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Forecasting and modeling of monthly runoff using ANN model in Mazandaran province

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Abstract

Nowadays, water flow modeling and forecasting plays a key role in flood hazard reduction, reservoir optimization, and Water resource management. These models are mostly developed and applied for simulation and prediction. In this research, to model and forecast the monthly runoff, the data of 2 hydrometric stations of Siahrood and Talar in Mazandaran province were used in a period of 20 years (2002-2021). The time series homogeneity was examined using the Chow`s method. Since, monthly runoff data are time-dependent, these data were first arranged as time series. After sorting the data, artificial neural network (ANN) model was used to forecast the monthly runoff in selected hydrometric stations. Data entry into the model (ANN) was done using the forward algorithm. After modeling the (ANN), monthly runoff changes were forecasted in selected hydrometric stations for the next 12 months with SPSS 25 software. Lastly, based on the forecasted values and using MAD, RMSE, MAPE and R2 indices, the accuracy and precision of (ANN) model was evaluated. The results showed that the artificial neural network model performed very well for predicting monthly runoff values for both Siahrood (R2=0.9945) and Talar (R2=0.9864) hydrometric stations. Also, consecutive overestimation and underestimation, which increases the error and decreases the performance of the models, was not observed for (ANN) model.

Keywords: Modeling, Monthly runoff, Artificial Neural Network, Forward Algorithm, Mazandaran Province.

Introduction

Due to the limitation in the supply of fresh water resources, accurate forecasting of runoff and its changes is one of the basic elements of planning and management of surface water resources. Depending on the purpose of the study, this forecast may be short-term or long-term. Therefore, water experts are always trying to improve the accuracy of models

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for predicting river runoff. Nowadays, intelligent models are widely used to predict nonlinear phenomena. Considering the importance of predicting runoff in rivers, which is important from different aspects, it seems necessary to find a suitable model in this regard(Farzin
et al., 2020). The artificial neural network (ANN) method is one of these models that has attracted the attention of researchers to predict runoff values. So far, various studies have been conducted around the world that have modeled and predicted periodically correlated time series such as runoff, precipitation, groundwater level, etc., using artificial neural networks. In this regard, we can refer to the following studies:
Dolling and Varas (2007) used the forward artificial neural network model to predict the runoff in a mountain basin in Argentina. The results of this research showed that the use of the artificial neural network model for predicting the runoff had a good accuracy. Unal and colleagues (2010) predicted runoff using an artificial neural network model and compared the results with one-dimensional and two-dimensional mathematical models. The results showed that the use of artificial neural network models has higher accuracy than mathematical models. Fathian and Hormozinejad (2011) used several models to predict the flow of the Karun River quantitatively and qualitatively. The results of this research showed that the use of artificial neural network model has a high ability to recognize the complex relationship between input and output data. Salahi (2014) used the artificial neural network model to predict river runoff in Ardabil province. Examining the performance indicators showed that the use of artificial neural network model for predicting runoff is highly accurate. Elsafi (2014) used an artificial neural network (ANN) model to predict floods in a part of the Nile River in Sudan. The results of this research showed that the use of the (ANN) model is a suitable method for detecting the risk of flooding in the Nile River.
Ghezelsofli and colleagues (2022) used 4 models including Box and Jenkins (SARIMA), Artificial Neural Network (ANN), Adaptive Neuro-Fuzzy Inference System (ANFIS) and Genetic Algorithm (GA) to model monthly runoff in Golestan province. They used the forward algorithm to investigate the structure of the artificial neural network model. The results of this research showed that the two models of (ANN) and (ANFIS) respectively had the highest accuracy for predicting monthly runoff. Jandaghi (2023) used artificial neural network model and forward algorithm to predict monthly rainfall in Golestan province and compared its results with the time when the complete series of data were entered into the model. The results showed that when the forward algorithm (RMSE=1.2434 mm) is used, the performance of the model is significantly improved compared to entering the complete series of data (RMSE=5.4061 mm).
Today, accurate forecasting and modeling of river runoff and checking its changes throughout the year is very necessary. Therefore, in the current research, using the artificial neural network model and forward algorithm, monthly runoff has been predicted in the hydrometric stations located in the east of Mazandaran province in order to check the efficiency and accuracy of this model for water resources management.

Method and materials

To conduct this research, the monthly runoff data of Talar and Siahrood hydrometric stations were used, which are located in the east of Mazandaran province. The source of the Talar River is the height of the Alborz Mountains in Sawadkooh. After joining several branches to this river, it enters Qaemshahr from the west and flows into the Caspian Sea after traveling a distance of 180 kilometers. The source of the Siahrood River is the height of Qaemshahr and Sari in the Mazandaran province. This river after passing through Qaemshahr, flows into the Caspian Sea after traveling a distance 62.25 kilometers. Figure (1) shows the location of Talar and Siahrood hydrometric stations in Qaemshahr city. Table (1) shows the Characteristics of Talar and Siahrood hydrometric stations in Mazandaran province.

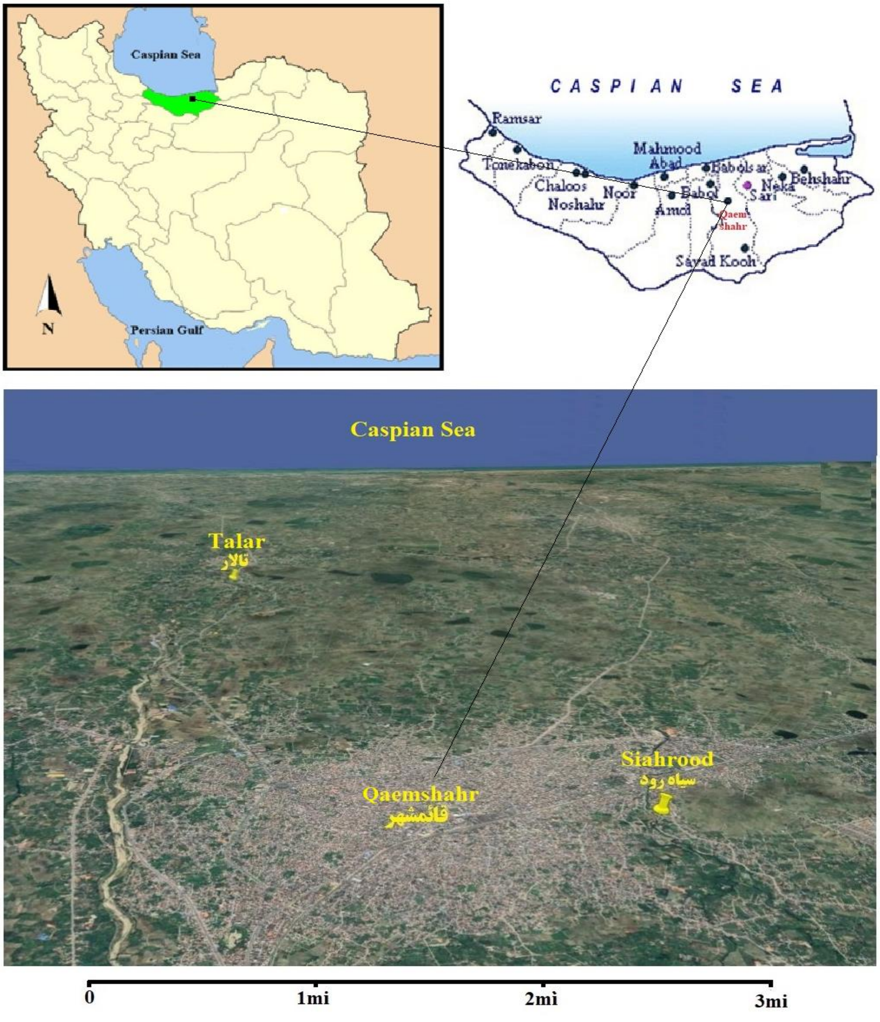

Figure 1. Location of Talar and Siahrood hydrometric stations in Qaemshahr city

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Table 1. Characteristics of Talar and Siahrood hydrometric stations in Mazandaran province

Distance to Joibar (km)	Distance to Qaemshahr (km)	Height (m)	UTM		Name of hydrometric station
			Y	X	
19	2	49	4037309	668844	Siahrood
12	11	-1	4047513	662094	Talar

In this research, after checking the monthly runoff data, two hydrometric stations, Talar and Siahrood, were selected in the east of Mazandaran province. Then a period of 20 years (2002-2021) was selected to conduct this research. The required data was obtained from Regional Water Company of Mazandaran. Since, monthly runoff data are time-dependent, these data were first arranged as time series. Then, the time series homogeneity was examined using the Chow`s method (Ceylan and Ceyda, 2016).
In this research, after sorting the data, the artificial neural network (ANN) method was used to model the monthly runoff values in selected hydrometric stations. After fitting the model, monthly runoff changes were predicted in selected hydrometric stations for the next 12 months.
Due to the type of design, the model of artificial neural networks has very good flexibility, which has good performance in different conditions. The neural network model is not based on a specific hypothesis, which is one of the important advantages of this model. Also, these models can be used with all types of linear, non-linear, seasonal and non-seasonal trends. In case of changes in the pattern of time periods, the artificial neural network model identifies them well and there is no need to remove them from the data. Although different types of artificial neural networks have been presented, but forward neural networks are usually used for time series (Khan and Khan, 2019). This model can be written as equation (1):

Eq. (1) $$y_t = \alpha_0 + \sum_{j=1}^{n} \alpha_i f\left(\sum_{i=1}^{m} \beta_{ij} y_{t-j} + \beta_{0j}\right) + \varepsilon_t$$

where in: m the number of input nodes, n the number of hidden nodes, f a transfer function from input to output, which is usually considered sigmoidal and its usual form is the logistic function (equation 2), α_j the weight of paths from hidden nodes to the output layer and β_{ij} the weight of the paths between the input layer and the hidden nodes is determined (Zhang, and Qi., 2005).

Eq. (2) $$f(x) = \frac{1}{1+e^{-x}}$$

To prepare a suitable artificial neural network model, the data is divided into three categories. The first part is the training observations that are used to estimate the

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parameters of the model, the second part is the observations that are used for the internal validation of the model, and the third part is used for the external validation or prediction of the model. In periodically correlated time series, observations are divided into multiples of the periodic period. In periodically correlated time series, it is very important to determine how many previous time periods are used for modeling, which can be answered by using artificial neural networks model and forward algorithm. In this research, the following steps were carried out to model artificial neural networks based on the forward algorithm (Ghezelsofli et al., 2022; Jandaghi, 2023).

First step: The previous year's observations were considered as predictor variables in the model. Then the predicted values were determined and the RMSE index was calculated for the predicted values.

Second step: The second year was added to the model and the predicted values were determined with two variables. Then the RMSE index was calculated.

The third step: Adding previous years in the model for forecasting was done until there is no noticeable change in the results of the RMSE index. Finally, the most suitable artificial neural network model was selected for the data series. In periodically correlated time series, it is suggested to use one or two previous periods in forecasting. This research was done using SPSS 25 software.

In the next step, the (ANN) model was validated. Time series model validation can be done in two ways, internal and external. In internal validation, the fitted values of the model are calculated and compared with the observed values of the time series. In external validation, usually one or more periods of the time series are not included in the modeling. After fitting the model, the predicted values for the excluded periods are calculated and compared with the observed values. So far, various standard indices have been presented to compare the predicted values from the model and the observed values, the most important of which (equations 3 to 6) are introduced below (Moriasi, 2007):

a) Mean Absolute Distance

$$MAD = \frac{1}{m}\sum_{i=1}^{m}\left|Y_t - \hat{Y}_t\right| \qquad \text{Eq. (3)}$$

b) Root Mean Squares of Errors

$$RMSE = \sqrt{\frac{\sum_{i=1}^{m}(Y_t-\hat{Y}_t)^2}{m}} \qquad \text{(4) Eq.}$$

c) Mean Absolute Percentage Error

$$MAPE = \frac{\sum_{i=1}^{m}\left|\frac{Y_t-\hat{Y}_t}{Y_t}\right|}{m} \qquad \text{(5) Eq.}$$

D) Coefficient of Determination

$$R^2 = 1 - \frac{\sum_{i=1}^{m}(Y_t-\hat{Y}_t)^2}{\sum_{i=1}^{m}(Y_t-\bar{Y})^2} \qquad \text{Eq. (6)}$$

where in: $\hat{Y}_t$ is the values fitted or predicted by the model, Yt is the value of the observed time series at time t and m is the number of fitted values or predicted values.

Result

In this research, due to the existence of a seasonal trend with a period of 12 months in the runoff time series, the monthly observations were categorized as multiple time series with a dimension of 12 months, then the observations of the past years were considered as predictive variables in the artificial neural network model. Since the years closer to the current situation have more detailed information about this time, years were considered as forward algorithms in artificial neural networks model.

Since the goal is to predict the time series for the future values, the runoff values of the last year as the response variable and the previous years as predictor variables were entered into the model and the network was trained. Then, based on this network, the predicted values were calculated. According to Figure (2a), based on the forward algorithm, the runoff values of the last 10 years (the number of effective years) of Siahrood hydrometric station were entered into the (ANN) model as predictor variables and performed the best. Also, the investigation of the structure of the (ANN) model in Talar hydrometric station is similar to Siahrood station, and the runoff values of the last 10 years of this station were entered into the model as predictor variables and performed the best (Figure 2b).

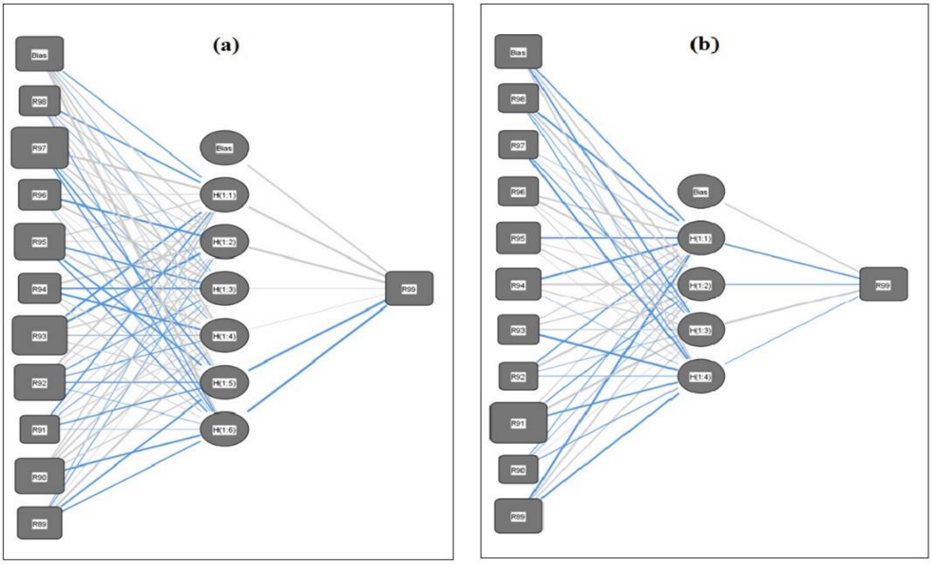

Figure 2. Structures of ANN model in Siahrood (a) and Talar (b) hydrometric stations in Mazandaran province

Figure (3) shows the comparison of observed and estimated monthly runoff values by artificial neural network model in 2 selected hydrometric stations in Mazandaran province. According to Figure (3), it can be stated that the artificial neural network model has performed well in predicting the monthly runoff values in both Siahrood and Talar hydrometric stations and has been fitted very well.

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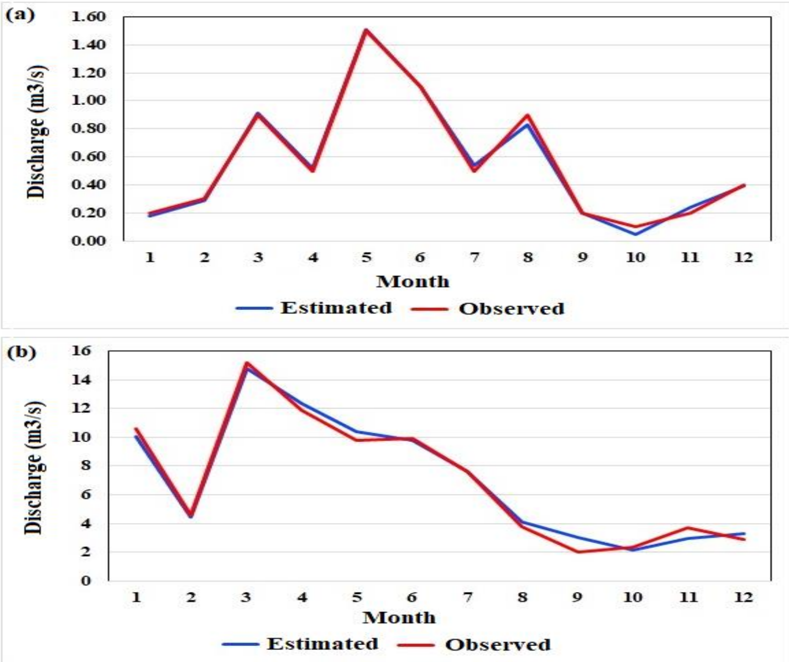

Figure 3. Comparison of observed and estimated monthly runoff by ANN model in Siahrood (a) and Talar (b) hydrometric stations in Mazandaran province

To validate the artificial neural network model for predicting monthly runoff in 2 selected hydrometric stations, 4 standard indices RMSE, MAD, MAPE and R2 were used and the results are presented in table (2).

Table 2. Validation results of ANN model to predict the monthly runoff in selected hydrometric stations

Standard indicators				Name of hydrometric station
R2	MAD	RSME	MAPE	
0.9945	0.0233	0.0313	0.0894	Siahrood
0.9864	0.4216	0.4959	0.1043	Talar

Table (2) clearly states that when using the artificial neural network model with the forward algorithm structure and based on all 4 indicators RMSE, MAD, MAPE and R2 the performance of the model for predicting monthly runoff has been very accurate. The amount of calculation error based on the RMSE index when using the (ANN) model at the Siahrood and Talar hydrometric stations was 0.0313 and 0.4959 m3/s, respectively, which indicates the higher prediction accuracy at the Siahrood hydrometric station compared to the Talar station. Also, the results of MAD and MAPE index were exactly similar to the results of RMSE index. Based on the R2 index, similar to the other three indices, the monthly runoff prediction using artificial neural network model has been accurate in both stations. However, it has been more accurate in Siahrood hydrometric station (R2=0.9945) than Talar station (R2=0.9864).

Discussion and conclusion

In the present research, using the 20-years data (2002-2021) in 2 hydrometric stations of Siahroood and Talar located in Mazandaran province, using the artificial neural network model and forward algorithm, modeling and forecasting the monthly runoff values were predicted for the next 12 months. Then, based on the forecasted values and using MAD, RMSE, MAPE and R2 indices, the accuracy and precision of (ANN) model was evaluated.

In general, the validation results of the (ANN) model using 4 indexes MAD, RMSE, MAPE and R2 revealed that the artificial neural network model for predicting the monthly runoff data in two selected hydrometric stations had performed very well (R2=0.9945, 0.9864). In both selected hydrometric stations, consecutive overestimation and underestimation, which increases the error and decreases the performance of the models, was not observed for (ANN) model. Also, based on all 4 indicators used, it was found that the artificial neural network model for predicting the monthly runoff in the Siahrood hydrometric station had higher accuracy than the Talar station. The results of this research are consistent with the studies of Unal and colleagues (2010), Fathian and Hormozinejad (2011), Elsafi (2014), Salahi (2014), all of whom stated that the artificial neural network model has relatively high accuracy for fitting and prediction.

In this research, since the years closer to the current situation have more detailed information about this time, years were considered as forward algorithms in artificial neural networks model. Finally, after determining the number of effective years, the most suitable artificial neural network model was selected for the data series. The use of the forward algorithm has increased the prediction accuracy using the artificial neural network model. The results of this research are consistent with the studies of Dolling and Varas (2007), Ghezelsofli and colleagues 2022) and Jandaghi (2023), all of whom stated that the use of forward algorithm increases the prediction accuracy in artificial neural network models.

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