DESERT

DESERT
Online at http://jdesert.ut.ac.ir

DESERT 16 (2011) 39-48

Application of artificial neural networks on drought prediction in Yazd (Central Iran)

M.T. Dastorani[a*], H. Afkhami[b]

[a] *Associate Professor, Faculty of Natural Resources, Yazd University, Yazd, Iran*
[b] *MSc Graduate, Faculty of Natural Resources, Yazd University, Yazd ,Iran*

Received: 1 December 2009; Received in revised form: 1 July 2010; Accepted: 11 April 2011

Abstract

In recent decades artificial neural networks (ANNs) have shown great ability in modeling and forecasting non-linear and non-stationary time series and in most of the cases especially in prediction of phenomena have showed very good performance. This paper presents the application of artificial neural networks to predict drought in Yazd meteorological station. In this research, different architectures of artificial neural networks as well as various combinations of meteorological parameters including 3-year precipitation moving average, maximum temperatures, mean temperatures, relative humidity, mean wind speed, direction of prevalent wind and evaporation from 1966 to 2000, have been used as inputs of the models. According to the results taken from this research, dynamic structures of artificial neural networks including Recurrent Network (RN) and Time Lag Recurrent Network (TLRN) showed better performance for this application (due to higher accuracy of its out puts). Finally TLRN network with only one hidden layer and hyperbolic tangent transfer function was the most appropriate model structure to predict 3-year moving average precipitation of the next year. In facts, by prediction of the precipitation 12 months before its occurrence, it is possible to evaluate drought characteristics in advance. Results indicated that the combination of precipitation and maximum temperature are the most suitable inputs of the models to get the most outputs accuracy. In general, it was found that ANN is an efficient tool to model and predict drought events.

Keywords: Prediction; Drought; Artificial neural networks; Yazd; Recurrent Network; Time Lag Recurrent Network

1. Introduction

Drought is a generally occurring phenomenon which its effects intensify gradually. In some cases drought continues for longer time and causes destructive damages to human communities. During recent years climate change impacts have been combined with drought effects and caused serious problems in different parts of the World. Characteristics of a drought event are not often easily known until it occurs. During 1967 to 1992, about 50% of the 2.8 billion people who suffered from all natural disasters, have been affected by relatively sever drought. From 3.5 million people who were killed by disasters, about 1.3 million were victims of the drought (Obasi, 1994). About 50% of the World intensive populated regions containing the most agricultural lands are very vulnerable to the drought (USDA, 1994).

Prediction of drought can play an important role on mitigation of its effects. In other word, fundamental to mitigating the detrimental effects of droughts is the ability to forecast drought conditions in advance by either a few months or seasons. Accurate drought forecasts would enable optimal operation of water use systems. Various tools and methods for drought forecasting have been suggested and tested in different regions over

* Corresponding author. Tel.: +98 351 8210312,
Fax: +98 351 8210312.
E-mail address: mdastorani@yazduni.ac.ir

the last decades. Application of statistical models has a long history in drought forecasting. It goes back to Gabriel and Neumann (1962) and Torranin (1976) who were the first to apply Markov and regressions models for drought forecasting respectively. Yevjevich (1967) was also one of the first people who investigated the properties of droughts using the geometric probability distribution, defining a drought of *k* years as *k* consecutive years when there were not adequate water resources. Incorporating concepts of time series analysis, Saldariaga and Yevjevich (1970) employed the run theory for predicting the drought occurrence. Sen (1977) continued this line of work for Evaluating run sums of annual flow series and predicting water resources. Rao and Padmanabhan (1984) used stochastic models to forecast and simulate a yearly and monthly Palmer's drought index (PDI). Sen (1990) derived exact probability distribution functions of critical droughts in stationary second-order Markov chains for finite sample lengths and predicted the possible critical drought durations that may result from any hydrologic phenomenon. For characterizing the stochastic behavior of droughts, Lohani and Loganathan (1997) used the PDSI in a non-homogeneous Markov chain model and used an early warning system for drought management. Chung and Salas (2000) used low-order discrete autoregressive moving average (DARMA) models for estimating the occurrence probabilities of droughts. As it is seen, most of the methods used to predict drought in the past, are regression or auto-regression linear models which their ability is limited in dealing with natural phenomena with non-linear trend.

However, in recent decades artificial neural network models have shown great ability to deal with non-linear hydrology and water resources problems. Some advantages of ANN models are as follows:

1- Good ability to recognize the relationship between input and output data.

2. Considerable resistance to noisy and unreliable data.

3. Flexibility to cope with various ranges of data.

4- Easy to use and get acceptable outputs by training of the model.

Most of the previous investigations have indicated that ANN is an efficient tool with superior abilities, and is widely used in different areas of water-related research. Silverman and Dracup (2000) used Artificial Neural Networks for Long-Range Precipitation Prediction in California, and confirmed the possibility of making long-range predictions using ANNs and large-scale climatological parameters. Crespo J.L. and E. Mora (1993) used a feed forward multilayer perception with linear output deal with the problem of drought analysis. They tried to predict number of droughts; average drought length and deficit level, and compared the results with the actual data. The results showed that very simple neural network models can give fine results. Kim and Valdes (2003) developed a conjunction model to forecast droughts based on dyadic wavelet transforms and neural networks. The model was applied to forecast droughts in the Conchos River Basin in Mexico, which is the most important tributary of the Lower Rio Grande/Bravo. The performance of the conjunction model was measured using various forecast skill criteria. The results indicate that the conjunction model significantly improves the ability of neural networks to forecast the indexed regional drought. Hwang and Carbone (2009) applied stochastic approaches for estimating uncertainty of the process of drought index predictions. In this study National Oceanic and Atmospheric Administration (NOAA) Climate Prediction Center (CPC) seasonal forecasts and resampling of nearest-neighbor residuals were incorporated to measure uncertainty in monthly forecasts of Palmer drought severity index (PDSI) and standardized precipitation index (SPI) in central South Carolina. Results indicate good forecast performance with up to 3-month lead time for PDSI and improvements for 1-month-lead SPI forecasts. Moye *et al*, (1988) developed a pertinent probability distribution based on difference equations using the rudiments of run theory to predict drought. This distribution allows estimating the expected number of droughts of a pre-specified duration, and the average drought length over the desired time period. The applicability of this new mathematical approach is demonstrated using precipitation records for different climatic regions of Texas. Dastorani & Wright (2004) employed artificial neural networks to optimize the results of a hydrodynamic approach for river flow prediction. Using SPI as a drought index, Mishra and Desai (2005) employed stochastic models for forecasting droughts in the Kansabati River basin in India. Sarangi and Batacharia (2005) compared the application of regression methods and ANN models to predict the rate of erosion and sediment, and mentioned the superiority of ANN models over the regression methods. Ramireza *et al*. (2005) used ANN model for daily rainfall forecasting. Mishra and Desai (2006) used ANN technique to predict drought in Kansabati catchment in India. In this research, they also used ARIMA and SAMIRA models and compared the results to those of ANN, then recommended more efficiency of ANN over other used methods. Morid *et al* (2006) carried out an investigation on drought prediction using ANN models. In fact, it was tried to predict two drought indexes including EDI and SPI with 12 months lead time (12 months ahead) In Tehran, Iran. Mishra *et al* (2007) completed the research project on drought forecasting using a hybrid stochastic and neural network model, and stated that the hybrid model which was a combination of statistical linear and non linear models is a suitable method to model and predict drought events. Dastorani *et al.* (2009) used neural network as well as neuro-fuzzy models to reconstruct flow data series, and compared the results of these new techniques to some traditionally used methods, and mentioned superiority of the new techniques (especially neuro-fuzzy system) over traditional methods.

Present research describes the application of ANN to predict drought in hyper arid region of Yazd (with about 50 mm annual precipitation and more than 3500 mm potential evapotranspiration) in Iran. Different ANN architectures and also different combination of input variable including precipitation, evaporation, temperature, relative humidity, and wind speed and wind direction were used in this research. It must be added that precipitation data was used in different forms such as normalized rainfall data, SPI (Standardized Precipitation Index), seasonal and 3 year moving average of precipitation data. Monthly precipitation data of the next year (12 month before it occurs) was the output of the models in this research. The main purpose was to specify the best type and structure of the ANN and also the most appropriate input variables to have a reliable and accurate prediction of the drought.

2. Materials and methods

2.1. Study area and data

The study area was Yazd meteorological station located in Yazd city in Iran with geographical longitude of 54º, 17´ and latitude of 31º, 54´ with a hyper arid climate condition according to the extended Demartonn climatic classification. Various combinations of climate factors including monthly precipitation, evaporation, wind speed, prevalent wind direction, relative humidity, maximum temperature and mean temperature for the period of April 1953 to December 2005 were used as inputs of the models. Different types of ANN were used and evaluated (to choose the most appropriate one) in this research including Multi Layer Perceptron (MLP), Generalized Feed Forward (GFF), Modular Neural Network (MNN), Principal Component Analysis (PCA), Recurrent Network (RN) and Time Lag Recurrent Network (TLRN). Neuro Solution software package was used to construct and run the ANN models of this research.

In the first stage, normalized monthly precipitation was used to calibrate the models in all ANN structures. Data of 1975 to 2001 was used for training purpose and the data of 2002 to 2007 was used to test the model performance. In all models three transfer functions including linear, tangent hyperbolic and sigmoid were used and tested in hidden and output layers and then in each case the results were compared to the measured values to select the best structure for ANN models. For statistical comparison of the outputs to the measured values, coefficient of efficiency (R) and root mean square error (RMSE) were employed.

2.2. Drought prediction process

Today, due to advances in data processing technology as well as simulation tools, relatively acceptable prediction processes have been developed. In a prediction process, in addition to the accuracy and reliability, the timing is also an important task. What is important in timing is the lead time which is time period between the end of the prediction process and the occurrence of the related event. It is clear that when lead time is longer, the accuracy of the prediction becomes lower. In this research, prediction lead time was 12 months. In fact by using the information of the past and present, prediction is made 12 months later in the future. If *P* is the amount of precipitation of time *t* (present month), the amount pf precipitation in month 12 (P_{t+12}) can be dependent on different factors:

$P_{(t+12)}=f P_{(t)}, P_{(t-1)}, ….. P_{(t-n)}$ (1)

$P_{(t+12)}=f(T_{Max(t)}, T_{Max(t-1)}, ….. T_{Max(t-n)}$ (2)

$P_{(t+12)}=f(T_{av(t)}, T_{av(t-1)}, ….. T_{av(t-n)}$ (3)

$P_{(t+12)}=f RH_{(t)}, RH_{(t-1)}, ….. RH_{(t-n)}$ (4)

$P_{(t+12)}=f EP_{(t)}, EP_{(t-1)}, ….. EP_{(t-n)}$ (5)

$P_{(t+12)}=f Ws_{(t)}, Ws_{(t-1)}, ….. Ws_{(t-n)}$ (6)

$P_{(t+12)}=f Wd_{(t)}, Wd_{(t-1)}, ….. Wd_{(t-n)}$ (7)

Where:
P is the monthly precipitation (in the form of measured values, SPI or normalized values), *T* is the monthly air temperature, *RH* is the monthly relative humidity, *EP* is the monthly pan evaporation, *Ws* is the monthly prevalent wind speed and *Wd* is the direction of monthly most intensive wind. As multiple variables are used as inputs, the real prediction process is as follows:
$P_{(t+12)} = f\ [P_{(t)}, P_{(t-1)}… P_{(t-n)} + ….. + Wd_{(t)}, Wd_{(t-1)}, ….. WdP_{(t-n)}$ (8)

2.3. Artificial neural network

Artificial Neural networks operate on the principle of learning from a training set. There are a variety of neural network models and learning procedures. Two classes of neural networks that are usually used for prediction applications are feed-forward networks and recurrent networks. Both of these networks are often trained using backpropogation algorithm. When this algorithm is used for weight change, the state of the system is doing gradient descent; moving in the direction opposite to the largest local slope on the performance surface. In other words, the weights are being updated in the downward direction.

An advantage of backpropagation is that it is simple, but it has some problems:
1. The search for the optimal weight values can get caught in local minima, i.e. the algorithm thinks it has arrived at the best possible set of weights even though there are other solutions that are better.
2. Backpropagation is also slow to converge. In making the process simple, the search direction is noisy and sometimes the weights do not move in the direction of the minimum.
3. The learning rates must be set heuristically as there is no efficient rule.

Back propagation algorithm, developed by Rumelhart *et al.* (1986) is the most prevalent of the supervised learning models of ANN. This algorithm uses the steepest gradient descent method to correct the weight of the interconnectivity neuron. Back propagation algorithm easily solves the interaction of the processing of processing elements by adding hidden layers. In the learning process of this algorithm, the interconnection weights are adjusted using error convergence technique to obtain a desired output for a given input. In general, the error at the output layer in the back propagation algorithm model propagates backward to the input layer through the hidden layer in the network to obtain the final desired output. The gradient descent method is utilized to calculate the weight of the network and adjusts the weight of interconnections to minimize the output error. The error function at the output neuron is defined as:

$$E = \frac{1}{2}\sum_k (T_k - A_k)^2 \quad (9)$$

In which T_k and A_k *represent* the actual and predicted values of output neuron, *k*.

The final weight vector of the successfully trained network, which represents its knowledge about the problem, is used to apply to a new set of data to evaluate the performance of the model. In this research, for all applied models backpropogation algorithm with momentum term has been used.

2.4. Network design

Prediction networks usually take the historical measured data, and after some processing stages future condition is simulated. In this research after evaluation and testing of different ANN structures, TLRN and RN networks were selected due to their higher performance, and then between these two, TLRN network showed slightly higher abilities. Therefore TLRN was the final selected ANN type for drought prediction in this study. These two networks are briefly introduced in the below.
- Recurrent Networks (RN)

This type of network can be divided into fully and partially recurrent. Having a memory element distinguishes this network from MLP (Fig. 1).

Although recurrent networks are generally more powerful, they are more difficult to train and their properties are not as well understood. To construct the best architecture of the network for this study, many structures were tested and the results were considered. The number of hidden layers, number of processing elements in hidden layers, type of transfer and output functions and type of learning rule and its parameters have been considered and evaluated. After using different types of transfer and output functions for hidden and output layers, it was realized that a tangent hyperbolic function was the most suitable one for the hidden layer. However, for output layer the sigmoid function is a more compatible function. Between the dynamic processing elements of Gamma, Laguarre and Time delay, the Laguarre and Time delay gave better results.

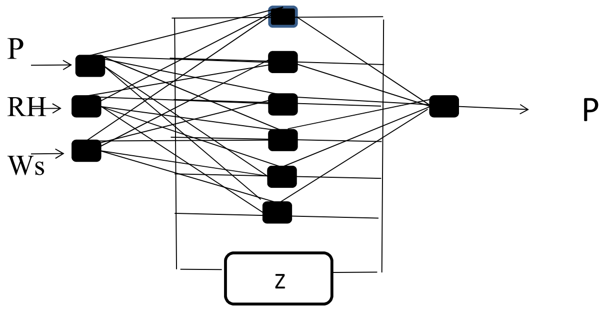


Fig. 1. Typical Recurrent Network with unit memory in hidden layer

-Time Lag Recurrent Networks (TLRN)
This type of network contains locally recurrent layers with a single adaptable weight (figure 2). As opposed to the recurrent networks stability in Time Lag Recurrent networks is guaranteed. It usually suits temporal problems with short temporal dependency however it does not seem appropriate for more difficult temporal problems. For this type of neural network it was found that the tangent hyperbolic function was the best one for hidden layer. However, for output layer the sigmoid function suited better for all tests. Between the dynamic processing elements of Gamma, Laguarre and Time delay, the Gamma was found to be the most compatible.

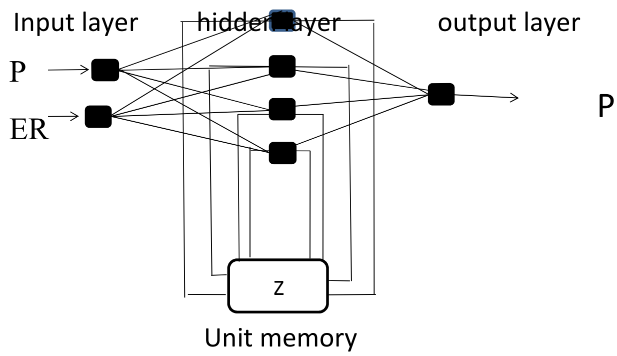


Fig. 2. Typical Time Lag Recurrent Network with unit memory in hidden layer

The most appropriate transfer function for both hidden and output layers was the hyperbolic tangent function, which was selected after a try and error process. Input data of the models are used in different formats as follows:

1- Measured values without any normalization or scale change.

2- Data used as standardized precipitation index (SPI) calculated by the following equation:

$$SPI = \frac{Po - \overline{P}}{\sigma} \qquad (10)$$

Where: Po is the measured data values. P is the mean of monthly measured data and δ is the standard deviation of monthly measured data. It needs to be mentioned that SPI is a common index used to specify and evaluate meteorological drought. In addition to the specification of drought period, severity of the drought is also determined using this index.

1- Normalized data using equation (11)

$$P_n = \frac{P_O - P_{Min}}{P_{Max} - P_{Min}} \tag{11}$$

Where: *Pn* is the normalized value. *Po* is the measured value. P_{min} and P_{max} are the minimum and maximum values of measured values respectively.

2- Seasonal data (data separated seasonally and used for the model).

3- year moving average for precipitation data.

It must be added that study area (Yazd) located in a hyper arid climate condition; therefore monthly as well as yearly precipitation data are very variable. This high variability of data decreases the accuracy of the predictions. To eliminate this problem, 3-year moving average of precipitation data was introduced to the model, and caused improvement of the result accuracy. In addition to different formats of data, different combinations of input variable were also used to take the most accurate results. Table 1 shows the type and code of variables used in this research.

Table 1. Type and code of the variable used to predict drought.

Variable No.		Variable	Code
1	-	Measured monthly precipitation	P
2	-	Standardized pre index	SPI
3	-	Normalized precipitation	Pn
4	-	Normalized Seasonal precipitation	Pns
5	-	Normalized 3-year moving average of precipitation	Pn3-yr-ma
6	-	Maximum temperature	Tmax
7	-	Mean temperature	Tmean
8	-	Mean wind speed	Ws
9	-	Direction of intensive wind	Wd
10	-	Pan evaporation	ER
11	-	Relative humidity	RH

The number of processing elements in input layer of the ANN was equal to the number of input variables. Only one hidden layer was the most appropriate number of hidden layer for all ANN structures. The number of processing elements in hidden layer is usually set by try and error (Cybenko, 1989). Different studies have proposed different rules to set the number of processing elements for this layer. For example, 2n+1, 2n and n have been suggested as the number of processing elements in hidden layer where n is the number of input variables (Lippmann 1987, Wong 1991 and Tang and Fshwick 1993). In the present study, 2n was the most appropriate number of processing elements (neurons) for hidden layer. For example, for a test where 2 input patterns are used the suitable number of processing elements is 4.

To compare the outputs of the simulations to the measured values and evaluate the applicability of the ANN types and architectures as well as type of input variables and combinations, RMSE and R^2 were calculated using following equations.

$$RMSE = \sqrt{\left(\frac{1}{P}\sum_{i=1}^{P}\left[(P_m) - (P_{es})\right]^2\right)^2} \tag{12}$$

$$R = \sqrt{1 - \frac{\sum_{i=1}^{n}(P_m - P_{es})}{\sum_{i=1}^{n}(P_m - \overline{P})}} \tag{13}$$

In which RMSE is the Root Mean Square Error and R^2 is the Coefficient of efficiency, P_m is the measured value, P_{es} is the predicted (estimated) value and $\overline{P}$ is the measured values mean.

3. Results and discussion

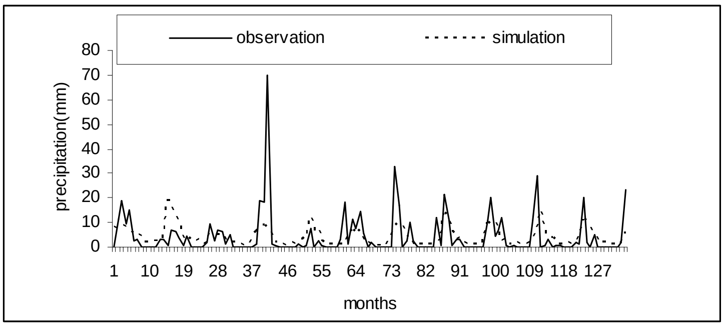
As Table 2 shows although both RN and TLRN in some cases presented quite acceptable results but the accuracy of the prediction made by TLRN is higher. As table shows the most accurate predictions have been produced when 3-year moving average precipitation and temperature (max and mean) data have been used as inputs to TLRN artificial neural network architecture. Other forms of precipitation data including SPI normalized and seasonal did not make considerable improvement on results accuracy.

It must be mentioned that Table 2 shows only a part of simulations which their outputs have been relatively acceptable (as samples for different input variables and ANN structures). As mentioned earlier, input data have been used in different forms including measured values (without scale change), SPI, seasonal and normalized values. Therefore, the values range of RMSE in Table 2 is various depending on the form of data used as inputs. Using 3-year moving average precipitation as well as maximum temperature as inputs of the models considerably improved the results. Apparently these variables have the most important role on prediction of the future precipitation. The combination of 3-year moving average precipitation and maximum temperature presented the best results with R of 0.95 and RMSE of about 0.05. In this simulation TDNN was the most suitable dynamic element of the TLRN network. The most appropriate convergence was obtained after 22000 iteration, and the prediction was for the year ahead (12 months lead time).

Table 2. Quality of the results produced by RN and TLRN networks using different input combinations

No	Input combination	Model	R	RMSE	Average value of prediction
1	1-8-9-11	RN	0.44	8.77	4.22
2	1-6	TLRN	0.64	5.4	4.6
3	2	RN	0.55	0.67	0.143
4	2	TLRN	0.60	0.60	0.371
5	3-11	RN	0.67	0.07	0.055
6	3-6-10	TLRN	0.67	0.08	0.070
7	4-6-8-9-11	RN	0.78	0.01	0.069
8	4-6-8-9-11	TLRN	0.56	0.08	0.059
9	5-7-8-9-11	TLRN	0.84	0.07	0.122
10	5-6-8-10	TLRN	0.85	0.08	0.118
11	5-11	TLRN	0.86	0.08	0.13
12	5-7-8-11	TLRN	0.88	0.08	0.124
13	5-6-10-11	TLRN	0.88	0.07	0.127
14	5-8-9-11	TLRN	0.88	0.07	0.096
15	5-6-8-11	TLRN	0.88	0.08	0.123
16	5-6-8-10-11	TLRN	0.89	0.07	0.121
17	5-8-10-11	TLRN	0.89	0.07	0.118
18	5-7-8-10-11	TLRN	0.89	0.07	0.123
19	5-7-8-9	TLRN	0.90	0.07	0.125
20	5-6-11	TLRN	0.90	0.07	0.106
21	5-10	TLRN	0.90	0.06	0.118
22	5-6-10	TLRN	0.92	0.06	0.119
23	5-8	TLRN	0.92	0.06	0.122
24	5-7-11	TLRN	0.93	0.06	0.111
25	5-7	TLRN	0.95	0.07	0.125
26	5-6	TLRN	0.95	0.05	0.135

Figures 3 to 8 show the outputs of a part of different simulations against the measured values. In these figures, “input combination no.” refers to the left column of Table 2.



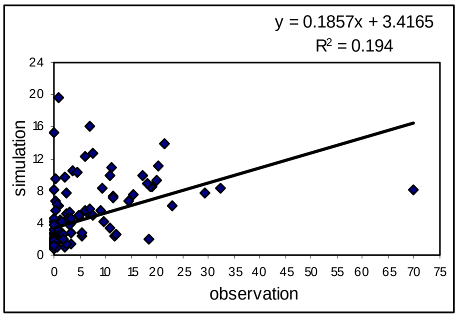


Fig. 3. Input combination no. 1 and Recurrent Network

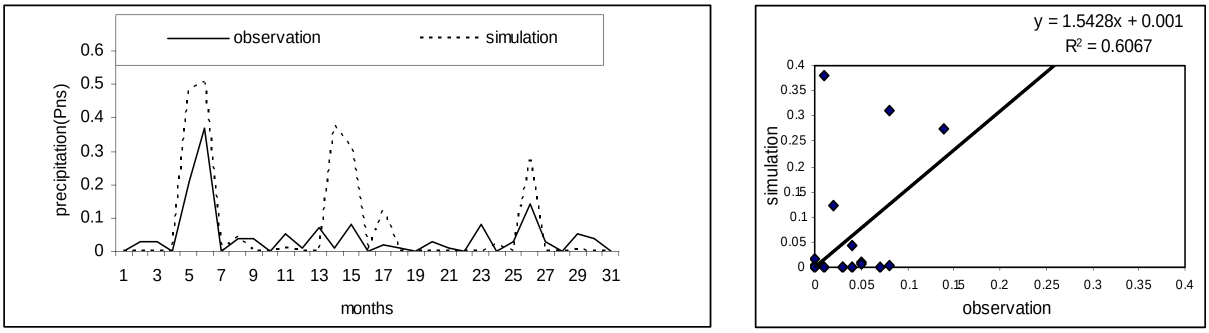


Fig. 4. Input combination no. 7 and Recurrent Network

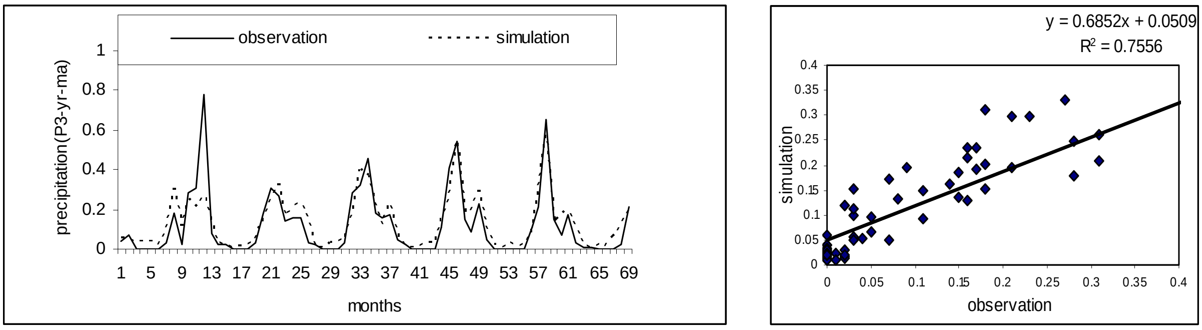


Fig. 5. Input combination no. 11 and Time Lag Recurrent Network

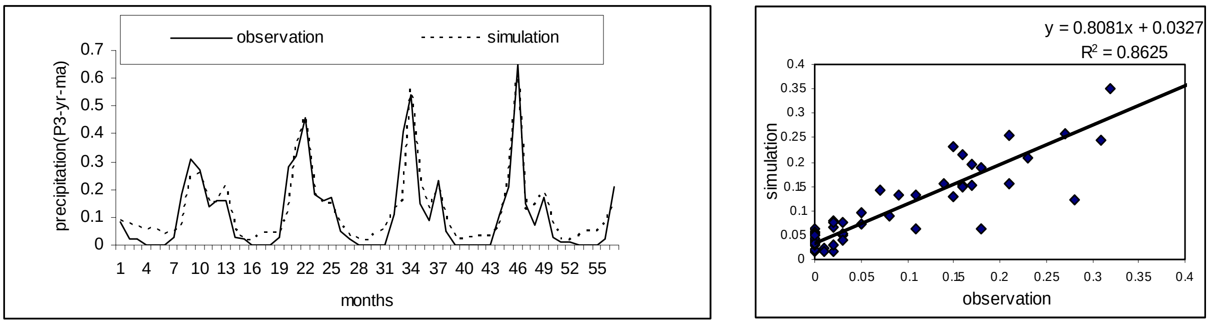


Fig. 6. Input combination no. 23 and Time Lag Recurrent Network

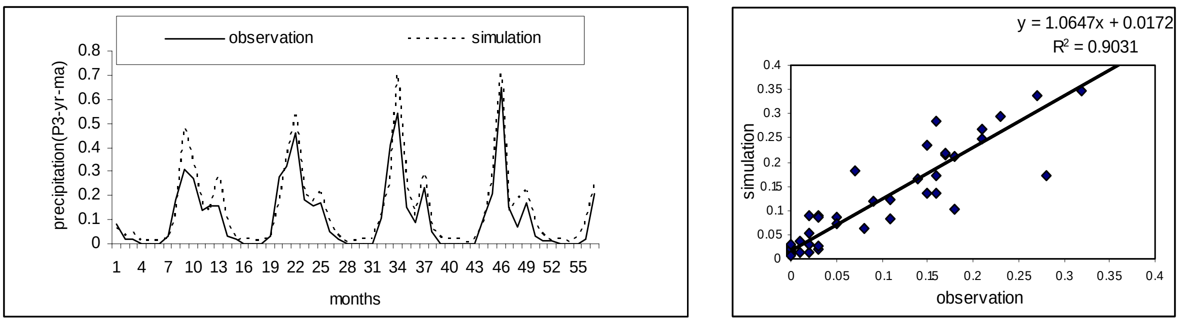


Fig. 7. Input combination no. 25 and Time Lag Recurrent Network

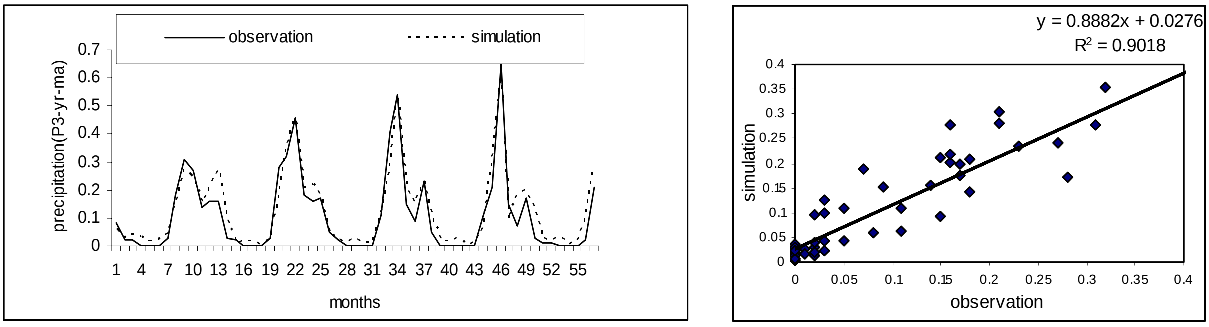


Fig. 8. Input combination no. 26 and Time Lag Recurrent Network

As figures show, the accuracy of predictions has been improved step by step by changing the type and number of input variables. The final obtained results of this study is encouraging, as precise prediction of a phenomenon like drought is quite a difficult task due to its complexity and variability. Comparing the results of this research to those carried out by Morid, *et al* (2007) and also Mishra and Desai (2006) indicates that although the study area of the present research has been located in a hyper arid climate condition where rainfall amount and distribution is extremely variable but the obtained predictions are quite acceptable. In Morid *et, al.* (2007) the best prediction had the R^2 value of 0.79 (R= 0.89) for the lead time of 6 months, in an area where mean annual precipitation varies from 700 mm to 120 mm (in different stations). About the results of Mishra and Desai (2006) the highest R for the predictions with 6 months lead time has been 0.631 (for one month lead time it is 0.925). Study area of Mishra and Desai (2006) is Kansabati catchment in India with mean annual precipitation of about 1268 mm. However, in the present study where mean annual precipitation is about 64 mm and for prediction lead time of 12 months the highest R for the predictions is about 0.95 which shows the higher quality of predictions in comparison to both mentioned studies. It is quite clear that normally as lead time increases the accuracy of predictions decreases, and also in humid climate conditions the variability of precipitation decreases and therefore the accuracy of predictions increase.

4. Conclusions

This paper presented the application of artificial neural network on drought prediction in the hyper arid climate of Yazd in central Iran. Study was completed in two phases: In first phase the most appropriate architecture of ANN was selected for drought modeling and prediction 12 months before it occurs. In the second phase it was tried to choose the most important and affective input variables for this specific application. TLRN with only one hidden layer containing four processing element with hyperbolic tangent transfer function and TDNN dynamic element and momentum learning rule was the suitable ANN architecture for this purpose. Between the input variable combinations of 3-year month's precipitation moving average and monthly maximum temperature presented the most appropriate prediction results. It must be mentioned that drought is a highly variable, randomic and complicated phenomena, which is quite difficult to predict especially with enough lead time and acceptable accuracy. Comparing the finding of this research to Mishra (2006) and Morid et.al (2007) indicated that accuracy of predictions in this research is higher than those presented in both mentioned studies.

References

Chung C.H., and Salas J. D. 2000, Drought occurrence probabilities and risks of dependent hydrologic processes, *Journal of Hydroogic Engineering* 5(3): 259–268.

Crespo J.L. and E. Mora, 1993, Drought estimation with neural networks, Engineering software advances, V. 18, Issue 3, PP 167-170

Cybenko, G., 1989, Approximation by superpositions of a sigmoidal function, Mathematics of Control Signals and Systems, 2, 303-314.

Dastorani M.T. and Wright N.G., 2004, A Hydrodynamic/Neural Network Approach for Enhanced River Flow Prediction, International Journal of Civil Engineering, 2 (3): 141-148.

Dastorani M.T. and Wright N.G., 2003, Flow estimation for ungauged catchments using a neural network method, 6th International River Engineering conference, Ahwaz, Iran.

Dastorani Mohammad T. & Nigel G. Wright, 2002, Artificial neural network based real-time river flow prediction, Proceedings of the Fifth International Conference of Hydrodynamics, July 1-5 Cardiff, UK.

Dastorani, M.T., Moghadamnia A., Piri J. and Rico-Ramirez M., 2009, Application of ANN and ANFIS Models for Reconstructing Missing Flow Data, Journal of Environmental Monitoring and Assessment, Springer, DOI: 10.1007/s10661-009-1012-8

Gabriel K.R., Neumann J., 1962, A Markov chain model for daily rainfall occurrences at Tel Aviv. Quarterly Journal of the Royal Meteorological Society, 88: 90–95.

Hwang Y. and G.J. Carbone, 2009, Ensemble Forecasts of Drought Indices Using a Conditional Residual Resampling Technique, Journal of Applied Meteorology and Climatology, 48, 1289-1301.

Kim T., and Valdes J. B., 2003, nonlinear model for drought forecasting based on a conjunction of wavelet transforms and neural networks, Journal of Hydrologic Engineering, 8(6): 319–328.

Lippmann R.P., 1987, an introduction to computing with neural networks, IEEE ASSP Mag., 4-22.

Lohani V. K. and Loganathan G. V., 1997, An early warning system for drought management using the Palmer Drought Index. *Journal of American Water Resources Association*, 33(6): 1375–1386.

Mishra, A.K., Desai, V.R., 2005b. Drought Forecasting using Stochastic Models Journal of Stochastic Environmental Research and Risk Assessment (Earlier Stochastic Hydrology and Hydraulics), Springer Verlag, Published online: http://dx.doi.org/10.1007/s00477-005-0238-4.

Mishra A.K. and Desai V.R, 2006, Drought forecasting using feed-forward recursive neural network, Ecological Modelling, 127-138.

Mishra A. K., Desai V. R. and Singh V. P., 2007, Drought forecasting using a hybrid stochastic and neural network model, Journal of Hydrologic Engineering, ASCE, Nov./Dec. 626-638.

Morid S., Smakhtin V. and Bagherzadeh K., (2007), Drought forecasting using artificial neural networks and time seried of drought indices, International Journal of Climatology, 27: 2103-2111

Moyé L.A., A.S. Kapadia, I.M. Cech and R.J. Hardy, 1988, The theory of runs with applications to drought prediction, Journal of Hydrology, Volume 103, Issues 1-2, Pp 127-137

Obasi G.O.P., 1994, WMO's role in the international decade for natural disaster reduction, Bull. Am. Meteorol. Soc.75 (1), 655-1661.

Ramıreza M.C.V., Velhob H.F.C. and Ferreiraa N.J., 2005, Artificial neural network technique for rainfall forecasting applied to the Sa˜o Paulo region, Journal of Hydrology, 301: 146–162.

Rao A.R. and Padmanabhan G., 1984, Analysis and modelling of palmer's drought index series. Journal of Hydrology, 68: 211–229.

Rumelhart D.E., Hilton G.E. and Willams R.J., 1986, learning representations by back-propagating errors. Nature 323: 533–536.

Saldariaga J., and Yevjevich V., 1970, Application of run-lengths to hydrologic series, Hydrol Paper, Colorado State Univ., Fort Collins, Colo.

Sarangi A., Bhattacharya A.K., 2005,.Comparison of Artificial Nrural Network and regression models for sediment loss prediction from Banha watershed in India. Agricultural Water Manangment, 78:195-208.

Sen Z., 1977, Run sums of annual flow series, Journal of Hydrology, 35: 311–324.

Sen Z., 1990, Critical drought analysis by second order Markov chain, *Journal of Hydrology*, 120: 183-202.

Silverman D. and J.A. Dracup, 2000, Artificial Neural Networks and Long-Range Precipitation Prediction in California, Journal of Applied Meteorology, 39: 57-66

Tang Z., Fishwick P.A., 1993, Feedforward neural nets as models for time series forecasting, ORSA J. Comput.5 (4): 374-385.

Torranin P., 1976, Unpredictability of hydrological drought, In Proceeding of the Second International Symposium in Hydrology, Fort Collins, Colorado, 595–604.

USDA, 1994, Major World crop areas and climatic profile, World Agricultural Outlook Board, US department of Agriculture, Agricultural Handbook No.664, PP.157-170.

Wong F.S., 1991, Time series forecasting using backpropagation neural networks, Neurocomputing 2: 147-159.

Yevjevich V., 1967, an objective approach to definitions and investigations of continental hydrologic droughts, Hydrol. Papers, Colorado State Univ., Fort Collins, Colo.