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Application of Time Series Method and Artificial Neural Networks in Drought Simulation (Case study: Bojnourd city)

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Abstract:
Drought is a climatic phenomenon that is considered part of a region's climate. It has a hidden nature whose duration of occurrence is long, and its effects appear in a non-structural way. As a result, its damages gradually appear in various sectors such as agriculture, social, economic, environmental, and so on. In this research, an artificial neural network was used as a powerful tool in simulating the drought of Bojnourd city. For this purpose, the statistical data of precipitation, relative humidity, and temperature from 1997 to 2014 constituted the basis of the research. SPI drought index was used as sample output. Specifically, 70% of the data were considered as training data and 30% as testing data. The networks used were of backpropagation type and radial basis function with error backpropagation algorithm plus Levenberg–Marquardt learning method. Box Jenkins method from MINITAB software and BPI to BP24 models from MATLAB software were employed in drought simulation. The value of the correlation coefficient for the training phase (R) was 0.95, while for the test phase it was 0.81, showing the lowest error in the test phase. Meanwhile, the results of the training phase were close to each other in most of the models. Among the selected models of the post-release network, the BP19 model was selected as the selected example. The RMSE determination coefficient was estimated with a value of 0.16 for the training stage and MAE (mean absolute error) was estimated as 0.0071.

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Introduction

Droughts are recurring natural hazards that result from abnormally low rainfall, and if such conditions persist for long periods, they may spread to other components of the water cycle, such as soil, streams, and aquifers (Meng Dai et al., 2020). Drought is a phenomenon that has different meanings from different perspectives. So far, there have been many definitions of drought, but each of these definitions has taken into account a specific point of view. Accordingly, the lack of a comprehensive and accurate definition of drought and its different meanings from different points of view have hindered the understanding of the concept of drought. Since drought has a direct and indirect effect on all aspects of life and different parts of society, especially the change of the natural environment, the lack of understanding of its meaning causes doubt and recession in various economic, managerial, and policy-making sectors. Compared to other forms of natural disasters, drought is considered one of the most unknown and costly natural disasters (Hong et al., 2019). Finally, from the point of view of climatology, if the amount of rainfall falls to less than 60% of its annual normal in a period of more than two years in 50% of the region, there will be a drought and the economic-social effects will be widespread. All regions of the world may be affected by drought from time to time, but this situation is more observed in regions that are irregularly and randomly affected by climate systems (Raziei et al., 2012: 307). Knowing about the occurrence of drought in the future can be very useful to prevent or reduce the harmful effects of its occurrence. Thus, so far, there have been various methods related to drought prediction. Studies suggest that in most cases, statistical models are used to predict different types of drought, and these models are designed based on time series models. Regression and autoregression methods are types of time series models that are used in forecasts. These models are types of linear models in which the data are assumed to be fixed and have limited capabilities in dealing with non-linear and non-statistical data. According to what has been said, non-statistical and non-linear models are necessary in predictions. In recent decades, the use of artificial neural network technique among the types of non-linear models has shown brilliant results in predicting problems related to water engineering and hydrology. Today, one of the efficient methods that are widely used in air and water science is the artificial neural network (ANN). According to researchers, the main reason for its increasing acceptance and usage is its high power and speed in simulating the processes that need to be properly understood, which does not exist or checking them with other available methods is very difficult and time-consuming. In general, it can be expected that the artificial neural network model would be a strong model with high capability that can be viewed with a positive perspective in predicting climate-hydrological issues, especially since this network is able to extract the law governing data, even confusing data (Dehghani and Ahmadi, 2017). Neural networks are a kind of simplistic modeling of real neural systems that are widely used in solving various problems in science. The field of these networks is very wide, spanning from classification applications to applications such as interpolation, estimation, detection, etc. Perhaps the most important advantage of these networks is their notable ability in addition to their ease of use (Sayadi, 2007).

The first attempts at simulation using a logic model were made in the early

1940s by Warren McCullock and Walter Pitts, which is the building block of most artificial neural networks today. He approached the issue by creating a computational model for neural networks. The use of artificial neural networks for monitoring droughts, water resources management, and hydrology topics has started since the first decades of the 20th century. In water resources management, according to the nonlinear management of phenomena, artificial neural networks have shown the greatest ability in modeling and forecasting time series in hydrology and water resources engineering (Mishra & Desai, 2005). This method, which is one of the efficient and useful methods in climate science, has been an artificial neural network, which, according to researchers, whose main reason of popularity and acceptance is its high power and speed in simulating processes that require proper understanding, which does not exist, or it is very difficult and time-consuming to check them with the existing methods (Dehbozorgi et al.). DiKshit et al. (2022) used artificial neural network in predicting droughts in the 21st century. They found that by using a complex input, artificial intelligence-based solutions that are used to predict the drought of water and meteorological variables are promising, especially in complex geographical scenarios. Future research needs to focus on interpretable models, use deep learning architectures for long-term forecasting, and employ neural networks to predict different drought characteristics, such as drought propagation and sudden droughts. They also presented the most widely used neural network approaches in spatial drought forecasting, which serves as a foundation for future research in drought forecasting studies. Fan et al. (2021) evaluate the climate change effects on temperature, precipitation, and evapotranspiration in eastern Iran using CMPI5. The results revealed that the GFDLCM2, MPI, and IPSL models were more accurate in terms of precipitation, while the GISS E2 and GFDLCM2 models were the suitable option for predicting the maximum and minimum temperatures and evapotranspiration. Considering the evaluated parameters, minimum temperature, maximum temperature and evapotranspiration had approximately constant trends and were accompanied by a slight increase and decrease for the next two decades. However, for precipitation, large fluctuations were predicted for the next period. Further, in the study years for the four parameters in all simulated models, the RCP 8.5 scenario estimated a higher value than the RCP 4.5 scenario. Wabel et al. (2023) investigated the application of hybrid artificial neural network techniques for drought prediction in the semi-arid region of India. In this research, four ANN models have been developed, which include a normal ANN model and three hybrid ANN models: A: Wavelet-based ANN (WANN), B: Bootstrap-based ANN (BANN), and C: Wavelet-basedANN.Bootstrap(WBANN). They used the standardized precipitation evaporation and transpiration index (SPEI), which is one of the best drought indices identified for the studied area, as a variable for predicting drought. In their research, three drought indices, including SPEI-3, SPEI-6, and SPEI-12 represented drought conditions respectively. "Short-term", "medium-term" and "long-term" were used for a forecast period of one month to three months. The results of their research revealed that the bootstrap-based model offered the best performance for analyzing the uncertainty associated with different drought predictions. Among the developed models for drought forecasting for the period of 1 to 3 months, WANN and WBANN models outperformed simple ANN and BANN models for 3-SPEI-, 6-SPEI- and 12-SPEI- up to 3 months. Helmi & Shahidi (2023) employed SPI and SPEI to evaluate the effect of drought on the quality of surface water resources in the Kashafroud River). The results of their research showed that the average concentration of cations and anions in Olang Asadi station had an increase of about 5 times compared to Golmkan station. Finally, they concluded that with decline in rainfall, increase in temperature and drought, the water quality has decreased, especially in the downstream stations.

Evkaya & Kurans (2020) dealt with drought forecasting using neural network approaches with transformed time series data. The main goal of this research was to study drought forecasts for a meteorological station located in Marmara region. For this purpose, the widely used univariate drought index, the standard precipitation index for Bursa station, has been calculated. Thereafter, both the historical information retrieved from the time series data and its wavelet transformation were considered for examining automatic nonlinear models and automatic nonlinear regression with external input (NARX) and neural network (NN) type. According to a set of GOF[1] tests, the prediction performance of models with different numbers of hidden neurons was compared. Finally, the results of this study showed that with the transformation of wavelets (NARX-NN), the prediction capacity of the drought index increased. Amiri et al., (2024) tried to evaluate different drought indices to find the most applicable index in Aleshtar Plain. According to the results, the CZI index outperformed other indices by correctly estimating one out of four cases. They also investigated Spearman's correlation between precipitation parameters and drought indices. The results showed a significant correlation between all indices at all stations except for MCZI, which had a poor performance. Finally, considering the total scores, the CZI index, which obtained 21 points out of the total tests, was selected as the superior index for the region. The SPI and ZSI indices also yielded satisfactory and accurate results in this area.

Mishra et al. (2018) developed and analyzed artificial neural network models to forecast rainfall using time series data. In this study, they used the artificial neural network (ANN) technique to develop one-month and two-month prediction models for rainfall forecasting using monthly rainfall data from North India. In this model, feed forward neural network (FFNN) was used via back propagation algorithm and Levenberg–Marquardt training function. The performance of both models was evaluated based on regression analysis, mean square error (MSE), and magnitude of relative error (MRE). The proposed ANN model revealed promising results for forecasting and showed that the one-month forecasting model predicted better than the two-month forecasting model. This research also provided some future directions for precipitation forecasting and time series data analysis. Esfandiyari et al. (2016) used artificial neural network to predict drought in Isfahan. The results of their research revealed that among the different artificial neural network models, the perceptron network was able to predict SPI values in the future with a high correlation in most stations. Among the used stations, the Kohpayeh station indicated the best performance with the

1. Goodness-of-Fit

highest correlation coefficient equal to 0.96 and with the average performance error equal to 0.04. Ziyar station with a correlation of 0.86 and an average error of 0.087 presented a lower performance than other stations.

Sharifipour et al. (2021) examined four artificial intelligence methods for drought prediction. The results of their study showed that all networks had the ability to predict drought, based on the evaluation criterion of the macro, f1-deep learning network in the time scale of 1 month with 22.71% was the most inefficient method while decision tree with 64.65% was the most efficient method. However, with the increase of the time scale, the deep learning network improved its performance, so that in the time scale of 24 months with 65.35%, the best performance was related to the deep learning network followed by the support vector machine network with 57.40%. Salehi (2016) presented an algorithm to capture the uncertainty of artificial neural network model in drought prediction. The final results showed that although the ANFIS model presented a lower R2 value than the ANN model, it had less uncertainty than the ANN model, thus demonstrating the superiority of the ANFIS model over the ANN model. Dastorani et al. (2008) investigated the use of artificial neural network models in drought simulation and prediction. In this research, various artificial neural network structures were used in this respect, in which various meteorological parameters were employed as model inputs. The amount of rainfall as the main effective factor in drought for the next year was as the output of the models. The results showed that the dynamic structures of neural networks had a better performance in this field and especially TLRN networks provided the best results.

Golabi et al. (2013) examined the performance of artificial neural network and time series in modeling standard precipitation drought index (case study: selected stations of Khuzestan province). They reported that time series models outperformed artificial neural networks in predicting standard precipitation index values in all studied time periods. Also, multi-layered perceptron artificial neural networks showed a better performance than radial basis function artificial neural networks in all periods, and predicted the standard precipitation index better. Sadeghiyan et al. (2019) evaluated the performance of time series models, neural network, and neural-fuzzy inference system in meteorological drought prediction (case study: Semnan synoptic station). In this research, using time series methods, artificial neural network (ANN) and adaptive neural fuzzy inference system (ANFIS), they tried to provide suitable models for predicting the drought of Semnan city. In these modeling, monthly average data including rainfall, temperature, maximum and minimum temperature, relative humidity, maximum and minimum relative humidity, and SPI drought index were used during the statistical period of 1966 to 2013. Based on the results, SPI and its previous values outperformed precipitation. By examining all models, ARIMA model 6 (1,0,1)(0,0,1) with proper fitting of SPI data with the lowest root mean square error (RMSE) value equal to 0.442 in the training phase and 0.521 in the test phase as well as the most appropriate correlation coefficient (R) equal to 0.889 in the training phase and 0.846 in the test phase was selected as the best model. Using this model, SPI values were predicted for the next 12 time steps. ARIMA was followed by ANFIS model with RMSE = 0.513 MAE = 0.377 and correlation coefficient (R) equal to 0.861 in the training phase and RMSE = 0.518 = MAE = 0.41 and R = 0.841 in the test phase and ANN with values of 534 RMSE = 0.393 MAE and R = 0.85 in the training phase and RMSE = 0.532 MAE = 0.402 and R = 0.837 in the test phase.

Future studies need to focus on interpretable models, use deep learning architectures for long-term forecasting, and employ neural networks to predict various drought characteristics such as drought propagation and sudden droughts (Dikshit et al., 2022). Khoshgoftar et al. (2018) compared ARIMA and neural network methods in drought modeling and monitoring using remote sensing time series data (case study: Arak city). The results of their research indicated that TVX, NDVI, and SPI indicators can be used to predict the drought situation in the studied area. Najafi et al. (2021) predicted drought using artificial neural network and SPI index. In this research, the drought situation from 2020 to 2024 for the city of Kermanshah was determined by predicting precipitation amounts through artificial neural network, which was employed to predict each year from the data of the last five years, as well as calculating the SPI drought index on an annual scale. Mirdar Soltani et al. (2019) used the artificial neural network and regression method in the modeling of precipitation time series. In this research, the prediction of the annual rainfall time series of Nigeria was done using the artificial intelligence method. In this context, feedforward artificial neural network method was utilized for modeling and finally the results were compared with linear regression. The results revealed that the neural network method had a far better performance than linear regression. Yonesi et al. (2017) predicted drought using the combined wavelet-artificial neural network model and ARIMA time series model. In this research, artificial neural networks of multilayer perceptron (MLP) and radial basis function (RBF) of ARIMA time series, as well as artificial neural networks - wavelet of multilayer perceptron (WA-MLP) and radial basis function (WA-RBF) were used for prediction. In this regard, the rainfall data of Bedistan station with a statistical period of 44 years in the Shore catchment area were applied. The humidity condition was calculated using the standardized precipitation index (SPI) in the three-month period. To estimate the value of SPI in each time period, the corresponding values in previous times were employed. The results showed that the WA-MLP model predicted SPI values and short-term drought conditions with higher accuracy (R^2=0.87). Mohamadyarian et al. (2013) utilized the SPI index to zoning droughts in northeastern Iran. This study revealed that in recent years, the recurrence and persistence of this phenomenon has increased in all three provinces of North, Razavi, and South Khorasan. According to the results of the research, the most severe drought has occurred in the stations of Golmkan, Ghoochan, and Sabzevar, while the most moderate drought has been found in the station Golmakan, Torbetjam and Bojnourd floods.

Material and Methods

Study Area

As the capital of North Khorasan province (area of 35 km^2), Bojnourd city, with an area of 579,959 hectares covers about 20% of the total area of the province. This city is located in the northeast of Iran at 57 degrees and 20 minutes of geographic longitude and 37 degrees and 28 minutes of geographic latitude, in the south of the Kopeh Dagh mountain range and the east of the Aaladagh Mountain range. It is also located in the north of the Alborz Mountain. The altitude of Bojnourd is 1070 meters above sea level. According to the climate classification of the Köppen, the climate of the city is dry and semi-arid, and the maximum temperature in summer (August) reaches 40 degrees Celsius while the lowest temperature during the months of January and February reaches -15 degrees Celsius. Bojnourd city shares border with Republic of Turkmenistan from the north, Esfarayen city from the south, Shirvan city from the east, and Ashkhaneh and Jajarm cities from the west. Due to its mountainous nature, Bojnourd city is a favorable area for floods and destructions, especially with regard to the destruction of forests and pastures in the city, as well as illegal cultivation and excessive livestock grazing in the slopes and steep areas of this region; favorable conditions have been found for massive landslides and ditch erosions. Atrak river is the most important the river of the city. In terms of underground water sources, Bojnourd city has a large number of springs, deep and semi-deep wells, and aqueducts, so that about 90% of the city's water consumption is supplied from underground water. Finally, since the water resources of the city are often in the form of temporary springs, hand wells as well as temporary and permanent rivers, the lack of necessary credits for storing temporary and permanent river water is the main problem of the city regarding water resources and soil erosion.

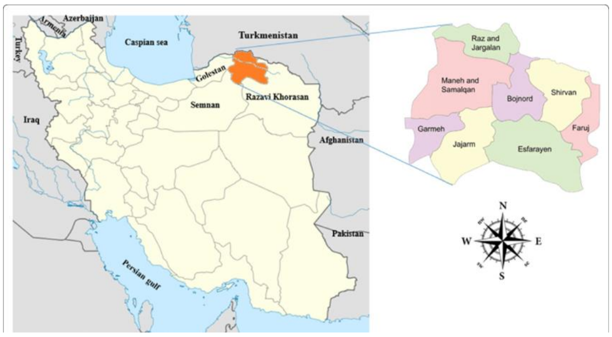


Fig 1. Geographical location of the study area

Methodology

This research has used the monthly statistics of climatic elements such as precipitation, relative humidity, temperature together with climatic indicators affecting drought from 1977 to 2018. In the neural network, 70% of the data were used for training (269 months from January 1, 1977 to the end of December 2008) and 30% of the data (from January 1, 2009 to the end of December 2014) for testing the models. The seals from 2020 to 2030 were predicted by the Box Jenkins model and simulated. The data used in the present study were standardized and then applied to the neural network model with a 70:30 combination (70% of data for training and 30% of data for testing). The reason for using relative humidity and temperature data is that during the occurrence of drought, the normal state of these data has undergone changes so that the lack of humidity due to the decline in the entry of moist air masses affects the relative humidity and causes its reduction. Temperature fluctuations are also influential and increase it. This is because the presence of humidity in the region is a good guarantee for reducing the range of temperature changes while its lack causes the range of temperature fluctuations to increase. In this research, nineteen climate indices with a time delay of one to three months along with monthly data of relative humidity and average monthly temperature with a delay of one to three months were used to predict and simulate drought. Standard precipitation index (SPI) has been used as the output of the models.

Standard precipitation index

This index was presented in 1993 by McKee and his colleagues. This index is obtained based on the difference of precipitation from the average for a certain time scale and then dividing it by the standard deviation, where the only effective factor in its calculation is the rainfall element. This index can be calculated in time scales of 3, 6, 12, 24, and 48 months. Another feature of the standardized precipitation index is that based on this index, in addition to calculating the severity of the drought its duration can also be determined. The standardized precipitation index is based on the probability of precipitation for each time period. Indeed, it is very important for the purpose of early warning and monitoring the severity of drought. This index is designed to quantify the lack of precipitation in multiple time periods (Bazarafshan, 2018). Experience has shown that the gamma distribution is a suitable distribution to fit on rainfall data; if it is assumed that the rainfall in a region follows the gamma distribution and χ is the rainfall values, the two-parameter probability density function of gamma is defined as follows: (Jahangiri et al. 2014)

$$f(x) = \frac{1}{\beta^{\alpha} r(\alpha)} x^{\alpha-1} e^{\frac{-x}{\beta}} \qquad x>0 \qquad (1)$$

In Equation 1, α is the shape parameter, β denotes the distribution scale parameter, and r(α) represents the gamma function, which are defined as follows:

$$\int_0^{\infty} \gamma^{\alpha-1} e^{-\gamma} dy = (\alpha)\Gamma \qquad (2)$$

The optimal β and α coefficients are also calculated through the following relations:

$$\hat{a} = \frac{1}{4A}\left[1 + \sqrt{1 + \frac{4A}{3}}\right] \qquad (3)$$

$$A = \text{In}(\bar{x}) - \frac{\sum \text{In}(x)}{n} \qquad (4)$$

$$\hat{\beta} = \frac{\bar{x}}{\hat{\alpha}} \qquad (5)$$

In order to calculate A, it should be noted that the parameter n is the number of rainfall observations. Gamma cumulative probability distribution is used to calculate the SPI index, whose relationship is as follows:

$$f(x) \frac{1}{\Gamma\hat{a}} \int_0^{\infty} t^{\hat{\alpha}-1} e^{-t} dt \qquad t = x/\hat{\beta} \qquad (6)$$

Since the logarithm value of zero is not defined in the above relation and the rainfall distribution may have zero values, thus in this situation cumulative probability is calculated from Equation 7.

$$H(x) = q + (1-q)F(x) \qquad (7)$$

In this relationship, the probability of rain q is zero. To calculate q, one can use the California equation (Equation 8).

$$q = \frac{m}{n} \qquad (8)$$

In this relationship, m denotes the number of zero data in the time series and n represents the total number of rainfall data. The next step in SPI calculation is to transfer the cumulative probability H(x) obtained from the cumulative gamma distribution to the normal distribution. It is a cumulative standard with a mean of zero and a standard deviation of one. Indeed, the standardized precipitation index is a variable of the standard normal distribution function, whose cumulative probability value is equal to the cumulative probability value of the considered variable in the gamma distribution. Drought is severe when the SPI index is -1 or lower, and if it becomes positive, the drought event will end. The duration of the drought period is determined by the beginning and end of negative SPI figures, and the cumulative values of SPI also show the magnitude and intensity of the drought period (Ensafi Moghadam, 2016). The classification of SPI index varies from Very severe drought to Moderate drought. Table 1 reports the classification of drought intensity based on the standard precipitation index.

Table 1. Classification of drought severity using the index (SPI) (Kamali & Nikzad, 1999).

SPI	Index value
>2	Excessive humidity
1.50 : 1.99	Very humid
1 : 1.49	Moderate humidity
-1 : 1	Normal
-1 : -1.49	Moderate drought
-1.5 : -1.99	severe drought
< -2	Very severe drought

Artificial Neural Network

Artificial neural networks, or neural networks (NNs) in simpler terms, are predictive methods based on simple mathematical models of the human brain. These methods enable the investigation of complex nonlinear relationships between the response variable and its predictors. In recent years, growing interest has been engendered for theoretical development of model-free intelligent dynamic systems. Artificial neural networks consist of several interconnected layers of neurons. Neurons are processing units that work in parallel in one layer. Each network consists of an input and output layer and possibly several intermediate hidden layers. When each neuron receives the input vector X from the previous neurons, it converts it to the y point with a matrix as well as functional operation and transmits the output to the next neurons. In this process, W and β are predetermined weight vectors and f is the transfer function:

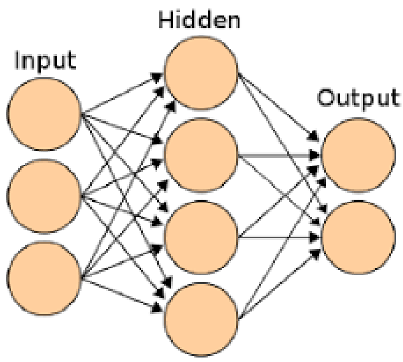
$$y= f(w.x- \beta)= f((\sum w_i x_i- \beta) \qquad (9)$$

This process reaches the final stage in the output layer whereby the optimal weights of the network are determined and fixed. Such a network, in which the messages pass only the input and output path to the front, is called a forward network. The method of determining the correct values of weights is called learning algorithm. The most popular learning algorithm is called error back propagation (BP)[1] in which, corresponding to the input matrix, the target matrix is also defined for the network; the learning process continues until the mean square of the error of the network reaches the lowest possible value. In addition to the input and output layers, such networks have also at least one hidden layer. The number of layers, the number of neurons in each layer, the weight matrix of each layer, the transfer functions as well as the learning algorithm are the determining elements in the design of a neural network. Neural networks, which are part of these dynamic systems, transfer the law hidden behind the data to the network structure by processing experimental data. These networks learn general rules based on calculations on numerical data (Menhaj, 2007). The structure of these networks follows biological neural networks, in which the way of communication between

1. Back-Propagation

its components is determined by adjusting the weights. After training the network, applying a specific input leads to receiving a specific response (Kia, 2007). The elements of the neural network are the input vector, weights, stimulus, and output functions. The basis of the neural network is indeed the simulation of thinking and processing the actions of the human brain, which is formed by modeling the cells of the community of neurons, where each neuron consists of three parts: framework, dendrite, and axon.

The learning function of the Marquardt-Levenberg algorithm and the driving function of the hidden layer is hyperbolic tangent, and the driving function of the output layer is linear. To train the network, the Marquardt- Levenberg algorithm, which follows the error back propagation rule, has been used. This co-algorithm is one of the standard numerical optimization tactics that tries to reduce calculations by not calculating the Hessian matrix. The Hessian matrix is calculated as follows:



Fi 2. A neural network with four inputs and a hidden layer consisting of three hidden neurons

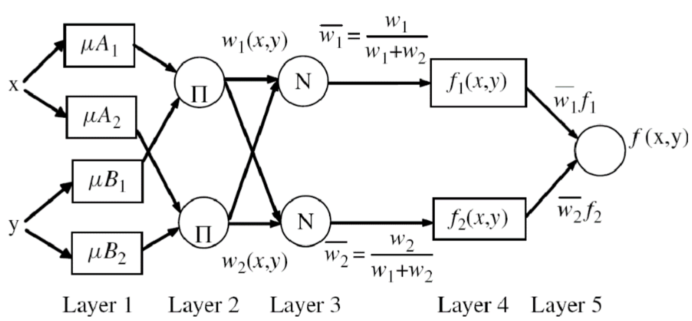


Fig 3. An example of a three-layer feed-forward network with an error back propagation training algorithm

Box Jenkins Model

Among the forecasting methods, the one-variable method is the Box-Jenkins model. This method basically involves fitting an ARIMA model to the data. In this method, after determining the order of differentiation as well as the order of each of the AR and MA processes, the parameters of the model are specified. The suitability of the model is checked by analyzing the residuals of the fitted model. If the model is correctly identified, the residuals should have the properties of independent normal random variables with zero mean and constant variance. For the prediction, first the time series of the data is drawn. A trending series is a non-stationary series, where stationarity can be checked by drawing autocorrelation diagram (ACF). A correlation chart in which r values do not approach zero at a reasonable rate indicates instability. If the values of r decline relatively quickly, the series will be stationary. However, if the values of the autocorrelation function slowly tend to zero, it confirms the instability of the corresponding series. Indeed, we need to calculate the sample autocorrelation function for the stationary time series. Therefore, any trend should be removed before calculating ACF.

Also, before any transformation in order to make the average of the series reliable, we should ensure reliability of its variance. The most important tool for variance analysis is the power transformation introduced by Box and Cox (1964). If, by drawing the Box-Cox diagram, the number one is within the 95% confidence limit, it can be accepted as an acceptable value of the transformation parameter. Therefore, data conversion can be omitted. The most important transformations are variance stabilizers and differential transformations. For the series to be stationary in the mean, it is necessary to convert it into a stationary series by performing appropriate transformations. In order to identify the model, it is necessary to draw the graph of the partial autocorrelation function of the stationary series and identify the orders of q plus p in the ARIMA model. In the next step, we fit this model to the data to predict the values. As a reminder, fitting means estimating the unknown parameters of the model. Finally, the suitability of the model is examined by analyzing the residuals of the fitted model.

Results and Discussion

The effective variables in monthly drought include temperature, relative humidity, and remote connection indices in the order of application in networks. Models 1 to 9 are simulated with climate index only. The model includes 10 to 24 climatic indicators along with the relative average and average monthly temperature of Bojnourd. The use of climate indicators alone would lower the accuracy of the neural network model, while the variables of relative humidity and temperature would enhance the accuracy of the models for monthly drought prediction. In the neural network model, first, only climatic indicators were used using the step-by-step regression method, and nine variables were selected by the regression model; models one to nine were implemented based on these inputs. Due to the low accuracy of the models, once again the variables affecting drought were identified from the climatic indices and monthly data of the synoptic station of Bojnourd, which include models 10 to 24. After developing the mass of models, 24 models from the post-release network were selected as suitable models (Table 2). Among the selected models, the BP19 model with 6 inputs and 1 hidden layer of 25 neurons was selected as the optimal model. The mentioned model had the highest correlation coefficient (R) value of 0.99 for the training phase as well as the highest correlation coefficient (R) value of 0.68 for the test phase, which caused the minimum error in the test phase. Meanwhile, the results of the test phase were close to each other in most of the models. RMSE in this model was estimated at 0.16 and MAE equal to 0.0071 in the training phase, while RMSE in this model was estimated at 0.59 and MAE equal to 0.759 in the testing phase.

Since the main aim of time series analysis is to identify and separate the effective factors in the past in order to predict and plan the future, thus, this analysis is related to data that are not independent and

Table 2. Specifications of the selected model in the neural network model in the monthly time frame

Test stage			Training stage			Specifications of selected models			
MAE	RMSE	R	MAE	RMSE	R	number of neurons	number of hidden layers	number of inputs	Model
0.0703	1.22	0.64	0.0083	0.21	0/96	20	1	8	BP01
0.0759	1.00	0.68	0.0037	0.20	0.98	25	1	8	BP02
0.1023	0.81	0.65	0.0077	0.17	0.95	20	1	8	BP03
0.0760	0.85	0.57	0.0135	0.08	0.98	30	2	8	BP04
0.0844	0.79	0.54	0.0196	0.22	0.99	15	2	7	BP05
0.1138	0.95	0.55	0.2225	0.13	0.95	25	2	7	BP06
0.0895	0.85	0.60	0.1400	0.18	0.96	30	3	7	BP07
0.0795	1.09	0.63	0.1492	0.09	0.99	20	3	9	BP08
0.0742	0.89	0.57	0.1731	0.22	0.95	25	3	9	BP09
0.1084	0.83	0.61	0.0902	0.23	0.96	15	2	9	BP10
0.1138	0.75	0.55	0.1204	0.11	0.98	20	2	10	BP11
0.1061	0.87	0.63	0.1292	0.22	0.95	30	4	10	BP12
0.1023	0.88	0.57	0.9860	0.08	0.99	20	4	5	BP13
0.0760	1.22	0.54	0.9668	0.17	0.96	15	3	5	BP14
0.8064	1.28	0.60	0.9868	0.14	0.98	25	3	5	BP15
0.0855	0.69	0.60	0.9880	0.09	0.99	10	2	6	BP16
0.0869	0.72	0.64	0.0083	0.22	0.99	15	2	6	BP17
0.0940	0.76	0.55	0.0067	0.12	0.95	20	2	6	BP18
0.0759	0.59	0.68	0.0071	0.16	0.99	25	1	6	BP19
0.0996	1.09	0.57	0.2226	0.17	0.96	15	1	5	BP20
0.0732	0.83	0.54	0.2213	0.18	0.98	10	4	5	BP21
0.0853	0.88	0.63	0.0603	0.12	0.94	15	4	5	BP22
0.0108	0.81	0.55	0.2646	0.15	0.95	25	4	5	BP23
0.1176	0.82	0.54	0.2213	0.17	0.99	30	4	5	BP24

are connected sequentially. Accordingly, to study the area in question, in the first stage, statistical information on the precipitation element has been collected at the selected station. To analyze the time series of seasonal rainfall, the inter-seasonal difference orders (d) of Bojnourd station were investigated. The results revealed that the seasonal rainfall time series of Bojnourd did not have any trend (random or non-random) and this trend was constant. In other words, over the last 30 years, there has been no evidence of a significant decrease or increase in seasonal rainfall at Bojnourd station. This does not indicate the temporal invariance of rainfall and its uniformity every year. Correlations in which the values cut off relatively quickly or decline relatively quickly indicate stationarity. If a time series has seasonal changes, its correlation graph also shows fluctuations. According to Figure 5 of the annual precipitation of Bojnourd station between the seals of 1977 and 2014, a descending trend can be observed in precipitation.

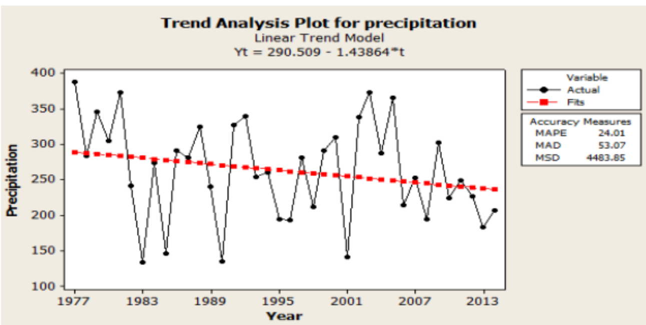


Fig 4. Bojnourd annual rainfall time series

Conclusion

Based on the results of autoregression orders and seasonal and inter-seasonal moving average results from the fitted models, the dependence of seasonal and inter-seasonal rainfall of Bojnourd station was investigated. In the study of the seasonal pattern, it was determined that Bojnourd station follows the seasonal pattern. In Bojnourd's seasonal autoregression, direct dependence of the rainfall of each season on the rainfall of the same season was found in 1 to 2 years before it. Also, the random fluctuation of seasonal rains 1 to 2 years ago had an indirect effect. In general, the timely prediction results indicated the effectiveness of the mentioned model in water resources management. Undoubtedly, what is meant by the word forecast in the hydrological studies of Mod is to present the values that have the highest probability of occurrence according to the historical time series, and it is not intended to provide exact values for future rainfall. This is because due to extreme temporal and spatial variability of climate parameters, this claim simply means a lack of correct understanding of the complex cycle of climate and its governing conditions. In any case, the researchers' studies indicate that the values obtained from these studies, despite the uncertainties governing them, have been very influential on the more efficient management of water resources. Therefore, the mentioned method can be used to know the amount of rainfall and the probability of drought in the coming years.

Drought is one of the natural phenomena that occurs in all climatic regimes and geographical regions, but its effects and frequency are abundant in arid and semi-arid regimes. The most important direct effect of drought is on the water resources of each region. Due to the ability of artificial neural networks (ANN) in predicting natural events, the use of this method for prediction and simulation has grown widely. In this research, the drought of Bojnourd city was predicted by the post-release network in a monthly period, and the results of the regression model were also mentioned to show the performance of the network and comparison. The accuracy and correctness of the predicted model was determined using evaluation methods such as correlation coefficient, absolute average of deviations, square of absolute average of deviations and percentage of absolute average of errors, where finally the best method was selected. Using the selected model, the amount of precipitation in 1991 and 1992 was predicted. According to the amount of errors, the neural model provided better results for prediction and simulation. Among the selected models of the post-release network, the BP19 model was selected as the selected model. The prediction data of the regression model was estimated using the ENTER method. RMSE in the model was estimated with a value of 0.16 for the training stage and the mean absolute error (MAE) was estimated at 0.0071. According to the research conducted worldwide, the Standardized Evaporation and Transpiration Index (SPEI), which is one of the best drought indicators identified for the studied area, was used as a variable to predict drought. The performance of both models was evaluated based on regression analysis, mean absolute error (MAE), and root-mean-square error (RMSE). Finally, the neural network method offered a far better performance than linear regression.

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