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Simulation of Monthly Precipitation in Semnan City Using ANN Artificial Intelligence Model

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ABSTRACT

Precipitation forecasting is of great importance in various aspects of catchment management, drought, and flood warning. Precipitation is regarded as one of the important components of the water cycle and plays a crucial role in measuring the climatic characteristics of each region. The present study aims to forecast monthly precipitation in Semnan city by using artificial neural networks (ANN). For this purpose, we used the minimum and maximum temperature data, mean relative humidity, wind speed, sunshine hours, and monthly precipitation during a statistical period of 18 years (2000-2018). Moreover, an artificial neural network was used as a nonlinear method to simulate precipitation. In this research, all data were normalized due to the different units of inputs and outputs in the forecasting model. Further, seven different scenarios were considered as input for the ANN model. Totally, 70% of the data were used for training while the other 30% were used for testing. The model was evaluated with appropriate statistics such as coefficient of determination (R^2), root mean square error (RMSE) and mean absolute error (MAE). Scenario 6, which included the inputs of minimum and maximum temperature, mean relative humidity, wind speed, and pressure, provided the best performance compared to other scenarios. The values of R^2, RMSE, and MAE for the superior scenario were 0.8597, 4.0257, and 2.3261, respectively.

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1. Introduction

Hydrological systems can be affected by many factors such as evapotranspiration, land vegetation, permeability, and other parameters that are multi-time scales depending on stochastic components[1]. Precipitation measurement is one of the most important parameters of the hydrological system. On the other hand, precipitation forecasting is a necessity for water resources management, drought, groundwater studies, floods, runoff, food security, and other hydrological, hydraulic, and even agricultural issues [2]. Precipitation is the product of oceanic and atmospheric phenomena and its forecasting in different regions is considered one of the important challenges for hydrologists [3]. Previously, the linear regression method was used to forecast precipitation and time series.

In 1987, Lapedes and Farber [4] showed that intelligent methods provided better efficiency in forecasting precipitation time series. Currently, various intelligent methods are used to forecast precipitation, most of which have a better ability to solve non-linear hydrological phenomena compared to regression and statistical methods [5– 12]. By detecting the complexity of nonlinear relationships between input and output data [3,12], ANNs[1] have been used in various parts of water engineering. In recent decades, this model has been used to predict meteorological and hydrological parameters.

Valverde Ramírez et al. [13] investigated the application of artificial neural network method in the forecasting of precipitation in Sao Paulo, Brazil. The results highlighted the higher accuracy of the predictions made by this method than that of other methods. Using artificial neural networks and comparing it with multivariate regression, Dahamsheh and Aksoy [14] forecasted monthly precipitation in Jordan's arid regions and revealed the better performance of the artificial neural network compared to other methods. Huo et al. [15] used hydrological and agricultural data in an integrated ANN model and compared its performance with the Lumped artificial neural network and the linear regression model. The results of this research showed the better performance of the integrated ANN model in estimating the monthly flow at the output. By applying the multi-layer perceptron neural network and Narex recursive neural network, Omidvar et al. [16] predicted daily precipitation in Kerman province in Iran based on effective climatic parameters. According to the results, the network has acceptable accuracy based on Levenberg–Marquardt training algorithm and sigmoid stimulus function with meteorological parameters of minimum and maximum temperature, wind direction and speed, mean pressure, and relative humidity. Ruigar and Golian [17] predicted maximum daily and monthly precipitation using artificial neural networks based on large-scale climatic signals in the Madareso catchment. The results indicated the suitability of artificial neural networks with the Levenberg–Marquardt training algorithm for estimating maximum daily and monthly precipitation. Pakdaman et al. [11] examined the ability of artificial neural network (ANN) models for processing after monthly precipitation forecast in the North American Multi-Model Ensemble project and proposed a new MME-NN[2] model.

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[1] Artificial neural networks
[2] Multi-model ensemble neural network

This research seeks to model the monthly precipitation of Semnan city using an artificial neural network. In this modeling, different scenarios composed of effective meteorological parameters of minimum and maximum temperature, relative humidity, wind speed, sunshine hours, and pressure were considered as model inputs to calculate monthly precipitation. Finally, the results were analyzed to select the best scenario, which provided a more accurate forecast of monthly precipitation.

2. Methods

2.1. Case study

The study area was the city of Semnan, located in Semnan province, with geographical coordinates of longitude 53° 26', latitude 35° 36', and altitude 1149 m above sea level. Furthermore, the data of 18 years, from 2000 to 2018, was studied in this study. Data included minimum and maximum temperature, air pressure, relative humidity, sunny hours, wind speed, and precipitation, which were received from the main synoptic station of Semnan. Fig. 1 illustrates the general location of the studied station.

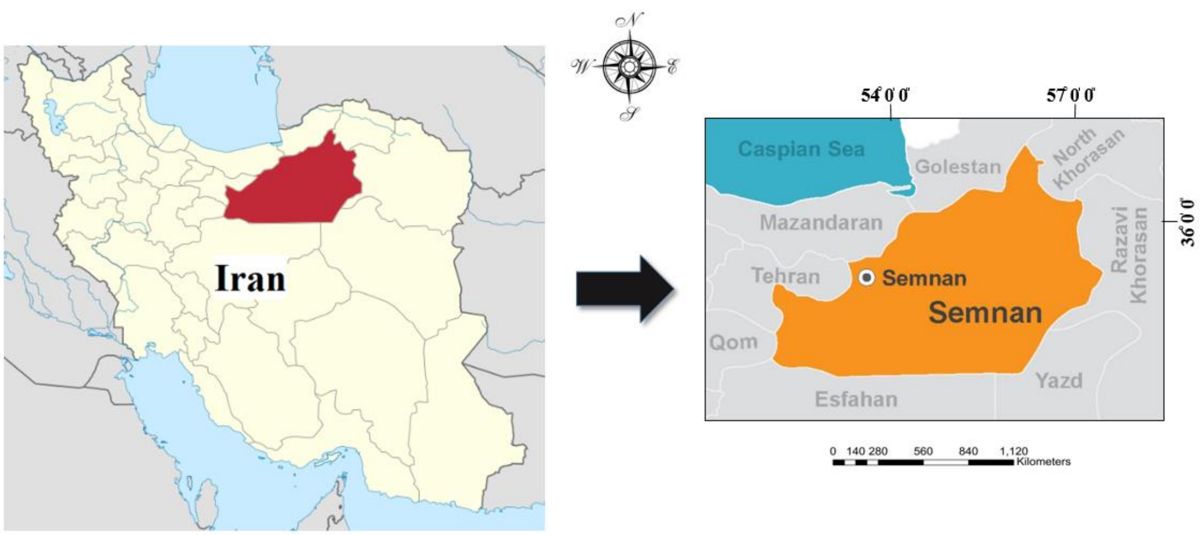

Fig. 1. Studied area.

2.2. Parameters and statistical characteristics of the data

In this study, the efficiency of the ANN model for predicting monthly precipitation was evaluated using data of minimum and maximum temperature, relative humidity, wind speed, sunshine hours, and air pressure, all of which are monthly parameters. Table 1 presents the studied parameters, abbreviations, and statistical characteristics used in this research. Fig. 2 shows the histogram diagram of the input and output data. For better performance, the input and output data were normalized using Eq. (1) and Table 2. A normalization relationship (Eq.1) within the value of 0.1–0.9 is used to reduce the interval of the variables to the same scale. With considering this equation, the values of all parameters (inputs and output) were normalized and randomly considered to train and test the ANN in this study.

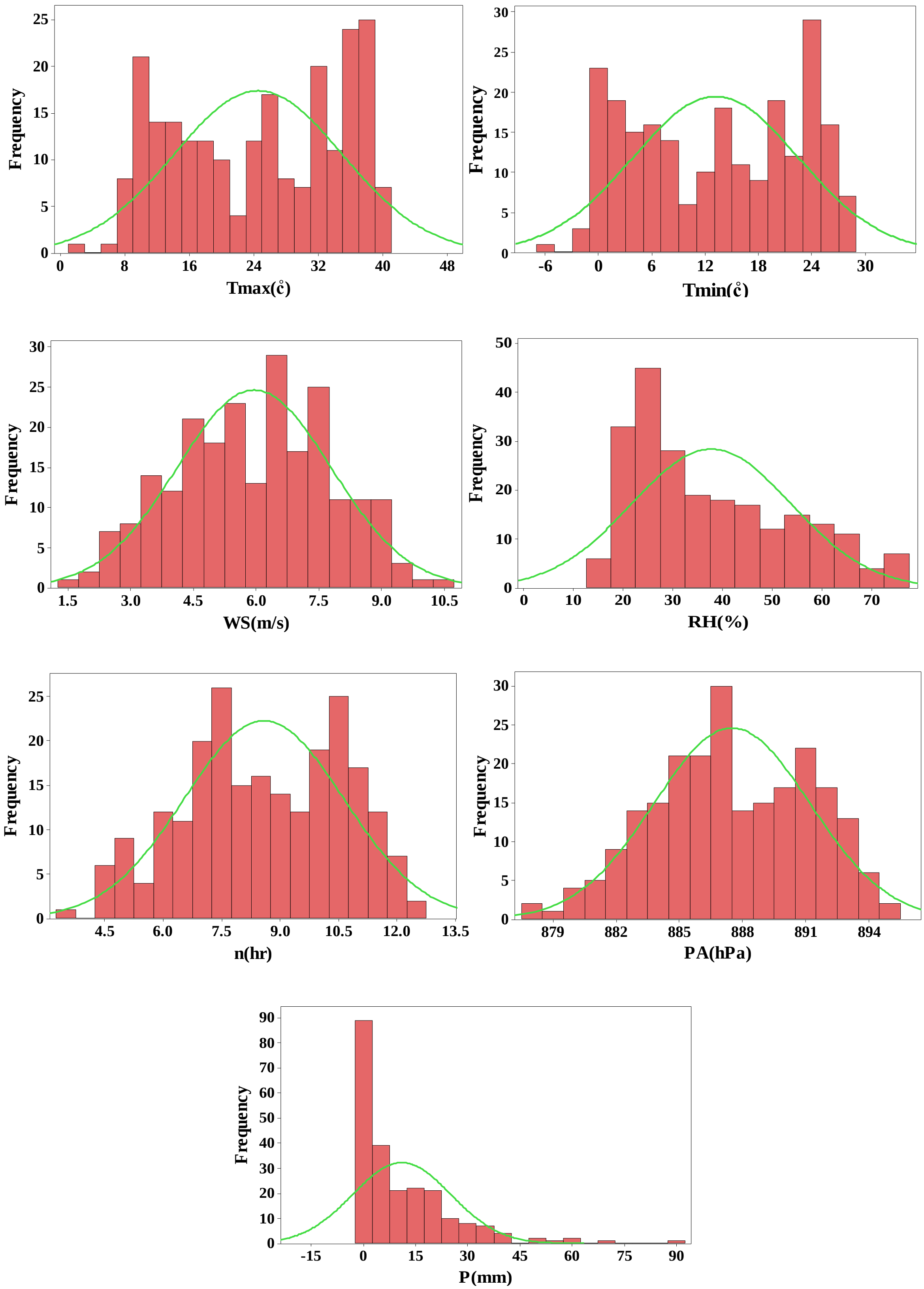

Fig. 2. Histogram of the studied data.

Table 1
Statistical specifications of the data.

Parameter	Unit	Symbol	Mean	Standard deviation	Minimum	Maximum
Minimum temperature	c̊	T_{min}	13.15	9.31	-6.87	28.53
Maximum temperature	c̊	T_{max}	24.52	10.43	2.14	40.41
Relative humidity	%	RH_{mean}	37.72	15.99	13.80	76.87
Wind speed	m/s	WS	5.95	1.84	1.70	10.25
Sunshine hours	hr	n	8.58	2.03	3.73	12.55
Air pressure	hPa	PA	887.49	3.68	878.11	894.63
Precipitation	mm	P	11.01	14.04	0	85.5

$$Parameter_{Scaled} = \left[(0.8)\left(\frac{Parameter - Parameter_{\min}}{Parameter_{\max} - Parameter_{\min}}\right)\right] + 0.1 \tag{1}$$

Table 2
Normalization of data used in this research.

Symbol	Parameter	Normalized value
Tmin	Minimum temperature	$T_{\min_{normal}} = 0.8\frac{T_{\min} - (-6.87)}{35.41} + 0.1$
Tmax	Maximum temperature	$T_{\max_{normal}} = 0.8\frac{T_{\max} - 2.14}{38.26} + 0.1$
RHmean	Relative humidity	$RH_{mean_{normal}} = 0.8\frac{RH_{mean} - 13.8}{63.07} + 0.1$
WS	Wind speed	$WS_{normal} = 0.8\frac{WS - 1.71}{8.55} + 0.1$
n	Sunshine hours	$PA_{normal} = 0.8\frac{PA - 878.11}{16.52} + 0.1$
PA	Air pressure	$n_{normal} = 0.8\frac{n - 3.73}{8.81} + 0.1$
P	Precipitation	$P_{normal} = 0.8\frac{P - 0}{87.2} + 0.1$

2.3. Artificial neural networks

A neural network consists of an arbitrary number of cells, nodes, units, or neurons that relate the input to the output. Neural network methods have been widely used to predict and solve complex processes in various sciences, including civil engineering and water [18,19]. An artificial neural network is a mathematical structure based on the biological model of the human brain. A neuron is a collection of small data processing components of each neural network. In this method, a neuron communicates with another neuron through a directional relationship that includes its unique weight. Weights represent the information required by the network to find the solution to a problem. A biological neuron has three main parts of dendrites, soma, and axons. Signals received from other neurons are corrected by a large number of dendrites. Soma, or in other words, the body of the processor unit collects the input signals. If the sum of the total inputs exceeds a certain limit, then the processor is activated and signals are transmitted through the axon to the next cell. The neuron method is available in series and parallel. After finishing the processing process, a set of outputs is generated by a set of parallel neurons. The resulting outputs can be used as inputs to another set of neurons that are connected to the original set of neurons in series. As a result, the output of each neuron is multiplied by weighting coefficients and given as input to the nonlinear stimulus function. A set of parallel neurons consists of a single layer. To create its outputs, each neural network can have one or more layers, which are commonly referred to as hidden layers. The output layer, or the last layer, generates network output [20,21]. The artificial neural network was designed and implemented in the MATLAB-R2018b Software platform. To forecast monthly precipitation using artificial neural networks, meteorological variables of minimum and maximum temperature, relative humidity, wind speed, sunshine hours, and monthly pressure were determined as input while the monthly precipitation variable was considered as output. Moreover, 70% of 240 monthly datasets were selected for training while the remaining 30% were chosen for testing. On the other hand, 8 neurons were used in the input layer and one neuron was utilized in the output layer. In the hidden layer, several layers with different neurons were used and their optimal number was determined by trial and error to minimize error. The hyperbolic tangent transfer function was used in the hidden layer while a linear transfer function was applied in the output layer. Further, the Levenberg-Marquardt learning method with a fixed number of 2,000 repetitions was utilized for training the network. Fig. 3 demonstrates the structure of artificial neural networks concerning the inputs and outputs of this study. To evaluate the possibility of using different combinations of meteorological data, seven different scenarios consisting of different meteorological data were defined to simulate monthly precipitation more accurately (Table 3). Then, these scenarios were used in the artificial neural network method to simulate precipitation at Semnan station.

2.4. Evaluation criteria

To evaluate the performance of the proposed forecasting model, it is necessary to calculate several indicators related to the performance [22–24]. In this research, the accuracy and capability of the model were assessed using the indicators of R2[1], RMSE[2] and MAE[3] according to Eqs. (2) to (4). The best values for these three criteria were one, zero, and zero, respectively.

$$R^2 = \left[\frac{\sum_{i=1}^{n} (x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_{i=1}^{n} (x_i - \bar{x})^2 \sum_{i=1}^{n} (y_i - \bar{y})^2}} \right]^2 \tag{2}$$

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[1] Coefficient of determination
[2] Root mean square error
[3] Mean absolute error

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(y_i - x_i)^2}{N}} \tag{3}$$

$$MAE = \frac{1}{N}\sum_{i=1}^{n}\left|(y_i - x_i)\right| \tag{4}$$

where N represents the number of data, x_i indicates the amount of monthly measured precipitation, y_i shows the amount of monthly forecasted precipitation, $\bar{x}$ depicts the mean measured precipitation, and $\bar{y}$ is the mean forecasted precipitation.

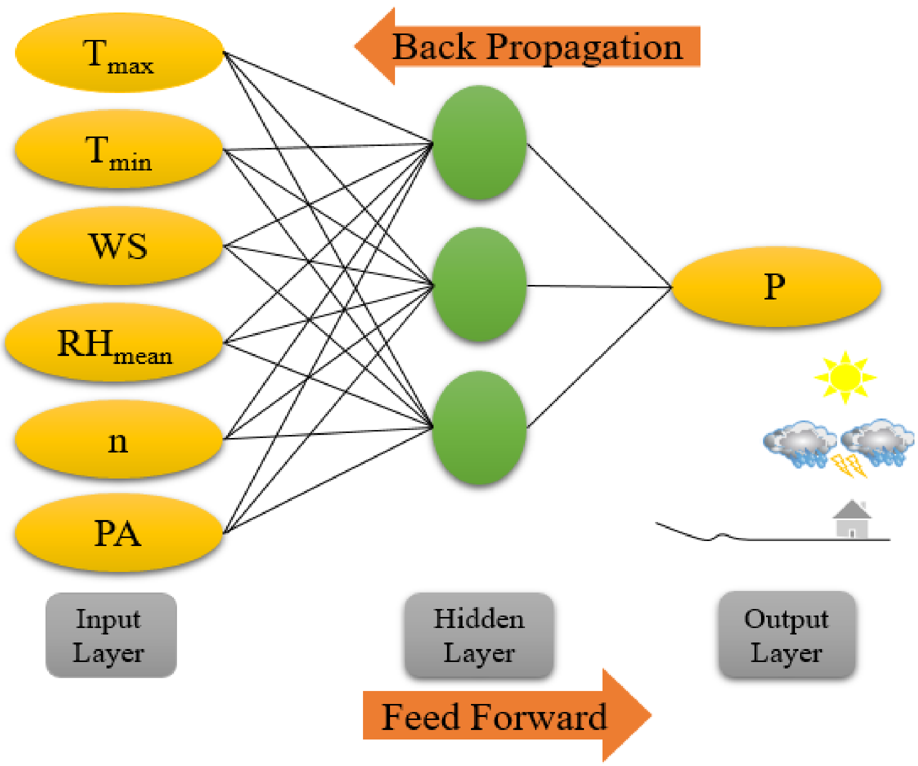


Fig. 3. Structure of artificial neural network.

Table 3
Input scenarios used in ANN.

Scenario No.	Input parameters
1	T_{min} - T_{max}
2	RH_{mean} - WS
3	T_{min} - T_{max} - RH_{mean}
4	T_{min} - T_{max} - WS
5	T_{min} - T_{max} - RH_{mean} - WS
6	T_{min} - T_{max} - RH_{mean} – WS - PA
7	T_{min} - T_{max} - RH_{mean} – WS – PA - n

3. Results

3.1. Results from determined scenarios

In this study, monthly precipitation was calculated through an artificial neural network model in Semnan station with different inputs in the form of seven scenarios. Generally, different scenarios were examined to select the optimal structure of each model. Table 4 reports the values of R2, RMSE and MAE of ANN model in the training and testing sections of the studied station. Based on the results provided in Table 4, the scenario 6 of the ANN model with $R^2 = 0.8597$, $RMSE = 4.0257$, and $MAE = 2.3261$ was selected as the best model in Semnan station, followed by scenario 4. In this scenario, having only the minimum and maximum temperatures and monthly wind speed allows simulating the monthly precipitation with an acceptable error.

3.2. Results from the selected scenario

Fig. 4 demonstrates the time series of the measured and simulated values with the artificial neural network for the selected scenario (scenario 6). The horizontal axis shows the time series (in terms of the moon) and the vertical axis indicates the precipitation values (in terms of millimeters). Accordingly, it can be said that the high conformity of the simulated values with the measured values reveals the high accuracy and the less error of the model, which is consistent to the results of research such as Ruigar and Golian [17] and Hejazizadeh et al. [25].

Fig. 5 shows the data predicted by the artificial neural network based on the superior scenario (Scenario 6) in terms of measurement data in two stages of training and testing. The horizontal axis represents the measured precipitation data (in millimeters) and the vertical axis indicates the simulated precipitation data (in millimeters). As shown, the low rate of data scattering around the best fit line leads to a greater correlation and causes fewer errors in the model. Furthermore, the correlation between the measured and simulated precipitation data in the two stages of training and testing is relatively high and equals to 0.8081 and 0.8598, respectively. These results are consistent with the results of research carried out by Mohammadi et al. [26].

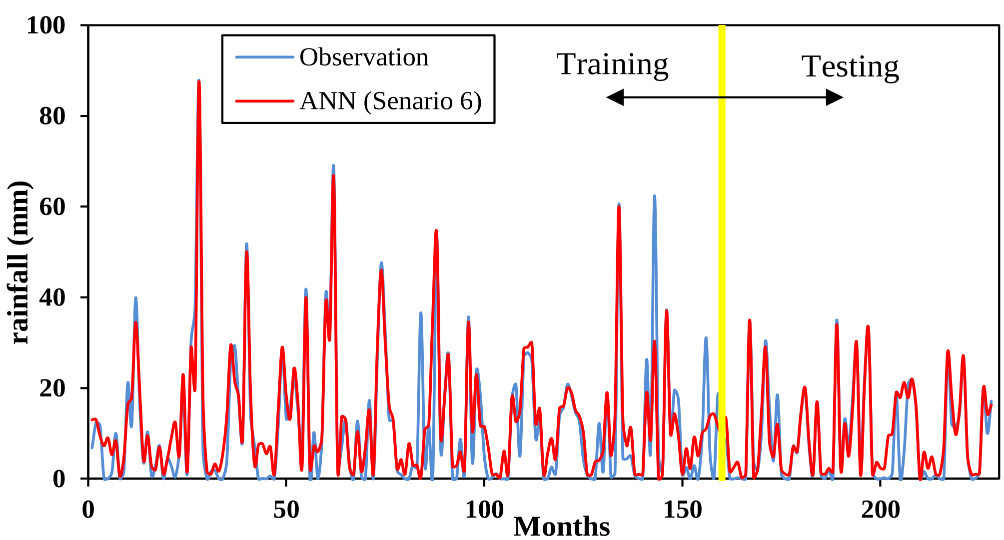
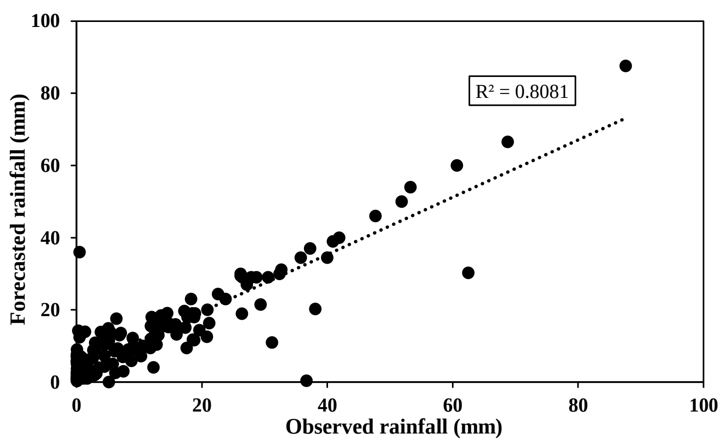


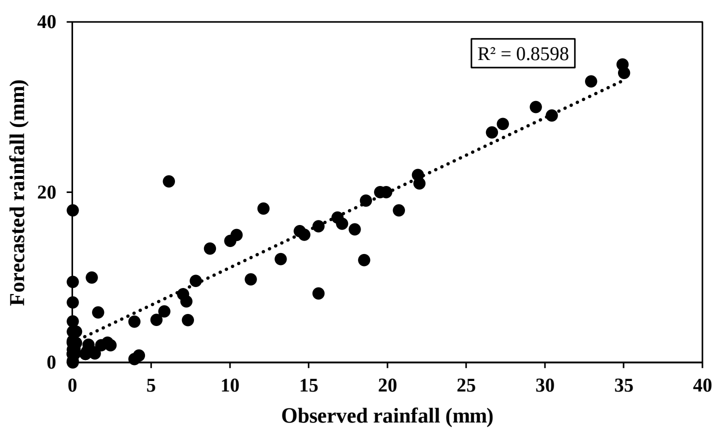
Fig. 4. Time series of observed and forecasted values with artificial neural network.

Table 4
General results of the calculations performed for the scenarios defined in the ANN method.

Scenario No.	Input parameters	R^2	RMSE	MAE
1	Training	0.6112	9.5658	5.8784
	Testing	0.6541	6.1583	4.1582
2	Training	0.5886	9.8782	7.1975
	Testing	0.6197	6.2868	4.1038
3	Training	0.6927	8.5183	5.1105
	Testing	0.7153	5.4629	3.6717
4	Training	0.7722	7.3203	4.2298
	Testing	0.8016	4.6646	3.1496
5	Training	0.6507	9.0703	5.9040
	Testing	0.6880	5.6961	4.0203
6	Training	0.8081	6.8192	4.0465
	Testing	0.8597	4.0257	2.3261
7	Training	0.7406	7.9561	5.0371
	Testing	0.7768	4.8630	3.3719



a



b

Fig. 5. Monthly precipitation values simulated with artificial neural network in terms of measured values a) training and b) testing.

4. Conclusions

Precipitation is regarded as one of the most important input data to hydrological systems. So far, various research has been conducted on precipitation forecasting, due to the importance of precipitation for a country with a dry climate like Iran. Regarding the nonlinear trend of the precipitation, the use of a linear regression model, as a semi-linear method, leads to poor results in such cases. In recent years, various methods have been developed to predict climatic variables, each of which has its advantages and disadvantages in forecasting precipitation. In the current study, the precision and accuracy of the ANN model was assessed in way of predicting the monthly precipitation of Semnan city station. All the data which were utilized as the input and output of the model were normalized. Seven varying scenarios representing the model inputs were utilized in order to predict precipitation. These inputs included: minimum and maximum temperatures, mean relative humidity, wind speed, and sunshine hours. By comparing the various scenarios, it can be indicated that increasing the number of inputs does not merely improve the performance of the model by 100 percent and does not increase the prediction accuracy. The 6th scenario, which included the inputs of minimum and maximum temperatures, relative humidity, wind speed, and air pressure indicated a better performance.

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