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Research Article

Monthly Streamflow Prediction Using ANN, KNN and ANFIS models: Example of Gediz River Basin

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Abstract

Stream flow forecasting is very important in many aspects, such as water supply, irrigation, building water infrastructure, and taking precautions against floods. The ability to forecast future streamflow helps us anticipate and plan for upcoming flooding, decreasing property destruction, preventing deaths, and managing water in the best way possible. Different hydrological models have been developed for predicting streamflow, and they have different characteristics, driven by the research area and available data. In this study, three types of Artificial Intelligence models; K-Nearest Neighbor (KNN), Artificial Neural Network (ANN) and Adaptive Neuro Fuzzy Inference System (ANFIS) have been used to study the Gediz River Basin, which is located in the Aegean region of western Turkey. The results varied due to the complication of the data and different parts of the study area as well as the structure of the models, over all, looking at the regression coefficient (R^2), Root Mean Square Error (RMSE) and Wilcoxon (WT) values, ANFIS is more accurate compared to ANN and KNN models. Conversely, according to Taylor diagram, KNN is more accurate compared to ANN and ANFIS.

Keywords: Streamflow Prediction, ANFIS, ANN, KNN, Gediz River Basin, Wilcoxon

YSA, KNN ve ANFIS Modellerini Kullanarak Aylık Akım Tahmini: Gediz Nehri Havzası Örneği

Öz

Akarsu akış tahmini, su temini, sulama, su altyapılarının inşası, taşkınlara karşı önlem alınması gibi birçok konu için çok önemlidir. Gelecekteki nehir akışını tahmin etme yeteneği, yaklaşan selleri tahmin etmemize ve planlamamıza, mülk tahribatını azaltmamıza, ölümleri önlememize ve suyu mümkün olan en iyi şekilde yönetmemize yardımcı olur. Akarsu akışını tahmin etmek için farklı hidrolojik modeller geliştirilmiştir. Bu modeller, araştırma alanı ve mevcut veriler tarafından yönlendirilen farklı özelliklere sahiptirler. Bu çalışmada, K-En Yakın Komşu (KNN), Yapay Sinir Ağı (ANN) ve Uyarlanabilir Nöro Bulanık Çıkarım Sistemi (ANFIS), olarak üç farklı yapay zeka modeli kullanılmıştır. Türkiye'nin batısındaki Ege bölgesinde yer alan Gediz Nehri Havzasının verileri ise eğitim ve test için kullanılmıştır. Sonuçlar, verilerin karmaşıklığı ve çalışma alanının farklı bölümleri ve ayrıca modellerin yapısı nedeniyle değişiklik göstermiştir, genel olarak, Regresyon katsayısı (R^2), Ortalama Karesel Hata (RMSE) ve Wilcoxon (WT) değerlerine bakıldığında ANFIS, YSA ve KNN modellerine kıyasla daha doğrudur. Taylor diyagramına göre ise KNN, ANN ve ANFIS'e kıyasla daha doğrudur.

Anahtar Kelimeler: Akış Tahmini, ANFIS, ANN, KNN, Gediz Nehri Havzası, Wilcoxon

1. Introduction

Flowing water is significant for all creatures. Using it effectively is one of the most important precaution that has to be taken against drought. In order to use it in an effective way, long-term streamflow has to be predicted. In some flowing water, it is possible to be forecasted accurately while in other it is impossible due to some drawbacks. Streamflow prediction is extremely important for taking a decision about a project, completing a newly established observation station's data with retrospective streamflow, and detecting data for an old incompleted station in the best way. Therefore, many studies have been developed. These research are mainly mathematical (Ergu et al., 2016), graphical (Williams et al., 2007), artificial intelligence (Langhammer and Česák, 2016; Dastgheib and others, 2022 Katipoglu, 2021), hybrid models (Li et al., 2021; Kilinc ve Yurtsever, 2022) and GIS based (Adeogun, 2014). Several research have been done using Artificial Intelligence (AI) based models (Kim and others, 2010; Dastorani and Moghadamnia, 2010; Al-Saati et al., 2021). Amongst them, ANN is one of the most commonly used model. Sudheer and Nayak (2003) used ANN for forecasting peak currents. Güçlü and Şen (2016) have predicted hydrograph using FCM model, which is a combination of Mamdani and ANFIS. Saplioglu and Küçükerdem (2018) have predicted the completion of missing flow data at Yeşilırmak basin in Turkey. Moreover, in the same study, it has been presented that ten year data has to be used for the accuracy of the model. Şenel and others (2020) have used ANN and Ant Lion together to determine time delay and predict streamflow from one station. Saplıoğlu and others (2020) have tried to complete missing flow data using Symbiotic Organisms Algorithm. Köyceğiz and Büyükyıldız (2022) have predicted streamflow using differend models of ANN. Kilinc and Haznedar (2022) have combined Genetic Algorithm (GA) and Long Short Term Memory (LSTM) and used this hybrid model for streamflow forecastion.

In this study, the streamflow of station 518 at Gediz basin in Turkey was predicted using 509, 525 and 527 stations as input data and 518 station as observed data. To predict it, several AI models; K-Nearest Neighbor (KNN), Artificial Neural Network (ANN) and Adaptive Neuro Fuzzy Inference System (ANFIS) were used and their performances were compared. In order to remark the best model; Coefficient of determination (R^2), Root Mean Square Error (RMSE) and Wilcoxon Test (WT) were used. Moreover, Taylor diagram was also used in order to find the best model.

2.Material and Method

2.1. Material

The GRB which is located in western Turkey is one of the largest and most important river basins of Turkey. The location of the basin is in the Aegean region and it lies between 38° 04′ - 39° 13′ northern latitudes, and 26° 42′ - 29° 45′ eastern longitudes. The drainage area of the basin is about 17146 km2 which is 2.2% of the entire Turkey's area. The GRB is vital for agriculture of the nation and other sectors (Elçi et al., 2015). Topographical map of the basin is shown in Figure.1.

The GRB climate is typical Mediterranean. Summer is hot and dry while winter is cool and rainy. Long-term precipitation of the basin is 617mm and mean annual temperature is 15.2 °C. In 2012, around 1.733 million people were living in the territory of the basin. Major socio-economical activities in the region are animal husbandry, agriculture, textile industry, food industry, and mining. Amongst them, agriculture's sector is the biggest water consumer. In 2014, approximately 351,000 hectares agriculture area was irrigated from the basin. The main crops planted in the region are grapes, cotton, olives and corn(DSI, 2014).

Stations that were used in the study are; 509, 518, 525, and 527. Table 1 shows the statistics of train and test data sets of the stations. Table 2 summarizes the Northern Latitudes, Eastern Longitudes, Areas(km^2), and Altitudes of all the stations.

Table 1. Statistical values for train and test data sets

Statistic	Train				Test			
	509	525	527	518	509	525	527	518
Average	2.38	0.67	4.49	27.54	2.43	0.58	4.85	21.14
Standard Error	0.24	0.07	0.55	2.13	0.4	0.08	0.85	1.87
median	0.63	0.25	1.02	17.8	0.51	0.27	1.45	14.9
Kip	1.58	0	0	19.1	0	0.01	0	14.4
Standard Deviation	3.97	1.11	8.98	34.9	4.32	0.83	9.06	20.01
Sample Variance	15.76	1.23	80.65	1217.6	18.64	0.69	82.1	400.48
Kurtosis	16.21	23.91	39.57	14.39	11.7	6.2	16.68	8.96
Skewness	3.47	4.11	5.08	3.33	3.07	2.37	3.57	2.54
Range	28.1	9.26	93.6	259.9	27.5	4.54	63.5	130.45
Min	0	0	0	0.1	0	0	0	0.55
Max	28.1	9.26	93.6	260	27.5	4.54	63.5	131
Total	641.2	180.79	1206.67	7409.35	279.06	66.93	557.6	2430.96
Number of Data	269	269	269	269	115	115	115	115
Conf Interval(95%)	0.48	0.13	1.08	4.19	0.8	0.15	1.67	3.7

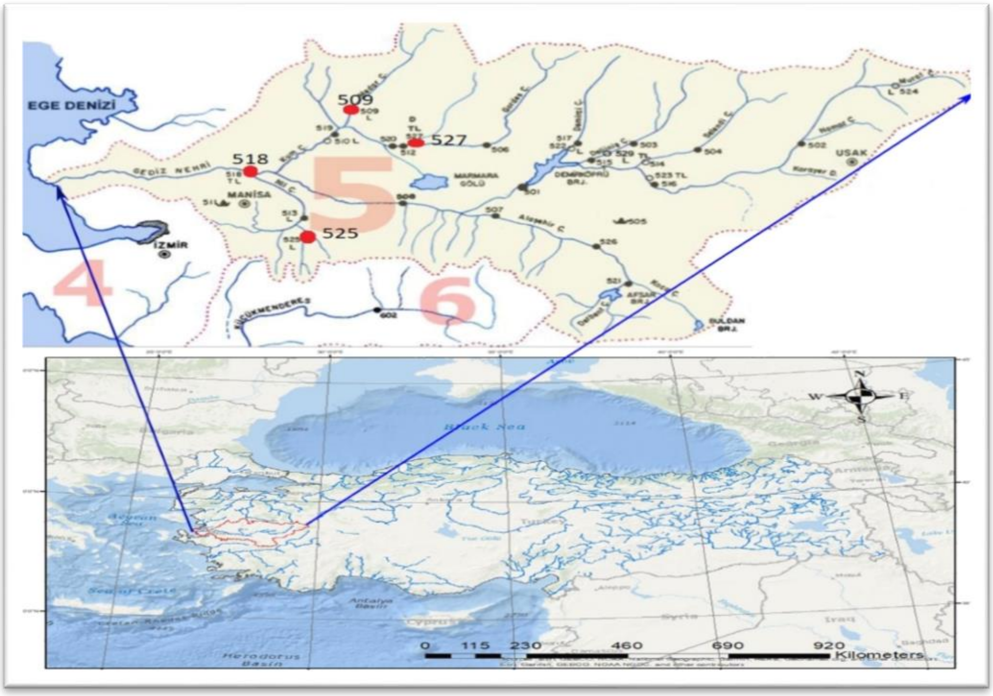

Figure 1. Location of the Gediz River Basin in the map.

Table 2. L, longitudes, areas and altitude of the stations.

Station	509	518	525	527
Northern Latitudes	38° 53' 25''	38° 38' 41''	38° 24' 44''	38° 46' 40''
Eastern Longitudes	27° 46' 09''	27° 26' 30''	27° 36' 47''	(27° 57' 58''
Area(km²)	901.6 km²	15616.4 km²	64.0 km²	430.5 km²
Altitude	77(m)	23(m)	158 m	128 m

2.2. Methods

2.2.1 Adaptive Neuro Fuzzy İnference System

The learning capabilities of neural networks and fuzzy systems are combined in an ANFIS model (Elçi1 and others, 2022). Sugeno's systems are the most widely utilised of the three ANFIS model types, Mamdani, Sugeno, and Tsumoto (Yaseen and others, 2017). Membership functions are used by fuzzy logic models to transform input data into fuzzy values that fluctuate between 0 and 1 (ekmiş and others, 2014). Both nodes and rules are components of an ANFIS model. While nodes are acting as membership functions, the rules allow one to establish the relationship between a predictor (input) and the predictand (output) (MFs). Sigmoid, Gaussian, triangular, trapezoidal, and other forms of membership functions could be taken into consideration when creating an ANFIS model. Earlier research that used the Gaussian equation in their ANFIS models were followed in order to select the best MF for this paper (Saploglu, 2018, Dastgheib, 2022). Due to its clear notation and smoothness, it is vital to note that the Gaussian shape is the most well-known MF for describing fuzzy systems (Gholami , 2017). The Gaussian MF offers some benefits over other equations, including smoothness, being non-zero, and being defined by just two parameters that are optimised during training. As a result, Equation has been used to implement this MF function in this study.

$$U_{Ni} = \frac{exp(-x(x-ci)^2)}{ó_j^2} \quad 1$$

In this equation, UNi is the MF and x is the input at i node. Ój and ci are the conditional factors of the function.

ANFIS needs feature subtraction rules that are applied to the input-target data and they are stocked in a fuzzy based rule system (i.e.,'the IF- THEN' rule). The rules are described based on their antece-dents (If part), and consequents (Then part). In a Sugeno MF,a rule is composed by weighted linear combination of the crisp inputs. Equations. (2) and (3) shows the rules for an ANFIS system in which there are two inputs; x and y as well as an output f.

Rule 1 : IF x is A1 and y is B1; then

$$f_1 = a_{1x}b_{1y} + w_1 \quad 2$$

Rule 2 : IF x is A2 and y is B2; then

$$f_2 = a_{2x}b_{2y} + w_2 \quad 3$$

In this equations, Ai and Bi are fuzzy sets, fi is the output therein the fuzzy region and ai, bi, and wi are the design parameters specified throughout the model's training process (i = 1, 2). Figure. 2 shows the architecture of an ANFIS model having two inputs; x and y and an output (f).

In this paper, an ANFIS model is adopted mainly because of its good ability of constructing, learning, classifying and expensing the input-target data. ANFIS has the benefits of extraction patterns in the input data based on fuzzy rules to search for expertise and adaptively construct a rule base. In a streamflow forecasting problem that is extremely complicated because of the chaotic nature of the data, an ANFIS model can easily extract information and transform it to fuzzy systems; however, a larger time expended in training the model is important for precise estimation.

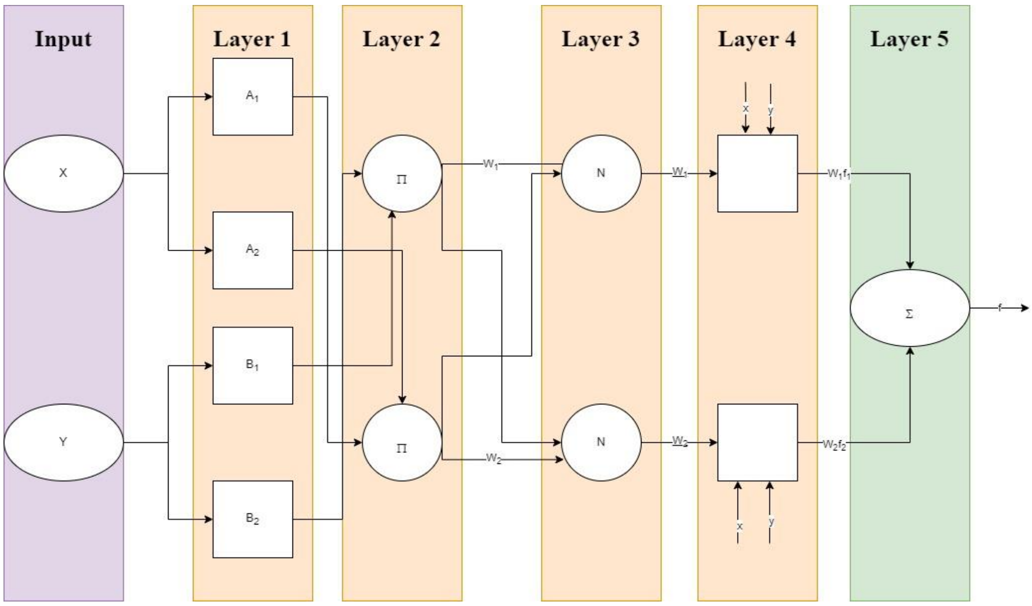

Figure 2. The structure of an ANFIS contains 5 layers and 2 inputs, with layers 1 and 2 being "Input Fuzzy Rules," layer 3 being "Fuzzy Neurons," and layer 4 being "Output MF." "Summation and Weights" Layer 5

2.2.2. Artificial Neural Network

The ANN has been widely employed in many areas of science and engineering as an intelligent learning paradigm, including improving peak flow predictions (Sudheer, and others 2003), detecting time dependency and forecasting streamflow (Şenel and others 2020), and reconstructing missing flow data (Dastorani, and others 2010). An input, a hidden layer, and an output layer make up a three-layer feed-forward back propagation ANN, as shown in figure 3. There are nodes in each layer, and those nodes are linked to other layer nodes (s). The connector also has a weight attached to it. Imagine a three-layer, simple neural network. As stated in Equation, the output of the j-th hidden node can be obtained.

$Hj = f((\sum_{i=1}^{n} wijxi - aj)$ j=1,2,,l (4)

The transfer function of the hidden layer is represented in this equation as f(x)=1/(1+exp(x)); n denotes the number of nodes in the input layer, l the number of nodes in the second "hidden layer," wij the connection weight from the i-th input node to the j-th hidden node, and aj the bias of the j-th hidden node.
The final output can be shown as follow, after calculations of the outputs of the hidden layer:

$Ok = \sum_{i=1}^{l} Hjwjk - bkk = 1,2,\ldots,$m 5

This equation has three parts: wjk, which represents the link weight from the jth hidden node to the kth output node, and bk, which represents the bias of the kth output node. M is the number of nodes in the output layer.

2.2.3. K Nearest Neighbor Algorithm (KNN)

The non-parametric K Nearest Neighbors approach was created by Hodges and Fix in 1951. KNN can be utilised for both problem classification and prediction in an undisclosed US Air Force paper (Poul1 and others, 2019). KNN regression is used to approximate constant variables for prediction-related purposes. The inverse of their distance is implemented by the weighted average of the k nearest neighbours, which is the foundation of the KNN algorithm's operation. The model's improvement steps are as follows:

1) Calculate the distances in Euclid between the predictor example and the existing instances.

2) Use an increasing or decreasing distance to arrange the current instances.

3) Take the KNNs into account while calculating an inverse distance weighted average.

4) Finding the optimal K nearest neighbours based on the lowest RMSE value.

The results obtained with three methods are frequently used in different studies (Aksakal and Gündoğay, 2022; Gündoğay and Aksakal, 2022), regression (Ünal et al., 2018), mean square error (Çatal and Saplioglu, 2018), Wilcoxon (Uzundurukan, 2023) and The results were compared by testing with a taylor diagram.

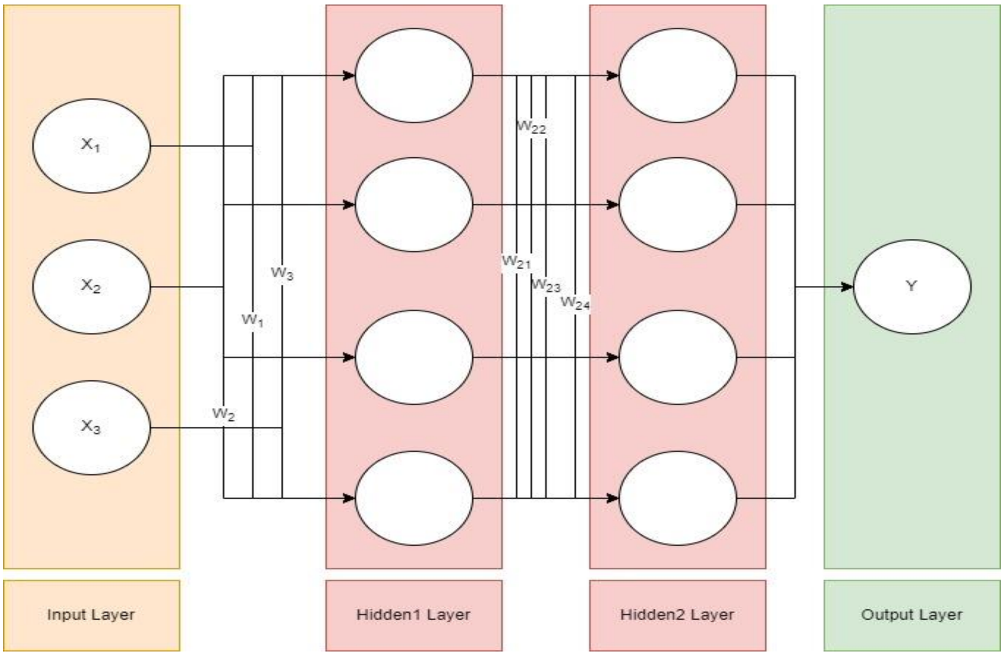

Figure 3. Architecture of a three-layer ANN model

3.Results

In this study, 518 station's streamflow was predicted using ANN, ANFIS and KNN models. Stations used in the study " 509, 525 and 527" were modeled in different combinations. They were arranges as single-handed (509, 525, and 527), together with one more station (509-525, 509-527, and 525-527) and all stations together (509-525-527). The input parameters were selected as 3, 4 and 5 for ANFIS models, and for modellig ANN models "6, 8, 10, 12, 14, and 16" neurons were opted. In modelling KNN 1, 3, 5 and 7 neighborhoods were selected. 70 % of the data were selected as train data and 30 % of the data were opted as test data.

With the combination of the model with 7 different input parameters, and the subset versions of these input parameters (3, 4 and 5), 21 ANFIS models were created.

In order to evaluate the performance of the models, the values of R^2, RMSE and Wilcoxon were observed (Table 3). In general, It was seen that the performances of the models with a low number of parameter showed less accuracy. Conversely, the accuracy of the model raised when the number of parameters were increased. In addition, when the number of ANFIS subsets was increased, model performances also increased. When we look at the training data, the Wilcoxon test confirms the models at the 95% confidence interval. On the contrary, none of the test data has this confirmation; however, the best Wilcoxon value was given by the model with all the inputs for the test data and 5 subsets each.

As in ANFIS, seven main models were created for ANN. These models were tried with different number of neurons and the performances were measured. Putting results that were gotten with the diffent number of neurons would increase the length of the article, so as just the best results from all the models were summarized in Table 4. The real number of created ANN model is 42 (in Table 4, only 7 with the best results were shown). Looking at these results, it can be observed that ANN's results are closed to ANFIS; however, ANFIS is more accurate compared to ANN.

In the models, the number of neurons was selected as 6, 8, 10, 12, 14 and 16 respectively. The number of neurons that gave the best results in each model were shown in Table 4 as a model result; however, the models which gave the best results were not always the models with the highest number of neurons.

The last model is KNN. In this model, the neighbor degrees were selected as 1, 3, 5 and 7. In the train data set, it has been observed that 1 neighbor degree gives 100% in the training data; however, in test data set, it was known from the memorization. When the other models except 1 neighborhood were examined, it was observed that models that were established with 5 neighbor degrees are the best models for both training and testing data (Table 5). When 3 different methods were examined, it was seen that the best models were the ones in which all input parameters were used. Amoungst these three models, ANFIS has attracted attention.

In the end, Taylor diagrams were extracted in order to evaluate the performances of the models. To prevent the complexity in these diagrams, models with the best results were used for ANN, ANFIS and KNN models. Model A which is shown in Figure 3 is ANFIS (model with 3 inputs 5-5-5 subset), Model B is ANN (model with 10 neurons and 3 inputs), and C model is created as KNN (model with 5 neighborhoods).

According to the Toylar diagram, when the train and test data results are analyzed, it is seen that for both the training and testing data sets, the A and C models shows better results compared to the B model. According to R^2, RMSE and Wilcoxon values, ANN and ANFIS are the best models while looking at the Taylor diyagram, KNN is the best model. This result reveals the importance of looking at many performance criteria in the evaluation of the best result. Looking at all the evaluations, it is thought that they can be used in these three methods.

Tablo 3. Train and test performances of the ANFIS model

		Train			Test		
Input	MFs	R^2	RMSE	Wilcoxon	R^2	RMSE	Wilcoxon
509	3-3-3	0,602	24,993	3,843	0,586	13,151	4,024
	4-4-4	0,616	28,426	3,789	0,588	12,486	3,754
	5-5-5	0,641	21,291	0,986	0,598	12,945	3,913
525	3-3-3	0,631	21,206	1,521	0,722	11,220	3,131
	4-4-4	0,659	20,389	1,227	0,739	11,024	3,237
	5-5-5	0,667	20,138	1,219	0,713	11,345	2,994
527	3-3-3	0,688	20,529	0,797	0,320	21,648	3,731
	4-4-4	0,692	21,178	0,737	0,442	18,935	3,787
	5-5-5	0,688	19,846	0,792	0,424	18,281	3,660
509-525	3-3-3	0,696	19,324	1,219	0,731	12,044	3,564
	4-4-4	0,735	18,144	1,241	0,789	10,465	3,364
	5-5-5	0,724	18,412	1,061	0,766	11,235	3,536
509-527	3-3-3	0,722	18,507	1,144	0,759	11,466	3,854
	4-4-4	0,740	17,950	1,100	0,711	11,723	3,017
	5-5-5	0,747	17,551	1,053	0,765	10,257	2,275
525-529	3-3-3	0,731	18,292	1,454	0,677	12,516	3,475
	4-4-4	0,735	18,051	1,368	0,747	11,510	3,494
	5-5-5	0,747	11,510	1,237	0,745	11,733	3,114
509-525-527	3-3-3	0,737	17,900	1,366	0,750	10,723	3,057
	4-4-4	0,752	17,528	1,333	0,754	10,595	3,120
	5-5-5	0,794	15,828	1,404	0,828	8,330	2,245

Table 4. Summary of the training and testing performances of the ANN model

			Train			Test	
Input	Neuron	R^2	RMSE	Wilcoxon	R^2	RMSE	Wilcoxon
509	14	0,740	17,795	1,115	0,592	18,743	3,221
525	16	0,712	18,705	1,451	0,594	14,724	3,114
527	10	0,725	18,306	1,212	0,603	14,550	3,054
509-525	10	0,798	16,363	0,954	0,622	18,662	3,425
509-527	12	0,762	17,002	1,127	0,631	12,331	2,987
525-527	16	0,762	17,110	1,119	0,589	12,787	3,021
509-525-527	10	0,741	17,768	0,897	0,715	11,381	2,875

Table 5. Performances obtained using KNN model

			Train			Test	
Input	N	R^2	RMSE	Wilcoxon	R^2	RMSE	Wilcoxon
509-525-527	1	1,000	0,000	0	0,360	26,110	3,721
	3	0,743	23,340	1,714	0,474	16,720	3,214
	5	0,809	18,870	1,412	0,771	13,454	2,954
	7	0,579	31,841	2,054	0,59	17,705	3,623

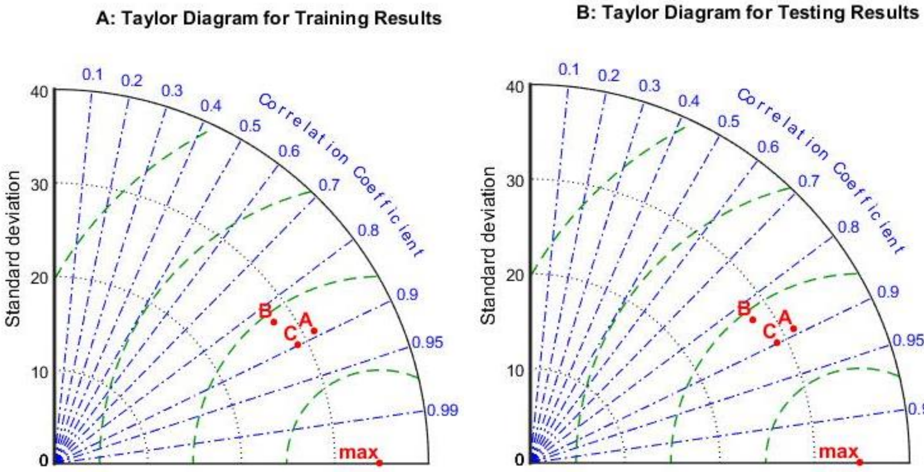

Figure 4. The performances of A, B, and C models according to Taylor diagram

4.Conclusion

The Gediz River Basin has plenty of water resources. Water resource fluctuations because of some reasons such as climate change, drought, and so on make integrated water management crucial. In this study, data were used from 509, 518, 525 and 527 hydrological stations, to predict the streamflow of the GRB (518 station). Forecasting water flow is extremely important for sustainable water resource planning and management. Accurate prediction of high and low flow occurrence provide information for taking deliberate decisions. In this study, three different artificial intelligence methods; ANN, KNN, and ANFIS were used to forecast streamflow in the GRB. This study indicated the feasibility of adopting the AI methods as streamflow forecasting tools, the model's results were accurate for the Gediz River Basin. All the methods results were compared with each other. The ANFIS's model performed better than the ANN and KNN in all studied cases. The performances of the models were assessed using correlation coefficient (R), root mean square error (RMSE), and the Wilcoxon Test (WT). Overall, all models performed well. Comparing them to each other, ANFIS performed better than ANN and KNN, and ANN was better than KNN for most cases.

In the last part of the article, the evaluation was done using the Taylor diagram. Taylor diyagram showed that the ANN and KNN models performed better than the ANFIS model. When the different performance criteria were examined, it was found out that all methods can be used to complete the missing data for this basin. In conclusion, AI models can be used to forecast streamflow by using the data from some stations of the river.

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