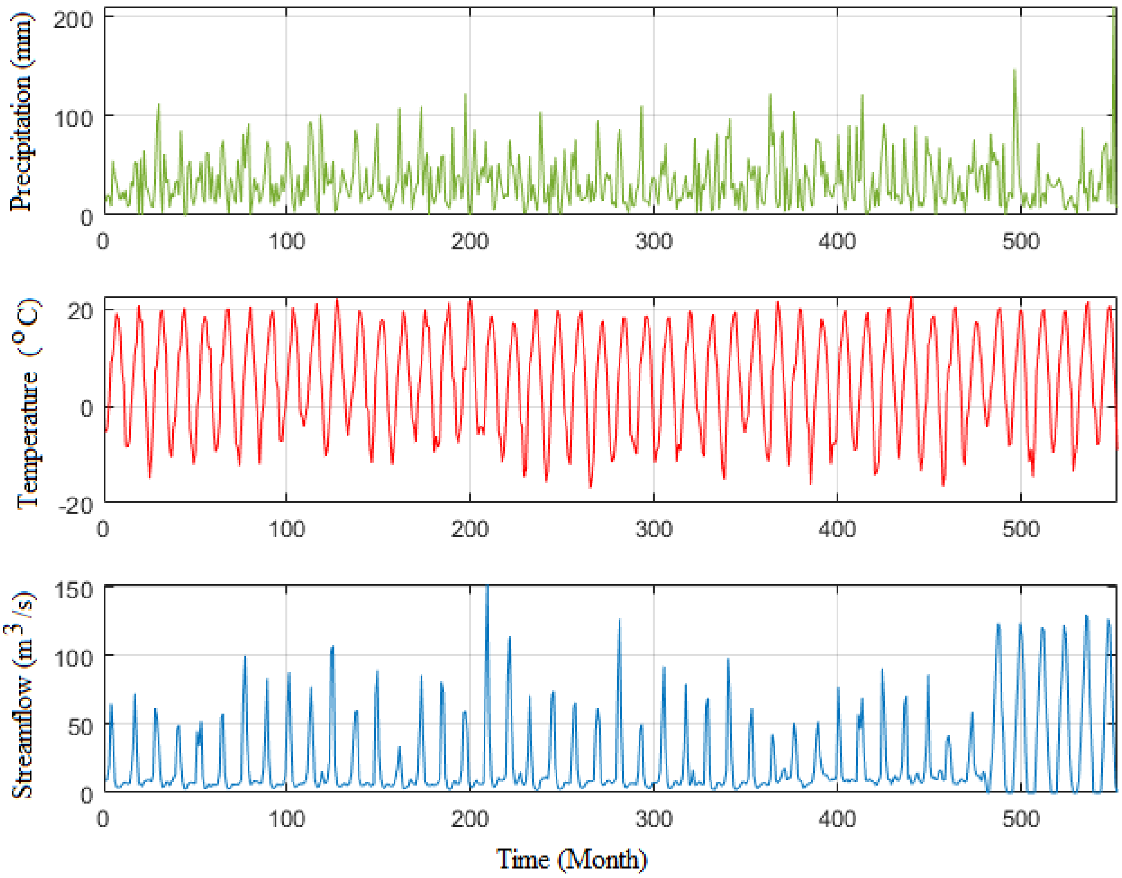

Figure 2. Data used in the establishment of the ANN model

The temporal changes of precipitation, temperature and flow data used to establish the ANN model are shown in Figure 2. In Table 1, the statistical properties of the data used in the study are indicated. According to this, in 1970-2015 in Erzurum meteorology station, precipitation varies between 210.8-0 mm and temperatures between 22.7--16.9 ^{0}C. In the Karasu river, the streamflow values in the 1970-2009 period vary between 152.5-2.01 m^3/s.

Tablo 1. Basic statistics of the data

	Precipitation (mm)	Temperature (⁰C)	Streamflow (m^3/s)
Mean	34.27	5.34	19.20
Maximum	210.8	22.7	152.5
Minimum	0	-16.9	2.01
Standard deviation	26.85	10.39	23.67

3.2. Rainfall-Runoff Models

The simplest relationship between precipitation and runoff is between runoff heights of various rainfalls and rainfall heights. When the precipitation heights are transferred to one axis, and the runoff heights to the other, the deviations of the points obtained around a curve to be drawn are usually very high. The effect of other variables can express the extreme deviation of the points around the curve. The most effective of these variables is soil moisture. However, since this variable cannot be measured directly, the following variables should be used:

- Rainfall before the considered rainfall
- The sequence number of the week in which the rainfall occurred
- The amount of runoff available in the stream at the beginning of rainfall
- The duration of rainfall above a certain intensity

It is important to consider these parameters together to successfully model the precipitation flow relationship (Bayazıt, 1995).

3.3. Artificial Neural Networks

The ANN is seen as one of the newest technologies developed with long-term efforts and can imitate nature. ANNs are programs designed to imitate the working principle of a simple biological nervous system. Stimulated nerve cells contain neurons, which connect differently to form a network. These networks can learn, memorize, and reveal the relationship between the data. In general, the ANN architecture is defined as 3 layers. The first layer is the input layer; the final layer is the output layer. The other layers are called the hidden layer or intermediate layer. There can be more than one intermediate layer in a network. It is unclear how many hidden layers are used in ANN and how many nerve cells are in each hidden layer. In this situation which varies according to the problem, a solution has been provided by a trial-and-error approach (Haykin, 1994; Krenker et al. 2011)

When Figure 3 is examined, in addition to layers in an ANN model, there are 5 basic elements; inputs, weights, net function, activation function, and outputs. In the input and output layers of the network, there are data related to the problem. The cell numbers in the input and output layers vary depending on the information defined in the question. The weights provide the activity in the system of information in the input layer and its importance. Data is stored in these weights; the intelligence of the network and the performance of learning depend on the correct determination of the weight values. The net function obtained by adding the weighted inputs expresses the effects of the inputs on this cell (Okkan and Mollamahmutoğlu, 2010).

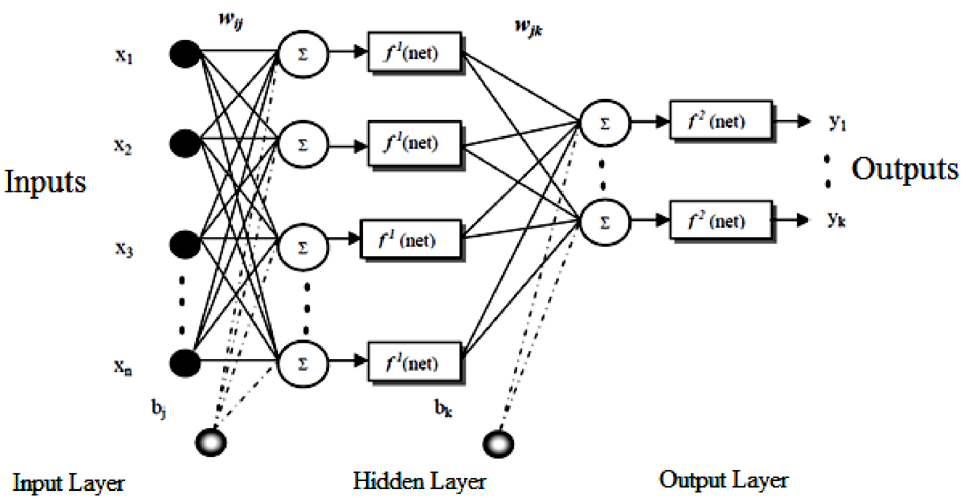

Figure 3. The architecture of the multi-layer artificial neural network

The activation function also referred to as the transfer function, is a nonlinear function that determines the cell output bypassing the net input from the combining process. In cell models, various types of activation functions can be used depending on the task the cell will perform. The most appropriate activation function becomes apparent due to the designer's experience. The selection of the activation function can be made according to the width of the ANN, the purpose of the network, and the input type. The most commonly used transitional functions are logistic sigmoid and hyperbolic tangent functions. Logistic sigmoid was used as the activation function in this study (Haykin 1999; Krenker et al. 2011).

3.3.1. Modeling phase

The establishment of the model of the ANN is generally carried out in 4 phases. These are; data collection and analysis, identification of network architecture, network training, testing, and validation. Alyuda NeuroIntelligence software is easy to use to model rainfall-runoff relationships. The design stages of the ANN model are shown in Figure 4.

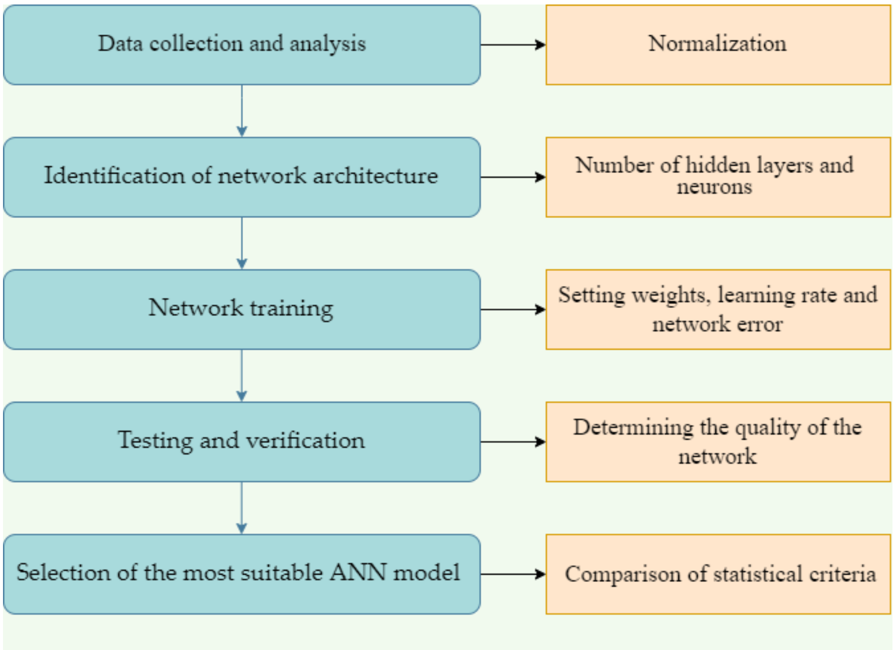

Figure 4. Flowchart for ANN

3.3.1.1. Data collection and analysis

In this study, rainfall, temperature, and runoff data between 1970 and 2009 were used. Approximately 70 % of the data were used for training, about 15 % of tests, and 15 % for validation purposes.

The input and output variables used in this study are firstly normalized in the range 0 and 1. This range has been chosen since the sigmoid logistics function (limited to 0.0 to 1.0) is used as the output layer activation function. Next, normalization is performed through Equation 1.

$$\bar{X} = \frac{X - X_{min}}{X_{max} - X_{min}} \quad (1)$$

where $\bar{X}$ is the standardized value of the input, $x_{min,}$ and x_{max}, respectively. The standardization process is done to express the variables measured in different units as a single type. Thus, a higher fit between the variables can be achieved.

3.3.1.2. Identification of network architecture

The fitness criterion was used to find the best network. The fitness criterion determines the network parameter to identify the best network. Each network is tested, and the network architecture is defined automatically.

In practice, ANNs are an effective method in learning, relationship building, classification, generalization, and optimization processes by taking advantage of the available data. This process is done by selecting the appropriate architecture of different architectural structures. There is a parallel-flow of information from the input layer to the output layer in the architectural structure. Such flow is provided by parallel placed cells.

3.3.1.3. Network training

As a result of the training process, it is expected that the error calculated in the ANN falls to an acceptable error rate. However, reducing the average error squares does not always indicate that the ANN reaches generalization. This is because the real purpose of the ANN is to reach generalization for input-output examples. Generalization is the ability of the ANN to correctly classify input-output samples from the same network that have not been used in training (Dawson and Wilby, 1998).

3.3.1.4. Testing and validation

Testing is a process used to predict the quality of a trained neural network and evaluate the model. At this stage, some of the data that is not used during the training is sent to the trained network according to the situation. Then, the estimation error is used to determine network quality. This step determines the success of the training (Dawson and Wilby, 1998; Ilie et al., 2012). The validation phase is necessary to monitor the network's development and solve the overfitting problem (Wang, 2015).

3.4. Thornthwaite Method

A method commonly used to estimate potential evapotranspiration is derived from Thornthwaite (Thornthwaite, 1948). This method correlates the monthly average temperature with evapotranspiration (ET_0) determined by the water balance for the valleys where sufficient moisture water is present to maintain active transpiration. The Thornthwaite formula is:

$$ET_0 = 16\, d\, \left({}^{10T}/_{I}\right)^{a} \qquad (2)$$

where T is the average temperature for the month (in °C), I is the annual thermal index, i.e. the sum of monthly indices i [$i = ({}^{T}/_{5})^{1.514}$], d is a correction factor which depends on latitude and month, and a is:

$$0.49 + 0.0179\, I - 0.0000771\, I^2 + 0.000000675\, I^3 \qquad (3)$$

The Drought Indices Calculator (DrinC) software is used to calculate PET values. PET values were calculated by the Thornthwaite method since monthly average temperature and latitude data could be obtained in the study area.

3.5. Model Performance

Many performance measurement methods have been developed to evaluate the accuracy of estimation. This study compared four different statistical parameter values to determine the optimum model. These parameters are the correlation coefficient (R), the determination coefficient (R2), absolute error (AE), and absolute relative error (ARE).

$$R = \frac{\sum_{i=1}^{N}(O_i - \bar{O}_i)(P_i - \bar{P}_i)}{\sqrt{\sum_{i=1}^{N}(O_i - \bar{O}_i)^2 \sum_{i=1}^{N}(P_i - \bar{P}_i)^2}} \qquad (4)$$

$$R^2 = 1 - \frac{\sum_{i=1}^{N}(O_i - P_i)^2}{\sum_{i=1}^{N}(O_i - \bar{O}_i)^2} \qquad (5)$$

$$AE = \frac{\sum_{i=1}^{N} |P_i - O_i|}{N} \qquad (6)$$

$$ARE = \frac{\sum_{i=1}^{N} \left| {}^{(P_i - O_i)}/_{O_i} \right|}{N} \qquad (7)$$

where O_i and P_i are respectively, the observed and predicted value of flow, $\bar{O}_i$ is the average of O_i values, $\bar{P}_i$ is the average of P_i values and N is the total number of data sets. The best value of R and R^2 is equal to 1. AE and ARE values are calculated from differences between the predicted and observed values. The best value of these errors is equal to 0.

4. Experimental Results and Discussion

This aimed to predict river flows by using various meteorological data as input. ANN, one of the largely utilized machine learning methods in recent years, has been used for flow prediction. While developing the model, the data were divided into 70% training, 15% testing, and 15% validation. The data were used by randomly dividing.

Table 2. Identification best fits architectures.

Architecture Search	
Architecture	**Fitness Criteria**
[4-1-1]	0.092
[4-10-1]	0.138
[4-6-1]	0.139
[4-4-1]*	0.145
[4-2-1]	0.093
[4-5-1]	0.137
[4-3-1]	0.083

Note: * marker indicates the best architecture

The fitness criterion was applied to select the most suitable network architecture. Considering Table 2, the optimum network architecture was found to be (4-4-1). Figure 5 shows the network architecture best suited to the neural network. It is seen that precipitation, temperature, and potential evapotranspiration values are used as inputs in the selected architecture.

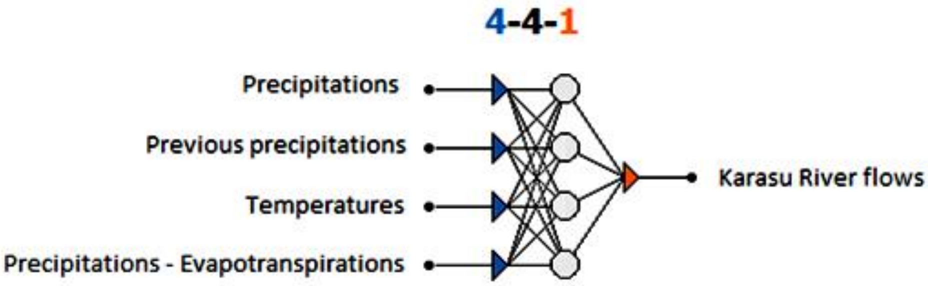

Figure 5. ANN architecture for prediction of Karasu River flows.

It is determined that the most appropriate model is type 6 by comparing the training, testing, validation, and overall model results. It is seen that the model of correlation and determination coefficients are the highest and errors are the smallest (Table 3). Correlation is high and positive, indicating that the predicted model is appropriate and correct. Furthermore, the fact that the coefficient of determination is close to 1 means that the data obtained by the current data are close to each other.

Quasi-Newton, Conjugate Gradient Descent, Levenberg-Marquart, Online Backpropagation, Quick Propagation, and Batch Backpropagation algorithms were used to build the rainfall-runoff model. The Quasi-Newton algorithm was realized as the best training algorithm. The optimum model was obtained by using the logistic sigmoid transfer function, 2000 iterations, the combination of input-hidden-output neurons (4-4-1) (Table 3).

Figure 6 shows the results of comparing the output values of all data sets and the target output values. Again, the overlap of the target and output values indicates that the established model has high R^2 and that the model is suitable for estimating the R-R relationship.

Table 3. Selecting the most suitable model.

	Type 1	Type 2	Type 3	Type 4	Type 5	Type 6**
Inputs	**P**	**P, P_{t-1}**	**P, T**	**P, P-PET**	**P, P_{t-1}, P-PET**	**P, P_{t-1}, T, P-PET**
Outputs	Q	Q	Q	Q	Q	Q
Best architecture	1-7-1	2-7-1	2-6-1	2-6-1	3-8-1	4-4-1
Best algorithm	Quick prop.	Quick prop.	Quasi-Newton	Quasi-Newton	Quasi-Newton	Quasi-Newton
Number of iterations	2000	5000	700	1000	1000	2000
	Correlation Coefficient (R)					
Training	0.58	0.69	0.70	0.75	0.79	0.90
Testing	0.55	0.47	0.72	0.66	0.69	0.86
Validation	0.48	0.45	0.80	0.60	0.71	0.79
Overall model	0.54	0.54	0.72	0.69	0.75	0.86
	Determination Coefficient (R^2)					
Training	0.34	0.48	0.49	0.56	0.62	0.81
Testing	0.30	0.22	0.52	0.44	0.48	0.74
Validation	0.23	0.20	0.64	0.36	0.50	0.62
Overall model	0.29	0.29	0.52	0.48	0.56	0.74
	Absolute Error (AE)					
Training	10.61	9.12	9.34	8.90	7.20	6.33
Testing	11.32	12.14	8.92	9.26	9.14	6.61
Validation	12.24	12.60	8.87	10.59	9.04	6.94
Overall model	11.04	10.95	8.89	9.51	8.30	6.42
	Absolute Relative Error (ARE)					
Training	0.90	0.93	0.83	0.76	0.60	0.55
Testing	1.25	1.29	0.82	0.94	0.68	0.56
Validation	1.20	1.40	0.61	0.96	0.65	0.67
Overall model	1.18	1.11	0.62	0.95	0.67	0.56

Note: **marker indicates the best model, P: Monthly average precipitations, P_{t-1}: Previous Month average precipitations, T: Temperatures, P-PET: Difference between precipitations and potential evapotranspiration, Q: Monthly average flows

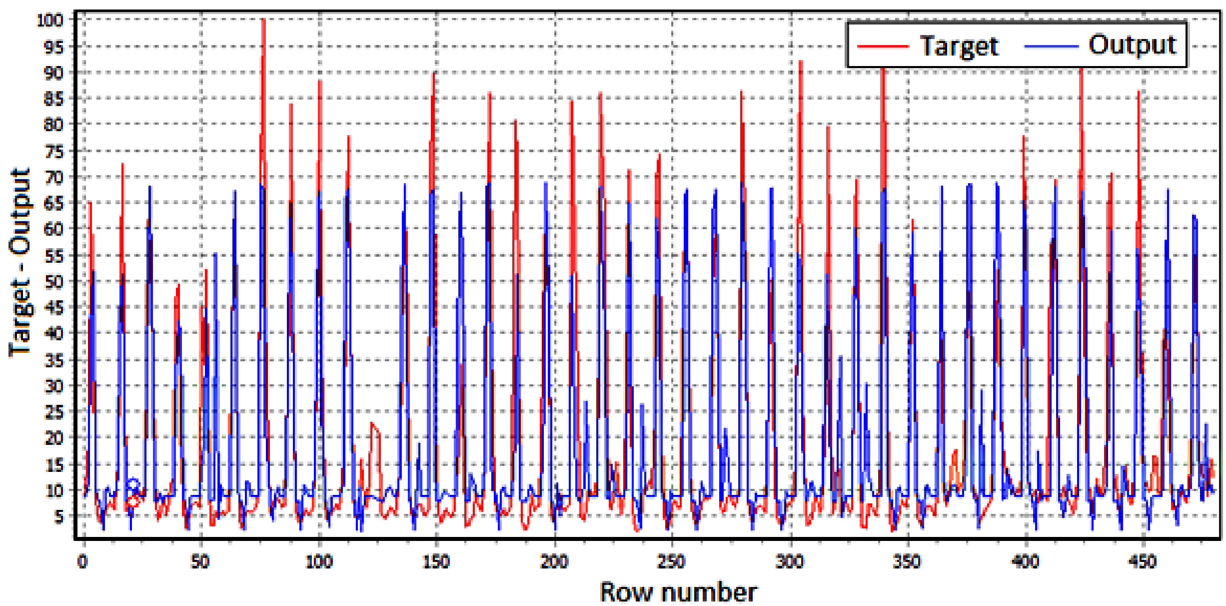

Figure 6. Target (actual) values vs output (simulated) values

Figure 7 presents the "error dependence graph," which displays the network error depending on the values of the numerical inputs of the network. Figure 7 also indicates model errors are minor.

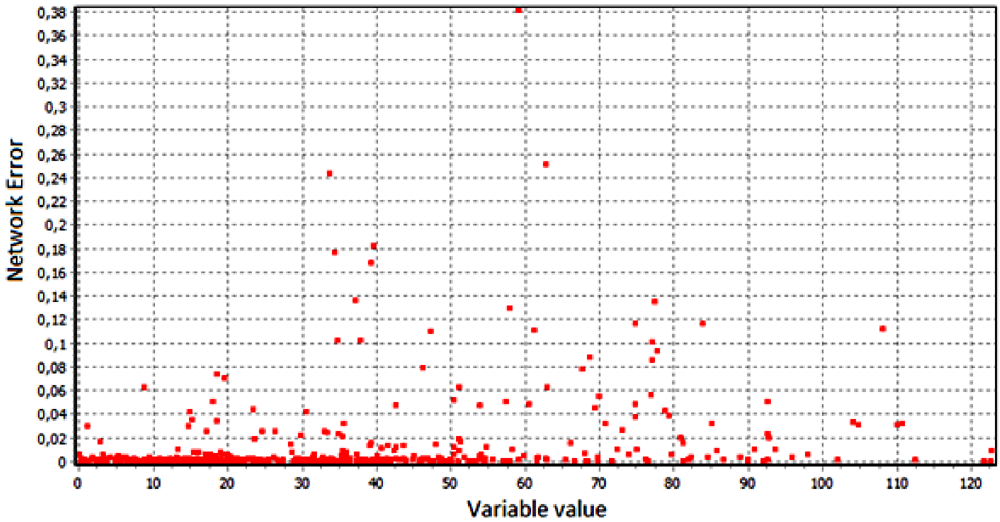

Figure 7. Error dependence on the values of the numerical inputs of the network

The most effective algorithm was determined according to the error status between the outputs produced by the network and the expected outputs. Then, an algorithm known as Quasi-Newton is used to adjust the weights to decrease the margin of error. Finally, the network is trained by doing this process repeatedly. The training process aims to achieve an optimum solution based on performance metrics. Figure 8 indicates the network output values' distribution graph and the target output values' specific time series. The distribution of points around the line indicates that the relationship between predicted and actual values is high.

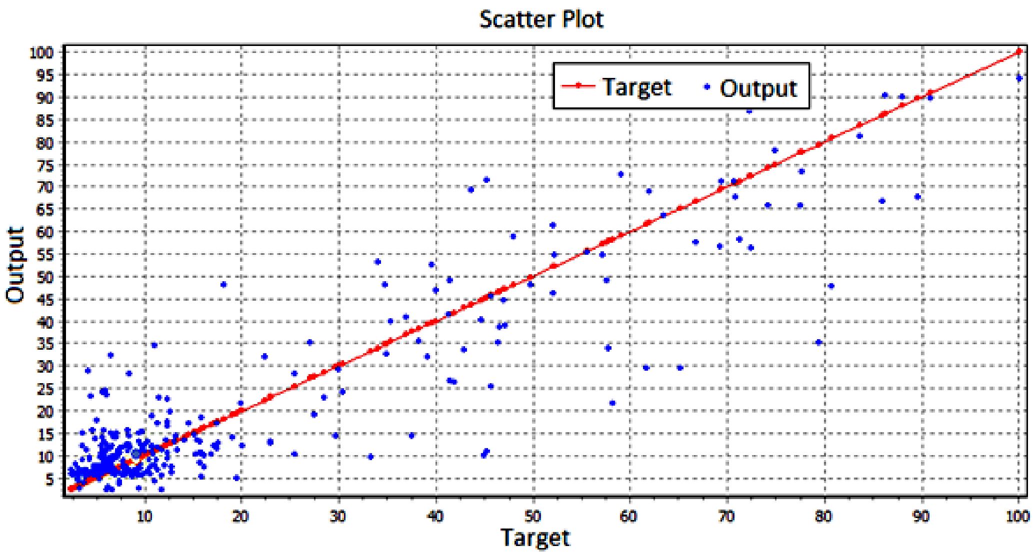

Figure 8. Scatter plot of the output values and the target output values of the overall model

Tombul and Oğul (2006) used precipitation and evaporation data as input to the ANN model for the estimation of flow values. As a result, the feed-forward back propagation neural network, which gives the largest determination coefficient (R^2= 0.72) and the smallest mean square error values (MSE = 0.60), has been determined as the best model. The stated study largely overlaps in terms of obtaining close statistical parameters (R= 0.86, R^2= 0.74, AE= 6.42 and ARE= 0.56) in runoff estimation and effective estimation. Our study is different and original from the stated study in terms of using the difference between temperature and precipitation and potential evapotranspiration values in flow estimation.

Machado et al. (2011) modeled the monthly R-R relationship using precipitation, flow, and potential evapotranspiration data. Consequently, it was revealed that ANN effectively models the rainfall-runoff relationship. This situation supports our work.

Bölük (2020) applied multiple linear regression, nonlinear regression, ANN, and generalized regression ANN methods, which are widely used today, to estimate precipitation-flow relationship with artificial intelligence technique. In direct proportion to the presented study, it has been concluded that the ANN method can be used as an alternative to classical methods in the R-R model.

In the study of Keskin (2020), runoff values were estimated by presenting daily precipitation, runoff, and temperature data as input data to the ANN model. As a result of the study, it was found that the ANN method in nonlinear cases produced more realistic results with fewer errors than the multiple linear regression method. In addition, it has been determined that the ANN model, which supports the presented study, is more than 92% accurate.

5. Conclusion

In this study, the rainfall-runoff relationship in the Karasu Aşağıkağdariç gauging station was modeled with the ANN approach. While P, P_{t-1}, T, P-PET values, which are the factors affecting runoff, are used as inputs, runoff values are presented to the model as output. The study has determined that the flow data can be estimated effectively by using precipitation, temperature, and difference between precipitation and potential evapotranspiration values as inputs. Decision-makers can use this situation in the planning and management of water resources.

To estimate the rainfall-runoff relationship, Quasi-Newton, Conjugate Gradient Descent, Quick Propagation, Levenberg-Marquart, Online Backpropagation, and Batch Backpropagation algorithms were tried. Quasi-Newton is the best algorithm, which shows the highest R^2 and the smallest errors.
In the best ANN model, R, R^2, AE, and ARE values are obtained 0.86, 0.74, 6.42, 0.56, respectively. These values indicate that the best model performance is achieved when P, P_{t-1}, T, P-PET data are used as input.

This study showed that it is possible to estimate and predict monthly streamflow by using ANN. In addition, it has been revealed that the Thornthwaite method-based potential evapotranspiration values increase the model's success.

Future studies suggest including hydrological parameters such as evaporation, wind speed, soil moisture, and solar radiation to establish more successful R-R models. In addition, it has been suggested to test daily and hourly R-R models and to use longer and continuous records.

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Conflict of Interest

No conflict of interest was declared by the author.

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